VERMONT AGENCY OF TRANSPORTATION

VERMONT SMART GROWTH, VMT, AND GHG RESEARCH PROJECT REPORT

Technical Report | July 2024

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VERMONT SMART GROWTH, VEHICLE MILES TRAVELED, & GREENHOUSE GAS RESEARCH

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16. Abstract			

16. Abstract

The Global Warming Solutions Act (GWSA) set targets for Vermont to reduce greenhouse gas (GHG) emissions to 80% below 1990 levels by 2050. Recognizing that transportation accounts for the largest share of the State's total GHG emissions, the Climate Action Plan identified reduction in vehicle miles traveled (VMT) as a key pathway to meet targets and acknowledged the need to quantify the effect of smart growth strategies on VMT and GHG reduction in the Vermont context. This project explored the hypothesis that compact, mixed use development patterns generate fewer VMT and GHG emissions per person than more dispersed or rural settlement patterns. A model was developed relating built environment measures in Vermont communities to weekly per capita VMT estimates by leveraging passively collected, location-based services data. Several future scenarios were quantified to demonstrate the degree to which smart growth strategies can reduce VMT to meet transportation related GHG emission reduction targets and quantify the co-benefits of smart growth strategies beyond GHG emission reductions.

Focusing future growth in areas with low VMT and emulating prototype smart growth communities were most effective in reducing weekly per capita VMT overall, reducing VMT by an estimated 10 miles per person per week compared to more dispersed growth scenarios. Smart growth strategies were demonstrated to contribute to over 15% of the annual GHG reduction needed to achieve the 2050 GWSA targets. Conversely, dispersed settlement patterns produced an increase in emissions of up to 20% of the annual target, working against other mechanisms to drive down annual GHG emissions. Future scenarios demonstrated the co-benefits of smart growth strategies on safety with 1 avoided traffic death and over 30 avoided traffic injuries per year; health with reduced physical inactivity mortality saving nearly 4 lives annually; and maintenance with reduced annual maintenance costs by over $1.5 million. Case study communities offered further insights on VMT and GHG reductions possible through implementation of smart growth strategies. Specifically, the scenario results for case study communities highlighted the need for jobs in proximity to denser, mixed land uses to achieve targeted VMT and GHG reductions; the opportunity to enhance the existing patterns in Vermont of denser centers surrounded by more rural areas through context sensitive modifications to density, land use mix, infrastructure, and proximity to jobs; and, the influence of regional neighbors on VMT where condensed movement patterns within town centers are often complemented by more expansive travel patterns to adjacent communities.

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EXECUTIVE SUMMARY

The Global Warming Solutions Act or Act 153, enacted by the Vermont Legislature in 2020, set targets for Vermont to reduce greenhouse gas (GHG) emissions to 26% below 2005 levels by 2025, 40% below 1990 levels by 2030, and 80% below 1990 levels by 2050. Recognizing that transportation accounts for the largest share of the State's total GHG emissions at 39.7%, the Climate Action Plan identifies reduction in vehicle miles traveled (VMT) as a key pathway for meeting GHG reduction. The Climate Action Plan further identified a high priority action to quantify the effect of smart growth strategies on VMT and GHG reduction in the Vermont context.

Delivering on this high priority action in the Climate Action Plan, this project explored the hypothesis that compact, mixed use development patterns generate fewer VMT and GHG emissions per person than more dispersed or rural settlement patterns. Further, this study explored built environment relationships with VMT across Vermont, inclusive of many rural areas across the state, which will help to fill a critical gap in the literature. Current and future patterns of built environment development, land use, population growth, and travel behavior were quantified in several scenarios to fulfill two primary focal points of the research:

- Demonstrate the degree to which smart growth strategies in the Vermont context can reduce VMT to meet transportation related GHG emission reduction targets; and,
- Quantify the co-benefits of smart growth strategies beyond GHG emission reductions to include health benefits of increased active and multimodal travel, safety benefits of reduced VMT, reduced maintenance associated with fewer vehicles and possibly fewer lane miles, and increased economic activity located in downtowns and community centers.

The consultant team of VHB and RSG worked in close collaboration with a Champion from the Vermont Agency of Transportation's Policy, Planning and Research Bureau, as well as a Technical Advisory Committee (TAC) composed of representatives from:

- Agency of Transportation | Environmental Policy & Sustainability
- Agency of Transportation | Highway Division
- Agency of Transportation | Policy, Planning and Intermodal Development Division
- Agency of Digital Services | Vermont Center for Geographic Information
- Agency of Commerce & Community Development | Community Planning & Revitalization
- Agency of Natural Resources | Climate Action Office
- Vermont Natural Resources Council
- Conservation Law Foundation

The study's TAC provided integral feedback at key decision points regarding the study scope, data exploration, findings, and applications discussed in greater detail below.

Passively collected, location-based services (LBS) data were leveraged to develop weekly per capita VMT estimates for the state. Location based data were gathered for any device seen within Vermont's boundary in each season of 2019. Devices were filtered to remove sporadic or anomalous behavior. Data processing entailed enriching the device data to identify device locations using transportation network, land use, and point of interest features. For each device's records, stops and anchor locations as well as visits or dwell times were determined. Anchor locations (e.g., home, work) were classified and trips between locations were identified and assigned trip attributes. Post-processing entailed assigning quality tiers and removing suspected commercial trucks and junk devices. All non-Vermont residents were also removed. The data were resampled to extract the most representative week for each device in each season. Based on the characteristics of each trip, mode was assigned categorizing every trip into motorized, non-motorized, flights, and ferry trips. A two-stage weighting was applied to scale the sample of devices to represent weekly VMT by all Vermont residents. A demographic expansion factor was used to scale the sample based on how many people are represented by a given device. An adjusted VMT factor was used to account for missing VMT relative to the Local Area Transportation Characteristics for Households estimates. This procedure resulted in LBS-derived VMT estimates based on a data set containing 750,000 trips from nearly 30,000 devices seen throughout 2019.

Informed by the body of research that explores the relationship between travel behavior and the built environment, a database of built environment measures was assembled. The built environment measures focused on representing the ‘five D’ variables that influence travel behavior, including density, diversity of land use, design, destination accessibility, and distance to transit. VMT estimates and built environment measures were resolved to a hex-grid spatial database across the state of Vermont to develop a model that relates the built environment measures to the weekly per capita VMT estimates.

Future growth scenarios were developed to represent a range of possible growth and built environment changes. The scenarios explored a few common themes – dispersed growth patterns versus concentrated growth patterns, concentrated growth prioritized to places with density versus places with low VMT, and employment growth in balance with concentrated residential growth versus allocated to places near established cores or lower density areas. The model was applied to these scenarios to predict how VMT and other related benefits might change under different future growth scenarios. The scenarios forecast growth to 2035 and 2050 time horizons, included both a low and high growth scenarios, and derived various growth patterns as follows:

- ***Dispersed growth:*** In this scenario, low-density residential development occurs across all developable land, ignoring existing community designations and wastewater service areas. From a smart growth perspective, this represents a “worst case” scenario.
- ***Concentrated growth, concentrated jobs:*** In this scenario, future residential and employment growth is concentrated in already dense neighborhoods. Growth “overflows” to less dense neighborhoods when density exceeds a maximum density threshold.

- ***Concentrated growth, dispersed jobs:*** Like above, future residential growth is concentrated in already dense areas of the state. However, employment growth is allocated to lower density areas (i.e., greenfield development of employment centers).
- ***Concentrated growth, balanced land use:*** In this scenario, future development is focused on copying places in Vermont that exemplify smart growth principles today. Growth is allocated so that future development mirrors the lowest VMT neighborhoods in Vermont currently by leveraging prototype smart growth neighborhood attributes.
- ***Concentrated growth, unbalanced land use:*** This scenario allocates residential growth as described above. Employment growth, on the other hand, occurs in locations near established cores, but not in locations with high population density.

The resulting VMT estimates were then used to estimate benefits associated with each scenario. In addition to changes in GHG emissions—the primary benefit explored in this study—co-benefits were estimated to quantify the following:

- **Safety:** Changes in fatal and injury crashes, for motorized and non-motorized travel modes;
- **Health:** Impacts associated with changes in physical activity from nonmotorized travel;
- **Cost Reductions:**
    - Changes in infrastructure maintenance costs associated with VMT; and,
    - Potential reductions on infrastructure construction costs associated with more compact development patterns.

Based on the analysis of future scenarios, concentrated growth reduced VMT by nearly 10 miles per person per week compared to dispersed patterns, demonstrating the opportunity for smart growth strategies in Vermont and the impact they might have on travel patterns. Of the scenarios evaluated, focusing growth in areas with low VMT and emulating prototype smart growth communities with low VMT were most effective in reducing weekly per capita VMT overall. **The GHG emission reduction potential of smart growth, based on scenario evaluations, could amount to over 15% of the annual reduction needed to achieve the 2050 Global Warming Solutions Act targets.** Conversely, dispersed settlement patterns can produce an increase in emissions of up to 20% of the annual target, working against other mechanisms to drive down annual GHG emissions. Beyond VMT and GHG emission reductions, the most effective future scenarios (i.e., emulating the lowest VMT communities) demonstrated the benefit of smart growth strategies on outcomes associated with the transportation system in Vermont, including:

- safety outcomes with **1 avoided traffic death** and over **30 avoided traffic injuries per year**;
- health outcomes with reduced physical inactivity mortality by **saving nearly 4 lives annually**; and,
- maintenance outcomes with **reduced annual maintenance costs by over $1.5 million**.

There are communities within Vermont where the built environment supports more condensed travel patterns. There are also locations in Vermont that seem to produce more VMT and GHG emissions on average even though characteristics of their built environment reflect patterns of smart growth. Zooming in on a few communities through the lens of these scenarios illuminated some key takeaways for contextualizing the results of this study, including:

- **Denser, mixed land uses require job proximity** to achieve targeted VMT and GHG reductions, necessitating holistic planning to co-locate jobs relative to compact centers and livable neighborhoods to strike a jobs-housing balance;
- **Vermont's historical settlement patterns and predominant landscape of denser centers surrounded by more rural areas lends itself inherently to smart growth strategies** where the state's "good bones" can be enhanced through thoughtful, context sensitive modifications to density, land use mix, proximity to jobs, and civil infrastructure;
- **Regional neighbors influence VMT and travel patterns** where condensed movement patterns within town centers may serve some needs complemented by more expansive travel patterns to adjacent communities to serve other needs.

These communities offer insights on the potential scope and scale of VMT and GHG reductions that are possible through implementation of smart growth strategies. The work at the local and regional level to encourage and operationalize smart growth principles can have a statewide impact, contributing over 15% of the year-over-year GHG reduction targets required to meet the goals set forth in the Global Warming Solutions Act.

1.0 INTRODUCTION

The Global Warming Solutions Act or Act 153, enacted by the Vermont Legislature in 2020, set targets for Vermont to reduce greenhouse gas (GHG) emissions to 26% below 2005 levels by 2025, 40% below 1990 levels by 2030, and 80% below 1990 levels by 2050. Recognizing that transportation accounts for the largest share of the State's total GHG emissions at 39.7%, the Climate Action Plan identifies reduction in vehicle miles traveled (VMT) as a key pathway for meeting GHG reduction. The Climate Action Plan further identified a high priority action to quantify the effect of smart growth strategies on VMT and GHG reduction in the Vermont context.

This project evaluates how future patterns of land use and built environment development for the state of Vermont may influence transportation GHG emissions. The project explores the overarching hypothesis that compact, mixed use development patterns intrinsically generate less VMT and GHG emissions per person than more dispersed or rural settlement patterns. In such an exploration, the two primary focal points of the research were to:

1. Demonstrate the degree to which smart growth strategies, particularly in the Vermont context, can reduce VMT to meet transportation related GHG emission reduction targets as promulgated in the Vermont Pathways Analysis Report ("Pathways").
2. Quantify the co-benefits of smart growth strategies beyond GHG emission reductions. Such benefits include health benefits of increased active and multimodal travel, safety benefits for reduced VMT, reduced maintenance associated with fewer vehicles and possibly fewer lane miles, and increased economic activity located in downtowns and community centers.

To achieve these research objectives, a project was funded through the VTrans Research Program assembling a team including a project champion from VTrans Policy & Planning and researchers from RSG and VHB. In order to guide the research project and support key decision making, a Technical Advisory Committee (TAC) was assembled with representation from the Agency of Transportation's Highway Division, Environmental Policy & Sustainability Section, Policy Planning and Intermodal Development Division, Agency of Digital Services' Vermont Center for Geographic Information, Agency of Commerce & Community Development's Community Planning & Revitalization Section, Agency of Natural Resources' Climate Action Office, Vermont Natural Resources Council, and Conservation Law Foundation. With this team and advisory assembled, the project encompassed five phases of work:

- **A review of built environment measures and travel behavior.** Described in Chapter 2, this foundational step reviewed academic literature exploring how the built environment shapes travel behavior. Findings from this review informed which built environment measures were to be included in a spatial database developed for the state of Vermont and used in the other phases of this project.
- **Developing estimates of baseline per capita VMT for Vermont residents.** The next phase of work, described in Chapter 3, leveraged passively collected location data to

develop estimates of typical weekly VMT based on a sample of approximately 30,000 Vermonters.

- **Developing a Vermont-specific VMT model.** The third phase of work combined the spatial database developed during the first phase with VMT estimates from the second phase to develop a regression model that can be used to estimate or predict how per capita VMT changes when built environment measure(s) in the spatial database change. This work is described in Chapter 4.
- **Estimating VMT for future development scenarios.** The fourth phase of work, described in Chapter 5, developed future growth scenarios in conjunction with the project's Technical Advisory Committee (TAC) for how the built environment might grow and change. The model developed in the third phase was applied to predict how these different scenarios would impact VMT and other benefits associated with reduced VMT. Potential benefits related to changes in VMT included greenhouse gas (GHG) emission reductions, public health and traffic safety benefits, and cost savings for VTrans. A dashboard tool was developed to support decisionmakers by providing a means to interact with scenario parameters and model outcomes in a GIS environment at the neighborhood scale and summarize the future scenario outcomes at the statewide scale.
- **Contextualizing future scenarios with case studies.** Finally, case study narratives were developed for several Vermont communities. Illustrative examples from different Vermont communities across the spectrum of outcomes for future scenarios offers a roadmap for using the dashboard tool to evaluate localized and regional smart growth initiatives. The case studies and final takeaways for the study are described in Chapters 6 and 7, respectively.

2.0 BUILT ENVIRONMENT MEASURES

The first phase of this project reviewed existing literature on how the characteristics of the built environment impact travel behavior. This work informed the development of a spatial database of built environment measures comprised of the characteristics most relevant to understanding this relationship between the built environment and travel behavior in Vermont. A foundational step in understanding how the built environment shapes travel behavior is developing measures that describe characteristics of the built environment. This chapter summarizes this literature with three specific aims:

- Inform the selection of built environment measures included in the spatial database.
- Provide guidance on data sources and methods used to develop such measures.
- Identify limitations and considerations that should be made in exploring the relationship between the built environment and travel behavior in the Vermont context.

Section 2.1 presents a high-level overview of the literature review and Section 2.2 digs deeper into how specific built environment measures shape travel behaviors. Section 2.3 introduces three cross-cutting themes and Section 2.4 summarizes limitations of the existing literature. Finally, Section 2.5 discusses issues specific to the Vermont context and Section 2.6 describes the database of built environment measures. An annotated bibliography is provided in Appendix A for reference.

2.1 LITERATURE REVIEW

The literature investigating the relationship between the built environment and travel behavior is large and complex. Several recent review papers have succinctly summarized this expansive body of work. Rather than conducting our own independent review of the literature, we instead began this review by identifying these review papers. We then conducted a brief supplemental review using the snowball method (i.e., identifying more recent papers that cited these keystone reviews) and targeted searches with keywords to uncover work in the rural context. Identifying cross-cutting themes, we performed a more targeted review of studies exploring the relationship between VMT and the built environment in the context of these themes.

Overview

The keystone papers used in our snowball sampling approach—two recently authored by Reid Ewing and others—explore the relationships between the built environment and travel behavior using the ‘five D’ variables to frame their findings.[1] These variables seek to independently characterize aspects of the built environment that influence travel choices. Each of these five elements typically represent built environment land use attributes that may or may not be intentionally designed to impact travel patterns:

[1] These two keystone papers are Ewing and Cervero 2017 and Ewing et al. 2019

The Five Ds

- *Density:* The number or concentration of land use opportunities per square mile, such as dwellings, households, people, and jobs.
- *Diversity:* The number and mix of different land uses within a certain area, which is often measured by land use mix and jobs-housing balance.
- *Design:* Physical features of the built environment that impact travel patterns, such as sidewalks, cycle paths, and street design. Metrics that are used to quantify design include intersection/street density and number of 4-way intersections.
- *Destination Accessibility*: When destinations are more accessible, people may be able to travel shorter distances and/or use non-automobile modes to reach goods and services.
- *Distance to Transit:* The proximity to transit service.

Additional dimensions (Ds) have been proposed to supplement the original five Ds research. Travel demand management is a sixth D that is sometimes included in this research and consists of policy interventions or strategies which are explicitly designed to impact travel demand.[2] Demand management is a broad category that may or may not include land use elements and includes strategies such as parking pricing, transit incentives, and technology. This review focuses on the traditional "five Ds" described above.

2.2 VMT AND THE FIVE DS

Within the five Ds framework, certain dimensions may impact different travel choices in different ways. For example, physical design and land use diversity may be more influential on mode choice decisions whereas destination accessibility may be more influential on trip distance. Importantly, VMT is influenced by many travel decisions, including mode choice, deciding when/how often to travel, and how much distance needs to be travelled to reach destinations. This complexity is well-described in Ewing et al:

> "…destinations that are closer, as a result of higher development density or greater land use diversity may be easier to walk or bike to than drive to. Also, origins that are closer to high quality transit, and hence to destinations regionally via transit, render transit a viable alternative to the automobile. People living in such environments will tend to own fewer vehicles. Also, a household's vehicle fleet can be utilized more efficiently when destinations are close by, as trip chaining and carpooling become more practical.[3]

Despite this complexity, the research consistently finds that households that live in dense, mixed-use, and transit served areas tend to drive less compared to households in areas that do not have these characteristics.

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[2] Ogra, 2014
[3] Ewing et al. 2019

Quantifying the Effects of the Five Ds on VMT

A prevailing approach in the literature is to develop *elasticities* describing how changes in the five Ds can be expected to change VMT. *Elasticity* refers to the relative change in an outcome variable (VMT) given a change in an exploratory variable (one of the five Ds). For example, the elasticity of a VMT in relation to the density of bicycle lanes would describe the expected percent change in VMT given a 1% change in the density of bicycle lanes. Ewing and Cervero presented elasticities for the five Ds using different methods and assert that the elasticities in the second column of the table below are the most reliable estimates available (Table 1).

TABLE 1. VMT & 5 D VARIABLE ELASTICITIES[4]

		WEIGHTED AVERAGE ELASTICITIES [a]	WEIGHTED AVERAGE ELASTICITIES [b]	META-REGRESSION ELASTICITIES ACCOUNTING FOR SELF-SELECTION [b]	META-REGRESSION ELASTICITIES ACCOUNTING FOR SELF-SELECTION AND REPORTING BIAS [b]
Density	Household/population density	-0.04	-0.15	-0.22	-0.22
	Job density	0.00	-0.01	-0.07	-0.07
Diversity	Land use mix (entropy index)	-0.09	-0.07	+0.03	+0.11
	Jobs-housing balance	-0.02	-0.03	NA	0.00
Design	Intersection/street density	-0.12	-0.16	NA	-0.14
	% 4-way intersections	-0.12	-0.06	NA	-0.06
Destination Accessibility	Job accessibility by auto	-0.20	-0.25	NA	-0.20
	Job accessibility by transit	-0.05	-0.07	NA	0.00
	Distance to downtown	-0.22	+0.01	-0.29	-0.63
Distance to Transit	Distance to nearest transit stop	-0.05	-0.06	NA	-0.05

[a] Ewing & Cervero sample
[b] Stevens sample

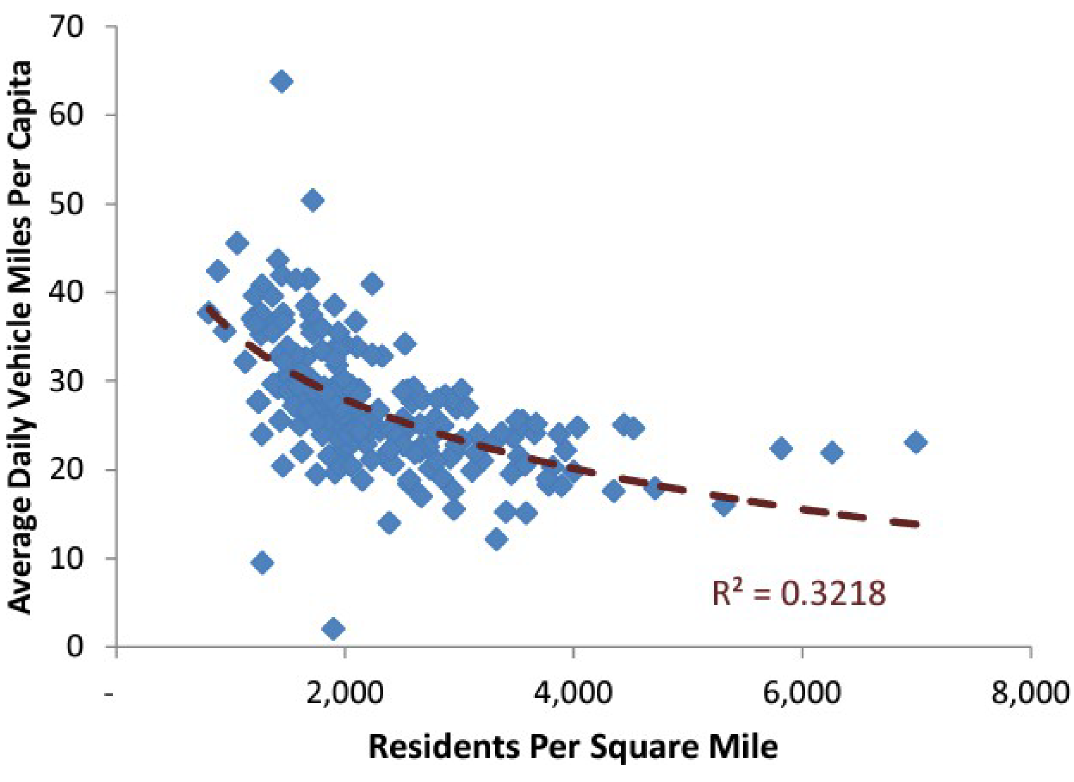
> *… increases in one built environment variable alone may not yield expected reductions in VMT without other variables supporting lower VMT levels—for example, increases in population density absent diverse land uses and access to transit may not result in VMT reductions below what would otherwise be expected. This highlights a possible "sum greater than the individual parts" characteristic of the five Ds.*

[4] Adapted from Ewing & Cervero 2017

Across different dimensions of the built environment, these elasticities vary dramatically. Within the "Weighted average elasticities: Stevens sample" estimates, for example, job density seems to have a minor effect—a 0.01% reduction in VMT given a 1% increase in job density—while job accessibility by auto has an effect size roughly 25 times higher (Table 1). Applying other methods, however, the impact of job density is larger while the impact of auto job accessibility is lower (column 4 of Table 1).

The variability across studies and the five D measures themselves reflect the nuances in the relationship between the built environment and travel behavior, as described previously by Ewing. While the five Ds are typically treated as (somewhat) independent of one another in the literature, these variables are often correlated. Further, increases in one built environment variable alone may not yield expected reductions in VMT without other variables supporting lower VMT levels—for example, increases in population density absent diverse land uses and access to transit may not result in VMT reductions below what would otherwise be expected. This highlights a possible "sum greater than the individual parts" characteristic of the five Ds. While the literature has sought to isolate the effects of each, the effects of these variables in VMT may be interrelated. Interestingly, while plotting a single built environment measure alone may reveal a relationship with VMT—as demonstrated in work by Litman (Figure 1)—accounting for variables across different dimensions often strengthens such associations.

FIGURE 1. VMT PER CAPITA AND POPULATION DENSITY[5]



To better understand the nuances of these relationships, a recent study sought to isolate the effects of the five Ds on specific travel choices to support the development of travel model

[5] Adapted from Litman 2022

enhancement in the Salt Lake City, Utah region.[6] This study reviewed existing work in the context of elements of the travel demand model, such as walk and bike mode choice models (Table 2 and Table 3, respectively). Walk mode choice tends to have a positive relationship with higher population, job density, higher commercial floor area ratio, more diverse land use, and short distance to commercial destinations.

TABLE 2. WALK MODE CHOICE AND THE 5DS[7]

		BUILT ENVIRONMENT MEASURES			
STUDY	**METHOD**	**Density**	**Diversity**	**Design**	**Destination accessibility**
Hamre & Buehler (2014)	MNL	Population density (+)	-	-	-
Reily & Landis (2002)	MNL	Population density (+)	Distance to closest commercial use (-)	-	-
Frank et al. (2008)	NL	Retail floor area ratio (+)	Land use mix (+)	Intersection density (+)	-
Ferrell et al. (2015)	MNL	Population density (+)	-	4-way intersection density (+)	-
Rajamani et al. (2003)	MNL	-	Land use mix (+)	% Cul-de-sac streets (-)	-
Mitra (2011)	BNL	-	Jobs-to-population ratio (-)	Block density (+)	-
Ozbil & Peponis (2012)	LNR	-	Mixed-use entropy (+)	Street connectivity (+)	-
Ewing et al. (2004)	MNL	-	-	Average sidewalk coverage (+)	Walk time to school (-)
Ewing et al. (2009)	MNL	-	-	Intersection density (+), Sidewalk coverage (+)	Jobs within one mile (+)
Aziz et al. (2017)	MNL	-	-	Street width (+)	-
Khan et al. (2014)	MNL	-	-	3-way/4-way intersection density (+)	

MNL: Multinomial logit regression
NL: Nested logit regression
BNL: Binomial regression
LNR: Linear regression
(+) = positive relationship
(-) = negative relationship

Similarly, bike mode choice related to higher population densities and greater mix of land uses. Interestingly, higher job and population densities have also occasionally been found to result in less biking—potentially due to other built environment measures such as street design and automobile traffic that may be present barriers to cycling in dense environments (Table 3).

[6] Ewing et al. 2019
[7] Adapted from Ewing et al. 2019

TABLE 3. BIKE MODE CHOICE AND THE 5DS[8]

		BUILT ENVIRONMENT MEASURES			
STUDY	METHOD	Density	Diversity	Design	Destination accessibility
Ferrell et al. (2015)	MNL	Population density (+)	Mixed use (+)	4-way intersection density (+)	-
Hamre & Buehler (2014)	MNL	Population density (+)	Urban core (+)	Bikeway supply (+)	-
Khan et al. (2014)	MNL	Population density (+), Job density (-)	-	4-way intersection density (+)	
Aziz et al. (2017)	MNL	-	-	Bike land length width (+), Fraction open space (+)	-
Ewing et al. (2004)	MNL	-	-		Walk time to school (-)

MNL: Multinomial logit regression
(+) = positive relationship
(-) = negative relationship

A recent study from Portland State University provides additional support for the relationship between built environment measures and multimodal travel across the US.[9] Controlling for sociodemographic variables, the author analyzed the relationship between multimodal travel behavior and built environment variables such as population density, accessibility, and job diversity for roughly 200,000 census block groups. Using linear regression and machine learning with American Community Survey and EPA Smart Location data, the author found statistically significant built environment predictors of multimodal travel. The author concludes that "planners who would like to encourage multimodal travel behavior should consider the features, particularly population density, regional accessibility, walkability index, and network density, when developing their land-use design strategies for the transportation system."

TABLE 4. REGRESSION ANALYSIS OF VMT, SMART LOCATION DATABASE VARIABLES[10]

VARIABLES	ESTIMATE	STD. ERROR	T-VALUE	P-VALUE	VIF
Constant	0.359	0.007	48.780	<0.001	-
Population density	0.010	<0.001	24.190	<0.001	1.535
HH, job diversity	-0.082	0.063	-1.294	0.196	1.017
Job diversity	-0.023	0.003	-7.851	<0.001	1.592
Network density	-5.998	1.140	-5.262	<0.001	6.031
Intersection density	2.223	0.123	18.091	<0.001	3.936
Walkability index	0.011	<0.001	45.797	<0.001	4.443
Job proximity	0.014	<0.001	32.686	<0.001	1.180
Auto accessibility	-0.080	0.002	-36.339	<0.001	1.559
Transit accessibility	0.146	0.003	42.948	<0.001	1.935
Household size	0.024	0.001	22.794	<0.001	1.606
Household income	0.001	<0.001	3.826	<0.001	2.995
White	-0.018	<0.001	-37.876	<0.001	6.550
Black	-0.015	<0.001	-30.829	<0.001	4.905
Asian	0.013	0.001	17.815	<0.001	2.202
Single	0.037	<0.001	78.524	<0.001	1.857
Low education	-0.002	<0.001	-5.323	<0.001	2.960
No car	0.025	<0.001	81.355	<0.001	1.410
Work at home	0.044	0.001	49.115	<0.001	1.180
Observations	206,380				
Model adjusted R^2	0.309				

8 Adapted from Ewing, Sabour, et al, 2019
9 Lee, 2022
10 Adapted from Lee 2022

2.3 CROSS-CUTTING THEMES

Apart from overall findings related to the five Ds and VMT, several other themes emerged during this review. First, a range of techniques are used to develop the built environment measures that are foundational to studies on this topic, and the way these variables are measured is important. Second, while there is strong evidence of these relationships in urban contexts, much less is known in rural contexts. Finally, built environments that support lower VMT often have other measurable benefits, such as reduced maintenance costs due to reduced infrastructure needs.

