TECHNICAL GUIDE: DEVELOPMENT AND MONITORING OF VTRANS LONG-TERM RISK & OPPORTUNITY REGISTER

VTRANS | VIRGINIA'S TRANSPORTATION PLAN

PREPARED BY THE OFFICE OF INTERMODAL PLANNING AND INVESTMENT FOR THE COMMONWEALTH TRANSPORTATION BOARD

December 2021

FOR MORE INFORMATION

Visit vtrans.org for additional details, updates, and documentation about the VTrans development process. Please contact the Statewide Transportation Planning (STP) Team at the Office of Intermodal Planning and Investment to request an alternative format.

VTrans, Office of Intermodal Planning and Investment
1221 E. Broad Street, 2nd Floor, East Wing
Richmond, VA 23219
comment@vtrans.org

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LIST OF ACRONYMS

AADT	Annual Average Daily Traffic
AC	Activity Center
ACS	American Community Survey
ADAS	Advanced Driver Assistance Systems
ADS	Automated Driving Systems
AEB	Automatic Emergency Braking
B2B	Business-to-Business sales (Wholesale trade)
B2C	Business-to-Consumer sales (Retail trade)
BCI	Backup Collision Intervention
BEV200	Battery Electric Vehicle with 200-mile range
BEV300	Battery Electric Vehicle with 300-mile range
BLS	US Bureau of Labor Statistics
BRT	Bus Rapid Transit
BSW	Blind Spot Warning
CACC	Cooperative Adaptive Cruise Control
CAGR	Compound Annual Growth Rate
CAV	Connected and Automated Vehicles
CDOT	Colorado Department of Transportation
CICAS	Cooperative Intersection Collision Avoidance System
CO	Carbon Monoxide
CoM	Coefficient of Imitation
CoN	Coefficient of Innovation
CoSS	Corridor of Statewide Significance
COVID-19	Coronavirus Disease 2019
CTB	Commonwealth Transportation Board
CTB	Commonwealth Transportation Bard
DOTs	Department of Transportation
DNPW	Do Not Pass Warning
DRPT	Department of Rail and Public Transportation
DSRC	Dedicated Short-range communication service
EEA	Equity Emphasis Area
EPS	Energy Policy Simulator
ESC	Electronic Stability Control
EV	Electric Vehicles
FCW	Forward Collision Warning

FEMA	Federal Emergency Management Agency
FHWA	Federal Highway Administration
FIRM	Flood Insurance Rate Map
FMCSA	Federal Motor Carrier Safety Administration
GMSL	Global Mean Sea Level
HBW	Home-based Work Trip
HEV	Hybrid Electric Vehicle
HRPDC	Hampton Roads Planning District Commission
ICEV	Internal Combustion Engine Vehicle
IF	Importance Factor
IPCC	Intergovernmental Panel on Climate Change
LCW	Lane Changing Warning
LEHD	Longitudinal Employer-Household Dynamics
LKA	Lane Keeping Assist
LODES	LEHD Origin-Destination Employment Statistics
MassDOT	Massachusetts Department of Transportation
MPO	Metropolitan Planning Organization
MSA	Metropolitan Statistical Area
NACTO	National Association of City Transportation Officials
NAICS	North American Industry Classification System
NBI	National Bridge Inventory
NCEI	National Centers for Environmental Information
NHC	National Hurricane Center
NHSTA	National Highway Traffic Safety Administration
NHTS	National Household Travel Survey
NOAA	National Oceanic and Atmospheric Administration
NOx	Nitrogen Oxides
NSC	National Safety Council
OIPI	Office of Intermodal Planning and Investment
PHEV	Plug-in Hybrid Electric Vehicle
PM	Particulate Matter
PMT	Person-miles Traveled
RAC	Residence Area Characteristics
RDCW	Road Departure Crash Warning
RN	Regional Network
ROC	Ratio of Concentration

SAE	Society of Automotive Engineers
SANDAG	San Diego Association of Governments
SLOSH	Sea, Lake and Overland Surges from Hurricanes
SLR	Sea Level Rise
SOC	Standard Occupational Classification
SOV	Single-Occupant Vehicle
SUV	Sport Utility Vehicle
TDM	Transportation Demand Management
TMC	Traffic Message Channel
UAV	Unmanned Aerial Vehicles (also called drones)
US DOT	United States Department of Transportation
USGCRP	U.S. Global Change Research Program
V2Cyclist	Vehicle to Cyclist
V2I	Vehicle-to-Infrastructure
V2Pedestrian	Vehicle-to-Pedestrian
V2V	Vehicle-to-Vehicle
V2X	Vehicle-to-Everything
VAST	Vulnerability Assessment Scoring Tool
VBRSP	Virginia Business Ready Sites Program
VDOT	Virginia Department of Transportation
VFRMS	Virginia Flood Risk Management Standard
VGIN	Virginia Geographic Information Network
VIMS	Virginia Institute of Marine Sciences
VMT	Vehicle-miles of Travel
VOC	Volatile Organic Compounds
VTRC	Virginia Transportation Research Council
WAC	Workplace Area Characteristics

DEFINITIONS

- Automated Vehicles – NHTSA[1] defines automated vehicles as those in which at least some aspects of a safety-critical control function (e.g., steering, acceleration, or braking) occur without human driver input.
- Autonomous Vehicles – The California DMV[2] defines an autonomous vehicle based on the technology modes used for vehicle operation. Autonomous technologies are a combination of hardware and software, remote and/or on-board, that have the capability to drive a vehicle without active physical control or monitoring by a human operator. Autonomous mode is the status of vehicle operation where autonomous technology performs the dynamic driving task, with or without a human actively supervising the autonomous technology's performance of the dynamic driving task. An autonomous vehicle is operating or driving in autonomous mode when it is operated or driven with the autonomous technology engaged.
- Levels of Automation – The Society of Automotive Engineers (SAE) has defined levels of driving automation as a way to describe the specific roles played by the human, the driving automation system and other vehicle systems to perform the dynamic driving task. Six levels of automation are identified. SAE J3016,[3] which defines these levels, has become the de facto standard of levels of automation.
    - SAE Level 0 Automation – Human driver with driver support features providing warnings and momentary assistance.
    - SAE Level 1 – Human is driving with steering OR brake/acceleration control support.
    - SAE Level 2 – Human is driving with steering AND brake/acceleration support.
    - SAE Level 3 – Human is NOT driving when automated driving systems are engaged. When system requests, human MUST drive.
    - SAE Level 4 – Human is NOT driving when automated driving systems are engaged. The automated driving system will not request a human to take over driving. The automated features are restricted to specific conditions and will not drive unless all conditions are met.
    - SAE Level 5 – Human is NOT driving when automated driving systems are engaged. The automated driving system will not request a human to take over driving.
- Cohort[2] – A group of individuals having a statistical factor (such as age or class membership) in common in a demographic study
- Connected Vehicles – USDOT[4] defines Connected Vehicle (CV) technologies as equipment, applications, or systems that use V2X communications to address safety, system efficiency, or mobility on our roadways. The concept uses data from short-range communication broadcasts and peer-to-peer exchanges within approximately 300 meters to "sense" what other travelers (vehicles, bicyclists, pedestrians, wheelchairs, motorcycles, buses, trucks, and others) are doing and identify potential hazards.
- Driver[5] – For the purpose of this document, the term "driver" refers to developments causing change, affecting or shaping the future. A driver is the cause of one or more effects.
- E-commerce – Trade conducted through the internet as the primary means of communication and sale
- Tailpipe Emissions – By-products of internal combustion engines
- Macrotrend[6] – An emerging pattern of change likely to impact state government and require a response. More than one macrotrend can be associated with a megatrend.
- Megatrend[5] – A large social, economic, political, environmental or technological change that is slow to form.
- Micromobility – Travel via small personal vehicles, such as scooters, bicycles, skateboards, etc.
- Opportunity – A situation or scenario wherein there is some uncertainty and at least some probability of a positive outcome or result.

[1] National Highway Traffic Safety Administration

[2] State of California Department of Motor Vehicles Autonomous Vehicle Definitions

[3] SAE International, "SAE International Releases Updated Visual Chart for Its "Levels of Driving Automation" Standard for Self-Driving Vehicles", December 11, 2018.

[4] USDOT, How Connected Vehicles Work

[5] European Foresight Platform

[6] Transportation Policy Task Force Suggested State Legislation Docket. 2009. California

- Resiliency[1] – The capability to anticipate, prepare for, respond to and recover from extreme weather event(s) with minimum damage to social well-being, infrastructure, the economy, and the environment.
- Risk – A situation or scenario wherein there is some uncertainty and at least some probability of a negative outcome or result.
- Risk & Opportunity Register – Listing of uncertainties that will also include some level of prioritization for the Commonwealth to consider mitigation, avoidance, transference, or acceptance strategies.
- Sea Level Rise – Incremental rising of the mean high water level over time.
- Shared Mobility – The shared use of a vehicle, motorcycle, scooter, bicycle, or other travel mode. Shared mobility provides users with short-term access to one of these modes of travel as they are needed.[2]
- Storm Surge[3] – Abnormal rise in seawater level during a storm, measured as the height of the water above the normal predicted astronomical tide.
- Vulnerability[4] – Vulnerability is a function of exposure to a hazard(s), the sensitivity to the given hazard, and adaptive capacity or the system's ability to cope.
- Workplace Flexibility – The ability to work at home or in a location other than the employer office or jobsite through the use of internet, email, and telephone.
- KABCO Scale[5] – The "KABCO" injury scale can be used for establishing crash costs. This scale was developed by the National Safety Council (NSC) and is frequently used by law enforcement for classifying injuries:
  - K – Fatal injury;
  - A – Severe injury;
  - B – Visible injury;
  - C – Non Visible injury; and
  - O – Property Damage Only

[1] This is a draft definition developed by the Office of Intermodal Planning and Investment (OIPI), pending feedback from the Commonwealth Transportation Board. For more details, please refer to the Technical Memorandum for the VTrans Vulnerability Assessment.

[2] SAE International, JJ3163 – Taxonomy and Definitions for Terms Related to Shared Mobility and Enabling Technologies. Accessed on July 8, 2021.

[3] National Oceanic and Atmospheric Administration. What is storm surge? Accessed on July 8, 2021.

[4] This is a draft definition developed by the Office of Intermodal Planning and Investment (OIPI), pending feedback from the Commonwealth Transportation Board. For more details, please refer to the Technical Memorandum for the VTrans Vulnerability Assessment.

[5] National Safety Council

CHAPTER 1. PURPOSE OF THE TECHNICAL GUIDE

This Technical Guide is a synthesis of technical methods and processes used to execute the Policy for the Development and Monitoring of the VTrans Long-term Risk & Opportunity Register as outlined in the Chapter 6 of the VTrans Policy Guide. This Technical Guide is developed for planners, engineers, and other professionals interested in the data sources, processes, and methods used to implement the CTB's policies.

Please note that there is a separate Technical Guide for Chapters 4 and 5 of the VTrans Policy Guide.

The purpose of developing a Risk & Opportunity Register is to create a systematic and methodical process to identify, monitor, and react to external factors that directly or indirectly impact goals and objectives established by the CTB. The purpose of this process is not to predict the future, but to be better prepared to address the impact of external factors to achieve more desirable outcomes.

1.1 Public Involvement

Gathering and considering feedback from local and regional transportation partners and the public is an integral part of the CTB's policy development process as well as integral to the methods used to implement the CTB policies. The outlined methods may continue to evolve and improve based upon advances in technology, data collection and reporting tools. To the extent that any such improvements modify or affect the policy and process set forth in the VTrans Policy Guide, they shall be brought to the CTB for review and approval.

1.2 Known Limitations and Opportunities for Continuous Improvement

The execution of this Policy for the Development and Monitoring of the VTrans Long-term Risk & Opportunity Register relies on available research, availability of data at the desired spatial and temporal levels, and computations to ensure transparent, data-driven, and replicable methods. The following should be noted:

- Uncertainties: There are several known uncertainties related to different datasets used for the execution of the Policy for the Development and Monitoring of the VTrans Long-term Risk & Opportunity Register. These uncertainties include, but are not limited to, the following:
  - Policy uncertainty: Globally, countries are making commitments to further accelerate certain macrotrends. For example, accelerating the adoption of electric vehicles or decelerating the risk of flooding. However, there are uncertainties around timeframes for implementation of and adherence to the commitments.
  - Scientific uncertainty: Impacts of mega- and macrotrends are an evolving area of scientific inquiry which influences understanding of economic, social, and ecological impacts (positive and negative) of the identified mega- and macrotrends. This evolving understanding introduces another source of uncertainty.