Theme 1: Measurement Matters

The five Ds can be calculated in different ways. Two common approaches in the literature use non-uniform geographies: 1) calculating variables within an underlying geography, such as census block groups; or 2) calculating variables within buffers around specific coordinates, such as home locations. Both non-uniform methods such as these have important drawbacks. First, calculating built environment measures within nonuniform geographies can present issues related to boundary effects and the modifiable unit problem, and tend to understate variation as the size of polygons in the underlying geography increases.[11] This can be particularly problematic in rural areas where Census geometries are typically very large. Calculating the five Ds within buffers tends to mitigate these limitations but can be computationally difficult as the number of buffer operations required increase (e.g., when calculating buffers for big data sources, such as passively collected location data).

Grid-based options, where built environment measures are calculated within grid cells spanning a study region offer a nice compromise between these two prevailing methods. Grid-based techniques can mitigate spatial sampling bias and the modifiable areal unit problem, result in less information loss when underlying data are available at high resolutions, and simplify computation across large geographic areas. An example of such an approach is described in Mansfield et al.[12]

Theme 2: Understanding the Rural Context

While there is ample research on the relationship between elements of the built environment and VMT in urban settings, there is less understanding of this relationship in rural settings where there are fewer, and lower densities, of both people and places. A 2009 study from the University of Vermont Research Center provides some evidence from two small size towns in Maine, Lisbon and Sanford, which have a similar built environment to many areas in Vermont.[13] The study showed relatively low reductions in VMT (less than 1%) for 3 different smart growth modeled scenarios, which assumed that household and employment growth would be redirected to dense, mixed-use infill developments in certain parts of each town. Notably, the study isolated the influence of dense mixed-use infill development without including significant upgrades to transit service. As a result, the authors concluded that “the efficacy of the smart

[11] Houston, 2014
[12] Mansfield et al 2023
[13] Weeks, 2009

growth scenarios to reduce VMT in Lisbon and Sanford is greatly limited without transit to complement the proposed dense, mixed-use developments." A more recent 2020 study from Florida provides some additional nuance about the VMT impact of land use strategies in rural areas[14]. This study was based upon a robust panel dataset of all 67 counties in Florida between the 2001 and 2014, with a total of 938 county/year data points, which the authors used to estimate a log-linear model of a county's VMT in relation to eight land use types. Like other studies, this one demonstrated the general observation that compact development is generally associated with reductions in VMT. Yet, the study showed that for rural counties in Florida, the effects depend on the type of land use that is included in built environment. In particular, the study showed that in rural areas concentrating industrial and institutional properties produces VMT reductions while the concentration of residential housing units did not produce similar reductions. Critically, the Florida study quantified built environment measures at the county level, potentially missing the role of within-county variability (e.g., small town centers accompanied by more traditional suburban development patterns) in shaping VMT—further highlighting the importance of the measurement matters theme described above.

Theme 3: The Benefits of VMT Reductions

There also exists ample research to indicate the benefits of compact development. The literature documents the relationship between urban form and other attributes related to the built environment such as cost of maintenance and operations of the assets, stormwater and other environmental impacts such as health and safety.

For example, a 2013 study in Nova Scotia showed that compact development that "increases the portion of new housing located in existing urban centers from 25%- 50% reduced infrastructure and transportation costs approximately 10% and helped improve public health and reduced pollution emissions"[15]. Furthermore, a 2017 analysis of 300 academic papers found that "69% identify positive effects associated with compact urban form: over 70% attribute positive effects of economic density (the number of people living or working in an area), 58% attribute positive effects to land use mix, and 56% attribute benefits to urban density[16]". Moreover, there are space benefits of compact development that go beyond VMT. As density increases, fewer roadway facilities are needed on a per capital basis (Figure 2). In fact, smart growth development patterns require less than half as much land for housing, roads, and parking facilities relative to sprawl (Table 5). Such reductions in total space consumed from the built environment can benefit roadway maintenance costs as well as stormwater costs (Figure 3). One estimate indicates that sprawl increases local road lane-miles 10%, annual public service costs about 10%, and housing development costs about 8%, increasing total costs an average of $13,000 per dwelling unit, or about $550 in annualized costs.[17] In a recent study, Mattson reached similar conclusions, stating that "construction and operating costs of municipal streets and highways, emergency services (expect police operations), parks and recreation,

[14] Ihlanfedlt, 2020
[15] Stantec, 2013
[16] Ahlfeldt and Pietrostefani, 2017
[17] Burchell and Mukherji (2003)

water, sewage and solid waste management tend to decline with density"[18]. Other work has reached similar conclusions related to the cost of fire protection in Charlotte, North Carolina[19] and simar overall cost reductions with increasing density in the Latin American context[20].

FIGURE 2. URBAN DENSITY VERSUS ROADWAY SUPPLY ACROSS REGIONS IN THE UNITED STATES[21]

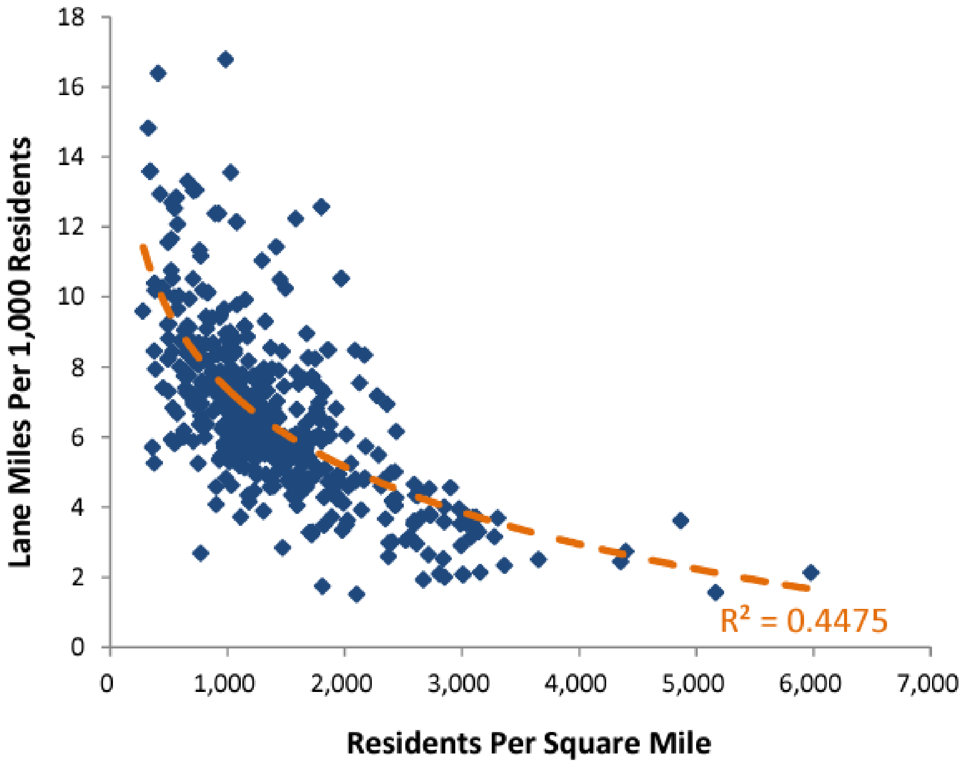
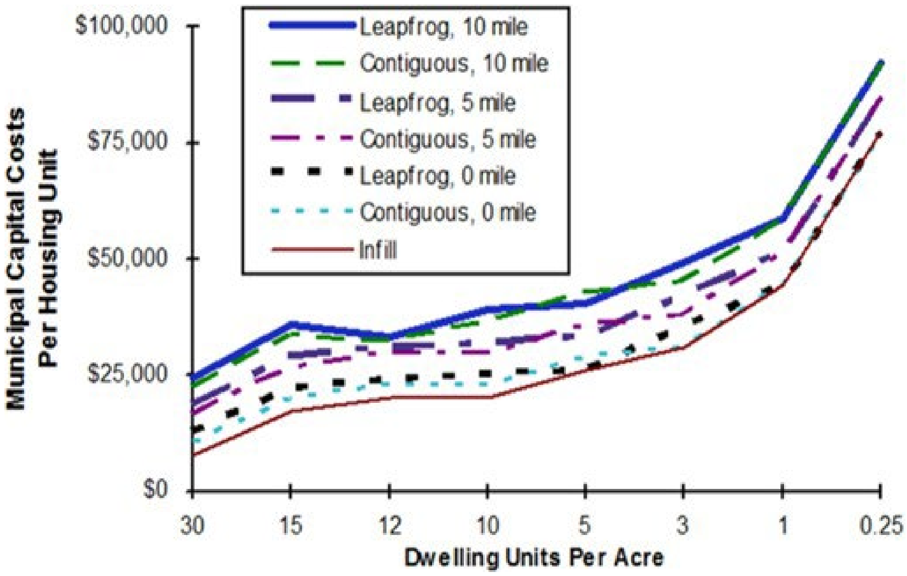


TABLE 5. PER CAPITA IMPERVIOUS SURFACE AREA, SMART GROWTH VS SPRAWL CONDITIONS[22]

	SMART GROWTH	MIXED	SPRAWL
Vehicles per capita	0.8	0.65	0.5
Road space per vehicle (ft^2)	235	453	670
Off-street parking spaces per capita	2	4	6
Land area per parking space (ft^2)	275	300	325
Housing footprint per capita (ft^2)	250	375	500
Road and parking land area per capita (ft^2)	878	1,344	1,810

[18] Mattson, 2021
[19] CDOT 2021
[20] de Duren and Compean, 2015
[21] Adapted from Litman, 2022
[22] Adapted from Litman, 2022

FIGURE 3. RESIDENTIAL SERVICE COSTS INCREASE AS DENSITY DECREASES[23]



2.4 LIMITATIONS

There are two notable limitations of the literature reviewed here. The first, described above, is the relative lack of rural studies on this topic. Critically, this study will help fill this gap in the literature by exploring built environment relationships with VMT across Vermont, inclusive of many rural areas across the state. Second, much of the existing literature relies on cross-sectional data, and self-selection may bias findings (i.e., individuals may sort into neighborhoods that support lower VMT, resulting in differences in underlying preferences for non-auto travel between neighborhoods that bias regression models). Two notable studies have addressed this issue using longitudinal panel data—Ihlanfeldt and Knuiman et al.—and both have still found associations between built environment and travel behavior, though attenuated relative to other studies that did not account for self-selection[24]. While the passively collected data that will be used for this study are longitudinal, privacy restrictions preclude our ability to control for possible self-selection bias. Nonetheless, using a novel data source to explore the relationship between VMT and the built environment will strengthen the findings of the literature.

Critically, this study will help fill this gap in the literature by exploring built environment relationships with VMT across Vermont, inclusive of many rural areas across the state.

2.5 UNDERSTANDING THE VERMONT CONTEXT

While the themes from the literature review describe the relationship between the built environment and VMT in more urban and suburban contexts, Vermont is a predominantly rural

[23] Adapted from Litman, 1989
[24] Knuiman et al., 2014

state with relatively low population density. There is evidence that, despite its predominantly rural character, areas in Vermont with more urban-like built environment still generate reduced VMT demonstrating a similar directional relationship to more urban places. Importantly, there is evidence that downtown residents across most of the state travel less than average, though there is variation across the state (Figure 4). While limited, there is also evidence from the 2009 National Household Travel Survey that downtown residents produced less VMT than others in the state (Figure 5).

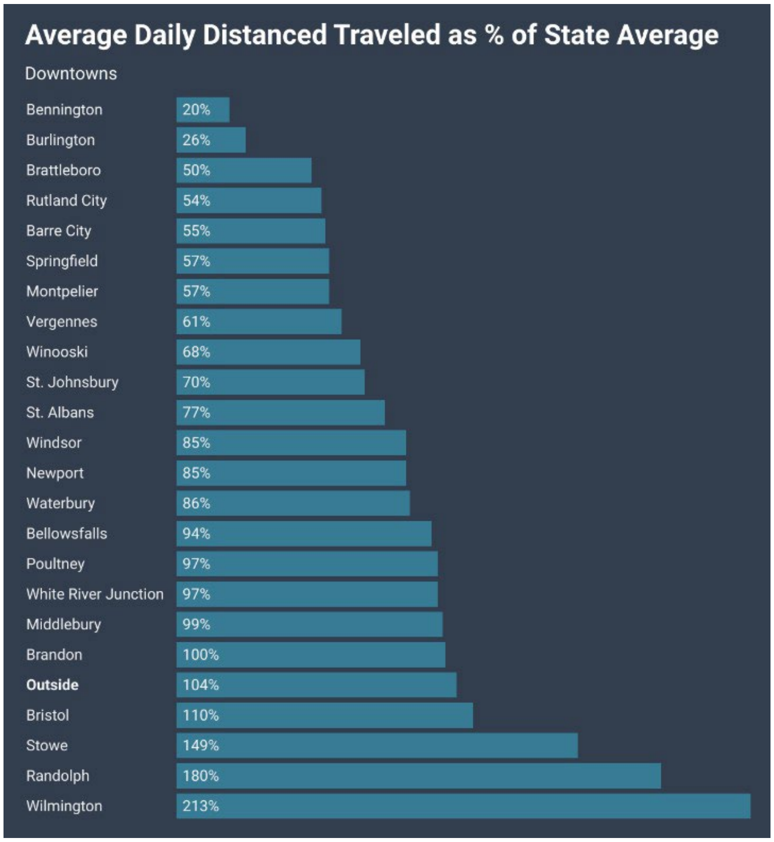


FIGURE 4. ANALYSIS OF OCTOBER 2019 SAFEGRAPH DATA IN VERMONT[25]

There is evidence that, despite its predominantly rural character, areas in Vermont with more urban-like built environment still generate reduced VMT demonstrating a similar directional relationship to more urban places.

[25] John E. Adams using Safegraph data from 2019

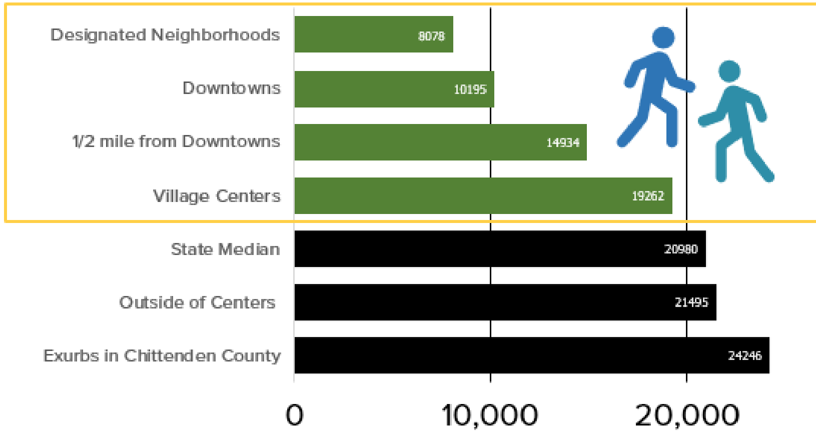


FIGURE 5. ANNUAL VMT BY LOCATION, FROM VERMONT 2009 NHTS[26]

2.6 SPATIAL DATABASE OF BUILT ENVIRONMENT MEASURES

Based on the findings of this literature review the project team assembled a built environment database for Vermont. Built environment measures included in this database characterize the five Ds described in this chapter, including measures of population and employment density, land use diversity, physical design, destination accessibility, and access to transit. A uniform hexagonal grid was used as the underlying geographic unit for calculating these measures, adopting the grid-and-buffer methods described previously.[27] A summary of this database is presented in Appendix B.

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[26] John E. Adams using the 2009 NHTS (Vermont purchased the add on)
[27] https://h3geo.org/docs

3.0 ESTIMATING BASELINE VMT

In addition to the built environment measures described in Chapter 2, estimates of VMT are required to develop a model predicting VMT based on built environment measures. To develop VMT estimates under current land use and built environment conditions, the project team leveraged passively collected location-based services (LBS) data. LBS data are generated by location-aware applications installed on mobile devices and typically offer samples sizes orders of magnitude larger than those in most travel surveys. However, unlike travel surveys, these data contain minimal contextual data in raw form and require extensive processing to develop useful transportation metrics. For this project, RSG obtained and processed passively collected LBS data for all devices seen in Vermont in 2019.

3.1 LBS DATA PROCESSING

Raw LBS data records have limited information—typically only a unique identifier, a timestamp, and a location. As a result of this limitation, all information on travel behavior and attributes of the device owner (home and work/habitual locations) must be imputed. Furthermore, raw LBS data includes devices with a wide range of data quality. Some devices may generate only a handful of location records per month while others may generate thousands of records daily. Thus, it is critical for data processing steps to include devices only with sufficient data quality to produce reliable inferences and apply methods, such as weighting, to account for differences in device quality. The workflow RSG has developed to process LBS data includes three primary components: preparing study geometry, data filtering, and data processing (Figure 6). These components are described in turn below.

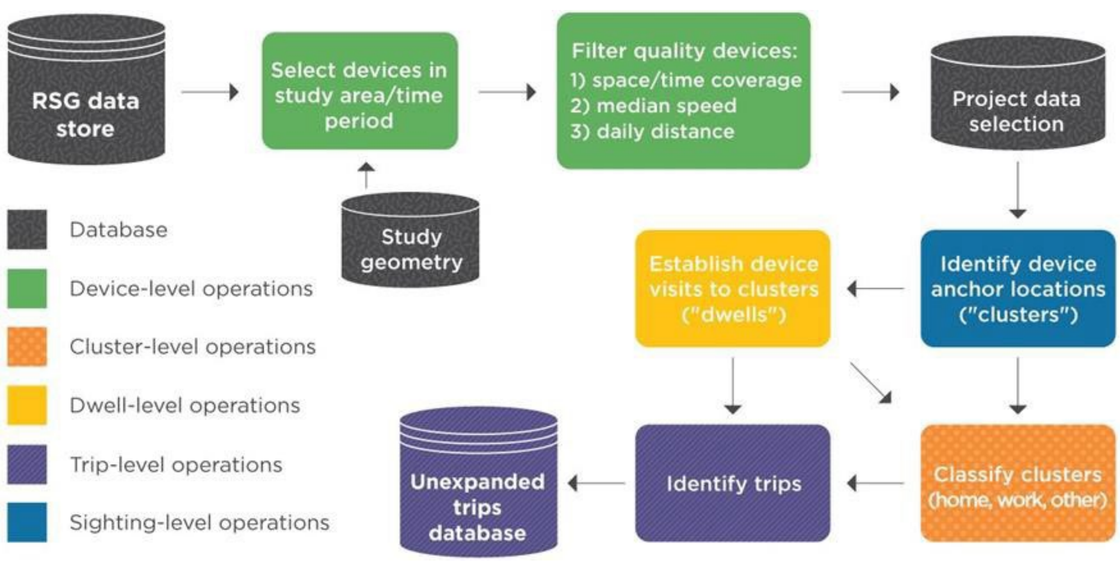

FIGURE 6. DATA PROCESSING WORKFLOW

Preparing Study Geometry

Before processing LBS data for Vermont, the project team compiled demographic, land use, transportation network, and point-of-interest (POI) data across the state. Census blockgroups were used to generate an underlying geometry for the region, and transportation network data were obtained via the OpenStreetMap (OSM) API using the *OSMnx* Python package.[28] Additionally, a nationwide layer of airports was obtained, and all airport polygons were included as airport POI data for the study.

The project team also obtained E911 data for the state, including point data with land use descriptions and building footprint polygon data (with no land use designation). The RSG team used E911 point data to append land use designations to the E911 building footprint data. To do so, the 133 unique land use descriptions in the point data were collapsed into 21 categories (Table 6). Next, the E911 point closest to each building footprint was calculated using a nearest neighbor search and land use designations were assigned to the building footprints. If multiple uses were present within a single building footprint, that building was assigned one of the mixed-use categories (mixed-use with residential or mixed-use without residential, depending on whether one of the uses tagged to the footprint was residential). Finally, non-building footprints categories (airport, agriculture, golf course, park, shopping, stadium, trail, quarry) were tagged as "non-building" POI. The resulted in a comprehensive land-use dataset spanning the state (Figure 7) and a POI dataset containing airports nationwide and other "non-building" POI within Vermont.

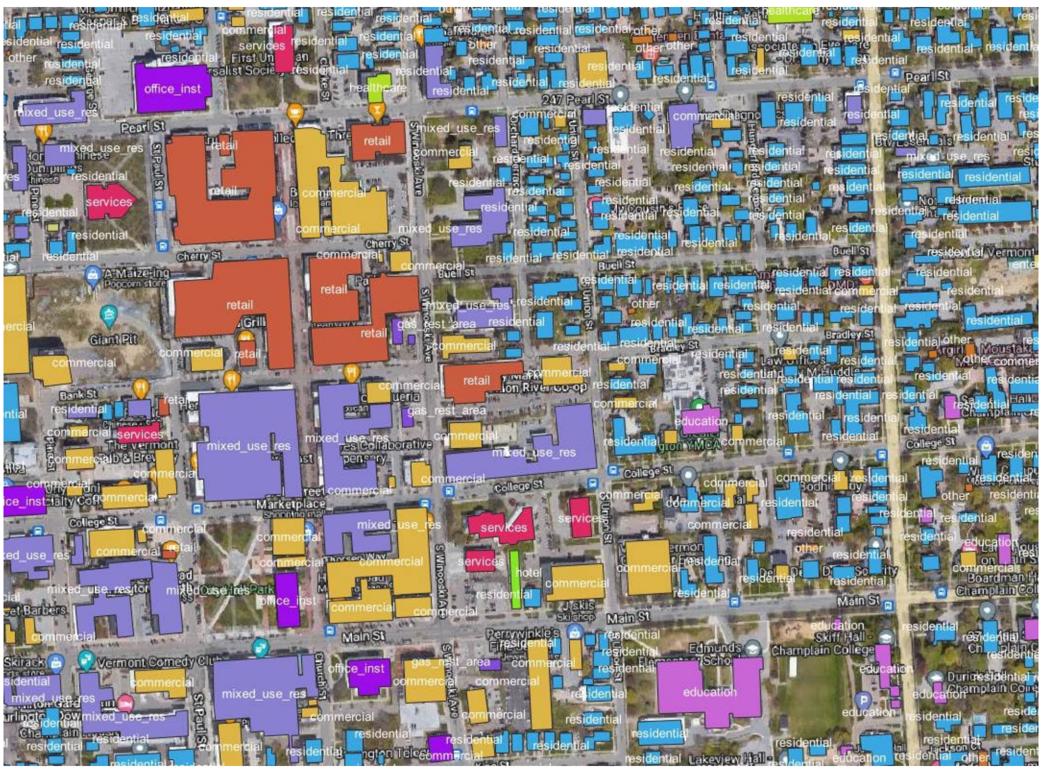

FIGURE 7. COMPILED LAND-USE DATASET IN BURLINGTON, VT

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[28] Boeing, G. 2017. "OSMnx: New Methods for Acquiring, Constructing, Analyzing, and Visualizing Complex Street Networks." *Computers, Environment and Urban Systems*. 65, 126-139. doi:10.1016/j.compenvurbsys.2017.05.004

TABLE 6. AGGREGATION OF E911 LAND-USE CATEGORIES

AGGREGATE LAND-USE CATEGORIES	E911 LAND-USE LABELS
Agriculture	Sugarhouse, accessory bard, greenhouse/nursery, commercial farm, fish farm/hatchery
Airport	Air support/maintenance facility, helipad/heliport/helispot, airport terminal
Commercial	Commercial, other commercial, bank, commercial garage
Education	Educational, school k-12, college/university
Entertainment	Museum, historic site/point-of-interest, fair/exhibition/rodeo grounds. auditorium/concert hall/theater/opera house, cultural, fitness facility, ice arena, public gathering, golf course
Gas stations, rest areas	Gas station, rest stop/roadside park, visitor/information center
Healthcare	Health clinic, veterinary hospital/clinic, ambulance service, outpatient clinic, hospital/medical center
Hotel	RV hookup, lodging b&b/hotel/motel/inn
Industrial/utility	Oil/gas facility, gravel pit/quarry/mine, industrial, lumber mill/saw mill, transfer station, manufacturing facility, commercial construction service, hazardous materials facility, communication box, communication tower, solar facility, utility pole w/phone, water tank, substation, pump station, public telephone, utility, hydroelectric facility, water tower, wastewater treatment plant, wind facility/wind tower, public water supply well, landfill, public water supply intake, hazardous storage facility, waste/biomass facility
Mixed-use w/ residential	Any combination of two uses in same building footprint, including at least one residential use
Mixed-use w/out residential	Any combination of two uses in same building footprint, including at least one residential use
Office/institutional	Government, office building, town office, city/town hall, town garage, state garage, state government facility
Other	Other, accessory building, unknown
Park-and-ride	Park-and-ride/commuter lot, bus station/dispatch facility
Recreation	Camp, campground, trailhead, shooting range, cemetery, boat ramp/dock, ski area/alpine resort, community/recreation facility, picnic area, state park, racetrack/dragstrip, sports arena/stadium, lookout tower, public beach, harbor/marina, youth camp
Residential	Commercial w/residence, single-family dwelling, multi-family dwelling, seasonal home, mobile home, condominium, other residential, residential farm, nursing home/long term care, institutional residence/dorm/barracks
Retail	Restaurant, grocery store, retail facility, brewery, pharmacy
Services	House of worship, fire station, national guard/armory, law enforcement, library, US government facility, courthouse, post office, day care facility, US forest facility, border crossing, morgue, state capitol, coast guard, border patrol, prison/correctional facility
Train station	Railroad station
Warehouse	Storage units, warehouse, food distribution center, private and express shipping facility
Ignore	Development site, access point, gated w/building, gated w/o building, abandoned, temporary structure, EBS tower, PSAP, emergency phone/callbox

Data Filtering

Once underlying geometry data were compiled, RSG's nationwide LBS datastore was queried to obtain all location records for any device seen within the Vermont state boundary in each season of 2019. Data from 2019 was selected as a full year of data with seasonal affects was desired for the study outside of the influence of the COVID-19 pandemic. For each device seen within Vermont, this query obtained all records (both within and outside the state) to infer home locations for both Vermont residents and Vermont visitors.

There is significant variation in quality across devices in the nationwide LBS sample. Some devices are seen only sporadically while others show anomalous behavior (e.g., impossibly fast travel times between locations records). Such devices are not useful for deriving travel behavior information and including them in later analysis would produce unreliable inferences. RSG uses a set of empirically derived inclusion criteria to isolate devices with data of sufficient quality to produce reliable travel behavior estimates. Specifically, devices are only included if:

- The median speed between sightings over the full study period less than 91 feet per second.[29]
- The average daily distance traveled is less than 2,400 miles (about the width of the United States).
- Location records are present in at least 5% of all possible 30-minute time bins over the study time period (referred to as "data density").
- The device is observed in at least 10 unique 7-digit geohashes over the course of the study time period.[30]

Data Processing

After filtering out poor quality devices, location records for all remaining devices are processed on a device-by-device basis. For each device, a series of processing steps are used:

Enrich location records. While raw LBS data contain limited information, the land use, POI, and transportation network data described above contain a wealth of contextual information that can improve the accuracy of data processing. The following pieces of contextual information were appended to each location record in the dataset:

1. Distance from nearest transportation network link and classification of nearest link[31]
2. Distance from nearest building footprint and land-use classification for nearest building footprint
3. Boolean indicating whether location record was inside a POI polygon and, if true, the POI type

[29] The set of all sightings for any given device includes both stationary and moving sightings. Devices removed by this filter either periodically jump between locations at extreme speed or are rarely at rest.
[30] Geohashing is a method to encode geographic coordinates. A seven-digit geohash represents approximately a 153-meter by 153-meter square.
[31] Classification based on OSM facility types (motorway, trunk, primary, secondary, tertiary, residential street)

Identify stops. First, a smoothing algorithm is applied to calculate 5-minute average speed across all location records and records are classified as “stopped” if smoothed speed is below 3 miles per hour. This smoothing algorithm helps identify true stopped sightings while not falsely classifying short stops (e.g., stops at traffic lights or stops due to congestion) as “stopped.”

Identify anchor locations. Next, a spatial clustering algorithm[32] is applied on all stopped sightings for each device. A weighting function is used so that location records within or near building footprint are more likely to produce clusters while location records near transportation network links are less likely to produce clusters. The resulting groups of stopped sightings represent anchor locations for the device; these are referred to as “clusters.” These clusters are tagged to the study region’s underlying geometry—in this case, census block groups within the state of Vermont.

Identify visits. Once clusters are established for the device, a “dwell” (or visit) is formed each time a device is seen staying in the same cluster. The start of the visit is defined as the first location record within the cluster and the end of the visit defined by the last location record within the cluster.

Classify anchor locations. A device’s home location is inferred using observed overnighting at anchor locations. A device’s work/habitual location is inferred by assessing the importance of each location using methods from graph theory.[33] Inferred home locations are used to classify devices as resident devices (inferred home location inside Vermont) or visitor devices (inferred home location anywhere else).

Identify trips. A “trip” is formed each time a device is seen moving from one cluster to another. Each trip is routed on the OSM transportation network using a shortest travel time algorithm. Long-distance trips and intermediate stops (e.g., a quick stop at a service station on a longer trip) are identified as part of this process. Finally, trip attributes are calculated, including trip purpose (e.g., home-based habitual trip), time of day (e.g., AM period), and routed trip distance.

3.2 CUSTOM POST-PROCESSING

While the pipeline described in Section 2.1 includes devices that meet empirically derived inclusion criteria suitable for most applications of passively collected data, generating reliable VMT estimates requires stricter device filtering. To support device-level VMT estimation, a custom post-processing pipeline was developed (Figure 8). First, a clustering algorithm was applied to identify the highest quality tier of processed devices to improve the reliability of VMT estimates and remove devices that likely represent non-passenger (e.g., commercial truck) travel. Next, device records were resampled to identify the most representative travel week within each time period. Finally, a mode choice estimation model was developed to identify trips that do not contribute to VMT (non-motorized trips, ferry trips, and flights). These steps are described in greater detail below.

[32] Specifically, density-based spatial clustering algorithm with noise (DBSCAN).
[33] PageRank calculated for a directed graph representing all the devices’ dwells.

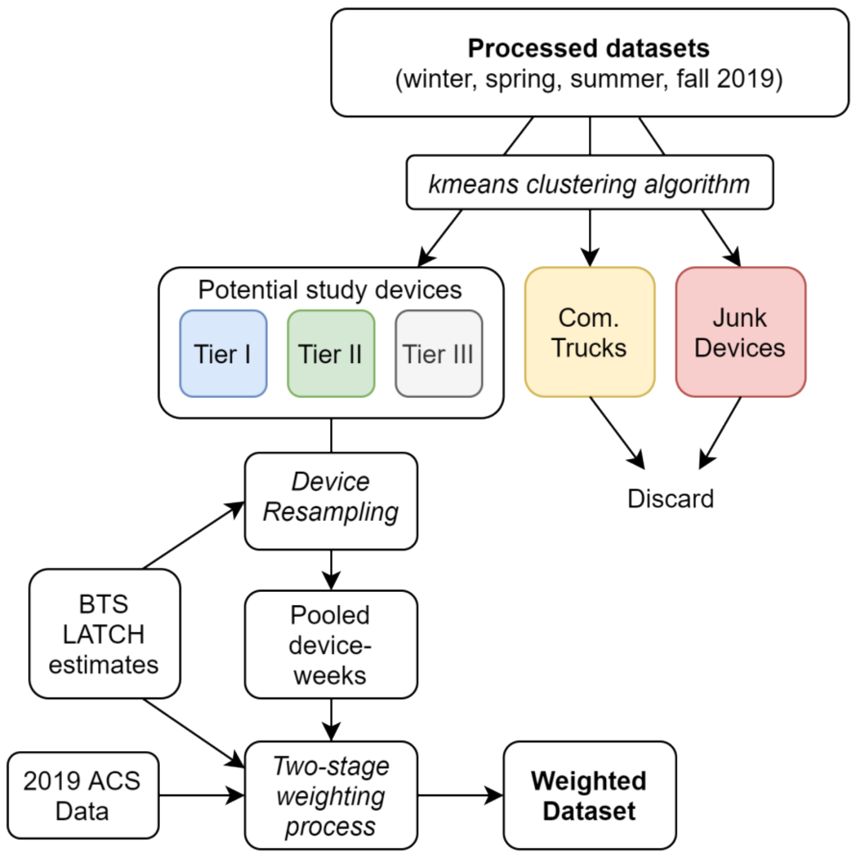


FIGURE 8. POST-PROCESSING WORKFLOW

Developing Device Quality Tiers

To further differentiate processed devices into quality tiers and device type (passenger versus commercial truck), several device quality metrics were calculated:

- *Data density*: the number of 15-minute timebins with at least one location record divided by the total number of 15-minute timebins between the device's first and last timestamp.
- *Average daily travel distance:* total distance travelled by the device divided by the number of days with at least one location record.
- *Percentage of days that start and end at home:* the percentage of days on which the device's first and last location records were within the device's home cluster divided by the number of days with at least one location record.
- *Typical location score:* the mean value of the location frequency score for all four-digit geohashes visited by the device over the week, where the location frequency score for each four-digit geohash is the percentage of all days in which the device visited the four-digit geohash.[34]
- *Average trip distance:* the average great circle (as the bird flies) distance of all trips identified for the device.

[34] A four-digit geohash represents approximately a 24-mile by 12-mile rectangle.

- *Average trip duration:* the average duration of all trips identified for the device.
- *Percentage of truck visits:* the percentage of visits identified for the device inside Vermont for which the nearest land use is associated with commercial truck activity (gas stations, industrial/utility land uses, rest areas, or warehouses)
- *Percentage of flights:* the percentage of trips that were flagged as suspected flights.
- *Frequency of data anomalies:* the average number of anomalous data events[35] identified per day for the device.

Next, a *kmeans* clustering algorithm was applied, using the quality metrics above to identify five device clusters. *kmeans* is an unsupervised machine learning technique which splits a dataset into *n* clusters (in this case, 5) by maximizing the differences in metrics between clusters and minimizing the differences in metrics within clusters. However, there is no guarantee that the groups identified will be labeled consistently across applications of the algorithm (i.e., in some cases the highest-quality devices may be labeled as group 1, in other cases the highest-quality devices may be labeled as group 4, and so on). To ensure comparability across the four seasons, a set of rules was developed to re-label kmeans-derived clusters into useful categories (three quality tiers, commercial trucks, and junk devices. These rules were:

- Median *data density* and *percentage of days that start and end at home* scores were calculated for each cluster and clusters were sorted based on the average of these two scores.
- The cluster with the highest *percentage of truck visits* was labeled as “commercial trucks”.
- The cluster with the highest combined *frequency of data anomalies* and *percentage of flights* was labeled as “junk devices”.
- The three remaining unlabeled clusters were labeled as Tier 1 (highest mean *data density* and *percentage of days that start and end at home* scores), Tier 2 (second-highest scores) and Tier 3 (lowest scores).

Over the year, nearly 700,000 devices were seen in Vermont, over 145,000 of which were identified as Vermont resident devices. Nearly 50,000 of these devices were identified as commercial trucks or junk devices. Around 95,000 devices (including 26,651 Vermont residents) were placed in the quality Tier 1, with larger numbers of devices in Tiers 2 and 3 (Table 7).

TABLE 7. PROCESSED DEVICE COUNTS, BY KMEANS-DERIVED GROUP

	ALL DEVICES					VERMONT RESIDENT DEVICES				
Group	Winter	Spring	Summer	Fall	Year	Winter	Spring	Summer	Fall	Year
Tier 1	23,772	16,162	38,948	16,911	95,793	**6,811**	**5,447**	**9,422**	**4,971**	**26,651**
Tier 2	51,893	35,460	65,497	42,092	194,942	**13,901**	**10,567**	**13,150**	**9,449**	**47,067**
Tier 3	99,226	61,047	118,406	57,126	335,805	**19,931**	**13,233**	**18,675**	**10,390**	**62,229**
Trucks	3,585	2,390	3,794	2,289	12,058	1,715	1,111	1,009	534	4,369
Junk	7,881	7,109	12,105	4,928	32,023	1,786	1,553	2,154	950	6,443
Total	186,357	122,168	238,750	123,346	670,621	44,144	31,911	44,410	26,294	146,759

[35] Anomalous data events including sequential location records that are more than 100 kilometers apart that travel greater than 1,000 kilometers per hour

Given the scope of this project and in response to feedback from the Technical Advisory Committee received during the December 16th Technical Advisory Committee meeting, the commercial truck and junk devices were dropped from the dataset. Additionally, all non-Vermont residents were removed, leaving a dataset containing only Vermont residents grouped into three quality tiers (bolded and shaded groups in Table 7).

Resampling Devices

Previous studies examining the relationship between built environment factors and VMT have typically used travel survey data reporting only one day of travel, though a handful of studies have used longer time periods.[36] While passively collected data offer much longer time frames of data collection, data quality can vary dramatically over time and can include periods of atypical travel, like vacations. For this study, the project team developed a technique to resample passively collected data to provide data like the travel survey data used in previous studies, including only the highest-quality and most representative week for each device in each season processed.

To resample these data, a set of quality metrics were calculated over a 7-day rolling window over the length of each device's record (that is, calculated for each consecutive 7-day period of device records). To the extent possible, these quality metrics were different than those used to identify device quality tiers. Importantly, these metrics also reference a third-party ground truth per capita VMT datasets: the Bureau of Transportation Statistics (BTS) Local Area Transportation Characteristics for Households (LATCH) estimates. LATCH estimates were developed using data form the 2017 National Household Travel Survey (NHTS) and supply tract-level suites of per capita VMT and person-miles travelled (PMT) across the United States, based largely on socioeconomic characteristics and household types in each tract.[37]

Resampling was performed in two stages. First, device-weeks were included if they included all 7 days (i.e., had at least one location record for each day of the week), included at least one trip, included at least 4 days inside Vermont, and had a data density of 0.33 or higher (at least 252 15-minute timebins with at least one location record over the week). Next, a composite quality score was developed for each device-week using four quality indicators:

- *Data density*: the number of 15-minute timebins in the past week with at least one location record divided by 762 (the maximum number of timebins in a week)
- *Typical location score*: mean location frequency score for the week.
- *Deviation in trip rate relative to LATCH estimate*: the absolute value of the difference between the daily trip rate over the past week and the LATCH estimate of daily trips for the tract identified as the device's home location.

[36] For example, Mansfield, Ehrlich, Zmud, and Lee, Built environment influences on active travel in the Twin Cities region: evidence from a smartphone-based household travel survey, 2022
[37] https://www.bts.gov/sites/bts.dot.gov/files/docs/browse-statistical-products-and-data/surveys/224076/latch2017methodology.pdf

- *Deviation in observed miles travelled relative to LATCH estimate*: the absolute value of the difference between the sum of trip distances over the past week and the LATCH estimate of PMT for the tract identified as the device's home location.

For each device, the week with the highest quality score was retained and all other weeks were discarded. Across the 4 seasons, a total of 135,947 devices were processed, and 29,943 devices had at least one qualifying device-week (labeled "qualifying devices" in Table 8 below). Most Tier 1 devices (79%) had at least one week that met the inclusion criteria described above while relatively few Tier 2 and Tier 3 devices had qualifying weeks (8.3% and 8.5%, respectively; Table 8).

TABLE 8. DEVICES WITH AT LEAST ONE QUALIFYING DEVICE-WEEK AFTER RESAMPLING

	WINTER		SPRING		SUMMER		FALL	
	Devices	Qualifying devices	Devices	Qualifying devices	Devices	Qualifying devices	Devices	Qualifying devices
Tier 1	6,811	4,416	5,447	4,525	9,422	7,350	4,971	3,929
Tier 2	13,901	2,259	10,567	603	13,150	2,176	9,449	780
Tier 3	19,931	608	13,233	1,228	18,675	1,181	10,390	888
Total	**40,643**	**7,283**	**29,247**	**6,356**	**41,247**	**10,707**	**24,810**	**5,597**

Mode Choice Estimation

While LBS data contain information on all movements made by a device, not all movements contribute to VMT. Critically, trips inferred from LBS data contain flights, non-motorized trips, and trips made on public transportation modes such as ferries and buses. A multi-stage mode choice model was used to identify four transportation modes for this study: motorized, non-motorized, flights, and ferry trips. First, flights were identified directly using a combination of POI information and trip characteristics:

- Trips with an origin and destination in an airport POI
- Trips with on origin or a destination in an airport POI and a speed greater than 125 mph
- Trips longer than 340 miles with a speed greater than 125 mph

Similarly, ferry trips were identified if a device had a trip with more than 25% of its location records located in Lake Champlain.

To identify non-motorized trips, a logit regression model was fitted to Vermont trip data present in the 2017 NHTS (*n=2,620 trips*) predicting the likelihood of a non-motorized trip (walking or bicycling) based on trip attributes that could be calculated for trips in the passively collected data. Prior to estimating the model, flights and ferry trips—trips for which mode was estimated using other data sources—were removed:

$$\pi_i = \beta_0 + \boldsymbol{\beta X}_i + \varepsilon$$

where π_i is the probability that trip i used a non-motorized mode (walking or biking), $\boldsymbol{X}_i$ is a vector of trip variables for individual i with regression coefficients $\boldsymbol{\beta}$, and ε is an error term.

This regression model revealed largely expected relationship: A 1-mph increase in trip speed is significantly associated with a 6% decrease in the likelihood that a trip was non-motorized while a 1-unit increase in population density was associated with a 0.01% increase in likelihood (or a 1% increase in likelihood per 100-unit increase in population density). Weekend trips were 47%

more likely to be nonmotorized (Table 9). Trip distance was also borderline significant in the expected direction and was retained in the model to improve the application of the model to LBS trips.

TABLE 9. NONMOTORIZED REGRESSION MODEL RESULTS

TRIP VARIABLE	ODDS RATIO	T-STAT
Trip length (miles)	0.94	-1.56
Trip speed (mph)	0.79	-13.44***
Trip OD population density (persons/mi^2)	1.0001	4.36***
Trip on weekend	1.47	2.25*
Intercept	0.367	2.91**
AIC	1,292.4	
Pseudo-R^2	0.39	

****p<0.001 **p<0.01 *p<0.05*

To identify non-motorized trips in the LBS data, coefficients from the NHTS model were applied to calculate the non-motorized likelihood of each trip, after removing flights and ferry trips. For each season, all LBS trips were then ordered based on the calculated likelihood, forcing the likelihood to equal zero if the trip distance was greater than 25 miles (the longest non-motorized trip length reported in the NHTS). Then, the top *n* ordered trips in each were labelled as non-motorized so that the percentage of non-motorized trips in the LBS data matched the percentage non-motorized in the NHTS. In general, trip metrics differed as expected based on imputed mode, with the shortest mean distance and slowest mean speed for nonmotorized trips and the highest mean distance and speed for flights (Table 10).

TABLE 10. TRIP SUMMARY BY MODE

	MOTORIZED	NON-MOTORIZED	FLIGHTS	FERRY TRIPS
Mean trip length (miles)	7.80	0.89	286	8.34
Mean trip speed (mph)	18.0	1.23	139	11.8
Number of trips	665,768	89,989	159	2,927

3.3 DEVICE WEIGHTING

LBS data contain only a sample of all persons in the population and, even after isolating the highest quality available week for each device, may contain incomplete information on device travel. A two-state weighting process was applied to scale observed VMT in the sample of LBS devices for each season to the expected population-level VMT across the state of Vermont: a demographic expansion to scale the sample of LBS devices to represent the population and a temporal adjustment applied to account for travel that may have been missed when a device was not providing data.

First, the sample rate for LBS devices was calculated at the blockgroup level by dividing the number of devices with a home location in each blockgroup by the 2019 American Community Survey (ACS) population of adults[38]. A demographic weight (i.e., the number of devices represented by the device) was then calculated for each device by taking the inverse of the sample rate. A demographically expanded population-level VMT was then calculated at the tract level:

[38] LBS data obtained from our supplier do not contain data for children under the age of 18

$$VMT\_lbs_t = \sum vmt_{i,t} W_t$$

where VMT_lbs_t is the LBS-estimated VMT for tract t, $vmt_{i,t}$ is the estimated VMT for device i in tract t, and W_t is the demographic expansion factor for tract t.

Next, the daytime data density (i.e., data density calculated only during daytime hours when we would expect most trip making to occur) was calculated for each device. The difference between tract-level VMT estimates and expected values derived from LATCH estimates was the calculated, providing an estimate of “missing” VMT in the LBS estimates before any temporal adjustments:

$$VMT\_res_t = VMT\_latch_t - VMT\_lbs_t$$

where VMT_res_t is the error in LBS-estimated VMT relative to the LATCH VMT estimate for the tract, VMT_latch_t. Finally, missing VMT for each tract was assigned to devices proportionally based on the number of missing daytime timebins, in the form of a temporal adjustment factor:

$$vmt\_adj_{i,t} = vmt_{i,t} \cdot \frac{(1-d_{i,t}) \cdot VMT\_res_t}{\sum 1-d_{i,t}}$$

where $vmt\_adj_{i,t}$ is the adjusted VMT for device i in tract t and $d_{i,t}$ data density for device i in tract t.

After this two-stage weighting process, each device has two distinct expansion factors: a demographic expansion factor that represents how many persons are represented by the device and an adjusted VMT estimate ($vmt\_adj_{i,t}$) that accounts for “missing VMT” relative to LATCH estimates, accounting for difference in sampling across blockgroups. The difference in these two factors is important for Task 4: while the demographic factor may be useful as a weight in regression modeling, the temporal adjustment is critical in grounding LBS-based estimates of VMT to a third-party dataset and ensuring models estimated using these data fully account for expected VMT across the state.

3.4 RESULTS

The data processing steps described in Section 3.2 produced a dataset consisting of devices, trips made by these devices over the course of a week, and an adjusted estimate of weekly VMT. These data are described below.

VMT Dataset Summaries

The resampled dataset contains over 750,000 trips made by nearly 30,000 devices across the year (Table 11). This sample is orders of magnitude larger than survey data available in Vermont, including the 2017 NHTS, and much larger than most samples used to produce the studies summarized in Task 1. While very larger, the sample does exhibit expected bias towards more urban areas, resulting in higher sample rates in these areas and lower sample rates in more rural regions of the state (Figure 9). However, these biases can be addressed in the Task 4 model through the careful application of the demographic weights developed as described in Section 2.3.

TABLE 11. DEVICE AND TRIP COUNTS IN RESAMPLED DATASET

	TIER 1		TIER 2		TIER 3		TOTAL	
	Trips	Devices	Trips	Devices	Trips	Devices	Trips	Devices
Winter	97,987	97,987	20,695	780	36,155	888	154,837	5,597
Spring	115,679	4,525	18,010	603	47,776	1,228	181,465	6,356
Summer	173,825	7,350	53,782	2,176	33,129	1,181	260,736	10,707
Fall	94,010	4,416	51,156	2,259	16,815	608	161,981	7,283
Full Year	**481,501**	**20,220**	**143,643**	**5,818**	**133,875**	**3,905**	**759,019**	**29,943**

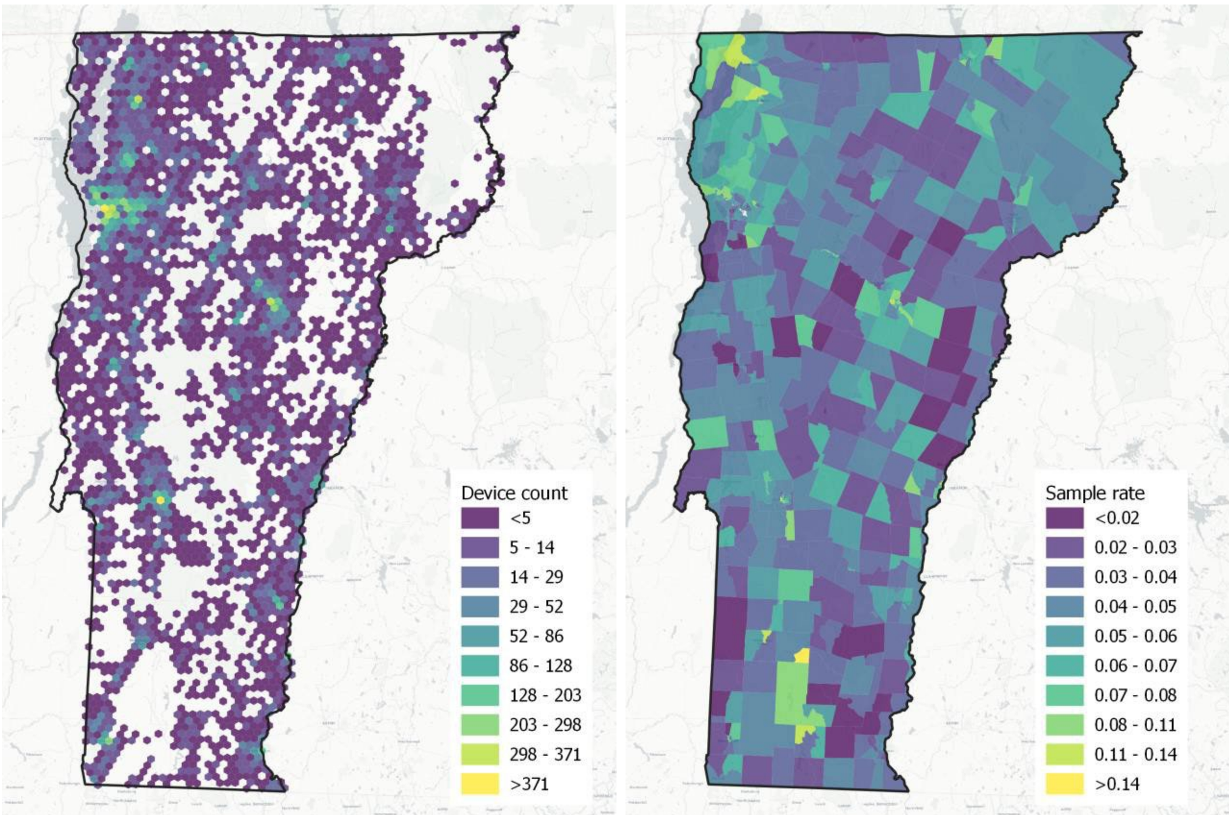


FIGURE 9. DISTRIBUTION OF DEVICE HOME LOCATIONS (LEFT) AND SAMPLING RATE (RIGHT) ACROSS VERMONT

A similar spatial distribution is present for trips origins. Interestingly, while trip counts are substantially higher in urban parts of Vermont, median trip distance in more urban areas is much lower than in rural areas (Figure 10). This finding harkens back to some of the Task 1 findings—namely, that neighborhoods with higher “five D” variables produce less driving, but not necessarily fewer trips, because trip distances may be shorter and non-motorized modes may be better supported. In fact, higher shares of non-motorized trips are estimated in more urban areas of the state and near large recreational areas, including trails and ski slopes (Figure 11).

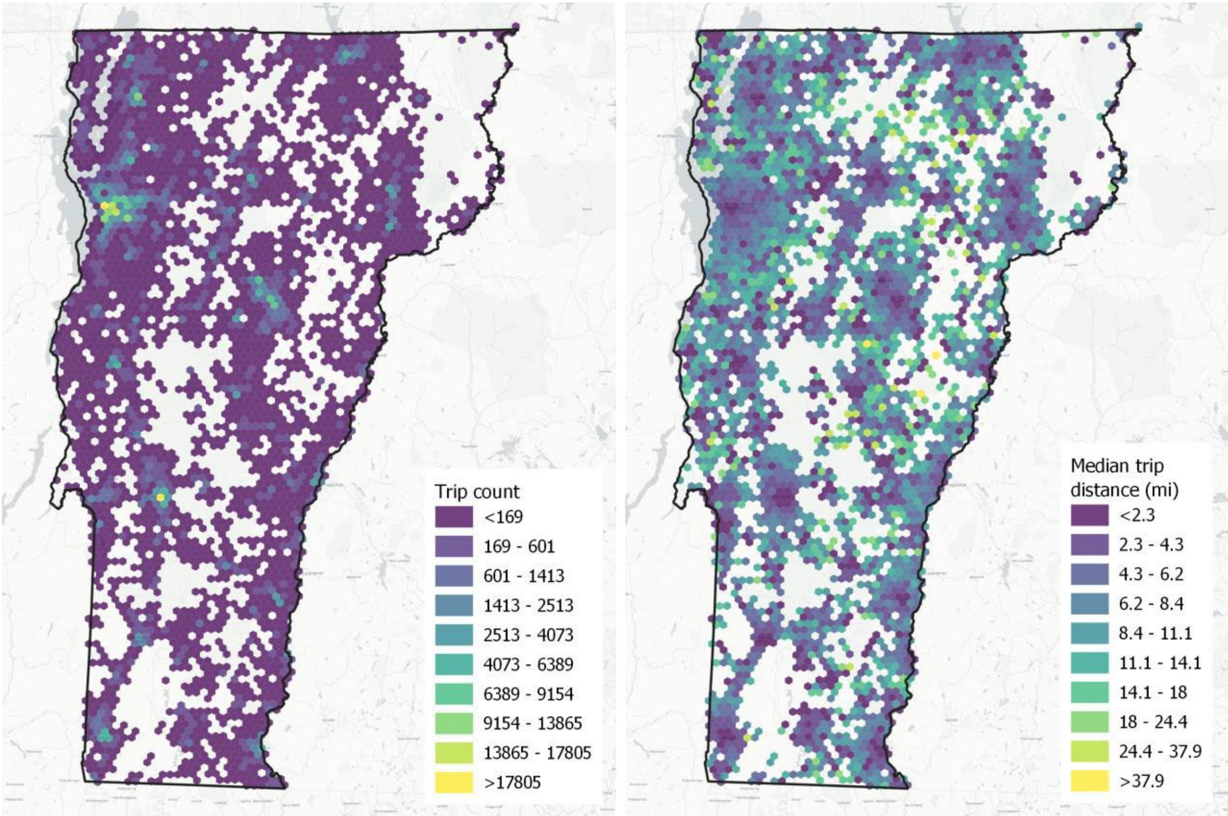


FIGURE 10. DISTRIBUTION OF TRIP ORIGINS (LEFT) AND MEDIAN TRIP DISTANCES (LEFT)

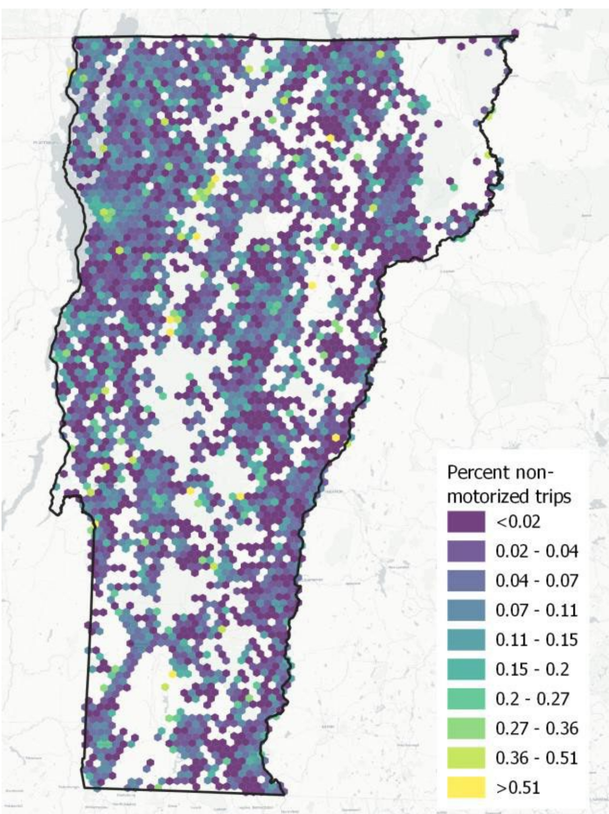


FIGURE 11. DISTRIBUTION OF NON-MOTORIZED MODE SHARE

Data Validation

An important data validation exercise for LBS-derived trip data is to check for expected weekday AM and PM peaking (and lack of peaking on weekends) in trip time-of-day profiles. Trip time-of-day distributions for Tier 1 devices show strong AM and PM peaking, as expected, while weekend trips rise slowly over the day (Figure 12). Further, AM peaking is especially prominent for home-based work trips, and home-based other trips dominate the weekend distribution. While the trip time-of-day distributions for Tier 2/3 devices have similar characteristics, peaking is slightly less prominent and a higher number of trips start very early in the morning, reflecting slightly lower quality data for the Tier 2/3 devices (Figure 13).