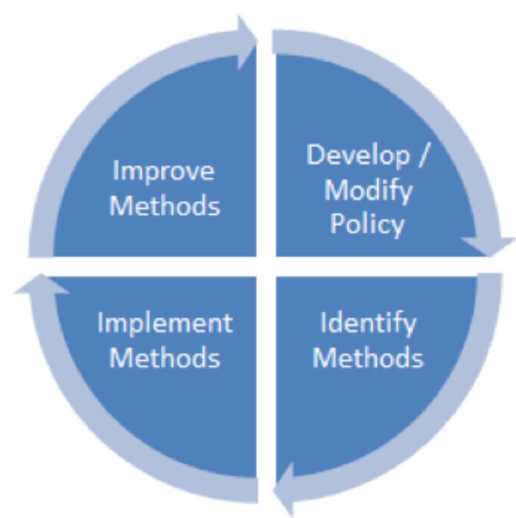
[1] Commonwealth Transportation Board, Actions to Approve the Policy for the Prioritization of the VTrans Mid-term Transportation Needs and Accept the Prioritized 2019 VTrans Mid-term Needs, March 17, 2021.

- Forecast Uncertainty: Forecasting conditions into the future holds uncertainty by nature - forecasts are rarely accurate and the further out in time a projection is, the more inaccurate it may be, due to the other uncertainties mentioned here or other random or non-random events or conditions.
- Model uncertainty: Even with a good understanding of scientific processes, it is difficult to represent them due to the data and computational limitations outlined below.

- Data: The execution of the Goal Metrics estimates described in this document relies on a variety of data from academic and non-profit institutions as well federal, state, and other sources. Each of these sources relies on various methods, techniques, and technologies to develop its datasets and, therefore, has its own limitations such as:
  - Lack of applicable research: Impacts of mega- and macrotrends are a relatively new research area. While a lot of research is available, there are several research gaps or, at minimum, need for further validation of available research. For example, there is relatively little research available on state or metropolitan-wide transportation impacts of the growth of e-commerce, a VTrans Macrotrend.
  - Lack of readily usable data: There are instances in which completeness and accuracy of datasets is not sufficient to execute the steps for the development of the VTrans Long-term Risk & Opportunity Register. For example, while impacts of VTrans Macrotrends on Vehicle Miles Traveled (VMT) is estimated as part of Step 3, the estimated VMT cannot be assigned using spatial and temporal dimensions to identify impacts of VTrans Macrotrends on roadway congestion or roadway travel time reliability.
  - Confounding variables: The development of the Long-term Risk & Opportunity Register, even in the presence of very precise, readily available data, can be prone to errors due to confounding variables. For example, a VTrans Macrotrend identified in Step 1 is estimated to reduce peak-hour home-based work trips, these estimates are based on the assumptions related to the desire to telework which are influenced by several non-transportation related factors such as school drop-off for children on the way to work, etc.
- Computations: The Goal Metric estimates described in this document require synthesis, format conversions, and computations, such as those required by the following examples, that could result in inadvertent errors. In those instances, the Board-adopted Policy and the methods, processes, and techniques documented in this Technical Guide take precedence.
  - Units: Different data sources are reporting at different units of aggregations. Some are available by directional segment (e.g. VTrans Macrotrend # 1: Increase in Flooding Risk) whereas other datasets are available by area or sub-area levels (e.g. VTrans Macrotrend # 5: Growth in E-commerce).
  - Frequency of updates: Some datasets can be updated on a monthly or annual basis (e.g. VTrans Macrotrend # 3: Adoption of Electric Vehicles) while other datasets are updated once every five years approximately (e.g. sea-level rise estimations used for VTrans Mactotrend # 1: Increase in Flooding Risk).

The limitations listed above can also be seen as opportunities for continuous improvement (Figure 1). By adapting to and adjusting to these limitations, the methodology outlined in this Technical Guide can change and improve based on an evolving understanding of mega- and macrotrends as well as to reflect advances in data quality, data collection, and reporting tools. To the extent that any such improvements modify or affect the policy, public review and CTB's approval will be sought.

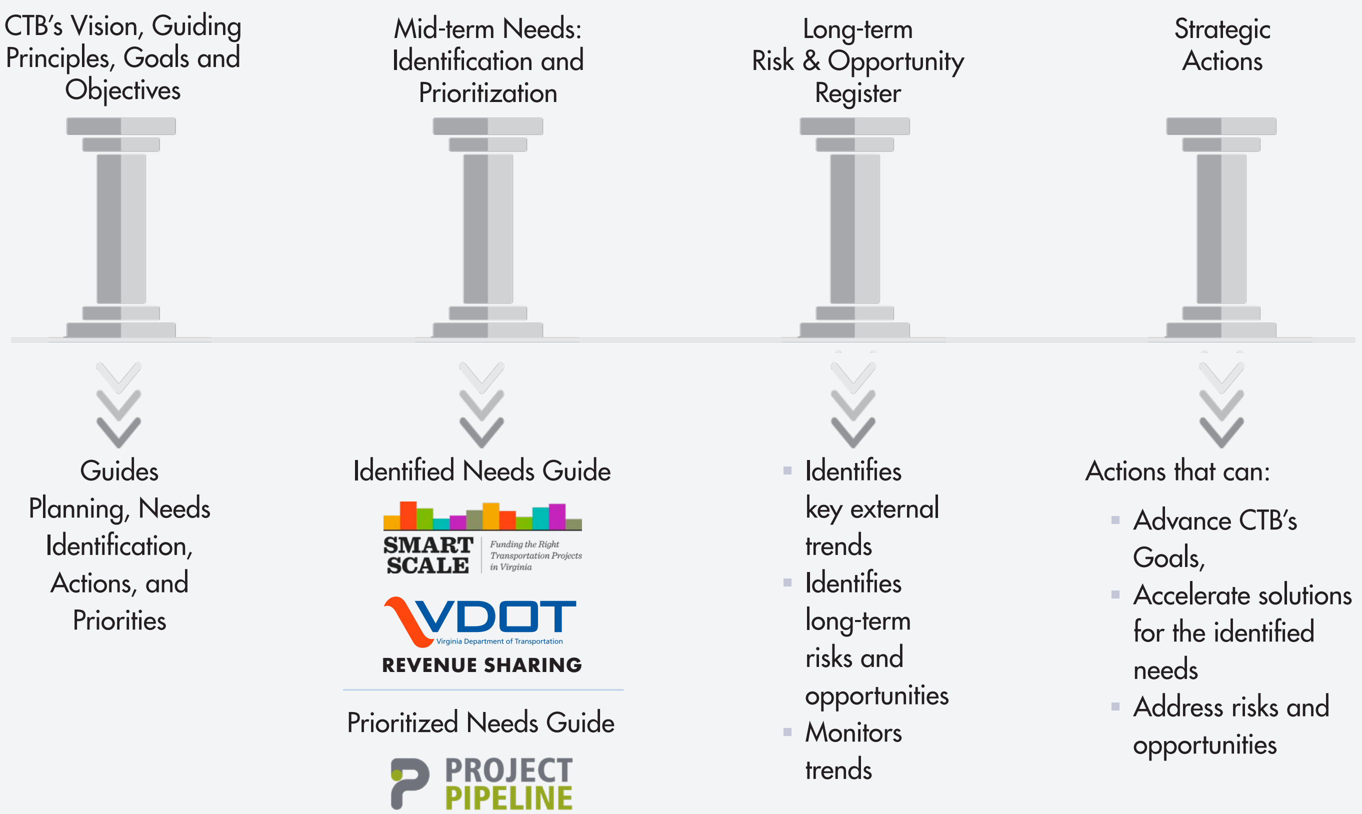
Figure 1: Opportunities for Continuous Improvement



CHAPTER 2. INTRODUCTION TO VTRANS – VIRGINIA'S TRANSPORTATION PLAN

VTrans is the plan to advance the Commonwealth Transportation Board's (CTB) vision for multimodal transportation in the Commonwealth. The CTB, with assistance from the Office of Intermodal Planning and Investment (OIPI)[1], develops VTrans to identify transportation needs which may be addressed by multimodal infrastructure improvement projects, transportation strategies, creation of new policies, or modifications to existing policies. This Technical Guide addresses technical methods and processes related to the Policy for the Development and Monitoring of the VTrans Long-term Risk & Opportunity Register as outlined in Chapter 6 of the VTrans Policy Guide.

Figure 2: Major Components of VTrans - Virginia's Transportation Plan



2.1 VTrans Vision, Guiding Principles, Goals, and Objectives

The first major component of VTrans, the development of the Vision, Guiding Principles, Goals, and Objectives, forms the basis upon which the remaining three major components, the VTrans Mid-term Needs, VTrans Long-term Needs, and Strategic Actions, are developed. The CTB updated and adopted the VTrans Vision, Guiding Principles, Goals, and Objectives in 2020.

2.2 VTrans Planning Horizons

The CTB identifies needs for the following two planning horizons. This Technical Guide focuses on the long-term planning horizon:

- **Mid-term Planning Horizon:** VTrans' analysis for the Mid-term Planning Horizon is developed to help identify some of the most pressing transportation issues that need to be addressed over the next ten years. These needs are referred to as VTrans Mid-term Needs. The needs are identified so that they can inform or guide transportation policies, strategies, and infrastructure improvements developed and implemented by the Virginia Department of Transportation (VDOT) and the Department of Rail and Public Transportation (DRPT), as well as local and regional entities.
- **Long-term Planning Horizon:** VTrans' analysis for Long-term Planning Horizon identifies risks and opportunities over the next 20+ year planning period. This Technical Guide is a synthesis of technical methods and processes used to execute the CTB Policy for the Development and Monitoring of the VTrans Long-term Risk & Opportunity Register as outlined in the Chapter 6 of the VTrans Policy Guide.

[1] Office of Intermodal Planning and Investment of the Secretary of Transportation established pursuant to § 2.2-229

CHAPTER 3. VTRANS LONG-TERM RISK & OPPORTUNITY REGISTER

The VTrans Long-term Risk & Opportunity Register is developed based on the following steps:

- Step 1: Megatrends and associated Macrotrends are identified.
- Step 2: CTB's priorities are identified based on CTB's Vision, Goals, and Objectives.[1]
- Step 3: Impact of Mega- and Macrotrends on CTB's priorities are estimated.
- Step 4: VTrans Long-term Risk & Opportunity Register is developed based on the estimated impacts on established priorities.
- Step 5: OIPI reviews and provides annual updates to the CTB for the identified risks and opportunities.

Figure 3: Steps for Development and Monitoring of VTrans Long-term Risk & Opportunity Register

Step 1: Identify Mega- and Macrotrends

Megatrends are identified as key external factors:
- Climate
- Technology
- Consumption
- Socio-demographics

Step 2: Develop Metrics for CTB Goals

Priorities associated with CTB Goals are identified:
- Goal A: Vehicle Miles Traveled (VMT) Index
- Goal B: Shared Mobility Index
- Goal C: Safety Index
- Goal D: At-risk Roadways
- Goal E: Tailpipe Emissions

Step 3: Estimate Impact of Macrotrends on Goal Metrics

A range of potential impacts of the megatrends (Step 1) on the Goal Metrics (Step 2) are identified.

Step 4: Develop VTrans Long-term Risk & Opportunity Register

The VTrans Long-term Risk & Opportunity Register is developed based on feedback from policy makers and stakeholders.

Step 5: Track Macrotrends

VTrans Trend Trackers are utilized for annual reporting to the CTB.

[1] Commonwealth Transportation Board, Actions to Approve the 2019 VTrans Vision, Goals, Objectives, Guiding Principles and the 2019 Mid-term Needs Identification Methodology and Accept the 2019 Mid-term Needs, January 15, 2020

3.1. Step 1: Identify Mega- and Macrotrends

Megatrends are defined as "the great forces in societal development that will very likely affect the future in all areas over the next 10-15 years. A megatrend is also defined as "a large, social, economic, political, environmental or technological change that is slow to form. Once in place, megatrends influence a wide range of activities, processes and perceptions, both in government and in society, possibly for decades. They are the underlying forces that drive trends."[1]

A macrotrend is defined as "An emerging pattern of change likely to impact state government and require a response. Multiple macrotrends can be associated with a megatrend."[2]

Mega- and Macrotrends that are directly or indirectly significant from a transportation planning and investment perspective are identified based on literature review and are shown in Table 1 below. These are referred to as VTrans Megatrends and VTrans Macrotrends to differentiate them from other mega and macrotrends that exist.