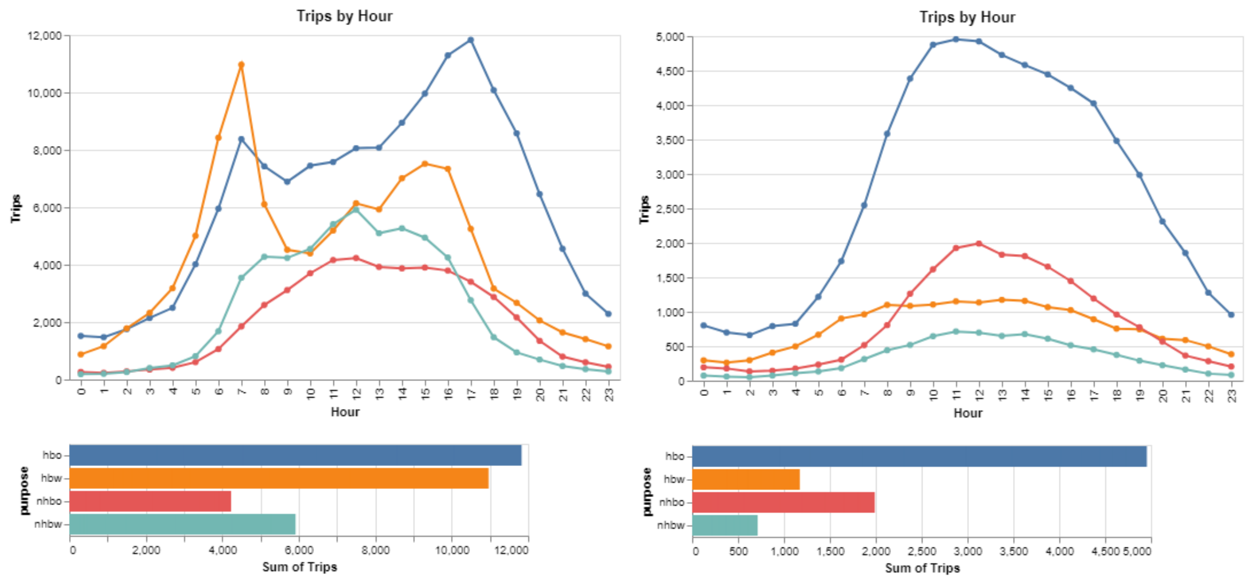


FIGURE 12. TIER 1 TRIP TIME-OF-DAY PLOTS BY TRIP PURPOSE FOR WEEKDAY (LEFT) AND WEEKEND (RIGHT)

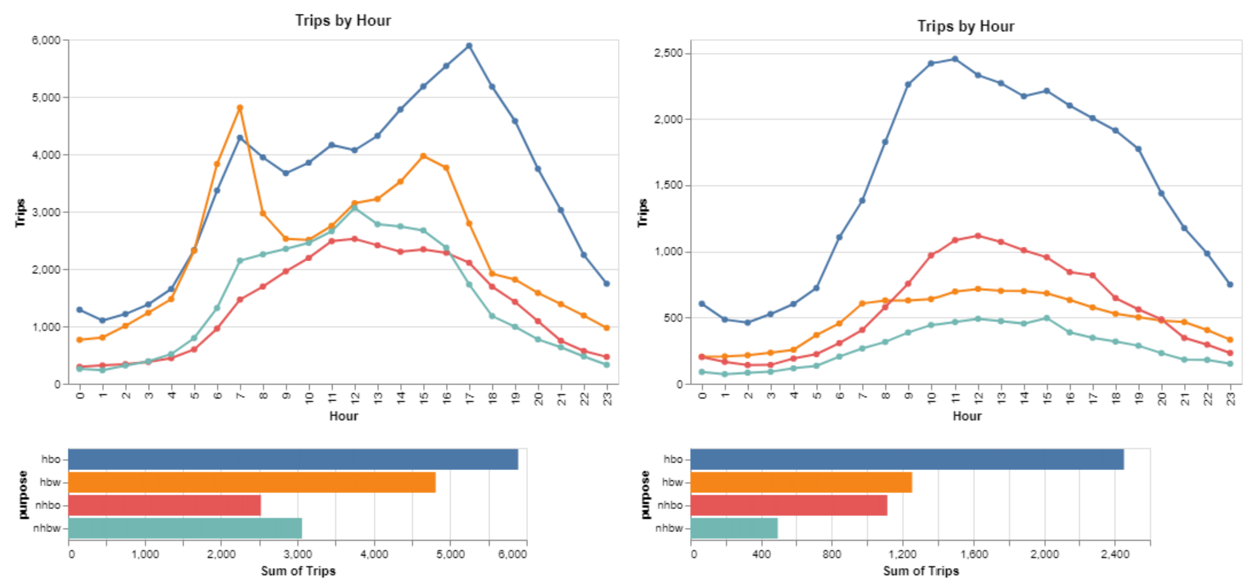


FIGURE 13. TIER 2/3 TRIP TIME-OF-DAY PLOTS BY TRIP PURPOSE FOR WEEKDAY (LEFT) AND WEEKEND (RIGHT)

As an additional validation step, tract-level VMT estimates derived from LBS data were compared to LATCH estimates. At the tract level, aggregate VMT from these two data sources are well aligned, with an R^2 value near 0.90 (Figure 14). Given this project's focus on VMT, this validation is particularly important and demonstrates that the methods described in this memo have produced VMT estimates from LBS data.

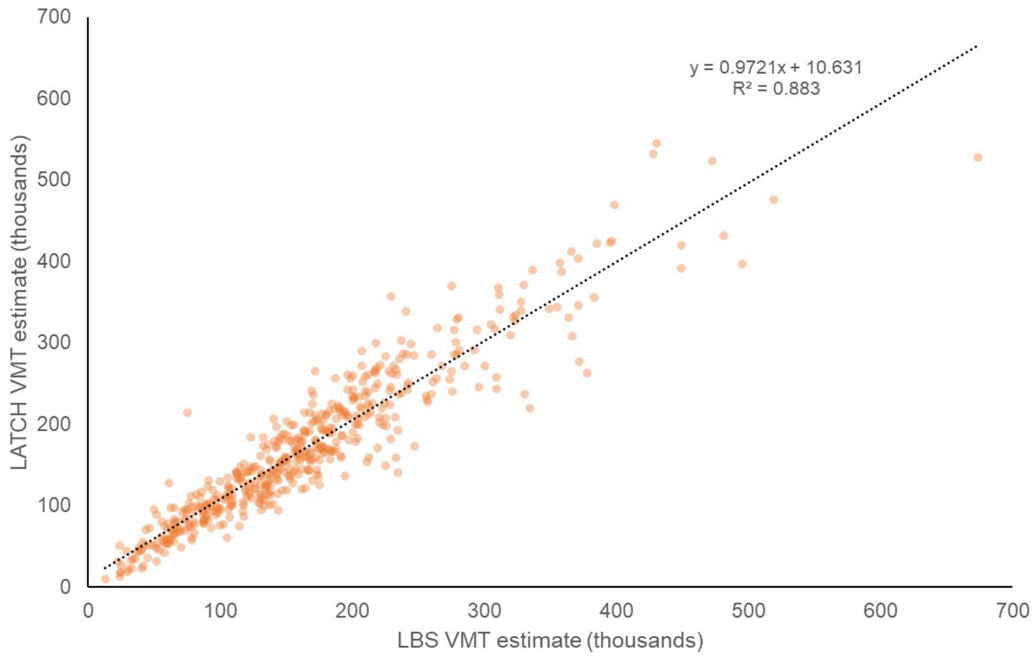


FIGURE 14. COMPARISON OF TRACT-LEVEL VMT DERIVED FROM LBS DATA (HORIZONTAL AXIS) AND LATCH ESTIMATES (VERTICAL AXIS)

The combination of RSG's standard LBS data processing approach and a custom-developed post-processing pipeline generated a high-quality, LBS-derived dataset containing over 750,000 trips from nearly 30,000 devices seen throughout 2019. Broadly, these data are aligned with the findings from Chapter 1: areas of the states with higher "5 d" variables tend to have lower average per capita VMT.

The development of the Vermont VMT model described in the next chapter will dig deeper into these relationships by joining the device-level VMT estimates described here to built environment measures developed in Task 2 modeling the relationships between built environment factors and VMT in Vermont.

4.0 DEVELOPING A VMT MODEL FOR VERMONT

This Chapter describes how the data developed during previous phases of this project were integrated to create a model that predicts how land use and built environment choices in Vermont will impact VMT. First, 2019 estimates derived from location-based services (LBS) data, as described in Chapter 2, were joined to the spatial database of built environment measures, as described in Chapter 2, using underlying hex cell geometry as described in Section 2.6. Next, exploratory analysis informed the development of additional built environment variables, including summaries of many "5d" variables in buffers of varying sizes around each hex cell across the state. Next, a structured variable selection process was employed to reduce the 200+ possible predictor variables in the built environment database to a more parsimonious set of variables for the regression model. Finally, the regression model was used to generate a 2019 VMT estimate, which could then be compared to other 2019 VMT estimates to validate the model for estimating VMT based on built environment measures. Each of these steps are described in greater detail below.

4.1 DATA PREPARATION

A foundational step in developing the regression model was to join LBS-derived VMT estimates to built environment measures. The built environment database described in Section 2.7 used hex cells covering the state as a base geometry. To join VMT estimates to these data, the hex cell containing devices' imputed home location was determined and built environment measures for that hex cell were joined to the VMT dataset. This resulted in a VMT dataset where each observation represents the LBS-derived VMT for a device (the outcome variable in the VMT model), with built environment variables describing the hex cell containing that device's home location joined to these VMT estimates.

Initial exploratory analysis revealed expected relationships between LBS-derived VMT and built environment factors: as density and land-use diversity increased, VMT tended to decrease (Table 12).

TABLE 12. RELATIONSHIP OF BUILT ENVIRONMENT VARIABLES AND OF LBS-DERIVED VMT

LBS VMT QUINTILE	LBS-DERIVED WEEKLY VMT (MEAN)	POP. DENSITY (MEAN)	EMPLOYMENT DENSITY (MEAN)	LAND-USE MIX (MEAN)
1 *(lowest 20%)*	36.4	1,383	1,118	0.85
2	92.3	754	552	0.77
3	122.1	406	260	0.66
4	145.7	304	175	0.60
5 *(highest 20%)*	247.8	295	182	0.58

However, this exploratory analysis revealed a shortcoming in the built environment database: density and diversity variables were calculated for each cell, which represent a very small spatial area. Commonly, built environment variables are calculated across larger spatial areas to better represent neighborhood-level effects of the built environment on travel behavior. To better capture such effects, a grid-and-buffer method was applied. First, population and employment density (by employment type) were calculated within each grid cell. Next, for each grid cell, all other grid cells within an *x*-mile buffer of that grid cell were identified, and average population and employment density were calculated across all identified grid cells. The resulting value was assigned to the grid cell used as the center of the buffer. This process was repeated for all grid cells in the state, using buffer sizes ranging from ¼ mile to 3 miles (Table 13). As illustrated below, the size of the grid cell has a significant impact on the distribution of density values, with smaller buffer sizes tending to generate "spikier" distributions and larger buffer sizes tending to generate smoother distributions (Figure 15).

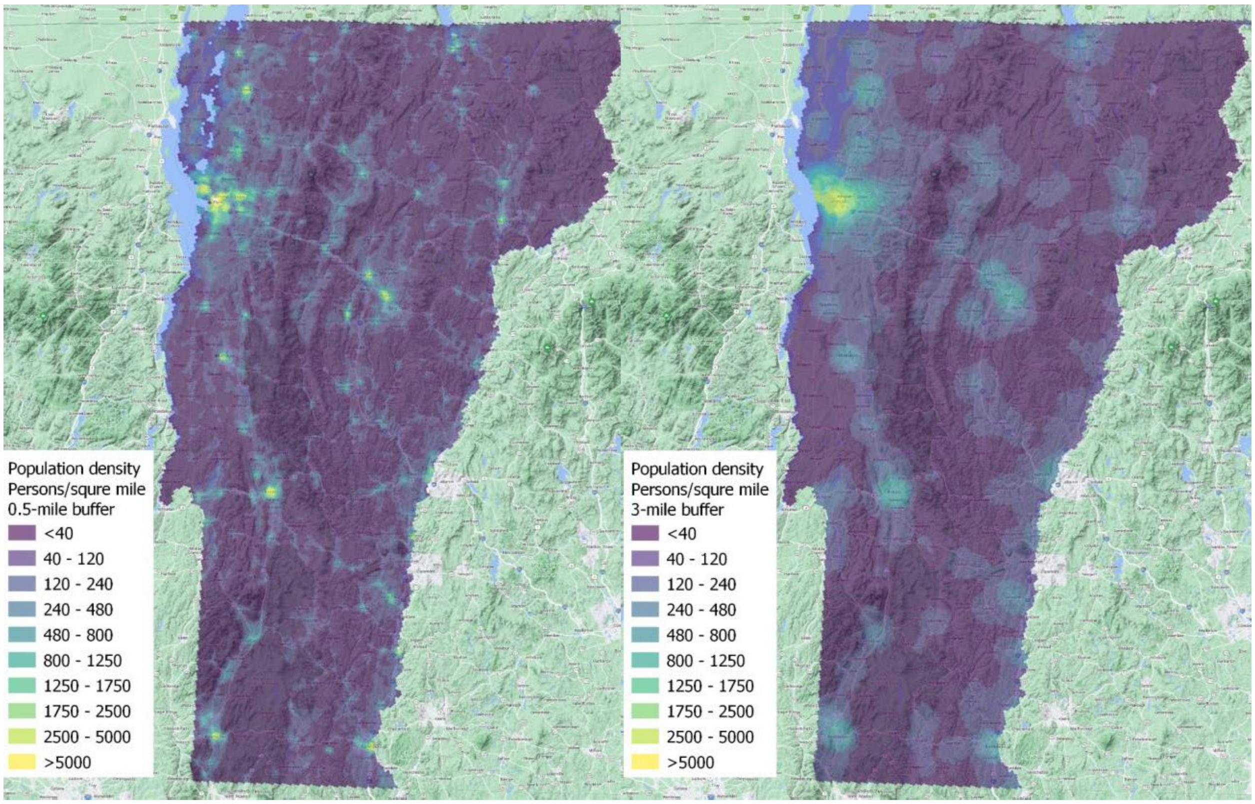


FIGURE 15. IMPACT OF BUFFER SIZE ON DENSITY VARIABLES

Exploratory analysis also revealed that the VMT variable and several predictor variables were not normally distributed in the sample, a common problem in regression analysis. As needed, log transformations were applied to these variables. Log-transformation of the outcome (VMT) variable improved model performance, so the regression models described below use log-transformed VMT as the outcome variable.

4.2 VARIABLE SELECTION

The joined dataset described above contained many possible predictive variables, and many of these variables were correlated with one another (e.g., high population density may be correlated with higher intersection density). To reduce this large set of possible predictive variables to a smaller set, a structured variable selection process was employed. First, an initial stepwise regression was performed using all non-buffered variables in the built environment database. Buffer variables were then assessed independently, and the highest-performing buffer variables were introduced to the model resulting from the initial stepwise regression and final variable selection was performed, once again using a stepwise regression approach. These steps are detailed below.

Initial Stepwise Regression

A linear regression model was specified, using log-transformed VMT as the outcome variable and all variables in the built environment database as possible predictor variables. Stepwise linear regression was performed using the *caret* package in R. Variables were retained if they met three criteria: 1) were identified by the TAC as variables that could respond to available policy levers (e.g., land use and transportation system variables) or controlled for important non-modifiable influences of travel behavior (e.g., household income), 2) improved the model's Akaike information criterion (AIC) value, and 3) had a sign in the expected direction, based on the Task 1 literature review (e.g., increased transit service should reduce VMT, and have a negative sign). This initial variable selection process yielded five significant variables with signs in the expected direction:

- Median household income
- OSM-derived sidewalk density
- Intersection density with auto-oriented intersections removed (variable *D3B* in the Smart Location Database)
- Transit service density (variable *D4C* in the Smart Location Database*; log-transformed)*
- Job accessibility within a 45-minute drive (variable *D5AR* in the Smart Location Database)

Buffer Variable Selection

The buffer variables calculated as described above present their own challenges in variable selection: within each type of buffer variable, different buffer sizes are highly correlated. For example, population density calculated using a 1-mile buffer is highly correlated with population density calculated using a 2-mile buffer, and so on. Because of this high degree of correlation, it was important to identify the set of buffer variables that most improved model fit before performing a final variable selection process.

To do so, a series of models was estimated, each using the five variables listed above and one of the buffer variables. Within each category of buffer variables (e.g., population density buffers), the model AIC was calculated, and the two-highest performing variables were identified.[39] Interestingly, across all categories of buffer variables, the highest performing models used buffer sizes between 1 and 3 miles and used a log transformation (Table 13).

[39] While the absolute value of the AIC does not indicate anything about model performance directly, the AIC can be used to test two variations of the same model (for example, one with an extra variable) and smaller AIC values indicate better model performance.

TABLE 13. EFFECT OF BUFFER SIZE ON VMT MODEL PERFORMANCE. TOP-TWO BUFFER VARIABLES IN EACH CATEGORY ARE BOLDED AND SHADED

BUFFER SIZE	POP. DENSITY	EMPLOYMENT DENSITY	RETAIL DENSITY	OFFICE DENSITY	INDUSTRIAL DENSITY	SERVICE DENSITY	ENTERTAIN. DENSITY
¼ mile	47,917	48,046	48,047	48,046	48,027	47,999	48,044
½ mile	47,849	48,027	48,055	48,044	48,019	47,978	48,044
¾ mile	47,840	47,988	48,054	48,054	47,999	47,954	48,053
1 mile	47,847	47,923	47,956	48,038	47,962	47,951	48,047
2 miles	47,929	47,953	47,928	47,984	47,906	47,989	48,016
3 miles	48,032	48,024	47,995	48,034	48,010	48,033	48,048
¼ mile*	47,600	47,597	47,822	47,870	47,833	47,588	47,797
½ mile*	47,540	47,528	47,691	47,771	47,753	47,527	47,624
¾ mile*	47,487	47,460	47,590	47,641	47,681	47,465	47,521
1 mile*	**47,426**	**47,383**	47,479	47,491	47,598	47,395	**47,394**
2 miles*	**47,380**	**47,302**	**47,356**	**47,402**	**47,501**	**47,310**	**47,297**
3 miles*	47,522	47,376	**47,362**	**47,464**	**47,576**	**47,386**	47,409

* log-transformed

Final Stepwise Regression

Final variable selection was performed by combining the set of variables from the initial stepwise regression process with the set of highest-performing buffer variables (i.e., the bolded and shaded variables in Table 13). A second stepwise regression was performed, again retaining variables if they improved the model's AIC and had a sign in the expected direction. This final variable selection process yielded eight significant variables:

- Median household income
- OSM-derived sidewalk density
- Intersection density with auto-oriented intersections removed (variable *D3B* in the Smart Location Database)
- Transit service density (variable *D4C* in the Smart Location Database*; log-transformed)*
- Population density in 2-mile buffer *(log-transformed)*
- Retail job in 3-mile buffer *(log-transformed)*
- Office job density in 2-mile buffer *(log-transformed)*
- Land-use mix in 3-mile buffer

4.3 REGRESSION MODEL

The final regression model performed quite well, with highly significant coefficients for each predictive variable and a coefficient of determination (r^2) of roughly 0.25. In simple terms, this means that the variables in the model are explaining roughly 25% of the observed variation in VMT in the sample which, considering the lack of demographic attributes in the LBS data sample and the complexity of travel behavior, is a strong result (Table 14).

TABLE 14. VMT MODEL RESULTS

BUILT ENVIRONMENT VARIABLE	COEFFICIENT	T-STAT
Median household income	0.003	15.91***
OSM-derived sidewalk density	-0.050	-20.18***
Intersection density	-0.001	-7.07***
Transit service density	-0.020	-2.36*
Population density in 2-mile buffer [a]	-0.048	-5.07***
Retail job in 3-mile buffer [a]	-0.027	-3.54***
Office job density in 2-mile buffer [a]	-0.038	-6.24***
Land-use mix in 3-mile buffer	-0.048	-2.36*
Intercept	5.016	146.23***
***$p<0.001$ **$p<0.01$ *$p<0.05$	AIC	50,145.6
[a] *log-transformed*	Adjusted-R^2	0.25

As expected, increases in population density, retail job density, office job density, and land-use mix are associated with reduced VMT. Increases in intersection density, transit accessibility, and sidewalk density are also associated with VMT reductions. Conversely, census block group median household income is associated with increased VMT.

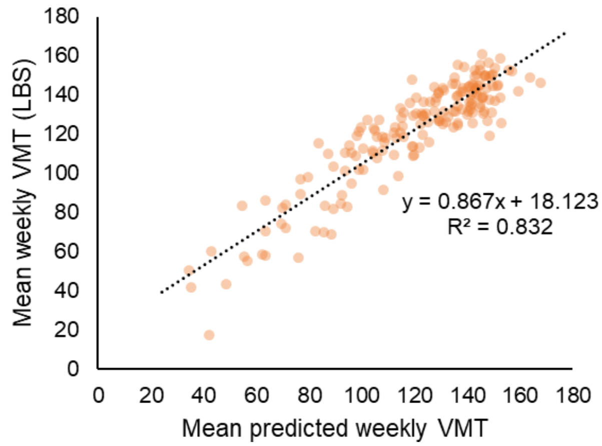
Because the outcome variable and several predictor variables are log-transformed in this model, interpreting the coefficients in Table 14 can be difficult. To better illustrate the effects of each variable, the marginal effect of a change in each variable on VMT was calculated (Table 15). To interpret these results, the marginal effect represents the average change in predicted VMT across the sample if the built environment variable were to be changed by the amount in the "unit change" column. For example, if population density was increased by 100 persons/mi^2 uniformly across all observations, the model would predict a 10.6 mile, or roughly 7%, reduction in per capita VMT.

TABLE 15. VMT MODEL MARGINAL EFFECTS

BUILT ENVIRONMENT VARIABLE	UNIT CHANGE IN BUILT ENVIRONMENT MEASURE	MARGINAL EFFECT ON WEEKLY VMT
Median household income	$10,000 increase in median income	+4.7 (+3%)
OSM-derived sidewalk density	1 unit increase in sidewalk density	-7.2 (-5%)
Intersection density	50-unit increase in intersection density	-8.4 (-6%)
Transit service density	5-unit increase in transit service density	-4.7 (-3%)
Population density in 2-mile buffer [a]	100 persons/mi^2 increase in population density	-10.6 (-7%)
Retail job in 3-mile buffer [a]	100 jobs/mi^2 increase in job density	-15.3 (-10%)
Office job density in 2-mile buffer [a]	100 jobs /mi^2 increase in job density	-21.4 (-15%)
Land-use mix in 3-mile buffer	0.10 increase in land-use mix	-0.7 (-0.5%)

4.4 MODEL VALIDATION AND APPLICATION

To validate the model, VMT was predicted for each observation in the sample, aggregated to census tracts, and compared to both LBS-derived VMT estimates and estimates from the Bureau of Transportation Statistics Local-Area Transportation Characteristics (LATCH) dataset. Model predictions match observed data very well, with an r^2 value over 0.80. Model predictions are not as well aligned with LATCH estimates, with an r^2 value approaching 0.65 (Figure 16).



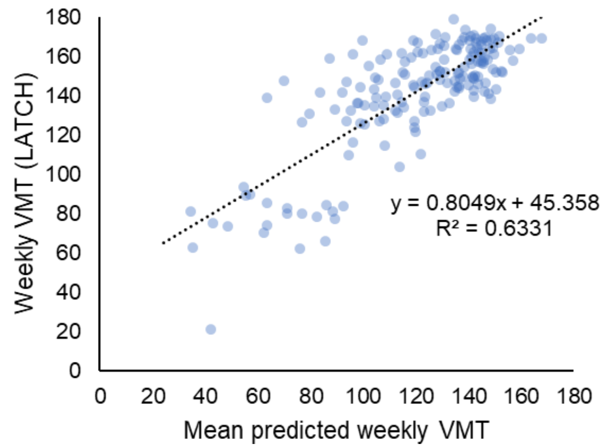


FIGURE 16. VMT MODEL PREDICTIONS VERSUS LBS OBSERVATIONS (LEFT) AND LATCH ESTIMATES (RIGHT)

However, the model does reliably tend to predict low VMT in places with low LATCH VMT estimates: for the lowest LATCH VMT quintile in the state, the model predicts an average weekly VMT of 81.2 miles compared to 93.7 miles in the LATCH data; in the highest LATCH VMT quintile, the model predicts an average weekly VMT of 141.5 miles compared to 169.2 miles in the LATCH data (Table 16). It is likely that the discrepancy between model predictions and LATCH estimates are due in large part to the lack of demographic information for LBS-derived data.

TABLE 16. COMPARISON OF MODEL PREDICTIONS TO LATCH ESTIMATES, BY LATCH VMT QUINTILE

LATCH VMT QUINTILE	MEAN WEEKLY VMT, LATCH	MEAN WEEKLY VMT, MODEL
1 *(lowest 20%)*	93.7	81.2
2	138.0	115.9
3	148.9	127.7
4	159.3	133.0
5 *(highest 20%)*	169.2	141.5

Finally, to apply the model across the state, 2019 Vermont population was distributed to hex cells using the E911 point and parcel datasets, which were joined as described in Task 3 memo. 2019 Census block group data were first used to calculate average household size for each census block, and households were allocated to hex cells based on the number of single-family residential parcels in each cell. Any remaining households were distributed evenly across all multi-family parcels in each cell. Finally, the number of households in each cell was multiplied by the block group average household size to obtain the number of persons residing in each cell across the state. To generate aggregate VMT estimates, the VMT model was used to generate a prediction for each resident of Vermont, using the built environment variables for the cell that person was allocated to as predictor variables in the model (Figure 17).

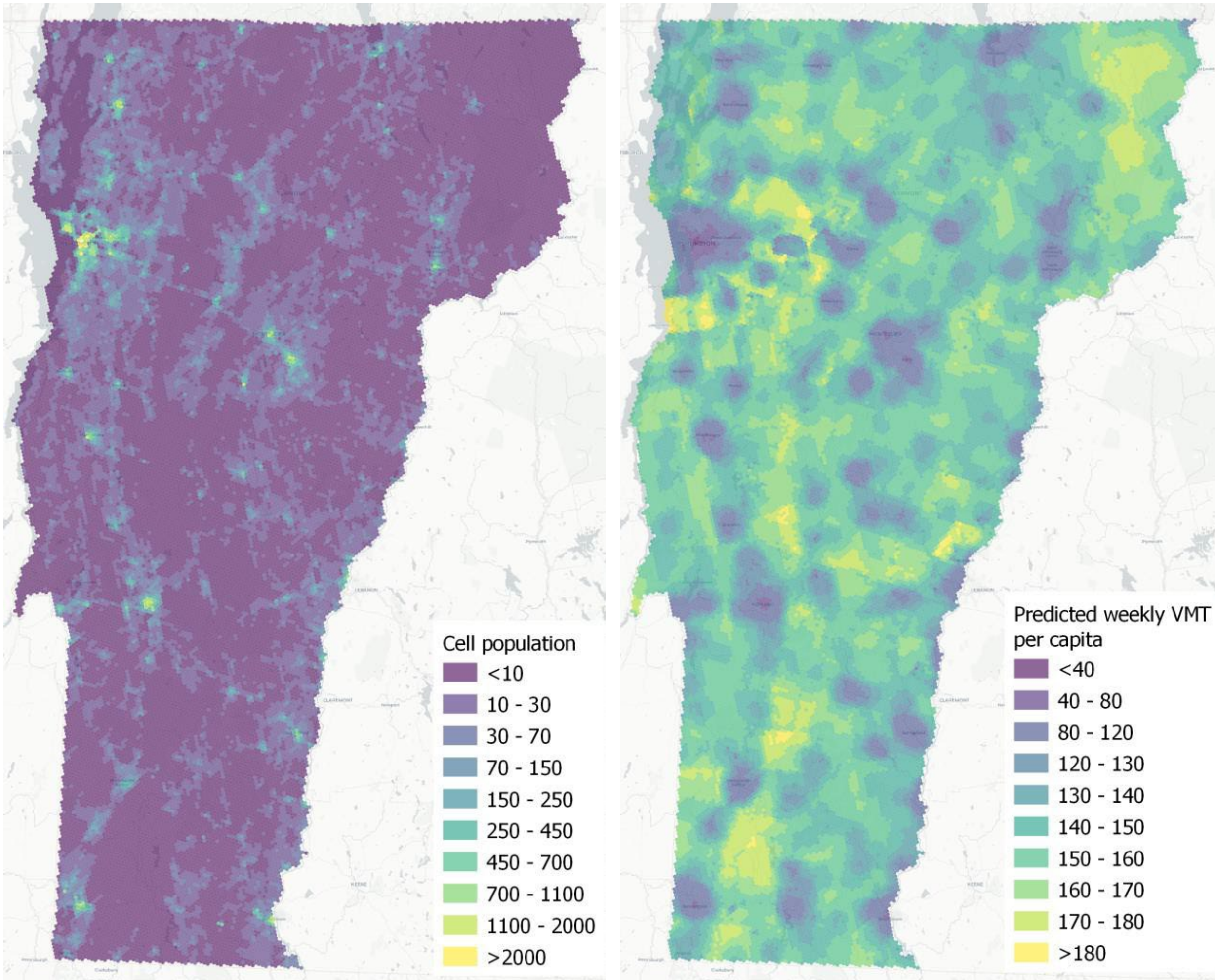


FIGURE 17. VERMONT RESIDENTS ALLOCATED TO CELLS (LEFT) AND VMT MODEL PREDICTIONS (RIGHT)

Overall, the VMT model provides intuitive results: denser regions across the state tend to have lower per capita VMT, with these areas with lower per capita VMT sprinkled evenly across the state. Interestingly, while some of the lowest per capita VMT predictions occur in and near Burlington, some of the highest per capita VMT predictions occur in communities that circle Burlington. This raises an interesting question that can be explored as scenarios are developed in future tasks: *is it more effective to focus on areas with already low VMT, or is it more effective to encourage dense development in areas near low-VMT areas, but that currently have high predicted VMT?* The future development scenarios described in the next chapter are designed in part to shed light on such questions.

5.0 VERMONT FUTURE GROWTH SCENARIOS

This chapter describes the methods used to develop future growth scenarios for Vermont, apply the VMT model described in Chapter 4 to these scenarios, and estimate for each scenario the benefits of the predicted change to VMT changes. This chapter is accompanied by an interactive online dashboard which allows readers to explore scenarios at greater depth.[40]

5.1 SCENARIO NARRATIVES

In coordination with the project TAC, the project team first developed a series of narratives to describe five possible patterns of future development of the built environment in Vermont. These narratives are provided below:

- *Dispersed growth:* In this scenario, low-density residential development occurs across all developable land, ignoring existing community designations and wastewater service areas. From a smart growth perspective, this represents a “worst case” scenario.
- *Concentrated growth, concentrated jobs:* In this scenario, future residential and employment growth is concentrated in already dense neighborhoods. Growth “overflows” to less dense neighborhoods when density exceeds a maximum density threshold.
- *Concentrated growth, dispersed jobs:* Like above, future residential growth is concentrated in already dense areas of the state. However, employment growth in allocated to lower density areas (i.e., greenfield development of employment centers).
- *Concentrated growth, balanced land use:* In this scenario, future development is focused on copying places in Vermont that exemplify smart growth principles today. Growth is allocated so that future development mirrors the lowest VMT neighborhoods in Vermont today (prototype smart growth neighborhoods).
- *Concentrated growth, unbalanced land use*: This scenario allocates residential growth as described above. Employment growth, on the other hand, occurs in locations near established cores, but not in locations with high population density.