Table 1: VTrans Mega- and Macrotrends

MEGATREND 1: CLIMATE	
	Macrotrend # 1: Increase in Flooding Risk[3,4]
MEGATREND 2: TECHNOLOGY	
	Macrotrend # 2: Adoption of Highly Autonomous Vehicles
	Macrotrend # 3: Adoption of Electric Vehicles
	Macrotrend # 4: Growth in Shared Mobility
MEGATREND 3: CONSUMPTION	
	Macrotrend # 5: Growth in E-commerce
	Macrotrend # 6: Greater Automation of Goods and Services
MEGATREND 4: SOCIO-DEMOGRAPHICS	
	Macrotrend # 7: Growth of Professional Services Industry
	Macrotrend # 8: Increase in Workplace Flexibility
	Macrotrend # 9: Growth of the 65+ Cohort
	Macrotrend # 10: Population and Employment Shift

1 European Foresight Platform
2 Transportation Policy Task Force Suggested State Legislation Docket. 2009. California
3 Definition of Vulnerability: Vulnerability is a function of exposure to a hazard(s), the sensitivity to the given hazard, and adaptive capacity or the system's ability to cope.
4 Definition of Resiliency: The capability to anticipate, prepare for, respond to and recover from extreme weather event(s) with minimum damage to social well-being, infrastructure, the economy, and the environment.

3.1.1. VTrans Macrotrend # 1: Increase in Flooding Risk

Description: This VTrans Macrotrend refers to increase in flooding risk due to: (1) sea level rise; (2) storm surge; and, (3) inland and riverine flooding.

Drivers[1]**:**

- Emissions of heat-trapping gases

Data sources for Scenarios

- **Sea level rise:** The sea level rise scenarios are based on National Oceanic and Atmospheric Administration's (NOAA) 2017 report, Global and Regional Sea Level Rise Scenarios for the United States and one of the scenarios is consistent with Governor Northam's Executive Order Number 24 *(2018): Increasing Virginia's Resilience to Sea Level Rise.* The Virginia Flood Risk Management Standard (VFRMS) (Executive Order 45) satisfies the directive in Executive Order 24 by setting standards for State-owned buildings in coastal and inland flood prone areas based on the NOAA Intermediate-High scenario curve.

  The sea level rise scenarios utilized Sewells Point tide gauge to determine Relative Sea Level Change (RSLC). With a baseline year 2000, these RSLC values were added to today's mean high water (MHW) level to determine future MHW levels. These datasets were obtained from the Center for Coastal Resources Management at VIMS and include both the extent and depth of flooding. The 2017 NOAA report (Appendix 1) provides six emission-based scenarios aligned with

[1] National Oceanic and Atmospheric Administration (NOAA). Climate Forcing. Accessed on July 8, 2021.

conditional probability storylines and global model projections, of which the following three were applied in the VTrans Vulnerability Assessment:

- Intermediate, Relative Sea Level Change (RSLC) of 1.38 feet
- Intermediate-High, RSLC of 1.78 feet
- Extreme, RSLC of 2.46 feet

- **Storm surge:** The storm surge scenarios are based on NHC hydrodynamic Sea, Lake and Overland Surges from Hurricanes (SLOSH) model which simulates storm surge from tropical cyclones based on present day sea levels. The SLOSH model uses a representative sample of hypothetical storms (up to 100,000) using varying intensity, forward speed, radius of maximum wind, storm direction, and tide level. Each storm combination is simulated at 5 to 10-mile increments along the coast. For each storm intensity (Category 1-5), the maximum storm surge height among all simulations is catalogued at each grid point in the model. The resulting Storm Surge Hazard Maps represent the worst-case flooding scenario during high-tide for each storm category.
- **Inland/riverine flooding:** The inland/riverine flooding scenarios are based on a combination of FEMA Flood Zones derived from the Flood Insurance Rate Map (FIRM) via FEMA's National Flood Hazard Layer database, and observed historical weather events from Virginia's 511 system.[1] The scenarios also rely on historical flooding documented by VDOT.

[1] See Appendix 2.

3.1.2. VTrans Macrotrend # 2: Adoption of Highly Autonomous Vehicles

Description: This Macrotrend refers to full or partial automation of driving activities in personal and commercial vehicles. This analysis relies on automation categorization developed by the Society of Automotive Engineers (SAE). Please refer to the definitions in Section 1 of this document.

Significance: Growth in the number of highly autonomous vehicles, referred to as AVs, in the fleet will potentially impact roadways' effective traffic-carrying capacity, roadway safety, and operation costs of vehicles, and may also impact travel demand.

Drivers:

- Advancement of vehicle sensing and information processing technologies for automation[1]
- Industry-wide push and investments towards development of automated vehicles[2]
- Consumer preferences for safety and openness to vehicle technology[3]

Data Sources:

- Adoption Curves for personal AVs: Bansal and Kockelman[4]
- Adoption Curves for commercial AV Technology: Mishra, Golias, et al.[5]
- Commercial Vehicles and Firms in Virginia: FMCSA[6]

[1] Reuters, Self-Driving Costs could drop 90% by 2025

[2] Forbes, Driverless Cars Gain Speed despite Global Slowdown

[3] AAA, Today's Vehicle Technology Must Walk So Self-Driving Cars can Run

[4] Bansal, P., Kockelman, K. (2017). Forecasting Americans' long-term adoption of connected and autonomous vehicle technologies.

[5] Mishra, Sabya, Mihalis Golias, and Evangelos Kaisar (2019). "Modeling Adoption of Autonomous Vehicle Technologies by Freight Organizations." College Park, MD: Freight Mobility Research Institute.

[6] FMCSA, Motor Carrier Census System. Accessed in February 1, 2021

Calculations:

Estimate the market penetration of personal/passenger AVs for years 2020 to 2045.

1. For personal vehicles, utilize personal/passenger AV adoption for low, medium, and high scenarios using adoption rates developed by Bansal & Kockelman (2017).[1]

Estimate the market penetration of commercial AVs for years 2020 to 2045.

2. Obtain data[2] related to motor carriers in Virginia as of February 1, 2021.
3. Utilize the fields 'Number of Power Units' (equivalent of vehicles) and 'Number of Drivers' to conduct a k-means clustering[3] to categorize 18,564 motor carriers as 'small,' 'medium,' or 'large.'
4. Use market studies/reports to estimate a commercial readiness year for the technology. For each technology, associate an adoption scenario type (baseline, conservative, or optimistic) also based on market studies and reports. If the technology has already been introduced, its actual introduction year is used. The results of this market analysis are listed in Table 2 by technology and adoption scenario type.

Table 2: Estimated Commercial Readiness Year for Vehicle Technologies

Commercial Vehicle Technology	Commercial Readiness Year	Adoption Curve Type
Platooning	2025	Conservative
Predictive Cruise	2016	Baseline
Adaptive Cruise	2019	Baseline
Automated Manual Transmission	2006	Optimistic
Level 4 Automation	2030	Conservative

5. For each automation technology, generate an adoption curve for each motor carrier size (small, medium, and large) and sum them. This results in one adoption curve for the state of Virginia for each automation technology. The adoption curves are generated using parameters based on the motor carrier size and the adoption scenario type, as defined in Mishra et al. (2019).[4]
6. Use the market readiness year from Step # 4 and the adoption curves generated in Step # 5 to estimate the market penetration rate of each commercial vehicle automation feature in 2045. Results are shown in Table 3 below.

[1] Bansal, P., Kockelman, K. (2017). Forecasting Americans' long-term adoption of connected and autonomous vehicle technologies. Tables 6, 7, and 8.

[2] FMCSA, Motor Carrier Census System

[3] K-means Clustering

[4] Mishra, Sabya, Mihalis Golias, and Evangelos Kaisar. Modeling Adoption of Autonomous Vehicle Technologies by Freight Organizations. College Park, MD: Freight Mobility Research Institute, 1/19

Step 1: Macrotrend # 3: Adoption of Highly Autonomous Vehicles Output

Table 3: Estimated Market Penetration of Vehicle Automation in Year 2045 by Vehicle Automation Levels

Vehicle Automation Levels	Estimated Market Penetration of Vehicle Automation Levels		
	Low Estimate	Medium Estimate	High Estimate
Passenger Vehicles			
Level 1 and 2 (Lane Centering)	41%	60%	98%
Level 1 and 2 (Adaptive Cruise Control)	47%	68%	98%
Level 3	9%	8%	3%
Level 4	25%	43%	87%
Commercial Vehicles			
Level 0 - Automated Manual Transmission		80%	
Level 1- Adaptive Cruise Control		40%	
Level 1 and 2 Platooning		18%	
Level 4		12%	

Assumptions

- Market penetration rates are based on considering the willingness to pay for one or more types of automated technologies in use. In reality, vehicle automation is expected to include many different types of automated technologies especially when considering Levels 1 to 3.
- Level 3 technologies are assumed to be a transition stage technology and hence have low levels of penetration in higher-end estimates of market penetration since they are assumed to have been replaced by Level 4 vehicles.
- Assume that the V2X connectivity is factored into the willingness to pay for level 4 technology and no separate estimation for connected vehicles are developed.

3.1.3. VTrans Macrotrend # 3: Adoption of Electric Vehicles

Description: Electric Vehicles (EVs) use electric motors powered by batteries, rather than internal combustion engines powered by petroleum-based fuels. This trend estimates the adoption of Electric Vehicles (EVs) in the Commonwealth of Virginia in the year 2045.

Significance: EVs are a small but growing share of the automobile market. As their price decreases, demand for EVs as well as for supportive infrastructure will increase. EVs promise higher efficiencies and lower tailpipe emissions. They also may require additional investment in infrastructure, such as electric vehicle chargers to support their operations.

Drivers:

- Technological advancements in EV battery technology
- Increased vehicle availability of EVs[1]
- Decreasing manufacturing costs[2]
- Growth in national charging infrastructure[3]
- Public policy drivers to reduce GHG emissions, for example, Corporate Average Fuel Economy Standards[4]

Data Sources:

- Market penetration of EVs from 2019-2045: Virginia Energy Policy Simulator
- Reduction in CO2e emissions due to EVs: Virginia Energy Policy Simulator

[1] Deloitte (2020). Electric Vehicles: Setting a Course for 2030.

[2] Baik, Y., Hensley, R., Hertzke, P., and Knupfer, S. (2019). Making Electric Vehicles Profitable. McKinsey & Company.

[3] Brown, A., Lommele, S., Schayowitz, A., and Klotz, E. (2020). Electric Vehicle Charging Infrastructure Trends from the Alternative Fueling Station Locator: First Quarter 2020. Technical Report. National Renewable Energy Laboratory, U.S. Department of Energy. Report number NREL/TP-5400-77508.

[4] Corporate Average Fuel Economy (CAFE) Standards | US Department of Transportation

Calculations:

1. Estimate the market penetration of EVs from 2019-2045 based on three scenarios: Business as Usual, Medium Scenario and Accelerated Electrification, from the Virginia Energy Policy Simulator (EPS) Tool.[1,2]
2. Based on the scenario used for market penetration of EVs, determine the potential reduction in tailpipe emissions due to EVs considering Virginia's current electricity generation sources. Using Virginia Policy Simulator, "Business as Usual" corresponds with the low scenario, "Accelerated Electrification" corresponds with the high scenario the percentage reduction of CO2e emissions between 2020 and 2045 is calculated for the low and high scenarios, and the percentage reduction for the medium scenario is the average of the low and the high scenarios.[3]

Table 4: Step 1 Outputs

Electric Vehicle Type	Estimated Market Penetration in 2045		
	Business as Usual	Medium Scenario	Accelerated Electrification
Cars and SUV	40%	98%	100%
Buses	23%	81%	92%
Light-Duty Trucks	41%	71%	100%
Medium and Heavy Duty Trucks	1%	48%	41%
Motorbikes	38%	92%	38%
Reduction in CO2e Emissions	39%	84%	85%

Assumptions

- Adoption of EVs and Reduction in emissions was calculated using the Virginia Energy Policy Simulator.[4] The assumptions for Virginia Energy Policy Simulator can be found in the model documentation.

[1] "Virginia Energy Policy Simulator." Virginia. Accessed April 08, 2021.

[2] Assumptions for the EPS tool can be found here. Energy Innovations (n.d.). Virginia Energy Policy Simulator (EPS) Summary Documentation.

[3] Assumptions of the Virginia Energy Policy Simulator related to electrification are available here: *Energy Policy Solutions (n.d.). Virginia Energy Policy Simulator (EPS) Summary Documentation.*

[4] Virginia Energy Policy Simulator

3.1.4. VTrans Macrotrend # 4: Growth in Shared Mobility

Description: Shared mobility services such as micromobility services (bikesharing, scooter sharing) and ridesourcing (e.g., transportation network companies) have seen recent explosive growth in scope and services offered.[1] This trend will show the number of trips that could be accommodated by micromobility and ridesourcing in 2045.

Drivers:

- Growth in broadband, and high prevalence and increasing capabilities of mobile communication devices[2]
- Increase in number of workers interested in work hour flexibility or willing to work in the 'gig' economy[3]

Significance: While shared mobility services are a small portion of the trips statewide, in certain geographies they play an important role in providing non-auto travel options.[4,5] Shared mobility has the potential to change travel costs and convenience, and to affect the amount traveled and the modes selected.

Data Sources:

- Vehicle Trips: StreetLight Data[6]
- Shared Mobility Growth Rates: Uber and Lyft S-1 Filings[7,8] and NACTO[9]
- Micromobilty local trip rates: Pilot program reports[10]

[1] Price, Jeff, Blackshear, Danielle Blount, Jr., Wesley and Sandt, Laura. Micromobility: A Travel Mode Innovation. US DOT FHWA Public Roads, Vol. 85 Issue 1, Spring 2021.

[2] Pew Research Center, Mobile Fact Sheet, 2021

[3] Brookings Instituion, Tracking the gig economy: New numbers, 2016

[4] Jin, S., Kong, H., Wu, R., Sui, D. (2018). *Ridesourcing, the Sharing Economy, and the Future of Cities.*

[5] Heineke, K., Kloss, B., Scurtu, D., Weig, F. (2019). *Micromobility's 15,000-Mile Checkup.* McKinsey & Company.

[6] Transportation Analytics On Demand | StreetLight Data

[7] Form S-1 Registration Statement, Uber Technologies, Inc. S-1 (sec.gov)

[8] Form S-1 Registration Statement, Lyft, Inc., S-1 (sec.gov)

[9] NACTO. "Shared Micromobility in the US: 2019," 2020.

[10] Portland, Arlington, Santa Monica, Kansas City, Chicago.

- Households by county: US Census Bureau (2019): American Community Survey[1]
- Daily vehicle trips per household FHWA (2017): National Household Travel Survey[2]
- Ridesource share of local VMT: Fehr & Peers[3]
- Micromobility distribution of trip lengths: Zou et al.[4]
- Percent of trips of different modes replaced by micromobility: McQueen et al.[5]
- Ridesource/taxi distribution of trip lengths: National Household Travel Survey[6]

Calculations:

Estimate possible micromobility and ridesource trip market for Virginia.

1. Develop a maximum trip length market for micromobility and ridesourcing services. Estimate the share of micromobility trips and ridesource trips by length as provided by Zou et al.[7] and Oak Ridge National Laboratory's (ORNL) National Household Travel Survey[8] (NHTS) respectively. Results are shown below in Tables 5 and 6, column (b).
2. Estimate base year (2019) overall daily auto trips and daily auto VMT by average trip starts in Virginia by county and by trip length categories established in calculation step # 1 above.
   (Daily Auto VMT) = number of daily auto trips × trip distance midpoint

Where:

- *number of daily auto trips 2019*[9]
- *trip distance midpoint*[10]

3. Estimate trips and VMT that could possibly be completed by micromobility or ridesourcing in future year (2045). For maximum switchable VMT, it is assumed that all localities in MSA's can support these systems. Inflate daily trips and VMT by population estimation to develop daily estimates for 2045. Trips and VMT in each county increase proportionally to an extrapolated population estimation for 2045.
   Trips (2045) = number of daily auto trips 2019 × county specific population growth rate, 2020-2045

   Where:

   - *Trips (2045)* is the estimated number of trips by trip length category in 2045
   - *number of daily auto trips 2019*[11]
   - *county specific population growth rate*[12]

[1] U.S. Census Bureau (2019). 2019 American Community Survey Five-year estimates.

[2] U.S. Department of Transportation (2017). *Summary of Travel Trends: 2017 National Household Travel Survey.* FHWA-PL-18-01.

[3] Fehr & Peers (2019). Estimated TNC Share of VMT in Six US Metropolitan Regions Memorandum

[4] Zou, Zhenpeng, Hannah Younes, Sevgi Erdogan, and Jiahui Wu. "Exploratory Analysis of Real-Time E-Scooter Trip Data in Washington, D.C." Transportation Research Record: Journal of the Transportation Research Board 2674, no. 8 (August 2020): 285–99.

[5] McQueen, Michael, Gabriella Abou-Zeid, John MacArthur, and Kelly Clifton. "Transportation Transformation: Is Micromobility Making a Macro Impact on Sustainability?" Journal of Planning Literature, November 15, 2020, 088541222097269.

[6] Federal Highway Administration. (2017). 2017 National Household Travel Survey, U.S. Department of Transportation, Washington, DC.

[7] Zou, Zhenpeng, Hannah Younes, Sevgi Erdogan, and Jiahui Wu. "Exploratory Analysis of Real-Time E-Scooter Trip Data in Washington, D.C." *Transportation Research Record: Journal of the Transportation Research Board* 2674, no. 8 (August 2020): 285–99.

[8] Federal Highway Administration. (2017). 2017 National Household Travel Survey, U.S. Department of Transportation, Washington, DC.

[9] Trip length categories are based on Zou et al.

[10] Streetlight data

[11] Trip length categories are based on Zou et al.

[12] Demographics Research Group of the Weldon Cooper Center for Public Service at University of Virginia.

4. Utilize the output of calculation step # 1 to develop trip distribution share by trip length category for micromobility trips and ridesource trips. Results are shown in column (c) in Table 5 and Table 6 below respectively.

Table 5: Share of Micromobility Trips by Length[1]

Trip Length Categories (Miles) (a)	Estimated VA Micromobility Trips in 2045 (b)	Share of Trips (c)
0 – 1	73,000	64%
1 – 2	29,000	25%
2 – 5	11,750	10%
Total		100%

Table 6: Share of Ridesource Trips by Length[2]

Trip Length Categories (Miles) (a)	Estimated VA Ridesource Trips in 2045 (b)	Share of Trips (c)
0 - 1	173,000	10%
1 - 2	347,000	19%
2 - 5	654,000	36%
5 - 10	380,000	21%
10 - 20	200,000	11%
20 - 30	61,000	3%
Total		100%

5. Estimate the maximum amount of trips and VMT that could be completed via micromobility and ridesourcing services. This estimate is created by assuming 100% conversion from SOV to micromobility or ridesourcing of trips that fit the trip length categories of shared mobility services.
6. Estimate potential additional market, for micromobility or ridesourcing based on the difference between the current market estimate and the overall maximum market estimate established in calculation step # 5.
    a. Estimate how much of the maximum micromobility and ridesourcing market is currently being served by these services in 2020 – call this the base discount factor. Calculate discount factors for micromobility pilots in Portland, OR[3]; Arlington, VA[4]; Santa Monica, CA[5]; Kansas City, MO[6]; and Chicago, IL.[7] The pilots provide a data point on the trips per day which is then divided by estimated daily vehicle trips in the jurisdiction, as illustrated in Table 7 below. Ridesourcing discount factors are based on a Fehr and Peers report.[8]

[1] Zou, Zhenpeng, Hannah Younes, Sevgi Erdogan, and Jiahui Wu. "Exploratory Analysis of Real-Time E-Scooter Trip Data in Washington, D.C." Transportation Research Record: Journal of the Transportation Research Board 2674, no. 8 (August 2020): 285–99.

[2] Federal Highway Administration. (2017). 2017 National Household Travel Survey, U.S. Department of Transportation, Washington, DC.

[3] Portland Bureau of Transportation (2018). E-Scooter Findings Report.

[4] Arlington County, VA (2019). Arlington County Shared Mobility Devices (SMD) Pilot Evaluation Report.

[5] City of Santa Monica (2019). Shared Mobility Pilot Program Summary Report.

[6] Kansas City (n.d.). KCMO Micromobility Pilot Program First-Year Analysis.

[7] City of Chicago (2021). 2020 E-Scooter Pilot Evaluation.

[8] Fehr & Peers (2019). Estimated TNC Share of VMT in Six US Metropolitan Regions Memorandum.

Table 7: Micromobility Discount Factor Calculation

City	Number of Days (a)	Micro-mobility Trips (b)	Micro-mobility Trips per Day (c=b/a)	Annual Micro-mobility Trips (d=c*365)	Number of households[1] (e)	Average Daily Vehicle Trips per Household[2] (f)	Total annual vehicle trips (g=e*f)	Annual Micro-mobility Trips as Percent of Regional Vehicle Trips (h=d/g)
Portland, OR	120	70,038	584	213,032	326,229	5.11	608,466,019	0.035%
Arlington, VA	243	453,690	1,867	681,469	107,032		199,630,735	0.341%
Santa Monica, CA	335	2,673,819	7,982	2,913,265	3,316,795		6,186,320,194	0.047%
Kansas City, MO	397	374,000	942	343,854	286,601		534,553,855	0.064%
Chicago, IL	122	540,005	4,426	1,615,589	19,72,108		3,678,277,236	0.044%
Average (Discount Factor for Micromobility):								0.106%

7. Develop compound annual growth rates for micromobility and ridesourcing trips based on market research. The assumed compounding annual growth rate is based on growth rates able to be determined from trip rates found in Lyft/Uber S-1 SEC filings and the National Association of City Transportation Officials (NACTO) 2019 micromobility report. Growth rates are assumed to decrease over time as systems mature, and will provide the stated compound annual growth rate (CAGR). Assumed CAGRs are:

   Micromobilty: 20% CAGR (from 2020-2035), 5% (2035-2045)
   Ridesourcing: 15% CAGR (from 2020-2035), 5% (2035-2045)

8. Apply compound annual growth rates to baseline discount factors to illustrate growth in services from 2020-2045 and estimate 2045 discount factors. The total trips that are estimated to replace vehicle trips are a product of the base total trips discount factor (based on region-wide estimated total vehicle trips data), assumed compound annual growth in percent of region-wide vehicle trips, and the distribution of trips by trip distance buckets.
   2045 discount factor = 2020 base discount factor (1 + CAGR)^t

   Where:
   - 2020 base discount factor as established in calculation step # 6.
   - CAGR is the compound annual growth rate established in calculation step # 7.
   - t is the number of years (25) to apply CAGR.

9. Estimate the amount of automobile VMT replaced by (or switched to) micromobility and ridesourcing in 2045 by Virginia locality, based on the results from calculation step # 8.
   $\text{automobile VMT replaced} = \sum_{i=\text{trip length category}} \text{locality automobile trips}_i \times \text{2045 discount factor} \times r \times m_i$
   - *automobile VMT replaced* is the total VMT by locality
   - *2045 discount factor* is from calculation step # 8.
   - *r* is the percent of trips of that mode replacing auto.[3]
   - *m* is the trip length category midpoint determined in calculation step # 1.

[1] U.S. Census Bureau (2019). 2019 American Community Survey.

[2] U.S. Department of Transportation (2017). *Summary of Travel Trends: 2017 National Household Travel Survey.* FHWA-PL-18-01.

[3] Assumed as 30%. McQueen, Michael, Gabriella Abou-Zeid, John MacArthur, and Kelly Clifton. "Transportation Transformation: Is Micromobility Making a Macro Impact on Sustainability?" Journal of Planning Literature, November 15, 2020, 088541222097269. For ridesourcing/transportation network companies (TNCs), this replacement is assumed as 40% based on Schaller Consulting.

3.1.5. VTrans Macrotrend # 5: Growth in E-commerce

Description: E- commerce is the process of purchasing products on the internet which are then delivered directly to a home or business.

Drivers:

- Customer convenience[1]
- Consumer willingness to pay for delivery shipping services[2]
- Automation of warehousing

Significance: Growth in e-commerce is expected to have impacts on transportation and the economy, including changing product sourcing and operating costs, product availabilities, changing delivery methods, and freight movements.