5.2 DEVELOPING FUTURE SCENARIOS

The narratives described in the previous section were used to develop a series of “allocation rules” for each scenario that assign projected population and employment growth to specific areas of Vermont based on the patterns of future development in each scenario. The allocations of population and employment are distributed across the 31,739 grid cells covering the state as described in Chapter 3. Growth projections are described below, followed by descriptions of these allocation rules.

[40] Dashboard tool link: https://rsginc.shinyapps.io/VTrans_Smart_Growth/

Growth Projections

Rather than develop population growth projections specifically for this project, we adopted population growth projections assumed in the LEAP developed in support of the Pathways report.[41] The LEAP model offers two projections—a 'low-growth' and a 'high-growth' projection. Each projection estimates county-level population totals from 2019 through 2050. Because the projections in the LEAP model pre-dated the 2020 Census., we adjusted these projections by re-indexing the projections to the 2020 Census values, maintaining growth rates through 2050 (Table 17).

TABLE 17. LEAP GROWTH PROJECTIONS

COUNTY	PROJECTION	2020	2035	2050
Addison	Low growth, unadjusted	36,777	38,929	39,618
	Low growth, adjusted	37,363	39,515	41,633
	High growth, adjusted	37,363	40,761	45,319
Bennington	Low growth, unadjusted	35,470	36,706	37,099
	Low growth, adjusted	37,347	38,583	39,777
	High growth, adjusted	37,347	39,786	43,332
Caledonia	Low growth, unadjusted	29,993	28,010	27,410
	Low growth, adjusted	30,233	28,250	26,499
	High growth, adjusted	30,233	29,267	29,505
Chittenden	Low growth, unadjusted	163,774	178,433	183,193
	Low growth, adjusted	168,323	182,982	197,782
	High growth, adjusted	168,323	188,536	214,195
Essex	Low growth, unadjusted	6,163	5,385	5,157
	Low growth, adjusted	5,920	5,142	4,494
	High growth, adjusted	5,920	5,351	5,112
Franklin	Low growth, unadjusted	49,402	50,887	51,357
	Low growth, adjusted	49,946	51,431	52,859
	High growth, adjusted	49,946	53,106	57,810
Grand Isle	Low growth, unadjusted	7,235	7,751	7,917
	Low growth, adjusted	7,293	7,809	8,322
	High growth, adjusted	7,293	8,054	9,047
Lamoille	Low growth, unadjusted	25,362	26,700	27,128
	Low growth, adjusted	25,945	27,283	28,594
	High growth, adjusted	25,945	28,143	31,136
Orange	Low growth, unadjusted	28,892	30,977	31,649
	Low growth, adjusted	29,277	31,362	33,438
	High growth, adjusted	29,277	32,342	36,334
Orleans	Low growth, unadjusted	27,037	26,132	25,853
	Low growth, adjusted	27,393	26,488	25,664
	High growth, adjusted	27,393	27,405	28,373
Rutland	Low growth, unadjusted	58,191	54,526	53,415
	Low growth, adjusted	60,572	56,907	53,661
	High growth, adjusted	60,572	58,881	59,493
Washington	Low growth, unadjusted	58,409	55,797	53,524
	Low growth, adjusted	59,807	56,059	52,742
	High growth, adjusted	59,807	58,040	58,596
Windham	Low growth, unadjusted	42,222	41,107	40,119

[41] https://climatechange.vermont.gov/sites/climatecouncilsandbox/files/2022-03/Pathways%20Analysis%20Report_Version%202.0.pdf

	Low growth, adjusted	45,905	44,296	42,838
	High growth, adjusted	45,905	45,728	47,069
Windsor	Low growth, unadjusted	55,062	53,863	52,795
	Low growth, adjusted	57,753	56,020	54,440
	High growth, adjusted	57,753	57,887	59,958
Statewide	**Low growth, unadjusted**	**623,989**	**629,845**	**636,234**
	Low growth, adjusted	**643,077**	**652,127**	**662,744**
	High growth, adjusted	**643,077**	**673,286**	**725,279**

Prototype Smart Growth Neighborhoods

The *concentrated growth, balanced land use* and *concentrated growth, unbalanced land use* scenarios are based on the concept of prototype smart growth neighborhoods. These prototype neighborhoods represent places in Vermont that embody smart growth principles today. Prototype neighborhoods were identified by first grouping counties into four typologies (Table 18). Within each of these typologies, cells were sorted by baseline per capita VMT and, depending on the value of the *smart growth prototype percentile* parameter, average built environment measures were calculated for cells in the top *X%* of this distribution. These values were then used to define the characteristics for prototype neighborhoods within each typology.

TABLE 18. COUNTY GROUPINGS FOR IDENTIFYING PROTOTYPE SMART GROWTH NEIGHBORHOODS

COUNTY TYPOLOGY	COUNTIES
Urban	Chittenden
Medium centers	Rutland, Washington, Windsor
Small centers	Addison, Bennington, Caledonia, Franklin, Lamoille, Orleans, Windham
Rural	Essex, Grand Isle, Orange

Allocation Rules

To estimate VMT for each future scenario, the scenario narratives developed in conjunction with the TAC needed to be transformed into a framework for allocating growth to certain locations in each county. To do so, we developed an allocation framework for each scenario narrative. Broadly, an allocation framework consists of four components:

- **Growth cells:** a list of cells within each county that are eligible to grow in the future. Depending on the scenario narrative, this list of cells can be restrictive (e.g., cells that currently have wastewater service) or unconstrained (e.g., cells with developable land)
- **Allocation parameters:** variables that impact how growth is allocated to cells. For example, the maximum population density parameter used in the concentrated growth, concentrated jobs scenario controls how dense cells are allowed to become when allocating growth. Multiple values are tested for each parameter to provide a range of possible futures for each scenario narrative.
- **Ruleset for growing counties:** for counties that are projected to gain population, a series of discrete steps are used to allocate growth projections to cells across the county. These rulesets are designed so that the distribution of population and employment in future scenarios is consistent with the scenario narrative.

- **Ruleset for shrinking counties:** several counties are projected to lose population in the LEAP growth projections. For these counties, a series of discrete steps are used to allocate growth projections to cells across the county. These rulesets are designed so that shrinking counties preserve population and employment in a manner consistent with each scenario narrative.

While the LEAP growth projections contain only population projections, employment projections are also needed to develop future scenarios. To calculate employment growth for each county, the population-to-employment ratio for each county is calculated for the base year. This ratio is applied to population growth projections in subsequent years to estimate employment growth projections. These aggregate employment totals are used for scenario allocations. At the end of each allocation process, employment allocation was assigned to industry sectors (retail, office/institutional, services, entertainment, or other) using the baseline ratio of these sectors in each cell.

Scenario Rulesets

Rulesets developed for each growth scenario are provided in a synopsis below and in detail in the Appendix C. Each of these rulesets is accompanied by Python code that generates allocations given baseline distribution of population and employment and county-level growth control totals (Table 17).

Ruleset 1: Dispersed Growth

For the ruleset for the dispersed growth scenario, all cells with non-protected land are eligible to receive future growth. The scenario employed a planning regulation density cap based on the population density above which planning regulations are required. For growing counties, population and employment growth was allocated up to the planning regulation density cap, prioritizing the least dense cells in the county to receive growth first and allocating with that priority until growth was exhausted or until all the cells had received growth up to their cap. In the latter case, remaining growth was split across all cells. For shrinking counties, population and employment was deallocated from cells. Starting with the densest cells, the difference between the baseline and planning regulation density cap was removed from the densest cell then the next densest cell and so on until the targeted total was deallocated or until removal from all cells had occurred. In the latter case, the remaining deallocation was split evenly across all cells.

Ruleset 2: Concentrated growth, concentrated jobs

For the ruleset for the concentrated growth, concentrated jobs scenario, all cells that have wastewater service in the baseline year (2019) were eligible to receive future growth. For this scenario, maximum allowed density and a jobs-population mix ratio were the parameters controlling the allocation. For growing counties, the amount of population allocated to the densest cells first was calculated as the new population the cell could receive before exceeding the maximum allowed density. Moving to the next densest cell and so on, the population was allocated until the county allocation was exhausted or all possible growth cells had received growth, with any remaining split evenly among the eligible cells. Employment was allocated using the same process, with the jobs-population mix ratio determining the number of jobs allocated to the growth cell. For shrinking counties, removal of population and employment was prioritized for the least dense, non-growth cells up to the target deallocation or until removal from all non-growth cells was achieved, in which case the remaining deallocation was split evenly across the non-growth cells.

Ruleset 3: Concentrated growth, dispersed jobs

For the ruleset for the concentrated growth, dispersed jobs scenario, cells that have wastewater service in the baseline year were again eligible to receive future population growth. For growing counties, the amount of growth that could be allocated to a cell was calculated as the amount it could receive before exceeding the maximum allowed density. This allocation was prioritized to the growth cells with the lowest employment density, moving to the growth cell with the next lowest employment density until the population allocation was exhausted or all growth cells had received population, in which case the remainder was split evenly among those eligible to receive growth. The employment was then allocated to non-growth cells, prioritizing those with the lowest employment density and using the jobs-population mix parameter to determine the number of jobs to allocate. For shrinking counties, the least dense non-growth counties were prioritized for population removal, continuing until the deallocation target was reached or population had been removed from all non-growth cells, at which point the remaining deallocation was evenly removed from the growth cells. The same process was used for employment.

Ruleset 4: Concentrated growth, balanced land use

For the concentrated growth, balanced land use scenario, the growth cells were identified as those cells within an Agency of Commerce and Community Development (ACCD) designated area (Tier 1), cells immediately adjacent to ACCD designated areas (Tier 2), or cells neighboring Tier 2 cells (Tier 3). Two parameters were used to allocate growth in this scenario. A smart growth prototype percentile represented the percentile value of baseline cell VMT used to define “exemplar” smart growth neighborhoods within each county typology. A prototype boost percentage represented a boost applied to the build environment characteristics calculated for prototype smart growth neighborhoods (e.g., 25% more dense). For growing counties, the Tier 1 growth cell with the lowest VMT was prioritized to receive growth up to the reference population density as derived from the exemplar smart growth neighborhoods. The growth was then allocated to the next lowest VMT Tier 1 growth cell and so on until the targeted population was allocated to all Tier 1 growth cells. If there was remaining growth to be allocated, the process was repeated for Tier 2 cells, then Tier 3 cells, then split evenly across all growth cells. Employment was allocated through the same process. For shrinking counties, population was removed from the highest VMT non-growth cell first, moving to the next highest VMT non-growth cell and so on, until reaching the target deallocation or exhausting all of the non-growth cells. Any remaining deallocation was removed evenly across all Tier 1, 2, and 3 growth cells. Employment was deallocated through the same process.

Ruleset 5: Concentrated growth, unbalanced land use

For the concentrated growth, unbalanced land use scenario, growth cells were similarly defined as those cells within ACCD designated areas (Tier 1), immediately adjacent to ACCD designated areas (Tier 2), and cells neighboring Tier 2 cells (Tier 3). Again, the smart growth prototype percentile and prototype boost percentage were leveraged in this scenario. For growing counties, the population was allocated in the same way as the ruleset above for concentrated growth, balanced land use. However, for employment the allocation was prioritized to the cell with the highest employment density, skipping any Tier 1 cells. For shrinking counties, removal was prioritized from the highest VMT non-growth cells, moving to the next highest VMT non-growth cell and repeating until the deallocation was exhausted or all non-growth cells had population removed. If there was remaining deallocation, that was removed evenly from the Tier 1, 2, and 3 growth cells. The employment deallocation for this scenario was conducted using the same process as the population.

5.3 CALCULATING SCENARIO BENEFITS

The resulting VMT estimates were then used to estimate benefits associated with each scenario. In addition to changes in GHG emissions—the primary benefit explored in this study—four co-benefits were estimated:

- Changes in fatal and injury crashes, for motorized and non-motorized travel modes.
- Health impacts associated with changes in physical activity from nonmotorized travel.
- Changes in infrastructure maintenance costs associated with VMT.
- Potential reductions on infrastructure construction costs associated with more compact development patterns.

Methods used to quantify each of these benefit pathways are described in turn below.

GHG Emission Reductions

To estimate changes in GHG emissions for each development scenario, per capita VMT estimates in each hex cell were multiplied by the population of that cell in each scenario to obtain an estimate of total weekly VMT produced by each cell. This total was then annualized and multiplied by fleet-average CO_2-equivalent (CO_2eq) emissions per mile to obtain GHG emissions for each cell and aggregated across the state to obtain a statewide total. This model can be expressed as:

$$GHG_{statewide} = \sum VMT_j \times pop_j \times emissions_{CO2} \times 52$$

Where $GHG_{statewide}$ is the estimate of statewide GHG emissions from private vehicles, VMT_j is the model estimated per capita VMT in hex cell j, pop_j is the scenario population in hex cell j, and $emissions_{CO2}$ is the fleet-average CO_2eq emissions per mile. Estimates for fleet average CO_2eq were adopted from a recent MOVES analysis performed for the Chittenden County region in 2020 and 2050 (Table 19). The key data is the CO_2eq per mile is 430 grams per mile today and expected to decrease to 86 grams per mile by 2050 with the shift toward higher shares of electrified transportation. The fleet electrification assumptions that underly this reduction in CO_2eq per mile for Chittenden County were adopted from the Vermont Climate Action Plan and thus assumed relevant for this statewide application.[42]

[42] https://climatechange.vermont.gov/readtheplan

TABLE 19: CHITTENDEN COUNTY LONG RANGE PLAN - MOVES OUTPUTS

	2020 MODEL YEAR	2050 YEAR WITH MTP TIP
CO_2eq (kilograms)	1,932,969	455,547
Methane (kg) CH_4	143	13.3
Nitrous Oxide (kg) N_2O	25	6.3
Total Energy (Million BTUs)	25,208	19,962
Distance (VMT)	4,497,488	5,268,122
CO_2eq / VMT (g / mile)	**430**	**86**

MTP: metropolitan transportation plan
TIP: transportation improvement program

Safety Co-Benefit

Changes in fatal and injury crashes were estimated for both motorized and non-motorized travel modes. To do so, crash data were obtained from the Vermont crash data portal for the base year (2019), split into motorized and non-motorized travel modes and injury severity (fatal and injury crashes). Baseline crash rates per mile travelled were obtained by dividing baseline fatal and injury crashes by baseline VMT estimates derived from passively collected data as described in Chapter 3. Similarly, non-motorized crashes were divided by estimated statewide non-motorized travel duration described in Chapter 3 to develop non-motorized fatal and injury crash rates per minute of non-motorized travel (Table 20).

TABLE 20: VERMONT CRASH RATES

	MOTORIZED	NON-MOTORIZED
Injuries	1,772	173
Fatalities	42	3
Total travel	3,867,005,887 (VMT)	1,112,933,520 (active minutes)
Injury rate	**0.109 per million VMT**	**0.027 per million active minutes**
Fatality rate	**4.58 per million VMT**	**1.56 per million active minutes**

For each future scenario, the rates derived above were multiplied by VMT and active travel estimates to obtain fatality and injury estimates for motorized and non-motorized modes at the neighborhood scale. Interestingly, because VMT reductions are often accompanied by increases in active travel, scenarios that tend to reduce VMT tend to have estimated reductions in motorized fatalities and injuries but small increases in non-motorized injuries and fatalities.

Health Co-Benefit

In addition to safety co-benefits described above, other health impacts associated with increases in active travel were estimated using the population attributable fraction (PAF) approach. The PAF approach is commonly applied in comparative risk assessment frameworks and is used in several leading transportation health impact tools including the World Health

Organization's Health Economic Assessment Tool (HEAT)[43] and the Integrated Transport and Health Impact Model (ITHIM).[44] The PAF model uses the estimated change in transportation physical activity to predict changes in mortality risks from all causes, using relative risk estimates obtained from epidemiological evidence that characterized this relationship.

The first step in developing this model was obtaining the baseline death rate for Vermont, excluding accidental deaths and intentional self-harm. The epidemiological evidence used for this estimate is valid only for persons aged 15 to 74, so the baseline death rate was calculated for this group of Vermonters. These data were obtained from the Vermont Department of Health and are summarized below.

TABLE 21. VERMONT DEATH RATES

AGE RANGE	POPULATION	DEATHS, EXCLUDING ACCIDENTAL AND SELF-HARM	DEATH RATE	INCLUDE IN RATE CALCULATION
Under 1	5,579	15	0.002689	No
1-4 years	23,464	8	0.000341	No
5-14 years	64,156	7	0.000109	No
15-24 years	86,646	38	0.000439	Yes
25-34 years	74,408	41	0.000551	Yes
35-44 years	71,267	95	0.001333	Yes
45-54 years	78,051	233	0.002985	Yes
55-64 years	95,379	671	0.007035	Yes
65-74 years	75,206	1,163	0.015464	Yes
75-84 years	35,396	1,355	0.038281	No
85+ years	14,437	1,911	0.132368	No
15-74 years	**480,957**	**2,241**	**0.002689**	

To estimate changes in mortality associated with changes in active travel, per capita active travel time for each cell were first converted in metabolic equivalents (MET-hrs), and the difference the MET-hrs between each scenario and the baseline scenario were used to calculated the population attributable fraction (PAF):

$$PAF_j = \frac{RR_{j,b} - RR_{j,s}}{RR_{j,b}}$$

where PAF_j is the population attributable fraction for cell j, $RR_{j,b}$ is the relative risk of all-cause mortality for cell j given estimated active travel in the baseline scenario b and $RR_{j,s}$ is the relative risk of all-cause mortality for cell j given estimated active travel for scenario s,. Relative risk values were estimated using a log-linear dose-response function:

$$RR_j = 0.90^{\frac{MET_j}{11.25}}$$

where MET_j is the estimated per capita transportation physical activity for cell j. Finally, attributable mortality for each cell was estimated:

$$AM_j = pop_j \times DR_b \times PAF_j$$

[43] https://www.heatwalkingcycling.org
[44] https://github.com/ITHIM/ITHIM-R

where DR_b is the baseline death rate as derived in Table 21.

Maintenance Co-Benefit

Reductions in per capita VMT are expected to reduce VTrans infrastructure maintenance costs related to wear and tear. Because this project focuses on passenger VMT, an estimate of the share of roadway maintenance costs contributed by passenger vehicles (auto) was required. The 2019 weight-based annual registration report apportions roadway maintenance costs to specific vehicles classes and derives estimates of maintenance costs per mile travelled within each vehicle class (Table 22). While the cost responsibility per mile for autos is substantially lower than for other vehicle types, the larger number of miles travelled by autos makes the total auto cost responsibility roughly 30% of the total across all vehicle classes. We adopted the estimate derived for private passenger vehicles in this report: $0.01 per mile.

TABLE 22. VTRANS MAINTENANCE COSTS PER MILE TRAVELED, FROM THE 2019 WEIGHT-BASED ANNUAL REGISTRATION REPORT

VEHICLE CLASS	BRIDGES ($THOUSANDS)	PAVEMENT ($THOUSANDS)	COST RESPONSIBILITY ($THOUSANDS)	COST RESPONSIBILITY PER MILE (CENTS PER MILE)
Auto	**$38.10**	**$5.90**	**$44.00**	**1¢**
LT4	$12.70	$2.50	$15.20	1¢
SU2	$6.50	$17.90	$24.50	9¢
SU3	$2.20	$6.70	$9.00	13¢
SU4+	$0.50	$1.60	$2.10	20¢
CS3	$0.70	$1.70	$2.40	11¢
CS4	$1.30	$3.10	$4.50	14¢
3S2	$5.80	$24.10	$29.90	39¢
CS5	$0.50	$1.60	$2.00	33¢
CS6	$1.40	$5.00	$6.40	47¢
CS7+	$1.20	$4.00	$5.20	1,357¢
CT4-	$0.00	$0.00	$0.10	16¢
CT5	$0.40	$1.80	$2.20	47¢
CT6+	$0.10	$0.20	$0.30	26¢
DS5	$0.10	$0.20	$0.40	33¢
DS6	$0.20	$0.30	$0.50	71¢
DS7	$0.10	$0.20	$0.40	794¢

Avoided Infrastructure Co-Benefit

To estimate potential reduction in required roadway miles for future smart growth scenarios, we applied the relationship between population density and per capita roadway miles described in Chapter 2. To do so, we first obtained data from Table HM 72 of the Federal Highway Administration's Highway Statistics 2019[45] and modeled the relationship between population density and lane-miles (Figure 18). We then assigned each grid cell within Vermont to its

[45] https://www.fhwa.dot.gov/policyinformation/statistics/2019/hm72.cfm

township and applied the derived function to estimate township-level roadway miles needed for each scenario:

$$RM_{town} = 192.02 \times e^{-0.48popden}$$

where RM_{town} is the number of road-miles per person for each township and $popden$ is the population density in the township.

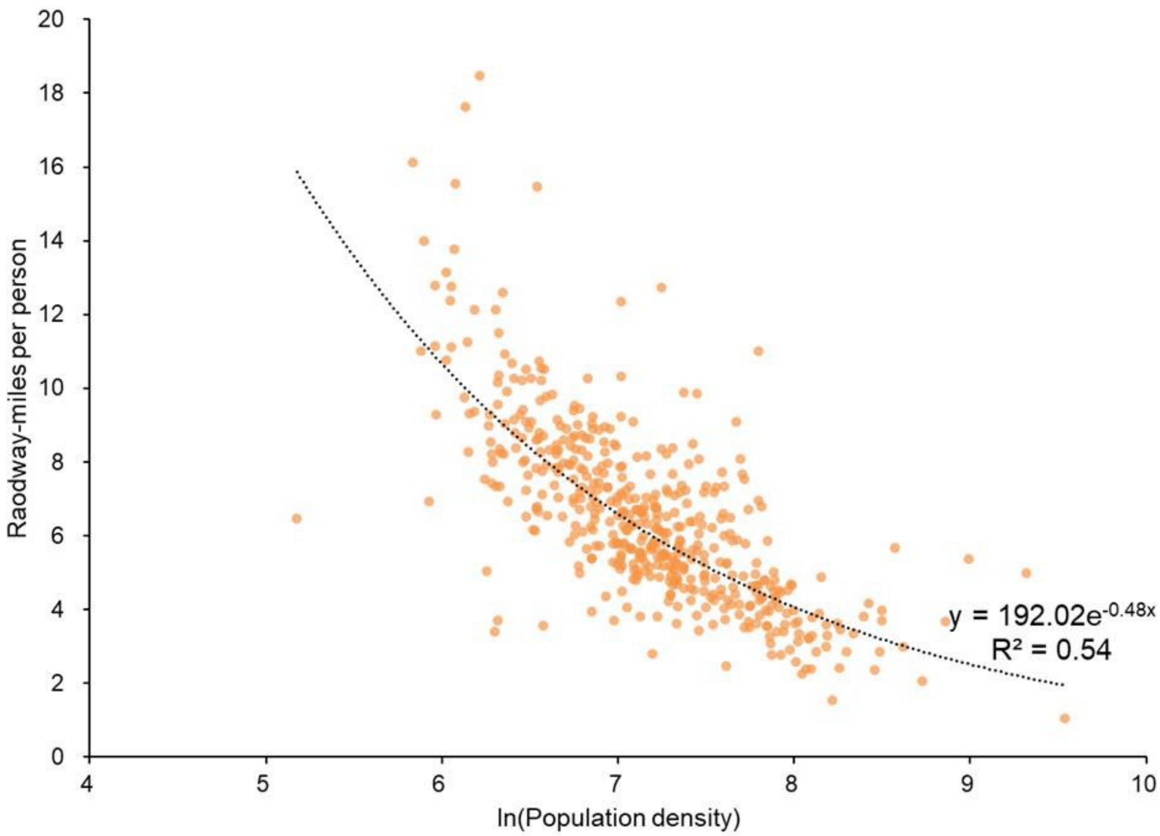


FIGURE 18. RELATIONSHIP BETWEEN POPULATION DENSITY AND ROADWAY MILES PER CAPITA

5.4 RESULTS

Applying the allocation rulesets as described in Section 5.2 resulted in unique distributions of population and employment by industry sector across the 31,739 cells covering Vermont for each scenario. Given that many of the benefits calculations presented in Section 5.3 are based on per capita VMT, a fundamental step in calculating the benefits associated with each of these scenarios is calculating VMT and non-motorized travel duration associated with each scenario. To do so, the VMT model and non-motorized travel duration models described in Chapter 3 were applied. As necessary, buffered built environment variables were developed as previously described, using scenario population and employment values instead of baseline values.

The VMT results for each of the scenarios are depicted in Figure 19. After calculating per capita VMT across the state, GHG emissions and associated co-benefits were calculated by applying each benefit calculation. These calculations were performed for both horizon years in the LEAP projections (2035 and 2050) and for both the low- and high-growth scenarios. All permutations of scenario parameters were also tested, resulting in a range of values for each scenario. These results are presented in Table 23 and Table 24. Statewide per capita VMT for each scenario is presented, alongside scenario benefits relative to the baseline scenario for each growth projection. When interpreting benefits, positive values indicate a benefit (e.g., avoided traffic fatalities or a reduction in GHG emissions) while negative values indicate a worsening of the situation (e.g., an increase in traffic fatalities or GHG emissions).

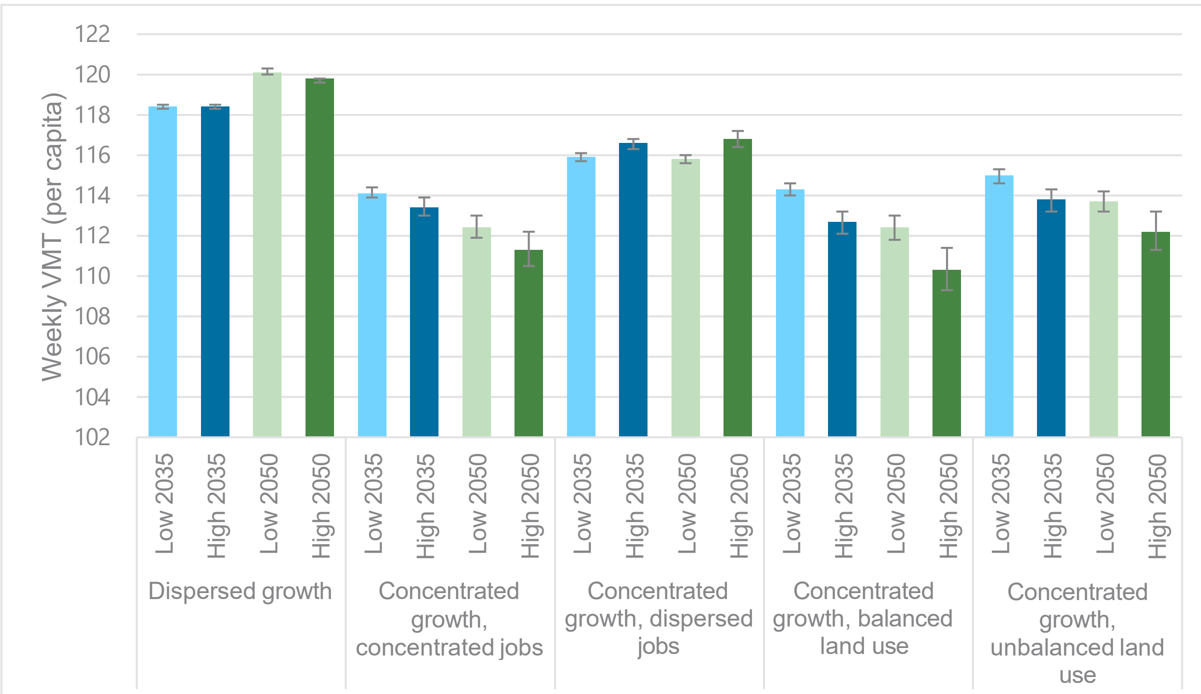


FIGURE 19. WEEKLY PER CAPITA VMT ACROSS ALL SCENARIOS

Across most benefit categories, the concentrated growth, concentrated jobs and concentrated growth, balanced land use scenarios perform best, illustrating the benefits of the smart growth strategies embedded in these scenarios. It is noted that the low growth futures in 2035 and 2050 produce similar outcomes for these two scenarios, but in the high growth futures concentrated growth, balanced land use outperforms concentrated growth, concentrated jobs scenarios. Results indicate that concentrating growth in areas with density and in areas where VMT is low are both capable of significantly reducing per capita VMT; however, in a high growth future, focusing growth in areas with low VMT while emulating prototype communities has an advantage in achieving further VMT reductions.

Further, the concentrated growth, concentrated jobs and concentrated growth, balanced land use scenarios indicate the importance of concentrating jobs in proximity and in balance with population growth. Each of these scenarios outperform the concentrated growth, dispersed jobs and concentrated growth, unbalanced land use scenarios in reducing VMT. This outcome has implications for future development patterns, indicating that statewide initiatives, regional planning, and local zoning should focus attention on the proximity and balance of job generating land uses with population density and growth.

Conversely, the dispersed growth scenario performs worse than the baseline across all outcomes, reinforcing the importance of smart growth principles in reducing transportation GHG emissions and providing important co-benefits to Vermont residents.