Data Sources:

- Historical wholesale trade or business-to-business (B2B) e-commerce and total sales for North American Industry Classification System (NAICS) industry: US Census, Annual Wholesale Trade Survey (AWTS)[3]
- US Monthly Retail Trade Survey (MRTS): US Census[4]
- US Quarterly Retail E-Commerce and Total Sales: US Census[5]
- Virginia Industry Mix: Multiple sources[6]
- Historical retail/business-to-consumer (B2C) e-commerce and total sales for NAICS industry

[1] National Retail Federation, Consumer View Winter 2020.

[2] Businesswire, New Research Finds 65% of Consumers Willing to Pay More for Faster Deliveries, June 16 2021.

[3] US Census Annual Report for Wholesale Trade, 2019 (last accessed on April 8, 2021)

[4] US Census Quarterly E-Commerce Report Historical Data (last accessed on April 8, 2021)

[5] US Census Monthly Retail Trade Survey Historical Data (last accessed on April 8, 2021)

[6] US Census, Monthly Retail Trade Survey, 1992-2020 Retail and Food Services Sales, as on December 16, 2020; US Census, Quarterly E-Commerce Report, 2018 Q1 to 2020 Q3 Supplemental Quarterly E-Commerce Tables as on November 19, 2020; US online retail forecast by FTI Consulting, 2019; Industry Articles; Virginia Department of Taxation via Weldon Cooper Center for Public Service, Historical Virginia State Annual and Quarterly Taxable Sales by NAICS 3-digit Industry, Year 2018, Year 2019, Year 2020 Q1-Q3; and Forecast and Market Penetration by Industry Assumptions.

- US Output (GDP) by Industry data: US Bureau of Economic Analysis[1]
- Virginia Annual taxable wholesale trade sales data: Virginia Department of Taxation via Weldon Cooper Center[2]
- Virginia Employment forecasts: Woods & Poole[3]
- 2020-2050 vehicle stock and fuel efficiency: US Energy Information Agency[4]
- Current local gas prices: AAA[5]
- Last-mile delivery and fulfillment center costs percent of sales: Dubai Multi Commodities Centre[6]

Calculations:

Estimate E-commerce Market Penetration, as share of Total Dollar Value of Sales, for the Wholesale/ Business-to-Business (B2B) market, for years 2019 and 2045

1. Estimate base year (2019) B2B e-commerce market penetration rates for the US by three-digit NAICS industry.
   $Base\ E\text{-}com\ Sales\ \%_i^{US} = Base\ E\text{-}Com\ Sales_i^{US} / Base\ Total\ Sales_i^{US}$

   Where:
   - $Base\ E\text{-}com\ Sales_i^{US}$ is the US's 2018 wholesale trade or B2B e-commerce sales for NAICS industry *i* gathered from US Census' US Annual Merchant Wholesaler data[7]
   - $Base\ Total\ Sales_i^{US}$ is the US's 2018 wholesale trade or B2B total sales for NAICS industry *i* gathered from US Census' US Annual Merchant Wholesaler data[8]
   - $Base\ Total\ Sales_i^{VA}$ is Virginia's 2018 Q1-2020 Q3 wholesale trade or B2B total taxable sales for NAICS industry *i* gathered from Virginia Department of Taxation's annual taxable wholesale trade or B2B sales data published on Weldon Cooper Center website[9]
   - *i* is the index for NAICS industries 423 (Durable Goods) and 424 (Nondurable Goods)

2. Apply the US e-commerce penetration rates by NAICS three-digit industry found in calculation step # 1 to estimate the base year (2019) e-commerce wholesale market penetration rates by industry in Virginia.
   $Base\ E\text{-}com\ Sales\ \%^{VA} = \sum_i Base\ E\text{-}com\ Sales\ \%_i^{US} \times Base\ Total\ Sales_i^{VA}$

   Where:
   - $Base\ E\text{-}com\ Sales\ \%^{VA}$ is the estimated Virginia's 2019 wholesale trade or B2B e-commerce share of total sales for NAICS industry *i*
   - $Base\ E\text{-}com\ Sales\ \%^{US}$ is the estimated US's 2018 wholesale trade or B2B e-commerce share of total sales for NAICS industry *i*

3. Develop future year (2045) estimations for B2B e-commerce market share[10] for NAICS industries 423 (Durable Goods) and 424 (Nondurable Goods). Use historical (2010-2018) US B2B e-commerce shares of total sales gathered from US Census' US Annual Merchant Wholesaler data. The national trendline forecasts for e-commerce share of total sales in NAICS industries 423 and 424 were adopted for Virginia.

[1] US Bureau of Economic Analysis, Integrated Industry-Level Production Account (KLEMS); GDP-by-industry tables; GDP & Personal Income tables (last accessed on April 8, 2021)

[2] Virginia Department of Taxation via Weldon Cooper Center for Public Service, Historical Virginia State Annual and Quarterly Taxable Sales by NAICS 3-digit Industry, Year 2018, Year 2019, Year 2020 Q1- (last accessed on April 8, 2021)

[3] Provided by the Virginia Transportation Research Council (VTRC)

[4] US Energy Information Agency, Annual Energy Outlook tables (last accessed on April 8, 2021)

[5] American Automobile Association, Virginia Average Gas Prices, (last accessed on April 8, 2021)

[6] DMCC (Dubai Multi Commodities Centre). 2016. "The Future of Trade." DMCC, Dubai, and Future Agenda. last accessed on April 8, 2021.

[7] US Census Annual Report for Wholesale Trade, 2019 (last accessed on April 8, 2021)

[8] US Census Annual Report for Wholesale Trade, 2019 (last accessed on April 8, 2021)

[9] Virginia Department of Taxation via Weldon Cooper Center for Public Service, Historical Virginia State Annual and Quarterly Taxable Sales by NAICS 3-digit Industry (last accessed on April 8, 2021)

[10] MS Excel trendline function - third degree polynomial function as follows was fitted using 2010-2019 data and yields R-square value of 0.99: -0.0000113×x3+0.0005558×x2+ 0.002322×x+0.0416073, where x = year minus 2009

For NAICS industry 423: *E-com Sales % in year* $X^{US} = 0.0986 \times \ln(X-2002) + 0.1337$; $R^2=0.85$

For NAICS industry 424: *E-com Sales % in year* $X^{US} = 0.1498 \times \ln(X-2002) + 0.0679$; $R^2=0.78$

Where:

- *E-com Sales % in year* X^{US} *is the estimated US B2B e-commerce share of total sales in year X for a given NAICS industry*

4. Develop a low and high scenario by subtracting and adding 5 percentage points to the 2045 values, respectively.
5. Use a weighted average of NAICS industry categories to develop low, medium and high scenarios for wholesale e-commerce 2045 market share by three-digit industry code.

Estimate E-commerce Market Penetration, as share of Total Dollar Value of Sales, for the Retail/Business-to-Consumer (B2C) market, for years 2019 and 2045

6. Estimate base year (2019) B2C e-commerce market penetration rates for the US by three-digit NAICS industry.
   Base E-com Sales $\%_i^{US}$ = *Base E-Com* $Sales_i^{US}$/*Base Total* $Sales_i^{US}$

   Where:

   - *Base E-Com* $Sales_i^{US}$ is the US's 2018 Q1-2020 Q3 retail trade or B2C e-commerce sales for NAICS industry *i* gathered from US Census' Quarterly E-Commerce Report, 2018 Q1 to 2020 Q3 Supplemental Quarterly E-Commerce Tables as of November 19, 2020[1]
   - *Base Total* $Sales_i^{US}$ is the US's 2018 Q1-2020 Q3 retail trade or B2C total sales for NAICS industry *i* gathered from US Census' Monthly Retail Trade Survey, 1992-2020 Retail and Food Services Sales, as of December 16, 2020[2]

7. Apply the US e-commerce penetration rates by NAICS industry found in Calculation Step 6 to estimate the base year (2019) e-commerce retail market penetration rates by industry in Virginia.
   Base E-com Sales $\%^{VA} = \sum_i$ *Base E-Com Sales* $\%_i^{US} \times$ *Base Total Sales* $_i^{VA}$

   Where:

   - *Base E-com Sales* $\%^{VA}$ is Virginia's estimated 2019 B2C e-commerce share of total sales
   - *Base E-Com Sales* $\%_i^{US}$ is the US's estimated 2018 Q1-2020 Q3 B2C e-commerce share of total sales for NAICS industry *i* determined in calculation step # 1
   - *Base Total Sales* $_i^{VA}$ is Virginia's 2018 Q1-2020 Q3 B2C total taxable sales for NAICS industry *i* gathered from Virginia Department of Taxation's annual taxable B2C sales data published on Weldon Cooper Center website[3]
   - *i* is the index for NAICS industries 441-448 and 451-454

8. Develop future year (2045) Estimates for Retail/Business-to-Consumer (B2C) e-commerce market share[4] using historical (2010-2018) US B2C e-commerce shares of total sales gathered from the US Census US Annual Merchant Wholesaler data.
   E-com Sales % in year $X^{US} = -1.10 \times 10^{-5} \times (X-2009)^3 + 5.5 \times 10^{-4} * (X-2009)^2 + 2.3 \times 10^{-3} \times (X-2009) + 4.2 \times 10^{-2}$; $R^2=0.99$

   Where:

   - *E-com Sales % in year* X^{US} is the US' estimated B2C e-commerce share of total sales in year X for a given NAICS industry

   The estimated 2045 national forecast B2C e-commerce share of 33 percent based on the above equation is used as a control check on the total market size of B2C e-commerce estimated for Virginia. Due to differences in industrial mix at national and state levels, the estimated shares may differ at these geographical levels.

[1] US Census Quarterly E-Commerce Report Historical Data (last accessed on April 8, 2021)

[2] US Census Monthly Retail Trade Survey Historical Data (last accessed on April 8, 2021)

[3] Virginia Department of Taxation via Weldon Cooper Center for Public Service, Historical Virginia State Annual and Quarterly Taxable Sales by NAICS 3-digit Industry, (last accessed on April 8, 2021)

[4] MS Excel trendline function - A third degree polynomial function as follows was fitted using 2010-2019 data and yields R-square value of 0.99: -0.0000113×x3+0.0005558×x2+ 0.002322×x+0.0416073, where x = year minus 2009

9. Through a study of research articles gathered on each 3-digit NAICS industry, 2045 medium scenario (most likely) assumptions are made on B2C e-commerce shares. These are upward adjustments to the 2019 retail trade or B2C e-commerce shares based on the NAICS industry mix in Virginia.[1]

10. A range of +/-5 percent by industry is assumed to represent the 2045 low and high scenarios.

11. Use a weighted average of NAICS industry categories to develop low, medium and high scenarios for B2C e-commerce 2045 market share. The weights used for the 3-digit NAICS industries in 2019, that is $Base\ Total\ Sales\ \%_i^{VA}$, to estimate the retail trade or B2C sector level e-commerce share are also used in 2045.

Estimate employment changes (full time equivalent) due to e-commerce for the Wholesale/B2B market at the Metropolitan Statistical Area (MSA) level for years 2019 and 2045

12. Estimate base year (2019) employment in industries related to wholesale trade sectors for Virginia and MSAs/rural areas. Use 2019 Virginia Employment by 3-digit NAICS industry for statewide and 2019 regional distribution of employment among Virginia's MSAs and Rural Areas by 2-digit NAICS Industry for MSAs/rural areas. Define MSAs by size:
    - Large MSAs: Richmond, Virginia Beach-Norfolk-Newport News and Northern Virginia
    - Medium MSAs: Charlottesville, Lynchburg, and Roanoke
    - Rest of State (Small MSAs + Rural Areas)

    $Base\ E\text{-}Com\ Emp_i^{Region} = Base\ Emp_i^{VA} \times Base\ E\text{-}Com\ Sales\ \%_i^{US} \times Base\ Emp\ \%^{Region}$

    Where:
    - $Base\ E\text{-}Com\ Emp_i^{Region}$ is the estimated regional (Virginia's MSAs and Rural Areas) 2019 B2B e-commerce employment by NAICS industry *i*
    - $Base\ Emp_i^{VA}$ is Virginia's 2019 Quarter 4 Month 3 B2B sector employment by NAICS industry *i* from US BLS data[2]
    - $Base\ E\text{-}Com\ Sales\ \%_i^{US}$ is an input to calculation step # 7
    - $Base\ Emp\ \%^{Region}$ is the regional 2019 employment share of Virginia's total employment in B2B sector from US BLS data[3]
    - *i* is the index for NAICS industries 423 (Durable Goods) and 424 (Nondurable Goods)

13. Estimate future year (2045) employment in industries related to wholesale trade sector for Virginia and MSAs/Rural Areas by using the 2019 estimate determined in calculation step # 10 and applying a growth factor.
    $Future\ E\text{-}Com\ Emp_i^{Region} = Emp\ GF^{VA} \times Base\ E\text{-}Com\ Emp_i^{Region}$

Where:
- *E-Com Emp* is the estimated regional 2045 wholesale/B2B e-commerce employment by NAICS industry
- *Emp GF* is the 2019 to 2045 employment growth factor in wholesale/B2B sector from Woods and Poole 2017 data and 2045 forecast for Virginia's employment[4]

Estimate changes in output (in 2012 chained dollars[5] per hour) due to e-commerce for the Wholesale/Business-to-Business (B2B) market at the MSA level, for years 2019 and 2045.