With a focus on quantifying the implications of smart growth principles in future scenarios, the concentrated growth, balanced land use scenario out to 2050 is poised to produce the following results:

- Reduce weekly VMT to 110 miles per capita;
- Reduce GHG emissions by over 13,000 metric tons annually;
- Avoid 1 traffic death per year;
- Avoid over 31 traffic injuries per year;
- Reduce physical inactivity mortality by nearly 4 lives annually;
- Reduce annual maintenance costs by over $1.5 million; and,
- Avoid 364 additional road miles.

Conversely, the dispersed growth scenario out to 2050 was poised to produce the following results:

- Increase weekly VMT to nearly 120 miles per capita;
- Increase GHG emissions by over 17,000 metric tons annually;
- Increase traffic deaths per year by 1.5;
- Increase traffic injuries per year by 52;
- Increase physical activity mortality by nearly 3 lives annually;
- Cost an additional $2 million in annual maintenance costs; and,
- Require over 500 additional road miles.

A comparison of the best (concentrated growth, balanced land use) to worst (dispersed growth) scenarios results in a difference of 10 additional miles per capita VMT, 2.5 traffic fatalities per year, over 80 traffic injuries per year, physical inactivity mortality of 7 lives annually, and approximately $3.5 million in maintenance costs.

To put these results in context, the GHG emission reductions were compared to the targets set forth in the Global Warming Solutions Act. To achieve the target of 80% below 1990 GHG emissions levels by 2050, annual reductions of 84,000 metric tons of CO_2 equivalent ($MTCO_2e$) would be required when starting from 2019 levels (i.e., 3.34 million $MTCO_2e$).[46] The GHG reductions produced by the concentrated growth, balanced land use scenario would represent approximately 15.5% of the annual reduction needed to achieve the target out to 2050.

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[46] Vermont Greenhouse Gas Emissions Inventory and Forecast: 1990-2020

Conversely, a dispersed growth scenario would contribute to an annual increase in GHG emissions, representing an adverse increase in emissions of approximately 20% of the annual change needed.

Full results for each of the scenarios out to 2035- and 2050-time horizons for both low and high growth scenarios are tabulated below. In addition, results for each scenario at the statewide and hex grid scale can be explored through the project dashboard.[47]

[47] Dashboard tool link: https://rsginc.shinyapps.io/VTrans_Smart_Growth/

TABLE 23. SCENARIO BENEFITS, 2035

	BENEFITS CATEGORY	DISPERSED GROWTH	CONCENTRATED GROWTH, CONCENTRATED JOBS	CONCENTRATED GROWTH, DISPERSED JOBS	CONCENTRATED GROWTH, BALANCED LAND USE	CONCENTRATED GROWTH, UNBALANCED LAND USE
Low Growth	Per capita VMT (weekly)	118.4 *(118.3 – 118.5)*	114.1 *(113.9 – 114.4)*	115.9 *(115.7 – 116.1)*	114.3 *(114.0 – 114.6)*	115.0 *(114.6 – 115.3)*
	GHG emission reductions (annual metric tons)	-7,484 *(-7,719 – -7,244)*	4,888 *(4,091 – 5,589)*	-284 *(-941 – 264)*	4,533 *(3,544 – 5,331)*	2,430 *(1,435 – 3,473)*
	Annually avoided traffic deaths	-0.66 *(-0.69 – -0.63)*	0.48 *(0.33 – 0.60)*	0.08 *(-0.02 – 0.16)*	0.25 *(0.05 – 0.46)*	0.19 *(-0.02 – 0.40)*
	Annually avoided traffic injuries	-23.33 *(-24.76 – -21.89)*	17.99 *(10.84 – 23.51)*	4.92 *(0.86 – 8.58)*	5.47 *(-4.16 – 16.07)*	6.14 *(-4.00 – 16.56)*
	Annually avoided physical inactivity mortality	-1.20 *(-1.23 – -1.17)*	0.67 *(0.41 – 1.02)*	-0.54 *(-0.63 – -0.46)*	1.55 *(1.17 – 1.83)*	-0.10 *(-0.31 – 0.07)*
	Annually avoided maintenance ($)	-870,313 *(-897,620 – -842,377)*	568,386 *(475,767 – 649,976)*	-33,040 *(-109,422 – 30,760)*	527,148 *(412,102 – 619,930)*	282,618 *(166,874 – 403,935)*
	Avoided road miles	-279.9 *(-295.5 – -267.5)*	225.1 *(215.2 – 237.2)*	95.32 *(75.93 – 114.05)*	95.65 *(80.88 – 104.01)*	77.59 *(49.03 – 98.47)*
High Growth	Per capita VMT (weekly)	118.4 *(118.3 – 118.5)*	113.4 *(113.0 – 113.9)*	116.6 *(116.3 – 116.8)*	112.7 *(112.1 – 113.2)*	113.8 *(113.2 – 114.3)*
	GHG emission reductions (annual metric tons)	-9,410 *(-9,707 – -9,224)*	6,060 *(4,519 – 7,282)*	-3,850 *(-4,507 – -3,017)*	8,085 *(6,414 – 9,751)*	4,717 *(3,083 – 6,457)*
	Annually avoided traffic deaths	-0.83 *(-0.87 – -0.80)*	0.58 *(0.32 – 0.81)*	-0.23 *(-0.33 – -0.11)*	0.57 *(0.20 – 0.95)*	0.46 *(0.14 – 0.79)*
	Annually avoided traffic injuries	-29.59 *(-31.41 – -28.34)*	21.47 *(9.50 – 32.62)*	-5.71 *(-9.93 – -0.68)*	16.81 *(-1.11 – 35.54)*	17.56 *(2.02 – 32.79)*
	Annually avoided physical inactivity mortality	-1.59 *(-1.63 – -1.51)*	0.95 *(0.66 – 1.30)*	-1.18 *(-1.31 – -1.05)*	2.36 *(1.76 – 2.95)*	-0.40 *(-0.62 – -0.20)*
	Annually avoided maintenance ($)	-1,094,272 *(-1,128,781 – -1,072,646)*	704,660 *(525,528 – 846,854)*	-447,695 *(-524,153 – -350,883)*	940,116 *(745,816 – 1,133,938)*	548,534 *(358,500 – 750,919)*
	Avoided road miles	-339.3 *(-345.3 – -331.1)*	254.6 *(226.4 – 275.8)*	-24.39 *(-53.85 – 2.29)*	217.5 *(175.9 – 250.8)*	177.6 *(136.9 – 237.3)*

TABLE 24. SCENARIO BENEFITS, 2050

	BENEFITS CATEGORY	DISPERSED GROWTH	CONCENTRATED GROWTH, CONCENTRATED JOBS	CONCENTRATED GROWTH, DISPERSED JOBS	CONCENTRATED GROWTH, BALANCED LAND USE	CONCENTRATED GROWTH, UNBALANCED LAND USE
Low Growth	Per capita VMT (weekly)	120.1 *(120.0 – 120.3)*	112.4 *(111.9 – 113.0)*	115.8 *(115.6 – 116.0)*	112.4 *(111.8 – 113.0)*	113.7 *(113.2 – 114.2)*
	GHG emission reductions (annual metric tons)	-14,324 *(-14,846 – -13,977)*	8,484 *(6,682 – 9,777)*	-1,630 *(-2,323 – -1043)*	8,384 *(6,527 – 10,244)*	4,608 *(2,983 – 6,181)*
	Annually avoided traffic deaths	-1.26 *(-1.33 – -1.21)*	0.83 *(0.52 – 1.11)*	0.05 *(-0.05 – 0.14)*	0.53 *(0.11 – 0.97)*	0.42 *(0.09 – 0.73)*
	Annually avoided traffic injuries	-44.67 *(-47.67 – -42.46)*	31.44 *(16.94 – 44.63)*	5.93 *(1.52 – 9.89)*	14.10 *(-6.46 – 35.94)*	15.19 *(-0.64 – 30.11)*
	Annually avoided physical inactivity mortality	-2.10 *(-2.16 – -2.04)*	1.39 *(0.84 – 1.95)*	-1.08 *(-1.26 – -0.91)*	2.89 *(1.94 – 3.60)*	-0.32 *(-0.56 – -0.01)*
	Annually avoided maintenance ($)	-1,665,668 *(-1,726,345 – -1,625,321)*	986,591 *(777,028 – 1,136,974)*	-189,581 *(-270,162 – -121,335)*	974,978 *(758,997 – 1,191,212)*	535,820 *(34,6890 – 718,807)*
	Avoided road miles	-477.6 *(-486.6 – -468.1)*	404.4 *(367.1 – 423.7)*	145.7 *(124.9 – 166.9)*	209.0 *(166.8 – 243.0)*	178.2 *(149.6 – 231.8)*
High Growth	Per capita VMT (weekly)	119.8 *(119.6 – 119.8)*	111.3 *(110.5 – 112.2)*	116.8 *(116.4 – 117.2)*	110.3 *(109.3 – 111.4)*	112.2 *(111.3 – 113.2)*
	GHG emission reductions (annual metric tons)	-17,418 *(-17,685 – -16,987)*	9,996 *(7,229 – 12,671)*	-7,708 *(-9,055 – -6,375)*	13,261 *(9,768 – 16,648)*	7,112 *(3,999 – 10,127)*
	Annually avoided traffic deaths	-1.49 *(-1.53 – -1.43)*	0.96 *(0.44 – 1.48)*	-0.45 *(-0.65 – -0.25)*	0.99 *(0.21 – 1.69)*	0.78 *(0.21 – 1.35)*
	Annually avoided traffic injuries	-52.06 *(-53.87 – -49.38)*	35.84 *(11.45 – 60.38)*	-10.83 *(-19.83 – -2.13)*	31.42 *(-6.79 – 65.03)*	30.87 *(4.24 – 58.04)*
	Annually avoided physical inactivity mortality	-2.96 *(-3.15 – -2.87)*	1.82 *(0.68 – 2.82)*	-2.16 *(-2.45 – -1.83)*	3.96 *(2.93 – 5.89)*	-1.20 *(-1.66 – -0.91)*
	Annually avoided maintenance ($)	-2,025,391 *(-2,056,434 – -1,975,310)*	1,162,389 *(840,682 – 1,473,478)*	-896,280 *(-1,052,971 – -741,281)*	1,5420,12 *(1,135,824 – 1,935,881)*	827,009 *(465,062 – 1,177,634)*
	Avoided road miles	-513.9 *(-527.6 – -500.2)*	430.5 *(350.8 – 491.2)*	-61.24 *(-107.70 – -16.57)*	364.0 *(273.7 – 451.1)*	298.8 *(191.1 – 385.1)*

6.0 CASE STUDIES

As observed through the estimation of vehicle miles travelled (VMT) from passively collected, location-based data, there are a number of exemplary communities that have lower VMT activity relative to other Vermont communities, due to their settlement pattern and characteristics of the local built environment. These prototype communities were identified as those with the top 10% performing (i.e., lowest VMT) hex cells in the base scenario within the particular county typology (i.e., rural, small centers, medium centers, urban). County typologies were identified with feedback from the TAC and their top 10% performing communities were identified as outlined in Table 25.

TABLE 25. COUNTY TYPOLOGIES AND PROTOTYPE COMMUNITIES

	TYPOLOGIES			
	RURAL	SMALL CENTERS	MEDIUM CENTERS	URBAN
Counties	Grand Isle Essex Orange	Addison Bennington Caledonia Franklin Lamoille Orleans Windham	Rutland Washington Windsor	Chittenden
Prototype Communities	Bradford Fairlee Randolph	Middlebury Vergennes Manchester Stowe St. Albans Bennington Brattleboro	Montpelier Barre Rutland	Burlington

Zooming in on these places, most prototype communities that have low per capita VMT travel patterns in the Vermont context tend to exhibit the following features:

- Dense core area (typically a main street, merchants' row, or center of a grid network);
- Mix of uses, services, and amenities;
- Concentration of population and employment;
- Water and sewer district;
- Sidewalk network; and,
- Access to transit.

In depth case studies were developed to examine a couple of communities more closely. A selection of communities was identified to represent different community sizes distributed across different parts of the state in coordination with the TAC. Springfield, Rutland, and Morrisville were selected as locations to be further investigated to contextualize the base and future forecasted scenarios while providing insights into opportunities for smart growth at the community level. Each case study serves to demonstrate the opportunities for VMT reduction through implementation of smart growth principles and the utility of the forecasted scenarios in identifying the potential challenges, opportunities, and benefits to employing smart growth principles at the community scale.

6.1 RUTLAND CITY

Rutland City is a relatively densely populated city that, like many Vermont communities, already has a lot of the elements in place to support smart growth. This includes a relatively dense downtown district with mostly three- to five-story buildings along Merchants Row, Center Street, and West Street as depicted in Figure 20. Most of these buildings have first floor retail spaces at the back of wide sidewalks connecting to a grid pattern street network.

These attributes contribute to the travel behaviors in the City and the identification of Rutland as a prototype community when compared to other places within the medium center county typology. The densest parts of downtown Rutland have weekly per capita VMT of less than 50 miles traveled in the base scenario.

Further, the surrounding area land uses outside of the City contribute to a smaller footprint of travel activity for Rutland City as demonstrated in Figure 21. The US-7 and US-4 corridors provide connectivity to the areas surrounding Rutland City, which are highlighted in the lighter color in Figure 21 based on observed travel patterns (i.e., >20% of devices). Travel along these corridors results in a relatively tight activity space, with the most concentration of trips occurring at the center within Rutland City and some concentration of trips further afield but generally not expanding beyond neighboring towns in each direction (i.e., Brandon, Killington, Wallingford, and Castleton).

RUTLAND PROFILE

City Population | **15,807** persons (2020)

County Population | **60,572** persons (2020)

City Land Area | **7.6** miles^2

Population Density | **2,096** persons / mi^2

✓ Transit Agency | Marble Valley Regional Transit District (The Bus)

✓ Designated Downtown District

✓ Water / Sewer District

FIGURE 20. RUTLAND'S CITY CENTER

Even though Rutland is a prototype community, future population growth projections forecast Rutland County to lose population. Although Rutland City, particularly the densest parts of the City's downtown district, would be ideal for concentrating growth with the aim of further reducing VMT, the anticipated contraction of population at the county scale may challenge the community when looking to enhance their smart growth strategy.

Looking to the future scenarios, maintaining density in the lowest VMT areas of the county results in marginal increases in population and employment opportunities in Rutland City. This is evident when comparing the concentrated growth scenarios to the baseline scenario. Despite the county contraction of population, slight increases to population and employment in the City's downtown enables slightly more density in the core area supporting a 0.1% decrease in weekly per capita VMT.

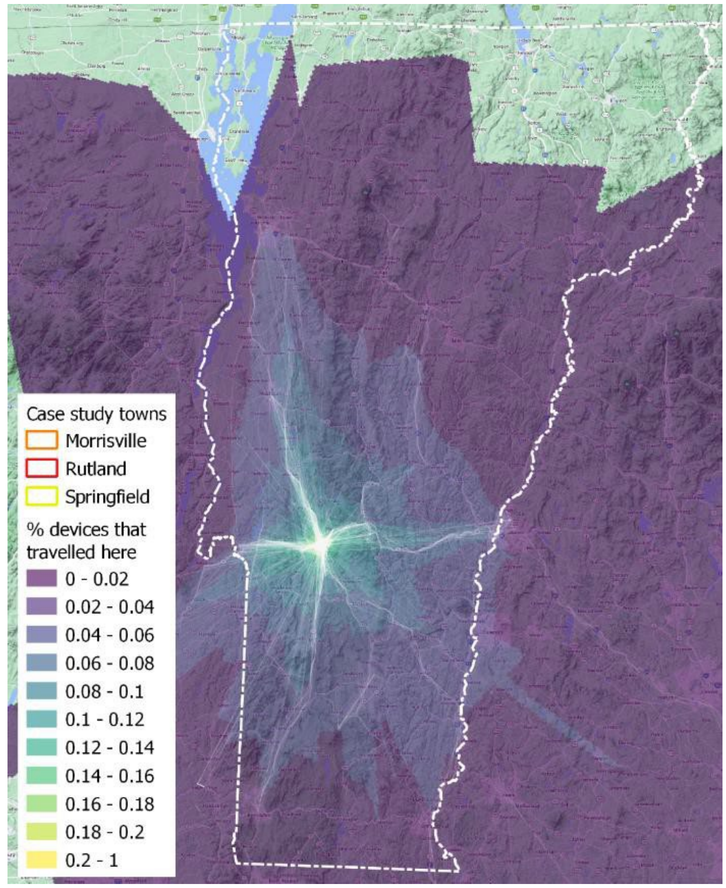

FIGURE 21. RUTLAND ACTIVITY SPACE

This contrasts with the dispersed growth scenario. Although low levels of VMT remain in the core area, the downtown loses population and jobs. Additionally, the settlement pattern stretches along the US-7 corridor, particularly south of the City, contributing to more sprawl. Although more moderate (i.e., slightly lower) weekly VMT per capita can be seen extending south along US-7 in the dispersed pattern depicted in Figure 22 as compared to the concentrated growth scenario, population is simultaneously drawn away from those core areas with low levels of VMT. The combination of the effects of population shifting from areas with low VMT to areas with moderate VMT has the net effect of a 1.1% increase in weekly VMT for the City.

The resulting travel pattern under the dispersed growth scenario can be visualized in contrast to the concentrated growth, balanced land use scenario as demonstrated in Figure 22. Further exploration of the scenarios within the dashboard tool[48] reveals the dynamics of shifting population and jobs, providing a fuller picture of the future scenarios for a prototype community that faces countywide reduction in population. With a contracting population anticipated for the county, more strategic approaches may be required to draw population, jobs, and other smart growth opportunities into the places with more density and lower VMT.

[48] Dashboard Tool: Vermont Smart Growth Project Dashboard (shinyapps.io)

Dispersed Growth

Concentrated Growth

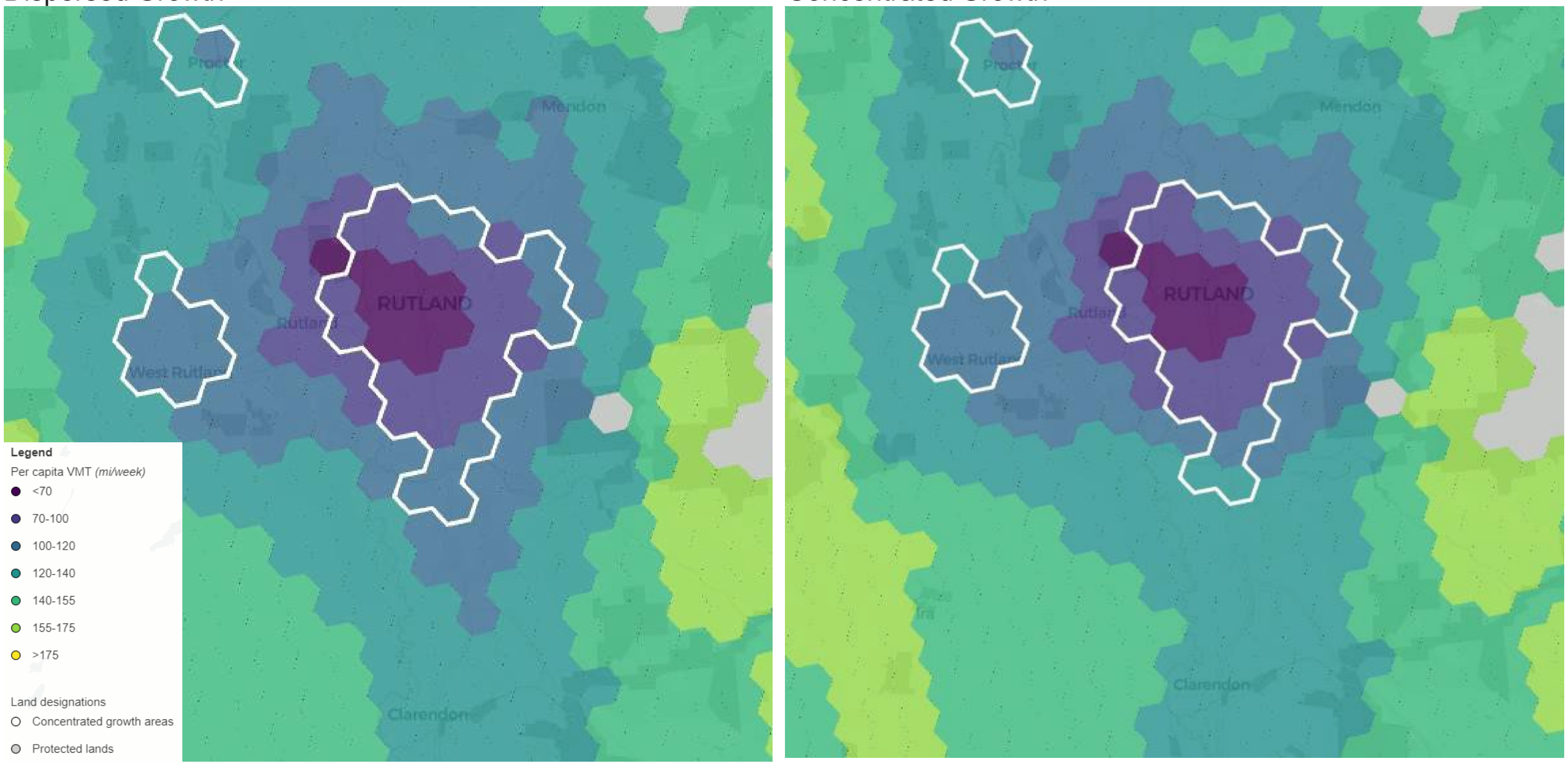

FIGURE 22. COMPARISON OF DISPERSED AND CONCENTRATED GROWTH SCENARIOS FOR RUTLAND

6.2 SPRINGFIELD

Springfield is a medium sized community situated adjacent to the Black River and Black River Falls, like many Vermont communities established along a river and water falls for the resources (i.e., water and power) they provide. The community has a designated downtown district that runs along Main Street and encompasses parcels on both sides of the river. The core of this area has two- and three-story buildings with first floor retail and a connected sidewalk network. There are also mill buildings within the district, some of which have been adaptively repurposed for other, updated uses.

SPRINGFIELD PROFILE

Town Population | **9,062** (2020)

County Population | **57,753** (2020)

Town Land Area | **49.3** miles^2

Town Density | **180** persons / mi^2

Downtown District Density | Approximately **1,200** persons / mi^2

✓ Transit Agency | Southeast Vermont Transit (MOOver)

✓ Designated Downtown District

✓ Water / Sewer District

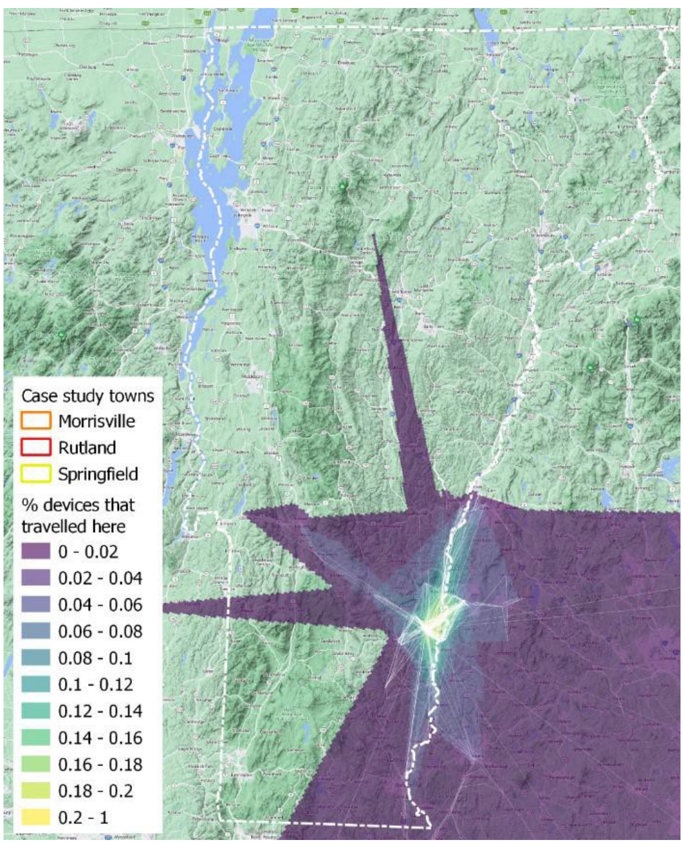

FIGURE 23. ACTIVITY SPACE FOR SPRINGFIELD

Springfield has neighboring small communities, like North Springfield, Chester, Bellows Falls, and Claremont, NH, that contribute to a tight network of trips to and from Springfield's downtown. The connections to these other small communities in close proximity to the area makes for a mix of jobs, services, and amenities that support one another through this clustered set of defined places. These complementary communities and land uses represent the majority of trips in the demonstrated activity space from the location-based data as shown in Figure 23.

Although the downtown is topographically restricted with the river and steep surrounding landscape, the area in the downtown district is ripe with opportunities to increase density, which would reduce VMT compared to a more dispersed growth pattern. Progress towards repurposing underutilized spaces is outlined in the Main Street Master Plan for Springfield[49]. The Plan recognizes the opportunity to draw more population and employment into the district, and the co-benefits this could create, such as activation of public spaces, support for economic development, and a more vibrant downtown.

Springfield on the Move is active in supporting the expansion of opportunities within the district. Challenges and costs associated with the repurposing of former industrial spaces and other barriers to increasing density can be overcome by some of the mechanisms already available, like the opportunity zone designation. Expansion of these types of programs can help to alleviate the significant burden in repurposing underutilized, developed areas and encouraging density.

FIGURE 24. DOWNTOWN SPRINGFIELD

Dispersed growth scenarios for Springfield indicate a less than 1% increase in weekly per capita VMT. However, the concentrated growth and balanced land use scenario could reduce VMT by 6.6%. Comparing the baseline pattern to the concentrated growth, balanced land use scenario reveals a broader area of reduced weekly per capita VMT (i.e., expanded dark purple area in Figure 25). As demonstrated in Figure 25, closer examination reveals the scale of increased population and employment in the core area and affiliated increase in active transportation and reduction in VMT. Looking at the same core area across scenarios, a reduction of 3.6 miles traveled and 9 additional minutes of active transportation per capita is associated with a concentration of population and jobs in the downtown core. The scenario is consistent with plans for the area in terms of redevelopment and adaptive reuse and aligns with the magnitude of change potentially achieved through the scale of revitalization and economic development anticipated for the area.

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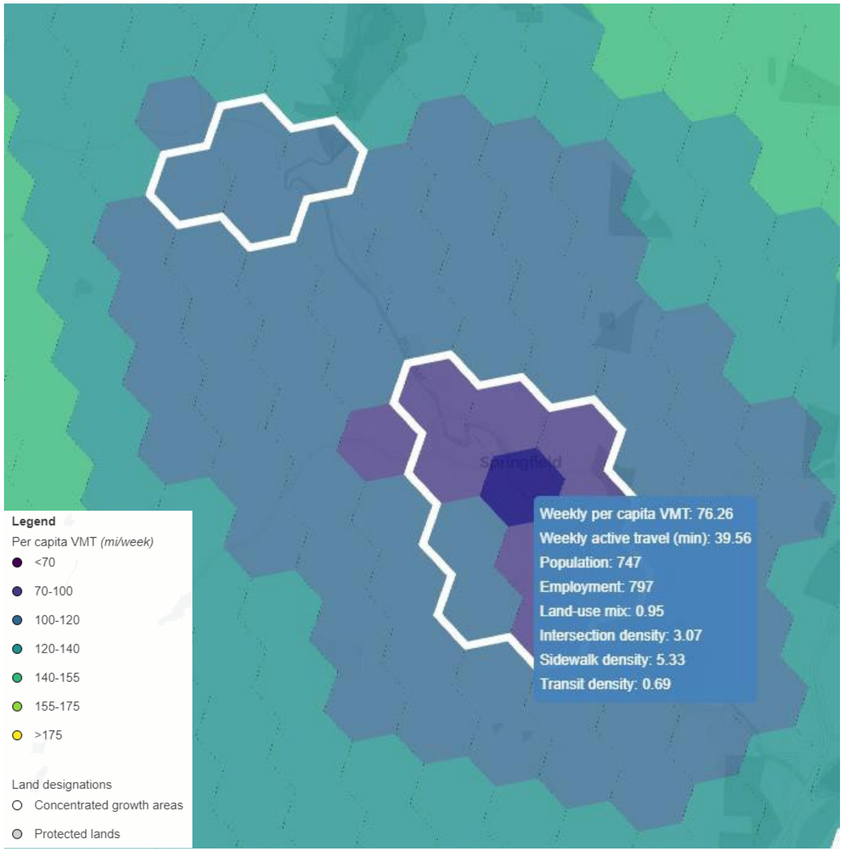
[49] https://springfieldvt.gov/vertical/sites/%7B234B28A5-DB73-489E-ABFA-F2FB1EF67C08%7D/uploads/Springfield_Report_6_30_17_Complete.pdf

Baseline



Concentrated Growth Balanced Land Use

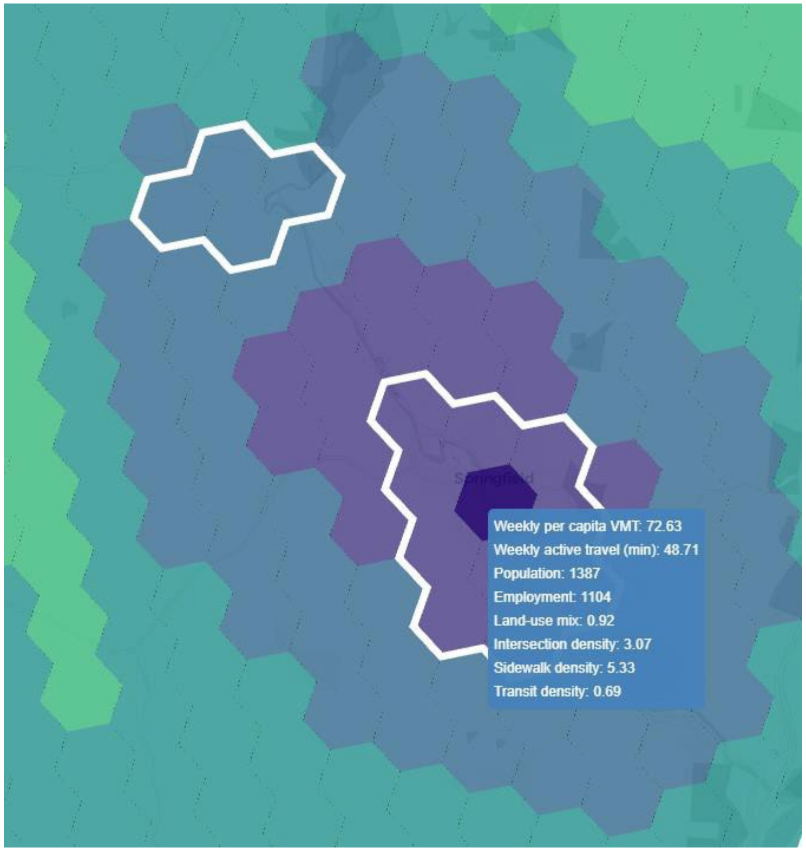


FIGURE 25. COMPARISON OF BASELINE AND CONCENTRATED GROWTH BALANCED LAND USE SCENARIOS FOR SPRINGFIELD

6.3 MORRISVILLE

Morrisville is a village in Morristown, Vermont. The downtown village area has a small, dense core along Main Street and Portland Street, coinciding with the Historic VT-100 corridor and junction with VT-15A and VT-12. Similar to other Vermont villages, it is adjacent to the Lamoille River and a set of falls. The core area has primarily two- and some three-story buildings with first floor retail running along a connected sidewalk network as shown in Figure 26. Morrisville has an adjacent alignment of VT-100 that connects the surrounding areas to VT-100 to the south and VT-15 to the north.