[1] US Census, Monthly Retail Trade Survey, 1992-2020 Retail and Food Services Sales, as on December 16, 2020; US Census, Quarterly E-Commerce Report, 2018 Q1 to 2020 Q3 Supplemental Quarterly E-Commerce Tables as on November 19, 2020; US online retail forecast by FTI Consulting, 2019; Industry Articles; Virginia Department of Taxation via Weldon Cooper Center for Public Service, Historical Virginia State Annual and Quarterly Taxable Sales by NAICS 3-digit Industry, Year 2018, Year 2019, Year 2020 Q1-Q3; and CDM Smith Forecast and Market Penetration by Industry Assumptions.

[2] US Bureau of Labor Statistics, Occupational Employment and Wage Statistics (last accessed on April 8, 2021)

[3] US Bureau of Labor Statstics, State and Metro Area Employment, Hours, & Earnings (last accessed on April 8, 2021)

[4] Provided by the Virginia Transportation Research Council (VTRC)

[5] According to the U.S. Bureau of Economic Analysis, "chain-type estimates provide the best available method for comparing the level of a given series at two points in time. Chained-dollar estimates are obtained by multiplying the chain-type quantity index for an aggregate by its value in current dollars in the reference year (currently 2012) and dividing by 100." Source: U.S. Bureau of Economic Analysis. National Economic Accounts.

14. Estimate base year (2019) share of e-commerce to total output in industries related to wholesale trade.
    $Base\ E\text{-}Com\ Emp_{i,j}^{Region} = Base\ E\text{-}Com\ Emp_i^{Region} \times Base\ SOC\ \%_{i,j}^{US}$

    Where:
    - $Base\ E\text{-}Com\ Emp_{i,j}^{Region}$ is the estimated regional 2019 B2B e-commerce employment by NAICS industry *i* and in Standard Occupational Classification (SOC) occupation *j*
    - $Base\ SOC\ \%_{i,j}^{US}$ is the US' 2019 SOC occupation *j* share of total wholesale trade sector employment in NAICS industry *i* from US BLS data[1]

15. Estimate base year (2019) output (in 2012 chained dollars per hour) for e-commerce in industries related to wholesale trade.
    $Base\ E\text{-}Com\ Output_i^{Region} = BaseProductivity^{US} \times Base\ E\text{-}Com\ Emp_i^{Region}$

    Where:
    - $Base\ E\text{-}Com\ Output^{Region}$ is the estimated regional 2019 wholesale trade or B2B e-commerce real gross output by NAICS industry *i*
    - $Base\ Productivity^{US}$ is the US' 2019 real gross output per hour worked in wholesale trade or B2B sector from US BEA-BLS data[2]

16. Estimate future year (2045) e-commerce employment in industries related to wholesale trade.
    $Future\ E\text{-}Com\ Emp^{Region} = Emp\ GF^{VA} \times Base\ E\text{-}Com\ Emp^{Region}$

    Where:
    - $Future\ E\text{-}Com\ Emp^{Region}$ is the estimated regional 2045 wholesale trade or B2B e-commerce employment by NAICS industry *i*
    - $Emp\ GF^{VA}$ is a 2019 to 2045 employment growth factor in wholesale trade or B2B sector from Woods and Poole 2017 data and 2045 forecast for Virginia's employment[3]

17. Estimate future year (2045) e-commerce employment in industries related to wholesale trade by three-digit NAICS code and SOC code.
    $Future\ E\text{-}Com\ Emp_{i,j}^{Region} = Future\ E\text{-}Com\ Emp_i^{Region} \times Future\ SOC\ \%_{i,j}^{US}$

    Where:
    - $Future\ E\text{-}Com\ Emp_{i,j}^{Region}$ is the estimated regional 2045 B2B e-commerce employment by NAICS industry *i* and in SOC occupation *j*
    - $Future\ SOC\ \%_{i,j}^{US}$ is the US' 2029 SOC occupation *j* share of total wholesale trade sector employment in NAICS industry *i* from US BLS estimate

18. Estimate future year (2045) output (in 2012 chained dollars per hour) for e-commerce in industries related to wholesale trade.
    $Future\ E\text{-}Com\ Output^{Region} = Future\ Productivity^{US} \times Future\ E\text{-}Com\ Emp^{Region}$

    Where:
    - $Future\ E\text{-}Com\ Output^{Region}$ is the estimated regional 2045 B2B e-commerce real gross output by NAICS industry *i*
    - $Future\ Productivity^{US}$ is the US' estimated 2045 real gross output per hour worked (in 2012 chained dollars per hour) in B2B sector using the following trendline equation (log-normal) fitted based on historical (2010-2018) US real gross output per hour worked (in 2012 chained dollars per hour) in B2B sector from US BEA-BLS data: *Productivity in year* $X^{US} = 40.949 \times \ln(X - 2000) + 48.782; R^2 = 0.88$

[1] US Bureau of Labor Statistics, Industry-occupation matrix data, by industry (last accessed on April 8, 2021)

[2] US Bureau of Economic Analysis, Integrated Industry-Level Production Account (KLEMS); GDP-by-industry tables; GDP & Personal Income tables (last accessed on April 8, 2021

[3] Provided by the Virginia Transportation Research Council (VTRC)

Estimate employment changes (full time equivalent) and output in dollars due to e-commerce for the Retail/Business-to-Consumer (B2C) market at the MSA level, for years 2019 and 2045.

19. Estimate the base year (2019) US share of total dollar value of B2C sales by state and 3-digit NAICS industry from calculation step # 6.

20. Estimate Virginia's base year (2019) retail e-commerce share of total sales by three-digit NAICS industry.
    $Base\ E\text{-}Com\ Sales^{VA} = \sum_i Base\ E\text{-}Com\ Sales\ \%_i^{US} \times Base\ Total\ Sales_i^{VA}$

    Where:
    - $Base\ E\text{-}Com\ Sales^{VA}$ is Virginia's estimated 2019 retail trade or B2C e-commerce share of total sales
    - $Base\ E\text{-}Com\ Sales\ \%_i^{US}$ is the US's estimated 2018 Q1-2020 Q3 average retail trade or B2C e-commerce share of total sales for NAICS industry *i*
    - $Base\ Total\ Sales_i^{VA}$ is Virginia's 2018 Q1-2020 Q3 B2C total taxable sales for NAICS industry *i* gathered from Virginia Department of Taxation's annual taxable B2C sales data published on the Weldon Cooper Center website[1]
    - *i* is the index for NAICS industries 441-448 and 451-454

21. Estimate the future year (2045) US share of total dollar value of retail trade or B2C sales by State and 3-Digit NAICS Industry using historical (2010-2018) US retail trade or B2C e-commerce shares of total sales gathered from US Census' US Annual Merchant Wholesaler data. The following trendline equation (polynomial) was fitted as follows:
    $E\text{-}Com\ Sales$ % in year X^{US}
    $= -1.10\times10^{-5} \times (X\text{-}2009)^3 + 5.5\times10^{-4} * (X\text{-}2009)^2 + 2.3\times10^{-3} \times (X\text{-}2009) + 4.2 \times 10^{-2}$; $R^2 = 0.99$

    Where:
    - $E\text{-}Com\ Sales\ \%\ in\ year\ X^{US}$ is the US' estimated wholesale trade or B2C e-commerce share of total sales in year *X* for a given NAICS industry

    The estimated 2045 national forecast retail trade or B2C e-commerce share of 33 percent based on the above equation was used as a control check on the total market size of retail trade or B2C e-commerce estimated for Virginia. Due to differences in industrial mix at national and state levels, the estimated shares may differ at these geographical levels.

    Through a study of research articles gathered on each 3-digit NAICS industry, 2045 medium scenario (most likely) assumptions were made on retail trade or B2C e-commerce shares. These are upward adjustments to the 2019 retail trade or B2C e-commerce shares. A range of +/-5 percent by industry was assumed to represent the 2045 low and high scenarios. The weights used for the 3-digit NAICS industries in 2019, that is $Base\ Total\ Sales\ \%_i^{VA}$, to estimate the retail trade or B2C sector level e-commerce share were also used in 2045.

Estimate changes in output (in 2012 chained dollars per hour) due to e-commerce for the Retail/ Business-to-Consumer (B2C) market at the MSA level, for years 2019 and 2045.

22. Estimate base year (2019) share of e-commerce to total output in industries related to retail trade.
    $Base\ E\text{-}Com\ Emp_{i,j}^{Region} = E\text{-}Com\ Emp_i^{Regio} \times Base\ SOC\ \%_{i,j}^{US}$

    Where:
    - $Base\ E\text{-}Com\ Emp_{i,j}^{Region}$ is the estimated regional 2019 retail trade or B2C e-commerce employment by NAICS industry *i* and in SOC occupation *j*
    - $Base\ SOC\ \%i,j^{US}$ is the US' 2019 SOC occupation *j* share of total retail trade sector employment in NAICS industry *i* from US BLS data[2]

[1] Virginia Department of Taxation via Weldon Cooper Center for Public Service, Historical Virginia State Annual and Quarterly Taxable Sales by NAICS 3-digit Industry (last accessed on April 8, 2021)

[2] US Bureau of Labor Statistics, Industry-occupation matrix data, by industry (last accessed on April 8, 2021)

[3] US Bureau of Economic Analysis, Integrated Industry-Level Production Account (KLEMS); GDP-by-industry tables; GDP & Personal Income tables (last accessed on April 8, 2021)

23. Estimate base year (2019) output (in 2012 chained dollars per hour) for e-commerce in industries related to retail trade.
    $\textit{Base E-Com Output}_i^{Region} = \textit{Base Productivity}^{US} \times \textit{Base E-Com Emp}_i^{Region}$

    Where:

    - $\textit{Base E-Com Output}_i^{Region}$ is the estimated regional 2019 retail trade or B2C e-commerce real gross output by NAICS industry *i*
    - $\textit{Base Productivity}^{US}$ is the US' 2019 real gross output per hour worked in retail trade or B2C e-commerce sector from US BEA-BLS data[3]

24. Estimate future year (2045) e-commerce employment in industries related to retail trade.

    $\textit{Future E-Com Emp}^{Region} = \textit{Emp GF}^{VA} \times \textit{Base E-Com Emp}^{Region}$

    Where:

    - $\textit{Future E-Com Emp}^{Region}$ is the estimated regional 2045 B2C e-commerce employment by NAICS industry *i*
    - $\textit{Emp GF}^{VA}$ is the 2019 to 2045 employment growth factor in B2C sector from Woods and Poole 2017 data and 2045 forecast for Virginia's employment[1]

25. Estimate future year (2045) e-commerce employment in industries related to retail trade by 3-digit NAICS code and SOC code.
    $\textit{Future E-Com Emp}_{i,j}^{Region} = \textit{Future E-Com Emp}^{Region} \times \textit{Future SOC }\%_{i,j}^{US}$

    Where:

    - $\textit{Future E-Com Emp}_{i,j}^{Region}$ is the estimated regional 2045 retail trade or B2C e-commerce employment by NAICS industry *i* and in SOC occupation *j*
    - $\textit{Future SOC }\%_{i,j}^{US}$ is the US' 2029 SOC occupation *j* share of total retail trade sector employment in NAICS industry *i* from US BLS estimation

26. Estimate future year (2045) output (in 2012 chained dollars per hour) for e-commerce in industries related to retail trade.
    $\textit{Future E-Com Output}^{Region} = \textit{Future Productivity}^{US} \times \textit{Future E-Com Emp}^{Region}$

    Where:

    - $\textit{Future E-Com Output}^{Region}$ is the estimated regional 2045 B2C e-commerce real gross output by NAICS industry *i*
    - $\textit{Future Productivity}^{US}$ is the US' estimated 2045 real gross output per hour worked (in 2012 chained dollars per hour) in retail trade of B2C sector using the following trendline equation (log-normal) fitted based on historical (2010-2018) US real gross output per hour worked (in 2012 chained dollars per hour) in B2C sector from US BEA-BLS data: $\textit{Productivity in year X}^{US} = 1.9551 \times (X\text{–}2000) + 39.488$; $R^2=0.95$

[1] Provided by the Virginia Transportation Research Council (VTRC)

3.1.6. VTrans Macrotrend # 6: Greater Automation of Production and Services

Description: Contemporary automation consists of a collection of cyber-physical systems that are enabled by the internet of things (IoT), advancements in prototyping and manufacturing (e.g., robotics, precision instruments, 3D printing), and "big data" algorithms (machine learning and artificial intelligence) applied to data and information collected by sensors. These developments in automation create the opportunity for varying productivity gains and impacts by industry.

Drivers:

- Digitalization (the process of employing digital technologies that transform business operations) of goods production and distribution systems
- Increased use of machine learning and autonomous robots
- Expanded just-in-time and lean production
- Demand for faster "time to market" goods production[1]
- Growth in high level of automation fulfillment centers[2,3]

Significance: Production automation changes job estimates, goods movement, location of services and skills requirements. All of these have direct transportation and economic impacts.

Data Sources:

- Industry Occupation Matrix data: US Bureau of Labor Statistics[4]
- State and Metro Area Employment data: US Bureau of Labor Statistics[5]

[1] Dóra Horváth, Roland Zs. Szabó, Driving forces and barriers of Industry 4.0: Do multinational and small and medium-sized companies have equal opportunities?, Technological Forecasting and Social Change, 146 (2019), 119-132.

[2] CNBC, Walmart to ramp up automated fulfillment at stores as online grocery grows (cnbc.com), January 27, 2021.

[3] Azadeh, Kaveh, De Koster, Rene, and Roy, Debjit. Robotized and Automated Warehouse Systems: Review and Recent Developments, Transportation Science, Volume 53: Issue 4, July-August 2019. pp 917–945.

[4] US Bureau of Labor Statistics, Industry-occupation matrix data, by industry (last accessed on April 8, 2021)

[5] US Bureau of Labor Statistics, State and Metro Area Employment, Hours, & Earnings (last accessed on April 8, 2021)

- Virginia Employment forecasts: Woods & Poole[1]
- US Output (GDP) by Industry data: US Bureau of Economic Analysis[2]
- Freight Analysis Framework: US Bureau of Transportation Statistics and FHWA[3]
- US Census Commodity Flow Survey[4]

Calculations:

Quantify the level of Production Automation in Goods-Movement-Dependent Industries

1. Find base year (2019) employment (full time equivalent) for goods-movement-dependent industries at the two-digit NAICS code level by Virginia MSA/ and rural areas. Define MSAs by size:
   - Large MSAs: Richmond, Virginia Beach-Norfolk-Newport News and Northern Virginia
   - Medium MSAs: Charlottesville, Lynchburg, Roanoke
   - Rest of State: Small MSAs + Rural Areas

   Virginia's 2019 employment by region and 2-digit NAICS industry is collected from US BLS data[5].

2. Estimate future year (2045) employment (full time equivalent) for goods-movement-dependent industries at the two-digit NAICS code level by Virginia MSAs and rural areas.
   $Future\ Emp_i^{Region} = Emp\ GF_i^{VA} \times Base\ Emp_i^{Region}$

   Where:
   - $Future\ Emp_i^{Region}$ is the estimated regional 2045 employment for 2-digit NAICS industry *i*
   - $Emp\ GF_i^{VA}$ is the 2019 to 2045 employment growth factor for 2-digit NAICS industry *i* from Woods and Poole 2017 data and 2045 forecast for Virginia's employment[6]
   - $Base\ Emp_i^{Region}$ is the regional 2019 employment for 2-digit NAICS industry *i* from US BLS data
   - *i* is the index for 2-digit NAICS goods movement dependent industries

3. Estimate base year (2019) output in dollars for goods-movement-dependent industries at the two-digit NAICS code level by Virginia MSAs and rural areas. Use US 2019 real gross output per hour worked (in 2012 chained dollars per hour) or productivity for goods movement dependent industries[7] from US BEA-BLS data.[8]
   - Estimate the future year (2045) productivity for the US for goods-movement-related industries. As output forecasts were not available from Woods and Poole, use a set of future productivity trendline equations based on historical (2010-2018) productivity data on goods-movement-dependent industries, as shown below.
   - For mining, logging, and construction: a growth factor of 1.0 was used for this industry as the historical data did not show a consistent trend
   - For manufacturing: $Productivity\ in\ year\ X^{US} = 29.305 \times \ln(X{-}2000) + 164.93;\ R^2{=}0.96$
   - For wholesale trade: $Productivity\ in\ year\ X^{US} = 40.949 \times \ln(X{-}2000) + 48.782;\ R^2{=}0.88$
   - For retail trade: $Productivity\ in\ year\ X^{US} = 1.9551 \times (X{-}2000) + 39.488;\ R^2{=}0.95$
   - For transportation, warehousing, and utilities: a growth factor of 1.0 was used for this industry as the historical data did not show a consistent trend

   This is used to estimate $Future\ Productivity_i^{US}$ (defined as US 2045 real gross output per hour worked) in 2012 chained dollars per hour for goods-movement-dependent industries in the next step.

[1] Provided by the Virginia Transportation Research Council (VTRC)

[2] US Bureau of Economic Analysis, Integrated Industry-Level Production Account (KLEMS); GDP-by-industry tables; GDP & Personal Income tables (last accessed on April 8, 2021)

[3] US Bureau of Transportation Statistics and Federal Highways Administration. Freight Analysis Framework. Last accessed July 15, 2021.

[4] US Census, Commodity Flow Survey, last accessed July 15. 2021.

[5] US Bureau of Labor Statistics, State and Metro Area Employment, Hours, & Earnings data (last accessed on April 8, 2021)

[6] Provided by the Virginia Transportation Research Council (VTRC)

[7] Note: includes manufacturing, wholesale trade, retail trade, transportation, warehousing, utility, mining and construction sectors

[8] US Bureau of Economic Analysis, Integrated Industry-Level Production Account (KLEMS); GDP-by-industry tables; GDP & Personal Income tables (last accessed on April 8, 2021)

4. Estimate future year (2045) output in dollars for goods-movement-dependent industries at the two-digit NAICS code level by Virginia MSAs and rural areas
   $Future\ Output_i^{Region} = Future\ Productivity_i^{US} \times Future\ Emp_i^{Region}$

   Where:
   - $Future\ Output_i^{Region}$ is the estimated regional 2045 baseline real gross output for 2-digit NAICS industry *i*
   - $Future\ Productivity_i^{US}$ is the estimated US 2045 real gross output for hour worked for NAICS industry i, from calculation step # 3.
   - $Future\ Emp_i^{Region}$ is the estimated regional 2045 employment for 2-digit NAICS industry i, from calculation step # 2.

Estimate 3D Printing as share of total manufacturing output (in dollars) for the state and 3-digit NAICS industry level for years 2019 and 2045

5. Estimate base year (2019) 3D printing market share (in dollars).
   $Base\ 3DP\ \%^{VA} = Base\ 3DP\ Market\ Value^{US} / Base\ Mfg\ Value\ Added^{US}$

   Where:
   - $Base\ 3DP\ \%^{VA}$ is Virginia's estimated 2019 3D printing share of total manufacturing output
   - $3DP\ Market\ Value^{US}$ is the US' 2019 3D printing market value in the U.S. Use Deloitte[1] estimations for the 2019 3D printing market value.
   - $Base\ Mfg\ Value\ Added^{US}$ is the US' 2019 real value added by manufacturing sector of U.S. economy in 2012 chained dollars from US BEA data[2]

Estimate 2019-2045 manufacturing sector growth factor for Virginia.

$Mfg\ GF=(Base\ Mfg\ Output^{VA}/Future\ Mfg\ Output^{VA})$

Where:
- $Base\ Mfg\ Output^{VA}$ *and* $Future\ Mfg\ Output^{VA}$ come from the sum of the base year output by MSA and rural areas in calculation Step 3 and the future output by MSA and rural areas in calculation step 4.

6. Estimate future year (2045) 3D printing market share (in dollars).
   $Future\ 3DP\ \%^{VA} = Future\ 3DP\ Market\ Value^{US}/(Base\ Mfg\ Value\ Added^{US} \times Mfg\ GF)$

   Where:
   - $Future\ 3DP\ \%^{VA}$ is Virginia's estimated 2045 3D printing share of total manufacturing output
   - $Future\ 3DP\ Market\ Value^{US}$ is the US' 2045 3D printing market value in the U.S. assumption
   - *Mfg GF* is Virginia's estimated 2019-2045 manufacturing sector growth factor

   The following sources and methods formed the basis for future 3D printing scenario assumptions:

   - **Low scenario:** Deloitte[3] estimated an annualized growth rate of 3D printing market value of 12.6 percent over the period of 2017-2020. This high annualized growth rate was expected to slow down with the turn of each decade. The annualized growth rate of 12.6 percent was maintained for the period 2021-2030, and then gradually reduced it to 6.3 percent (50 percent of the assumed growth rate in 2020-2030) for the period 2031-2040. It was further reduced to 3.1 percent (50 percent of the assumed growth rate in 2030-2040) for the period 2041-2045. The resulting 3D printing market value in the U.S. is estimated to be $21.7 billion in 2045, that is, about eight times the base (2019) market value.
   - **Medium scenario:** As per a Congressional Research Service (CRS) report on 3D printing[4], most experts expect 3D printing to form 5-10 percent of global manufacturing revenues (currently assumed as 7.5 percent). This is possible to achieve if the U.S. 3D printing market growth exceeds the global average in the short-term. The medium scenario or

[1] Deloitte Insights, "3D printing growth accelerates again" December 11, 2018. (last accessed on April 8, 2021)

[2] US Bureau of Economic Analysis, GDP-by-industry tables; (last accessed on April 8, 2021)

[3] Deloitte Insights, "3D printing growth accelerates again" December 11, 2018. (last accessed on April 8, 2021)

[4] Congressional Research Service Report, 3D Printing: Overview, Impacts, and the Federal Role, Prepared for Members and Committees of Congress, August 2, 2019.

the most likely value for the 3D printing market in the U.S. was thus determined as $167.8 billion.

- **High scenario:** As per an AT Kearney analysis[1], the U.S. 3D printing market is estimated to reach a value of $300-$500 billion dollars in the next 10 years, which was considered very aggressive. For the purpose of this trend analysis, the market was capped at $300 billion and used as the future year (2045) high scenario.

Estimate 3D printing-related employment (full-time equivalent) and output in dollars at the 3-digit NAICS industry and SOC (for employment only) level, for years 2019 and 2045

7. Estimate base year (2019) 3D printing-related employment (full-time equivalent) at the 3-digit NAICS industry level.
$Base\ 3DP\ Emp_i^{Region} = Base\ Mfg\ Emp_i^{VA} \times Base\ 3DP\ \%^{US} \times 3DP\ Industry\ \%_i^{US} \times Base\ Mfg\ Emp\%^{Region}$

   Where:
   - $Base\ 3DP\ Emp_i^{Region}$ is the estimated regional 2019 3D printing employment by 3-digit NAICS industry i
   - $Base\ Mfg\ Emp_i^{VA}$ is Virginia's 2019 Quarter 4 Month 3 manufacturing sector employment by 3-digit NAICS industry i [2]
   - $Base\ 3DP\ \%^{US}$ is derived from calculation step 5 (same as Virginia estimate)
   - $3DP\ Industry\ \%_i^{US}$ is the assumed share for the 3D printing industry for 3-digit NAICS industry i
   - $Base\ Mfg\ Emp\%^{Region}$ is the regional 2019 employment share of Virginia's total employment in manufacturing sector[3]
   - i is the index for 3-digit NAICS industries suited to 3D printing (315 - Apparel Manufacturing, 326 - Plastics and Rubber Products Manufacturing, 327 - Nonmetallic Mineral Product Manufacturing, 332 - Fabricated Metal Product Manufacturing, 333 - Machinery Manufacturing, 334 - Computer and Electronic Product Manufacturing, 335 - Electrical Equipment, Appliance, and Component Manufacturing, 336 - Transportation Equipment Manufacturing and 339 - Miscellaneous Manufacturing)

8. Estimate base year (2019) 3D printing-related employment (full-time equivalent) at the 3-digit SOC industry level.
$Base\ 3DP\ Emp_{i,j}^{Region} = Base\ 3DP\ Emp_i^{Region} \times Base\ SOC\ \%_{i,j}^{US}$

   Where:
   - $Base\ 3DP\ Emp_{i,j}^{Region}$ is the estimated regional 2019 3D printing employment by NAICS industry i and in SOC occupation j
   - $Base\ SOC\ \%_{i,j}^{US}$ is the US' 2019 SOC occupation j share of total manufacturing sector employment in NAICS industry i from US BLS data[4]

9. Estimate base year (2019) 3D printing-related output by Virginia MSA's and rural areas.
$Base\ 3DP\ Output_i^{Region} = Base\ Productivity^{US} \times Base\ 3DP\ Emp_i^{Region}$

   Where:
   - $Base3DP\ Output^{Region}$ is the estimated regional 2019 3D printing real gross output by NAICS industry i
   - $Base\ Productivity^{US}$ is the US' 2019 real gross output per hour worked (in 2012 chained dollars per hour) in manufacturing sector from US BEA-BLS data[5]

10. Estimate future year (2045) 3D printing-related Employment (full time equivalent) at the 3-digit NAICS industry level.
$Future\ 3DP\ Emp^{Region} = Emp\ GF^{VA} \times Base3DP\ Emp^{Region}$

    Where:
    - $Future\ 3DP\ Emp^{Region}$ is the estimated regional 2045 3D printing employment by NAICS industry i
    - $Emp\ GF^{VA}$ is the 2019 to 2045 employment growth factor in manufacturing sector from Woods and Poole 2017 data and 2045 forecast for Virginia's employment[6]

[1] HP and AT Kearney, 3D Printing: Ensuring Manufacturing Leadership in the 21st Century, 2017.