The core village area has many of the characteristics of smart growth; however, the area has a relatively high weekly per capita VMT at approximately 100 miles per week. This is significantly higher than other comparable village centers. Given the proximity to opportunities in surrounding communities and in neighboring Chittenden County, the activity space depicted in Figure 27 for the community indicates that travel to and from the Burlington area and other neighbors is a significant contributor to the high average weekly per capita VMT.

MORRISVILLE PROFILE

Village Population | **2,086** (2020)

County Population | **25,945** (2020)

Village Land Area | **1.96** miles^2

Village Density | **1,000** persons / mi^2

✓ Transit Agency | Rural Community Transportation

☐ Designated Downtown District

✓ Water / Sewer District

FIGURE 26. DOWNTOWN MORRISVILLE

For Morrisville, context and employment are key to the demonstrated travel patterns and the opportunities to reduce VMT. Not only do Morrisville residents access neighboring Chittenden County with frequency, but Morrisville also serves as an employment center drawing workforce from the Northeast Kingdom, or the large geographic area to the northeast. Jobs are concentrated northeast of the downtown and commercial services are dispersed outside of the core area. These employment opportunities and services are outside of a walkable distance from downtown. This lack of intermixing of uses locally combined with the draw from a wide geographic region may contribute to the higher per capita VMT demonstrated in the baseline scenario.

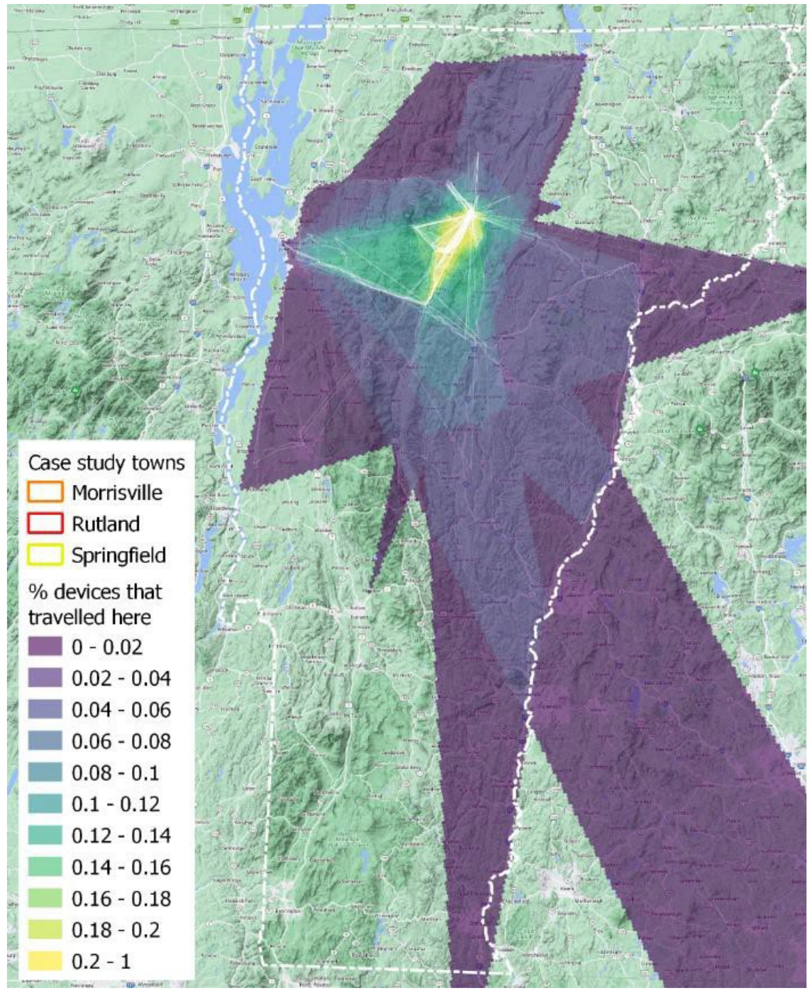


FIGURE 27. MORRISVILLE ACTIVITY SPACE

Examination of the future scenarios provides further insight. In the dispersed growth scenario, weekly per capita VMT increased by just over 1%. The concentrated growth, balanced land use scenario could reduce VMT by 2.1%. However, it is the concentrated growth, concentrated jobs scenario that seems to move the needle on bringing the area's weekly per capita VMT down. It may be that the wide commute shed and geographic pull of neighboring areas of employment imposes diminishing returns for the concentrated growth scenarios until employment is also concentrated in the area.

The area with the greatest demonstrated VMT reduction is spread across Morrisville north of the core downtown, where current industrial and commercial uses are more prevalent. Drawing more employment and thus commute trips into these areas in closer proximity to the population density may reduce the need for longer trip making to neighboring areas for employment, therefore reducing VMT. This indicates that other mechanisms to support job growth may be required to spur the type of smart growth patterns that will induce further decreases in VMT, particularly for the historic center of Morrisville. Further, more direct connections from the historic center to these areas north of the core may be required to facilitate improved access and VMT reductions. It is notable that some of these areas north of the historic center where growth and VMT reductions are anticipated fall outside of the existing water and sewer district.

The contrast between the dispersed scenario and concentrated growth, concentrated jobs scenario is depicted in Figure 28 and can be further explored in the dashboard tool[50]. For Morrisville, the concentration of growth and jobs combines to create a broader area where weekly per capita VMT reductions are possible. In this scenario, the concentration of population and employment is most significant in the area that encapsulates the historic center of Morrisville, which could achieve a reduction of nearly 5 miles of travel per week per capita and an increase of over 9 minutes of weekly active travel.

[50] Dashboard Tool: Vermont Smart Growth Project Dashboard (shinyapps.io)

Dispersed Growth

Concentrated Growth, Concentrated Jobs

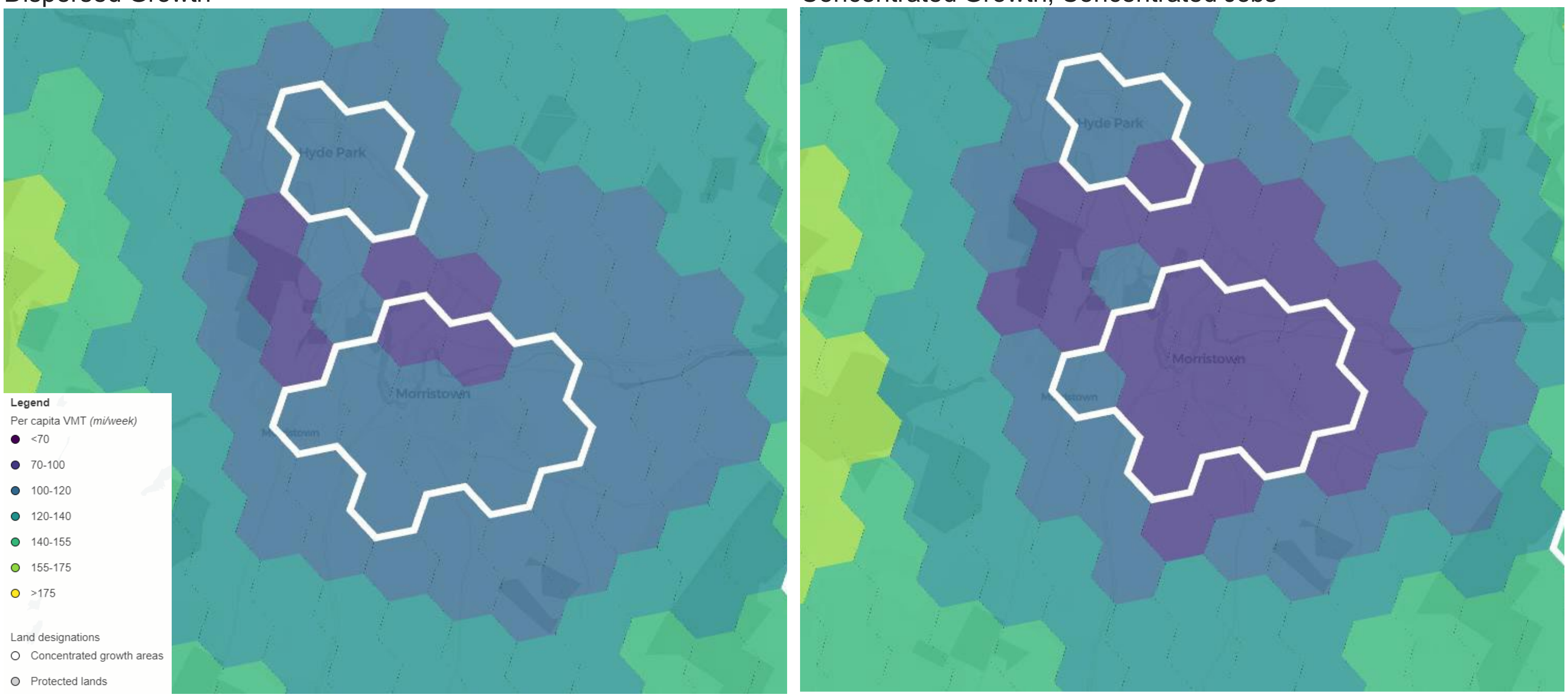


FIGURE 28. COMPARISON OF DISPERSED AND CONCENTRATED GROWTH, CONCENTRATED JOBS SCENARIOS FOR MORRISVILLE

6.4 KEY TAKEAWAYS

Combined with the results of the future scenarios overall, key takeaways demonstrated in these case studies include the following:

- **Land Use alone doesn't move the needle – balance with job proximity is needed;** while denser, mixed land uses reduce VMT by reducing trip lengths and inducing shift to active transportation modes, such as walking, biking or the use of public transit, for daily travel activities, an equally important factor that influences VMT is proximity to jobs. Each of the case study communities exemplifies the dynamic where, broadly speaking, the closer jobs are to where people live, the greater the additional VMT reduction exhibited. This inelasticity of VMT as a function of job proximity serves as a crucial reminder that wholistically planning communities from a smart growth perspective requires envisioning the location of jobs relative to town centers and lived neighborhoods.
- **Vermont has "good bones;"** smart growth land use patterns that inherently lead to reductions in VMT are rooted in Vermont's land use goal of town centers surrounded by rural countryside and can be enhanced through thoughtful modifications to density, mix of land use, and proximity to jobs. Contextual scaling that corresponds to character of place and careful coordination to align local actions with state and regional land use plans and visions are crucial next steps to build on Vermont's "good bones" and position the state to make further strides in the reduction of VMT. Each of the case study communities has a specific type of "good bones" that is elaborated on through the modelling undertaken in this study to test and demonstrate how VMT can further be reduced.
- **Regional neighbors influence VMT and travel patterns;** Vermont's scale lends itself to region- wide and state-wide travel patterns. This creates a dynamic where folks live, work, and play in condensed movement patterns in their town centers to service various needs, and complement these needs with more expansive patterns via travel to adjacent communities and regions. Each of the case study communities exemplifies and documents a specific corresponding VMT response to this complementarity.

7.0 CONCLUSIONS

This project explored the hypothesis that compact, mixed use development patterns generate fewer VMT and GHG emissions per person than more dispersed or rural settlement patterns. Current and future patterns of built environment development, land use, population growth, and travel behavior were quantified in several scenarios to demonstrate the degree to which smart growth strategies in the Vermont context can reduce VMT to meet transportation related GHG emission reduction targets.

Passively collected, location-based data were leveraged to develop weekly per capita VMT estimates for the state. VMT estimates and built environment measures were resolved to a hex-grid spatial database across the state of Vermont to develop a model relating these measures to the weekly per capita VMT. Future scenarios were developed to represent a range of possible growth and built environment changes. The passive data derived VMT estimates and model relating VMT to built environment measures was applied to the scenarios to predict how VMT and other related benefits might change across the potential futures.

Scenario Evaluations

Based on the analysis, compact development patterns in future scenarios reduced VMT by nearly 10 miles per person per week compared to dispersed patterns, demonstrating the opportunity for smart growth strategies in Vermont and the impact they might have on travel patterns. Further, **the most effective scenarios for smart growth were focused on concentrating balanced residential and employment growth in areas with demonstrated low VMT based on the characteristics of exemplary low VMT communities.**

The GHG emissions reduction potential of smart growth, based on the most effective scenarios evaluated, could amount to over 15% of the annual reduction needed to achieve the 2050 Global Warming Solutions Act targets. Conversely, dispersed settlement patterns could produce an increase in emissions of approximately 20% of the annual target, working against other mechanisms to achieve Vermont's GHG emissions reduction goals.

Beyond VMT and GHG emission reductions, smart growth strategies were demonstrated to benefit safety (e.g., 1 avoided traffic death and over 30 avoided traffic injuries), health (e.g., reduced physical inactivity mortality by nearly 4 lives annually), and maintenance (e.g., reduced annual maintenance costs by over $1.5 million) outcomes associated with the transportation system in Vermont.

Case Study Evaluations

There are communities within Vermont where the built environment supports more condensed travel patterns. These exemplary VMT communities, or places with lower VMT compared to other communities within the same county typology, tend to have a dense core area, mix of uses, concentration of population and employment, water and sewer districts, a sidewalk network, and access to transit. There are also locations in Vermont that seem to produce more VMT and GHG emissions on average despite a built environment that has smart growth characteristics. Zooming in on a few communities through the lens of the future scenarios illuminated some key takeaways for contextualizing the results of this study, including:

- **Denser, mixed land uses require complementary economic opportunities where job proximity is a factor** for some communities to achieve targeted VMT and GHG reductions. Achieving this requires holistic planning to locate jobs relative to compact centers and livable neighborhoods;
- Vermont's **historical settlement patterns and land use goal of denser centers surrounded by more rural areas lends itself inherently to smart growth strategies** where the state's "good bones" can be enhanced through thoughtful, context sensitive modifications to density, land use mix, proximity to jobs, and civil infrastructure;
- **Regional neighbors influence VMT and travel patterns** where condensed movement patterns within town centers may serve some needs complemented by more expansive patterns with travel to adjacent communities to serve other needs. Such activity is affected by proximity of neighboring communities to provide complementary services and amenities.

These communities offer insights on the potential scope and scale of VMT and GHG reductions that are possible through implementation of smart growth strategies. The work at the local and regional level to encourage and operationalize smart growth principles can have a statewide impact of contributing over 15% towards the annual reduction needed to achieve the targeted GHG emissions reduction in the Global Warming Solutions Act.

APPENDIX A. ANNOTATED BIBLIOGRAPHY

The existing literature outlined below includes a mix of peer reviewed studies, case studies, and policy guidance documents for practitioners. The peer reviewed literature methodologies include meta-regression, meta-analysis, case studies, and other statistical methodologies. Notable limitations of the existing studies include small sample size, homogenous sample composition, and the understanding that correlation between variables does not necessarily imply causation. Additional caveats about the existing literature include the use of only some of the D variables when there are interdependencies and the use of different metrics to represent the Ds.

Ahlfedt and Pietrostefani, 2017

The Economic Effects of Density: A Synthesis

This paper synthesizes the state of knowledge on the economic effects of density. We consider 15 outcome categories and 209 estimates of density elasticities from 103 studies. More than 50% of these estimates have not been previously published and have been provided by authors on request or inferred from published results in auxiliary analyses. We contribute own estimates of density elasticities of 16 distinct outcome variables that belong to categories where the evidence base is thin, inconsistent or non-existent. Along with a critical discussion of the quality and the quantity of the evidence base we present a set of recommended elasticities. Applying them to a scenario that roughly corresponds to an average high-income city, we find that a 1% increase in density implies positive per capita net present values of wage and rent effects of $280 and $485. The decrease in real wage net of taxes of $342 is partially compensated for by an aggregate amenity effect of $221 and there is a positive external welfare effect of $52. Density has important positive amenity and resource implications, but also appears to create a scarcity rent, which harms renters and first-time buyers.

Burchell and Mukherji, 2003

Conventional Development Versus Managed Growth: The Costs of Sprawl

We examined the effects of sprawl, or conventional development, versus managed (or "smart") growth on land and infrastructure consumption as well as on real estate development and public service costs in the United States. Mathematical impact models were used to produce US estimates of differences in resources consumed according to each growth scenario over the period 2000-2025. Sprawl produces a 21% increase in amount of undeveloped land converted to developed land (2.4 million acres) and approximately a 10% increase in local road lane-miles (188 300). Furthermore, sprawl causes about 10% more annual public service (fiscal) deficits ($4.2 billion US dollars) and 8% higher housing occupancy costs ($13 000 US dollars per dwelling unit). Managed growth can save significant amounts of human and natural resources with limited effects on traditional development procedures.

Burchell, Robert & Mukherji, Sahan. (2003). Conventional Development Versus Managed Growth: The Costs of Sprawl. American journal of public health. 93. 1534-40. 10.2105/AJPH.93.9.1534.

CAPCOA, 2021

Handbook for Analyzing Greenhouse Gas Emission Reductions, Assessing Climate Vulnerabilities, and Advancing Health and Equity

The California Air Pollution Control Officers Association (CAPCOA) produced an updated, 2021 handful which provides methods to quantify greenhouse gas emission reductions from a specified list of measures, primarily focused on project level actions. In particular, the handbook provides guidance for combining emission reductions from transportation measures and adjusting VMT reductions to expected GHG savings. For several of the measures, CAPCOA uses Stevens, 2016 meta-regression elasticities of VMT which accounts for self-selection.

https://www.caleemod.com/handbook/index.html

Project Level Strategy	Maximum GHG Reduction
Increased residential density	-30%
Increased employment density	-30%
Transit oriented development	-31%
Affordable housing	-28%

Increased Residential Density

$$A = \frac{\mathbf{B} - C}{C} \times D$$

GHG Calculation Variables

ID	Variable	Value	Unit	Source
Output				
A	Percent reduction in GHG emissions from project VMT in study area	0–30.0	%	calculated
User Inputs				
B	Residential density of project development	[ ]	du/acre	user input
Constants, Assumptions, and Available Defaults				
C	Residential density of typical development	9.1	du/acre	Ewing et al. 2007
D	Elasticity of VMT with respect to residential density	-0.22	unitless	Stevens 2016

Increased Employment Density

GHG Reduction Formula

$$A = \frac{B - C}{C} \times D$$

GHG Calculation Variables

ID	Variable	Value	Unit	Source
Output				
A	Percent reduction in GHG emissions from project VMT in study area	0–30.0	%	calculated
User Inputs				
B	Job density of project development	[ ]	jobs per acre	user input
Constants, Assumptions, and Available Defaults				
C	Job density of typical development	145	jobs per acre	ITE 2020
D	Elasticity of VMT with respect to job density	-0.07	unitless	Stevens 2016

Transit Oriented Development

GHG Reduction Formula

$$A = \frac{(B \times C)}{-D}$$

GHG Calculation Variables

ID	Variable	Value	Unit	Source
Output				
A	Percent reduction in GHG emissions from project VMT in study area	6.9–31.0	%	calculated
User Inputs				
	None			
Constants, Assumptions, and Available Defaults				
B	Transit mode share in surrounding city	Table T-3.1	%	FHWA 2017a
C	Ratio of transit mode share for TOD area with measure compared to existing transit mode share in surrounding city	4.9	unitless	Lund et al. 2004
D	Auto mode share in surrounding city	Table T-3.1	%	FHWA 2017b

Affordable Housing

GHG Reduction Formula

A = **B** × C

GHG Calculation Variables

ID	Variable	Value	Unit	Source
Output				
A	Percent reduction in GHG emissions from Project/Site VMT for multifamily residential developments	0–28.6	%	calculated
User Inputs				
B	Percent of multifamily units permanently dedicated as affordable	0–100	%	user input
Constants, Assumptions, and Available Defaults				
C	Percent reduction in VMT for qualified units compared to market rate units	-28.6	%	ITE 2021

de Duren and Compean, 2015

Growing Resources for Growing Cities: Density and the Cost of Municipal Public Services in Latin America

We find that per capita municipal spending on public services is strongly and non-linearly correlated to urban population density. Optimal expenditure levels for municipal services are achieved with densities close to 9,000 residents per square kilometre. In our study of about 8,600 municipalities of Brazil, Chile, Ecuador and Mexico, 85% of all municipalities are below this ideal density level. This result provides strong policy support for densification, particularly in medium-sized cities of developing countries, which are currently absorbing most of the world's urban population growth.

Libertun de Duren, N., & Guerrero Compeán, R. (2016). Growing resources for growing cities: Density and the cost of municipal public services in Latin America. Urban Studies, 53(14), 3082–3107. https://doi.org/10.1177/0042098015601579

EPA Smart Location Database

The U.S. Environmental Protection Agency's (EPA) and U.S. General Services Administration (GSA) Smart Location Database (SLD) addresses the growing demand for data products and tools that consistently compare the location efficiency of various places. The SLD summarizes several demographic, employment, and built environment variables for every Census block group (CBG) in the United States.2 The database includes indicators of the commonly cited "D" variables shown in the transportation research literature to be related to travel behavior. The Ds include residential and employment density, land use diversity, design of the built environment, access to destinations, and distance to transit. SLD variables can be used as inputs to travel demand models, baseline data for scenario planning studies, and combined into composite indicators characterizing the relative location efficiency of CBG within U.S. metropolitan regions.

https://www.epa.gov/smartgrowth/smart-location-database-technical-documentation-and-user-guide

Ewing and Cervero, 2001

Travel and the Built Environment: A Synthesis

The potential to moderate travel demand through changes in the built environment is the subject of more than 50 recent empirical studies. Elasticities of travel demand with respect to density, diversity, design, and regional accessibility are then derived from selected studies. These elasticity values may be useful in travel forecasting and sketch planning and have already been incorporated into one sketch planning tool, the Environmental Protection Agency's Smart Growth Index model. In weighing the evidence, what can be said, with a degree of certainty, about the effects of built environments on key transportation "outcome" variables: trip frequency, trip length, mode choice, and composite measures of travel demand, vehicle miles traveled (VMT) and vehicle hours traveled (VHT). Trip frequencies have attracted considerable academic interest of late. They appear to be primarily a function of socioeconomic characteristics of travelers and secondarily a function of the built environment. Trip lengths have received relatively little attention, which may account for the various degrees of importance attributed to the built environment in recent studies. Trip lengths are primarily a function of the built environment and secondarily a function of socioeconomic characteristics. Mode choices have received the most intensive study over the decades. Mode choices depend on both the built environment and socioeconomics (although they probably depend more on the latter). Studies of overall VMT or VHT find the built environment to be much more significant, a product of the differential trip lengths that factor into calculations of VMT and VHT.

Ewing R, Cervero R. Travel and the Built Environment: A Synthesis. Transportation Research Record. 2001;1780(1):87-114. doi:10.3141/1780-10

Ewing and Cervero, 2010

Travel and the Built Environment: A Meta-Analysis

Travel variables are generally inelastic with respect to change in measures of the built environment. Of the environmental variables considered here, none has a weighted average travel elasticity of absolute magnitude greater than 0.39, and most are much less. Still, the combined effect of several such variables on travel could be quite large. Consistent with prior work, we find that vehicle miles traveled (VMT) is most strongly related to measures of accessibility to destinations and secondarily to street network design variables. Walking is most strongly related to measures of land use diversity, intersection density, and the number of destinations within walking distance. Bus and train use are equally related to proximity to transit and street network design variables, with land use diversity a secondary factor. Surprisingly, we find population and job densities to be only weakly associated with travel behavior once these other variables are controlled.

Reid Ewing & Robert Cervero (2010) Travel and the Built Environment, Journal of the American Planning Association, 76:3, 265-294, DOI: 10.1080/01944361003766766

Ewing and Cervero, 2017

Does Compact Development Make People Drive Less?" the Answer Is Yes

Both Stevens (2016) and we measure effect sizes in terms of elasticities of vehicles miles traveled (VMT) per capita with respect to the five D variables. So we are measuring the same thing but getting different results, characterizing them differently, and reaching different conclusions. The questions are why the differences, and who has come closest to capturing the truth about travel and the built environment? We would never equate Stevens's well-documented, well-reasoned, empirical study to Echenique's poorly documented simulation study, but it may have the potential to do more harm simply because of its relative rigor combined with its overreaching on conclusions. Saying that relationships are "inelastic" is not the same as saying that relationships are "small." Inelastic means that elasticities have an absolute magnitude of less than 1.0, which means that a 1% change in an independent variable may produce up to a 1% change in a dependent variable. No one would call that upper limit "small." Indeed, we don't think an elasticity of −0.22 is small. A halving of distance to downtown leads to a 22% reduction in VMT.

Ewing et al, 2019

Key Enhancements to the WFRC/MAG Four-Step Travel Demand Model

In a National Transit Institute course on "Coordinating Land Use and Transportation," co-taught by Robert Cervero, Uri Avin, and the Principal Investigator on this project, the analytic tools session began with a hypothetical: assume that all households, jobs, and other trip generators are concentrated in a walkable village rather than segregated by use and spread across a traffic analysis zone in the standard suburban fashion. The instructor then asks: How would the outputs of conventional four-step travel demand models differ between these two future land use scenarios. The answer, to most participants' surprise, was "Not at all." Conventional four-step travel demand models are used by nearly all metropolitan planning organizations (MPOs), state departments of transportation, and local planning agencies, as the basis for long-range transportation planning in the United States. In the simplest terms, the four-step model proceeds from trip generation, to trip distribution, to mode choice, and finally to route assignment. Trip generation tells us the number of trips generated (produced or attracted) in each traffic analysis zone (TAZ), usually based on some prediction of vehicle ownership. Trip distribution tells us where the trips go, matching trip productions to trip attractions by considering the spatial distribution of productions and attractions as well as the impedance (time or cost) of connections. Particularly tricky are predictions of trips that remain within the same zone. Mode choice tells us which mode of travel is used for these trips, factoring trip tables to reflect the relative shares of different modes. Route assignment tells us what routes are taken, assigning trips to networks that are specific to each mode. A flaw of the four-step model is its relative insensitivity to the so-called D variables. The D variables are characteristics of the built environment that are known to affect travel behavior. The Ds are development density, land use diversity, street network design, destination accessibility, and distance to transit. This report develops a vehicle ownership model (car shedding model), an intrazonal travel model (internal capture model), and mode choice model that consider all of the D variables based on household travel surveys and built environmental data for 32, 31, and 29 regions, respectively, validates the models, and demonstrates that the models have far better predictive accuracy than Wasatch Front Regional Council (WFRC)/Mountainland Association of Governments' (MAG) current models.

Ewing, R., Sabouri, S., Park, K., Lyons, T., & Tian, G. Key Enhancements to the WFRC/MAG Four-Step Travel Demand Model. NITC-RR-1086. Portland, OR: Transportation Research and Education Center (TREC), 2019. https://dx.doi.org/10.15760/trec.246

Ewing et al, 2014

Varying Influences of the Built Environment on Household Travel in 15 Diverse Regions of the United States

This study pools household travel and built environment data from 15 diverse US regions to produce travel models with more external validity than any to date. It uses a large number of consistently defined built environmental variables to predict five household travel outcomes – car trips, walk trips, bike trips, transit trips and vehicle miles traveled (VMT). It employs multilevel modelling to account for the dependence of households in the same region on shared regional characteristics and estimates 'hurdle' models to account for the excess number of zero values in the distributions of dependent variables such as household transit trips. It tests built environment variables for three different buffer widths around household locations to see which scale best explains travel behavior. The resulting models are appropriate for postprocessing outputs of conventional travel demand models, and for sketch planning applications in traffic impact analysis, climate action planning and health impact assessment.

Ewing, R., Tian, G., Goates, JP., Zhang, M., Greenwald, M. J., Joyce, A., Kircher, J., & Greene, W. (2015). Varying influences of the built environment on household travel in 15 diverse regions of the United States. **URBAN STUDIES**, **52**(13), 2330-2348. https://doi.org/10.1177/0042098014560991

Ganson and Miller, 2015

Mitigating Vehicle-Miles Traveled (VMT) in Rural Development

Vehicle-miles traveled (VMT) as an environmental review metric is more effective at combating climate change than level of service (LOS), and policymakers are beginning to advance its adoption for this purpose. Years of research and development prove that VMT mitigation strategies such as density, diversity, and design succeed in urban areas, but doubts remain about how VMT can be mitigated in rural development. This report reviews the current understanding of both urban VMT mitigation and rural development. Finally, additional literature and evidential case studies are explored to identify urban VMT mitigation strategies that can be modified for the rural scale as well as mitigation strategies unique to the rural context.

Ruth Miller, 415-373-6442, ruth@blinktag.com and Christopher Ganson, Governor's Office of Planning and Research, 916-324-9236, Email: chris.ganson@opr.ca.gov for National Academies Transportation Research Board (TRB) Annual Meeting 2015

Houston, 2014

Implications of the modifiable areal unit problem for assessing built environment correlates of moderate and vigorous physical activity

This study assesses the influence of the Modifiable Areal Unit Problem (MAUP) in analysis of the effect of built environment (BE) exposure on moderate and vigorous physical activity (MVPA) during walking periods. Adults (n = 55) wore a GPS unit and accelerometer for up to 7 days. More nearby green space, residential use, and open space were positively associated with MVPA after controlling for socio-demographics. Scale and zoning effects were observed in models of momentary BE-MVPA relationships using different scales and zone configurations. Compared to larger aggregation zones, proximate measures may be better for assessing green space and land use exposure during walking periods. Results do not support a prescriptive recommendation whether future studies should use a buffer- or grid-based zonal configuration.

Douglas Houston, Implications of the modifiable areal unit problem for assessing built environment correlates of moderate and vigorous physical activity, Applied Geography, Volume 50, 2014, Pages 40-47, ISSN 0143-6228, https://doi.org/10.1016/j.apgeog.2014.02.008.

Ihlanfedlt, 2020

Vehicle Miles Traveled and the Built Environment: New Evidence from Panel Data

There has been considerable interest in the impact that the built environment has on vehicle miles traveled (VMT). While this issue has been extensively researched, due to the heavy reliance on crosssectional data, there remains uncertainty regarding how effective local land use planning and regulation might be in reducing VMT. Based on a 13-year panel of Florida counties, models are estimated that relate VMT to new measures of the spatial distribution of alternative land uses within counties and county urban expansion. Identification of causal effects is established by including year and county fixed effects, along with an extensive set of control variables, and instrumenting those land uses that may be endogenous. Incremental annual changes in the spatial concentration of alternative land uses are found to affect VMT. The policy implication is that appropriate land use policy can reduce VMT and should be considered part of the strategy for dealing with the problem of global warming.

Ihlanfeldt, K. (2020). Vehicle miles traveled and the built environment: New evidence from panel data. *Journal of Transport and Land Use*, *13*(1), 23–48. https://www.jstor.org/stable/26967234

Knuiman et al, 2014

A longitudinal analysis of the influence of the neighborhood built environment on walking for transportation: the RESIDE study

The purpose of the present analysis was to use longitudinal data collected over 7 years (from 4 surveys) in the Residential Environments (RESIDE) Study (Perth, Australia, 2003-2012) to more carefully examine the relationship of neighborhood walkability and destination accessibility with walking for transportation that has been seen in many cross-sectional studies. We compared effect estimates from 3 types of logistic regression models: 2 that utilize all available data (a population marginal model and a subject-level mixed model) and a third subject-level conditional model that exclusively uses within-person longitudinal evidence. The results support the evidence that neighborhood walkability (especially land-use mix and street connectivity), local access to public transit stops, and variety in the types of local destinations are important determinants of walking for transportation. The similarity of subject-level effect estimates from logistic mixed models and those from conditional logistic models indicates that there is little or no bias from uncontrolled time-constant residential preference (self-selection) factors; however, confounding by uncontrolled time-varying factors, such as health status, remains a possibility. These findings provide policy makers and urban planners with further evidence that certain features of the built environment may be important in the design of neighborhoods to increase walking for transportation and meet the health needs of residents.

Knuiman MW, Christian HE, Divitini ML, Foster SA, Bull FC, Badland HM, Giles-Corti B. A longitudinal analysis of the influence of the neighborhood built environment on walking for transportation: the RESIDE study. Am J Epidemiol. 2014 Sep 1;180(5):453-61. doi: 10.1093/aje/kwu171. Epub 2014 Aug 11. PMID: 25117660.

Lee, 2022

Exploring Associations Between Multimodality and Built Environment Characteristics in the U.S.

This study demonstrated associations between multimodality and built environment characteristics, and proposed policy implications for fostering multimodal travel behaviors. It conducted a U.S. nationwide analysis using ordinary least square regression and gradient boosting decision tree regressor models with American Community Survey 2015–2019 5-year estimates and the United States Environmental Protection Agency Smart Location Database version 3.0. Notable findings were as follows: First, built environment characteristics were found to be statistically significant predictors of multimodality across the U.S. Second, certain features were identified as having considerable importance, specifically including population density, regional accessibility, walkability index, and network density, all of which should be given particular attention by transportation and land use planners. Third, the non-linear effects of built environment characteristics on multimodality suggested an effective range to encourage multimodal transportation choice behaviors in various situations. The findings can guide the development of effective strategies to transform the built environment, which may subsequently be used to minimize reliance on automobiles and promote people to travel more sustainably.

Lee, Sangwan. 2022. "Exploring Associations between Multimodality and Built Environment Characteristics in the U.S." **SUSTAINABILITY** 14, no. 11: 6629. https://doi.org/10.3390/su14116629

Litman, 2022

Understanding Smart Growth Savings Evaluating Economic Savings and Benefits of Compact Development

How communities develop can have many direct and indirect impacts. Smart Growth policies create more compact, multimodal development which reduces per capita land consumption and the distances between destinations. This, in turn, reduces the costs of providing public infrastructure and services, improves accessibility, and reduces motor vehicle travel, which provides many economic, social and environmental benefits. This report examines these impacts. It defines Smart Growth and its alternative, sprawl, summarizes current research concerning their costs and benefits, investigates consumer preferences, and evaluates Smart Growth criticisms. This report should be useful to anybody involved in development policy analysis.

Todd Litman (2014), Analysis of Public Policies That Unintentionally Encourage and Subsidize Urban Sprawl, commissioned by LSE Cities (www.lsecities.net), for the Global Commission on the Economy and Climate (www.newclimateeconomy.net); at https://bit.ly/2QqPhzc.

Mansfield, Ehrlich, Zmud, and Lee, 2022

Built Environment Influences on Active Travel in the Twin Cities Region: Evidence from a Smartphone-based Household Travel Survey.

Using travel survey data collected via both smartphone and web-based survey methods, we found string associations between built environment factors and the likelihood of meeting Centers for Disease Control and Prevention (CDC) physical activity recommendations via active transportation. Additionally, we found that using location data beyond respondents' home location to characterize built environment factors strengthened our findings, particularly related to employment density for the smartphone sample. This finding speaks to the importance of built environment factors in supporting active travel at non-home locations for non-home based trips. In addition, we found that measuring aspects of the transportation system itself, such as the density of bike facilities and the relative absence of major roadway barriers, are significantly associated with an increased likelihood of meeting CDC physical activity recommendations through active transportation. More broadly, the findings of this study provide strong evidence that rich location information provided by smartphone-based travel survey instruments can further our understanding of how the built environment shapes travel behavior. Further, our findings demonstrate how such data can be useful to stakeholders beyond traditional transportation professionals, including public health researchers and practitioners.

Mansfield, Ehrlich, Zmud, and Lee, Built environment influences on active travel in the Twin Cities region: evidence from a smartphone-based household travel survey, 2022

Mattson, 2021

Relationships Between Density and Per Capita Municipal Spending in the United States

The objective of this research is to determine the relationship between land use, particularly density, and per capita spending levels in cities across the United States. A model was developed using data from the U.S. Census Bureau's Annual Survey of State and Local Government Finances to estimate the impacts of population-weighted density and other factors on per capita municipal spending. This study focused on municipal spending for eight categories that theoretically could be influenced by land use development: fire protection, streets and highways, libraries, parks and recreation, police, sewer, solid waste management, and water. Density was found to be negatively associated with per capita municipal expenditures for the following cost categories: operational costs for fire protection, streets and highways, parks and recreation, sewer, solid waste management, and water; construction costs for streets and highways, parks and recreation, sewer, and water; and land and existing facility costs for police, sewer, and water. Results were insignificant for other cost categories, and a positive relationship was found for police operations costs. In general, results support the conclusion that increased density is associated with reduced per capita municipal spending for several cost categories.

Jeremy Mattson (2021), “Relationships between Density and per Capita Municipal Spending in the United States,” Urban Science, Vo. 5/3: 69 (https://doi.org/10.3390/urbansci5030069).

Ogra, 2014

The Role of 6Ds: Density, Diversity, Design, Destination, Distance, and Demand Management in Transit Oriented Development (TOD)

This paper reflects on the efficacy of Transit Oriented Development (TOD) and the primary components that constitute it. These components are widely recognized as manifesting themselves through the concept of “6Ds": Design, Diversity, Density, Distance, Destination, and Demand management. The paper thus investigates the main aspects that underlie these “Ds" and how they can equally be taken up in TOD initiatives. The development of efficient and sustainable transport systems has become a key mitigation method for major traffic problems such as congestion, poor mobility and access to services, as well as greenhouse gas emissions. The primary argument of this paper centers on the premise that the application of “6Ds" through TOD can go a long way in addressing current challenges that confront urban transport within cities. Using a case study, the paper contextualizes one of the “6Ds" and subsequent conclusions are drawn thereof in the form of key determinants.

Aurobindo, Ogra, Robert, Ndebele, Department of Town and Regional Planning Faculty of Engineering and the Built Environment (FEBE)University of Johannesburg Beit Street, Doornfontein- 2028, Johannesburg, South Africa1aogra@uj.ac.za,2ziphoe@gmail.com

Stantec, 2013

Quantifying the Costs and Benefits to HRM, Residents and the Environment of Alternate Growth Scenarios

Stantec (2013), Quantifying the Costs and Benefits to HRM, Residents and the Environment of Alternate Growth Scenarios, Halifax Regional Municipality (www.halifax.ca); at https://bit.ly/2X9k0TI.

Stevens, 2016

Does Compact Development Make People Drive Less?

Planners commonly recommend compact development in part as a way of getting people to drive less, with the idea that less driving will lead to more sustainable communities. Planners base their recommendations on a substantial body of research that examines the impact of compact development on driving. Different studies, however, have found different outcomes: Some studies find that compact development causes people to drive less, while other studies do not. I use meta-regression analysis to a) explain why different studies on driving and compact development yield different results, and b) combine different findings from many studies into reliable statistics that can better inform planning practice. I address the following questions: Does compact development make people drive less, and if so, how much less? I find that compact development does make people drive less, because most of the compact development features I study have a statistically significant negative influence on driving. The impact, however, is fairly small: Compact development features do not appear to have much influence on driving. My findings are limited to some extent because they are derived from small sample sizes. Planners should not rely on compact development as their only strategy for reducing driving unless their goals for reduced driving are very modest and can be achieved at a low cost.

Stevens, M. R. (2017). Does Compact Development Make People Drive Less? *Journal of the American Planning Association*, *83*(1), 7–18. https://doi.org/10.1080/01944363.2016.1240044

Reid Ewing & Robert Cervero (2017) "Does Compact Development Make People Drive Less?" The Answer Is Yes, Journal of the American Planning Association, 83:1, 19-25, DOI: 10.1080/01944363.2016.1245112

Weeks, 2009

Transportation Impacts of Smart Growth Development in Maine – Town of Lisbon and Town of Sanford

This study evaluates the reductions in average trip lengths, daily vehicle miles traveled (VMT), and daily greenhouse gas (GHG) emissions from on-road automobiles due to smart growth development strategies in two Maine towns, Lisbon in Androscoggin County and Sanford in York County. In summary, analysis results for Lisbon and Sanford indicate that the densification and mixing of residential and employment growth as infill developments has a slight but observable impact on VMT and average trip lengths, some roadways in the towns experienced VMT increases, which were offset by greater VMT reductions on other roadways, resulting in net, network-wide VMT reductions, and greater reductions in VMT and GHG emissions could be attained through an increased share of daily transit trips by providing new transit service to/from the smart growth developments along existing transportation corridors. The results indicate that the efficacy of the smart growth scenarios to reduce VMT in Lisbon and Sanford is greatly limited without transit to complement the proposed dense, mixed-use developments.

Andrew Weeks, University of Vermont Transportation Research Center, 2009.Transportation Impacts of Smart Growth Development in Maine – Town of Lisbon and Town of Sanford. 802) 656-1312, www.uvm.edu/trc

APPENDIX B. BUILT ENVIRONMENT DATABASE

This document includes a list of built environment datasets compiled for the VTrans Smart Growth project. The source of each dataset is described along with any assumptions made or any pre-processing performed.

All datasets listed were aggregated to H3 cells at level 8 resolution to create statewide hex layers. These data are compiled here: https://vhb.maps.arcgis.com/apps/mapviewer/index.html?webmap=a4f2713286eb46a6ab19f48bccb7122e

Socio-Economic Data

Population

- Vermont Census 2020 Redistricting Blocks
  - Source - Esri
  - Source Data URL: https://services.arcgis.com/P3ePLMYs2RVChkJx/arcgis/rest/services/Vermont_Census_2020_Redistricting_Blocks/FeatureServer/0
  - 'Total Population Count' (POP100) attribute field was used to generate the hex layer
  - A lot of other demographic attributes are also available in this dataset
  - Technical documentation for the 2020 Census Redistricting block data: https://www2.census.gov/programs-surveys/decennial/2020/technical-documentation/complete-tech-docs/summary-file/2020Census_PL94_171Redistricting_StatesTechDoc_English.pdf

Employment

- ArcGIS Business Analyst Employment Data
  - Points of Interest Search for all business categories – Data Source: Data Axle
  - Statewide dataset had to be pieced together due to 5000 record display/export limit. Combined dataset available for project team to download from 'VTrans Smart Growth' ArcGIS Online group
  - Two hex layers were created from this dataset: 'Count of Employees' which summarizes the 'Number of Employees' (EMPNUM) attribute field for each cell, and 'Count of Employers' which totals the number of business point feature within each cell

Income

- ArcGIS Business Analyst 2022 Median Household Income
  - Statewide dataset had to be pieced together due to 5000 record display/export limit. Data downloaded in tabular format then joined to the Vermont Census 2020 Redistricting

Block dataset. Combined dataset available for project team to download from ‘VTrans Smart Growth’ ArcGIS Online group

Built Environment Data

Land-Use Diversity

- VT Data - Statewide Standardized Parcel Data - parcel polygons
  - Source: VCGI (Vermont Center for Geographic Information)
  - Source Data URL: https://services1.arcgis.com/BkFxaEFNwHqX3tAw/arcgis/rest/services/FS_VCGI_OPENDATA_Cadastral_VTPARCELS_poly_standardized_parcels_SP_v1/FeatureServer/0
  - Several hex layers were created to display statewide parcel data:
    - ‘Parcel Count’ – Count of parcels per hex cell
    - ‘Parcels – Residential’: Count of parcels categorized as 'Mobile Home/la', 'Mobile Home/un', 'Residential-1', 'Residential-2', Seasonal-1', or 'Seasonal-2'as‘ for the ‘Category (Real Estate Only)’ attribute field
    - Parcels – Commercial/Industrial: Count of parcels categorized as 'Commercial', 'Commercial Apt', 'Industrial' for the ‘Category (Real Estate Only)’ attribute field
    - Parcels – Woodland: Count of parcels categorized as ‘Woodland’ for the ‘Category (Real Estate Only)’ attribute field
    - Parcels – Utilities: Count of parcels categorized as 'Utilities Elec', 'Utilities Other' for the ‘Category (Real Estate Only)’ attribute field
    - Parcels – Farms: Count of parcels categorized as ‘Farms’ for the ‘Category (Real Estate Only)’ attribute field
    - Parcels – Other: Count of parcels categorized as 'Miscellaneous', 'Other' for the ‘Category (Real Estate Only)’ attribute field
- VT Data - E911 Site Locations
  - Source: VCGI
  - Source Data URL: https://services1.arcgis.com/BkFxaEFNwHqX3tAw/arcgis/rest/services/FS_VCGI_OPENDATA_Emergency_ESITE_point_SP_v1/FeatureServer/0
  - Hex layer for count of E911 Site Locations per hex was created
  - ‘SITETYPE’ attribute includes 136 categories. Groupings have been developed and consolidated into 8 categories and will be applied appropriately.
- ArcGIS Business Analyst Business Locations
  - See the entry for ArcGIS Business Analyst Employment Data above

Destination Access

- Microsoft Building Footprints
  - Source: Microsoft Open Data Commons Open Database License
  - Source Data page with download reference: https://github.com/Microsoft/USBuildingFootprints
- E911 Building Footprints
  - Source: VCGI
  - Source Data URL: https://services1.arcgis.com/BkFxaEFNwHqX3tAw/arcgis/rest/services/FS_VCGI_OPENDATA_Emergency_FOOTPRINTS_poly_SP_v1/FeatureServer/0
  - Hex layer for count of E911 footprints per hex was created
- SafeGraph POI Visitation Summary
  - CSV file provided by John Adams (VCGI)
  - Vintage: 2019
  - Summarized by 1) top level place category, 2) 2019 quarterly data 3) level 9 hex
  - Extrapolated to level 8 hex layers by VHB
  - Median weekly visit hex layers for each

Transportation Network

- VT Road Centerline
  - Source: VTrans
  - Source Data URL: https://maps.vtrans.vermont.gov/arcgis/rest/services/Master/General/FeatureServer/39
  - Summarized by total length per hex
- OpenStreetMap Sidewalks
  - Source: OpenStreetMap (OSM)
  - Extraction performed in R
  - Summarized by total length per hex
- Chittenden County Sidewalks & Paths
  - Source: CCRPC
  - Source Data URL: https://map.ccrpcvt.org/arcgis/rest/services/CCRPC/CloseTheGap/MapServer/1
  - Summarized by total length per hex

Public Transit

- VT Data - Public -Transit Stops from GTFS Data-Feeds
  - Source: VCGI
  - Data Source URL: https://services1.arcgis.com/BkFxaEFNwHqX3tAw/arcgis/rest/services/FS_VCGI_OPENDATA_Trans_PUBLICTRANS_point_stops_SP_v1/FeatureServer/0
  - Hex layer represents count of stops per hex
- VT Data - Public -Transit Routes from GTFS Data-Feeds
  - Source: VCGI
  - Data Source URL: https://services1.arcgis.com/BkFxaEFNwHqX3tAw/arcgis/rest/services/FS_VCGI_OPENDATA_Trans_PUBLICTRANS_line_routes_SP_v1/FeatureServer/0
  - Hex layer includes attributes for count of unique routes and summary of total route length per hex

Other Datasets

- Designated Growth Center
  - Source: ANR
  - Source Data URL: https://anrmaps.vermont.gov/arcgis/rest/services/map_services/ACCD_OpenData/MapServer/3
  - Display by presence/absence
- Existing Wastewater Service Area
  - Source: ANR
  - Source Data URL: https://anrmaps.vermont.gov/arcgis/rest/services/map_services/ACCD_OpenData/MapServer/11
  - Hex Display – Count of EWSAs per hex
- Electric Charging Stations
  - Source: ANR
  - Source Data URL: https://anrmaps.vermont.gov/arcgis/rest/services/map_services/ACCD_OpenData/MapServer/22
  - Display: Count of EV charging stations per hex

- VT Data – Broadband Status 2021
  - Source: VCGI
  - Source Data URL: https://maps.vcgi.vermont.gov/arcgis/rest/services/PSD_services/OPENDATA_PSD_LAYERS_SP_NOCACHE_v1/MapServer/48
  - Separate hex layers for each category in the 'BB_Status' attribute field displaying count per hex
  - Broadband Availability information with descriptions of categories: https://publicservice.vermont.gov/content/broadband-availability
  - Categories/layers:
    - Broadband Served 100/100
    - Broadband Served 100/20
    - Broadband Served 25/3
    - Broadband Served 4/1
    - Broadband Underserved
- Waterbody Coverage
  - Source: VCGI
  - Source Data URL: https://services1.arcgis.com/BkFxaEFNwHqX3tAw/arcgis/rest/services/FS_VCGI_OPENDATA_Water_VHDCARTO_poly_SP_v1/FeatureServer/0
  - Metadata: https://maps.vcgi.vermont.gov/gisdata/metadata/WaterHydro_VHDCARTO.htm
  - Percent waterbody coverage was calculated for each hex

APPENDIX C. SCENARIO RULESETS

Scenario rulesets

Rulesets developed for each growth scenario are provided in detail below. Each of these rulesets is accompanied by Python code that generates allocations given baseline distribution of population and employment and county-level growth control totals.

Ruleset 1: Dispersed growth

Growth cells: all cells with non-protected land are eligible to receive future growth.

Allocation parameters:

1. *Planning regulation density cap:* the population density above which planning regulations are required.

Ruleset for growing counties:

1. Starting with the least dense cell in the county, calculate the amount of new population the cell can receive before exceeding the planning regulation density cap. Allocate this population to the cell and subtract from the remaining county population allocation.
2. Move to the next least cell and repeat step 1. Continue until all new growth has been allocated or population has been allocated to all cells in the county.
3. If population has been allocated to all cells in the county up to the planning regulation density cap and the county allocation has not been exhausted, split the remaining growth across all cells.
4. Allocate employment using the same process as was used to allocate population, again using the planning regulation density cap to limit employment density in allocation cells.

Ruleset for shrinking counties:

1. Starting with the densest cell in the county, calculate the difference between the baseline population and the planning regulation density cap. Remove this population from the cell and subtract from the remaining county deallocation.
2. Move to the next densest cell and repeat step 1. Continue until the county deallocation has been reached, or population has been removed from all cells in the county.
3. If population has been removed from all cells in the county up to the planning regulation density cap and the county deallocation has not been reached, split the remaining deallocation across all cells.
4. Deallocate employment using the same process as was used to deallocate population.

Ruleset 2: Concentrated growth, concentrated jobs

Growth cells: cells that have wastewater service in the baseline year (2019) are eligible to receive future growth.

Allocation parameters:

1. *Maximum allowed density:* the highest population density allowed in any allocation cell.
2. *Jobs-population mix:* the ratio of jobs to population assumed when allocating employment.

Ruleset for growing counties:

1. Starting with the densest growth cell in the county, calculate the amount of new population the cell can receive before exceeding the maximum allowed density. Allocate this population to the cell and subtract from the remaining county population allocation.
2. Move to the next densest growth cell and repeat step 1. Continue until all new growth has been allocated or population has been allocated to all cells in the county.
3. If population has been allocated to all growth cells in the county up to the maximum allowed density and the county allocation has not been exhausted, split the remaining allocation across all growth cells.
4. Allocate employment using the same process as was used to allocate population, again using the planning regulation density cap to limit employment density in allocation cells. The jobs-population mix parameter is used to determine the number of jobs allocated to a given cell.

Ruleset for shrinking counties:

1. Starting with the least dense non-growth cell in the county, remove all population from the cell and subtract from the remaining county deallocation.
2. Move to the next least dense non-growth cell and repeat step 1. Continue until the county deallocation has been reached, or population has been removed from all non-growth cells in the county.
3. If population has been removed from all non-growth cells in the county and the county deallocation has not been reached, split the remaining deallocation across all growth cells.
4. Deallocate employment using the same process as was used to deallocate population, deallocating employment until the jobs-population mix parameter is reached for a cell.

Ruleset 3: Concentrated growth, dispersed jobs

Growth cells: cells that have wastewater service in the baseline year (2019) are eligible to receive future growth.

Allocation parameters:

1. *Maximum allowed density:* the highest population density allowed in any allocation cell.
2. *Jobs-population-mix:* the ratio of jobs to population assumed when allocating employment.

Ruleset for growing counties:

1. Starting with the growth cell with the lowest employment density in the county, calculate the amount of new population the cell can receive before exceeding the maximum allowed density. Allocate this population to the cell and subtract from the remaining county population allocation.
2. Move to the next densest growth cell and repeat step 1. Continue until all new growth has been allocated or population has been allocated to all cells in the county.
3. If population has been allocated to all growth cells in the county up to the maximum allowed density and the county allocation has not been exhausted, split the remaining allocation across all growth cells.
4. Allocate employment using the same process as was used to allocate population, but only allocate employment to non-growth cells in the county. The jobs-population mix parameter is used to determine the number of jobs allocated to a given cell.

Ruleset for shrinking counties:

1. Starting with the least dense non-growth cell in the county, remove all population from the cell and subtract from the remaining county deallocation.
2. Move to the next least dense non-growth cell and repeat step 1. Continue until the county deallocation has been reached, or population has been removed from all non-growth cells in the county.
3. If population has been removed from all non-growth cells in the county and the county deallocation has not been reached, split the remaining deallocation across all growth cells.
4. Deallocate employment using the same process as was used to deallocate population.

Ruleset 4: Concentrated growth, balanced land use

Growth cells: cells within ACCD designations (Tier 1), as well as cells immediately adjacent to ACCD designations (Tier 2) and cells neighboring tier 2 cells (Tier 3).

Allocation parameters:

1. *Smart Growth Prototype Percentile:* the percentile value of baseline cell VMT used to define "exemplar" smart growth neighborhoods within each county typology.
2. *Prototype Boost Percentage:* a percentage "boost" applied to the built environment characteristics calculated for prototype smart growth neighborhoods (e.g., 25% more dense)

Ruleset for growing counties:

1. Starting with the lowest-VMT Tier 1 growth cell in the county, calculate the amount of new population the cell can receive before exceeding the reference population density (derived from the exemplar smart growth neighborhoods). Allocate this population to the cell and subtract from the remaining county population allocation.
2. Move to the next lowest-VMT Tier 1 growth cells and repeat step 1. Continue until all new growth has been allocated or population has been allocated to all Tier 1 growth cells.
3. If unallocated population growth remains after allocating to all Tier 1 growth cells, repeat the process for Tier 2 growth cells, and again for Tier 3 growth cells.
4. If unallocated population growth remains after allocating to all Tier 1, 2, and 3 growth cells in the county, split the remaining allocation across all growth cells.
5. Allocate employment using the same process as was used to allocate population.

Ruleset for shrinking counties:

1. Starting with the highest-VMT non-growth cell in the county, remove all population from the cell and subtract from the remaining county deallocation.
2. Move to the next highest-VMT non-growth cell and repeat step 1. Continue until the county deallocation has been reached, or population has been removed from all non-growth cells in the county.
3. If population has been removed from all non-growth cells in the county and the county deallocation has not been reached, split the remaining deallocation across all Tier 1, 2, and 3 growth cells.
4. Deallocate employment using the same process as was used to deallocate population.

Ruleset 5: Concentrated growth, unbalanced land use

Growth cells: cells within ACCD designations (Tier 1), as well as cells immediately adjacent to ACCD designations (Tier 2) and cells neighboring tier 2 cells (Tier 3).

Allocation Parameters:

1. *Smart Growth Prototype Percentile:* the percentile value of baseline cell VMT used to define "exemplar" smart growth neighborhoods within each county typology.
2. *Prototype Boost Percentage:* a percentage "boost" applied to the built environment characteristics calculated for prototype smart growth neighborhoods (e.g., 25% more dense)

Ruleset for growing counties:

1. Starting with the lowest-VMT Tier 1 growth cell in the county, calculate the amount of new population the cell can receive before exceeding the reference population density (derived from the exemplar smart growth neighborhoods). Allocate this population to the cell and subtract from the remaining county population allocation.
2. Move to the next lowest-VMT Tier 1 growth cells and repeat step 1. Continue until all new growth has been allocated or population has been allocated to all Tier 1 growth cells.
3. If unallocated population growth remains after allocating to all Tier 1 growth cells, repeat the process for Tier 2 growth cells, and again for Tier 3 growth cells.
4. If unallocated population growth remains after allocating to all Tier 1, 2, and 3 growth cells in the county, split the remaining allocation across all growth cells.
5. Allocate employment starting with the cell with the highest employment density, but skipping any Tier 1 cells (i.e., do not allocate any employment to Tier 1 cells).

Ruleset for shrinking counties:

1. Starting with the highest-VMT non-growth cell in the county, remove all population from the cell and subtract from the remaining county deallocation.
2. Move to the next highest-VMT non-growth cell and repeat step 1. Continue until the county deallocation has been reached, or population has been removed from all non-growth cells in the county.
3. If population has been removed from all non-growth cells in the county and the county deallocation has not been reached, split the remaining deallocation across all Tier 1, 2, and 3 growth cells.
4. Deallocate employment using the same process as was used to deallocate population.

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