[2] US Bureau of Labor Statistics, Occupational Employment and Wage Statistics (last accessed on April 8, 2021)

[3] US Bureau of Labor Statistics, Occupational Employment and Wage Statistics (last accessed on April 8, 2021)

[4] US Bureau of Labor Statistics, Industry-occupation matrix data, by industry (last accessed on April 8, 2021)

[5] US Bureau of Economic Analysis, Integrated Industry-Level Production Account (KLEMS); GDP-by-industry tables; GDP & Personal Income tables (last accessed on April 8, 2021)

[6] Provided by the Virginia Transportation Research Council (VTRC)

Estimate base year (2019) 3D printing-related employment (full-time equivalent) at the 3-digit SOC industry level.

$Future\ 3DP\ Emp_{i,j}^{Region} = Future\ 3DP\ Emp_{i}^{Region} \times Future\ SOC\ \%_{i,j}^{US}$

Where:

- $Future\ 3DP\ Emp_{i,j}^{Region}$ is the estimated regional 2045 3D printing employment by NAICS industry *i* and in SOC occupation *j*
- $Future\ SOC\ \%_{i,j}^{US}$ is the US' 2029 SOC occupation *j* share of total manufacturing sector employment in NAICS industry *i* from US BLS estimate

11. Estimate future year (2045) real gross output per hour worked (in 2012 chained dollars per hour) in manufacturing sector using the following trendline equation (log-normal) fitted based on historical (2010-2018) US real gross output per hour worked (in 2012 chained dollars per hour) in manufacturing sector from US BEA-BLS data:
$Productivity\ in\ year\ X^{US} = 29.305 \times ln(X–2000) + 164.93;\ R^2 = 0.96$

12. Estimate future year (2045) 3D printing-related output by Virginia MSA's and rural areas.
Future 3DP Output Region = Future ProductivityUS × Future 3DP EmpRegion

Where:

- $Future\ 3DP\ Output^{Region}$ is the estimated regional 2045 3D printing real gross output by NAICS industry *i*
- $Future\ Productivity^{US}$ is the estimated future year (2045) real gross output per hour worked (calculation step # 11).
- *Future 3DP EmpRegion* is the estimated regional 2045 3D printing employment by NAICS industry *i* calculated in step 10

Estimate the ratio between value-per-ton for 3D printing commodities and value-per-ton for average goods-movement-dependent industry commodities for Virginia

13. Use US BTS and FHWA's Freight Analysis Framework Version 5 (FAF5) database for value-per-ton for 3D printing-friendly goods[1] traveling to/from/within Virginia. This was estimated as $3,617 per ton, which was assumed to be a typical value-per-ton for 3D printed commodities. Using the same data, estimate overall value-per-ton of goods traveling to/from/within Virginia as $1,096 per ton. The value-per-ton ratio between 3D printed commodities and all goods-movement-dependent industry commodities was therefore estimated as 3.3.

Estimate gross truck tons change over base year (due to re-allocation from long-haul domestic and international cargo markets to short-haul domestic and national cargo markets) for Virginia MSAs and rural areas and truck class

14. Gross truck tons change due to 3D printing over base year conditions was assumed to be zero. However, shifts in sourcing and distribution of 3D printed commodities are assumed between the truck types. The commodity shifts were guided by the market shares in US BTS and FHWA's Freight Analysis Framework Version 5 (FAF5) data for Virginia and allocation of truck types to the markets.

Estimate the Long-Range Drone Delivery Share of total dollar value of domestic air cargo industry (within 500 miles and more than 55 pounds of drone weight) for Virginia

[1] Note: Includes the Standard Classification of Transported Goods (SCTG) commodities of Articles-base metal, Electronics, Machinery, Misc. mfg. prods., Motorized vehicles, Nonmetal min. prods., Plastics/rubber, Precision instruments, Textiles/leather, and Transport equip.

15. Estimate base year (2019) Long-Range Drone Delivery Share of total dollar value of domestic air cargo industry.
    Base LRDrone $\%^{VA}$ *= Base Civil UAV Market Value*^{Global}*/Base Civil Air Industry Value*^{Global}

    Where:
    - *Base Civil UAV Market Value*^{Global} is the estimated global 2019 civil long-range drone or UAV market value from industry forecasts,[1] which is $5 billion US dollars
    - *Base Civil Air Industry Value*^{Global} is the estimated global 2019 civil aviation market value from industry forecasts,[2] which is $875 billion US dollars.

16. Estimate future year (2045) Long-Range Drone Delivery Share of total dollar value of domestic air cargo industry. The following sources and methods formed the basis for future long-range drone scenario assumptions.
    - **Low Scenario:** It is assumed that long-range drones use will not grow faster than US domestic air cargo market which is 1.9 percent per year. The long-range drone market share of the domestic air cargo is assumed to remain at the base value of 0.6 percent estimated using the year 2019 calculation.
    - **Medium and High Scenarios:** Long-range drones will grow at a rate of 10.5 percent per year, which is much faster than the US domestic air cargo market. The long-range drone market share of the domestic air cargo will reach 4.6 percent.

Estimate the Ratio between value-per-ton for long-range drone delivery commodities and value-per-ton for average goods movement-dependent industry commodities for Virginia

17. Using the 2017 Commodity Flow Survey, value-per-ton for Virginia specific shipments by air to distances between 50 miles and 500 miles and less than 500 pounds by weight was estimated.
    Value-per-ton Ratio = Long-range drone value-per-ton / Overall goods traveling to/from/within Virginia value-per-ton

    $174,687 per ton was assumed to be a typical value-per-ton for long-range drone commodities. Using the US BTS and FHWA FAF5 data, the overall value-per-ton of goods traveling to/from/within Virginia was estimated as $1,096 per ton. The value-per-ton ratio between long-range drone commodities and all goods-movement-dependent industry commodities was estimated as 159.4.

Estimate the Short-Range Drone Delivery Share of total dollar value of B2C (retail) e-commerce sales for Virginia

18. Estimate base year (2019) short-range drone market share of B2C e-commerce. Define short-range drone delivery as those within 20 miles and less than 55 pounds of drone weight. Short-range drone delivery market share of B2C e-commerce in Virginia currently is assumed be negligible.

19. Estimate base year (2019) short-range drone market share of B2C e-commerce. Short-range drone delivery calculations assumed the B2C e-commerce share of total retail trade or B2C sales to be at the baseline level of 7.6 percent. The market potential for short-range drones was assumed as the percentage of e-commerce deliveries requiring same-day delivery, which is 25 percent as per an industry report.[3] The following future short-range drone scenario assumptions were additionally made:
    - **Low Scenario:** Slow market penetration due to the inability to operate short-range drones in some conditions: e.g., GPS signal is blocked by buildings or other fixed objects, perceived safety/regulation issues, insurance issues, and overcrowding of air space below 400 feet. Under this 20 percent of the market potential was assumed by 2045, that is 5 percent of retail trade e-commerce deliveries are assumed to use short-range drones.

[1] Teal Group, World Civil UAS Market Profile and Forecast: 2020/2021: (last accessed on April 8, 2021)
[2] International Air Transport Association, Economic Performance of the Airline Industry (last accessed on April 8, 2021)
[3] McKinsey & Company, "Parcel delivery; The future of last mile", September 2016. (last accessed on April 8, 2021)

- **Medium Scenario:** Short-range drones are assumed to serve 50 percent of the market potential by 2045, that is 12.5 percent of retail trade e-commerce deliveries.
- **High Scenario:** Short-range drones are assumed to serve 100 percent of the market potential for UAV delivery by 2045, that is 25 percent of retail trade e-commerce deliveries. This is driven by the lowering of drone cost per package cost, increase in weight capacity, and increase in the density of same-day delivery traffic.

Estimate the ratio between value-per-ton for short-range drone delivery commodities and value-per-ton for average goods movement-dependent industry commodities

20. Using the 2017 CFS,[1] value-per-ton for Virginia specific shipments by air and truck to distances less than 50 miles and less than 50 pounds by weight was estimated as $25,731 per ton, which was assumed to be a typical value-per-ton for short-range drone commodities. Using the US BTS and FHWA FAF5 data, the overall value-per-ton of goods traveling to/from/within Virginia was estimated as $1,096 per ton. The value-per-ton ratio between short-range drone commodities and all goods movement dependent industry commodities was estimated as 23.5.

[1] U.S. Department of Transportation. 2017 Commodity Flow Survey.

3.1.7. VTrans Macrotrend # 7: Growth of Professional Services Industry

Description: This trend refers to changes in the number and proportion of jobs in the professional and technical services industry.

Drivers: The drivers of this macrotrend include:

- Digitalization of the economy
- Changing economic forces moving the US to a service-based economy

Significance: Transportation infrastructure and services demand is influenced by commuting patterns, which vary by job type and location. Professional and technical services jobs tend to cluster in urban areas, for example.

Data source(s):

- Historic and Forecast Employment Estimates for Virginia: Weldon Cooper Center for Public Service[1]
- Historic and Forecast Employment Estimates for Virginia: Woods & Poole[2]
- Virginia Employment by 3-Digit NAICS Industry: US Bureau of Labor Statistics[3]
- Ten-year Occupation Projections: US Bureau of Labor Statistics[4]
- STEM Occupations Share of All Occupations by 2-Digit NAICS Industry: US Bureau of Labor Statistics[5]

[1] Weldon Cooper Center for Public Service at University of Virginia

[2] Woods & Poole forecasts provided by the Virginia Transportation Research Council (VTRC)

[3] US Bureau of Labor Statistics, QCEW Data Views, 2019 US BLS Quarter 4 Month 3 State Virginia Employment by 3-Digit NAICS Industry, last accessed July 22, 2021.

[4] US Bureau of Labor Statistics, Occupational Projections Data, last accessed July 22, 2021.

[5] US Bureau of Labor Statistics, Standard Occupational Classification (SOC) System datasets, Stem Occupation list, last accessed July 22, 2021.

Calculations

1. Develop a working definition of STEM related jobs for the purposes of this analysis. Instead of using industry designation, use occupational categorization to develop a listing of occupations assigned by the Bureau of Labor Statistics as "STEM" occupations.

   Estimate the current year (2019) percentage of STEM occupation employment by Virginian County.

2. Determine the current percentage of STEM occupation employment per NAICS 2-digit industry nationally, and apply that national percentage to jobs by NAICS industry for job estimates in Virginia localities.
   $EmploymentSTEM_{ilocality} = \Sigma\ (EmploymentSTEM_i \times Employment_i)$

   Where:

   $EmploymentSTEM_{ilocality}$ is the estimated STEM occupation jobs per Virginia locality
   $EmploymentSTEM_i$ is the national percentage of STEM occupation per 2-digit NAICS industry
   $Employment_{ilocality}$ is the estimated jobs by NAICS 2-digit industry per Virginia locality

3. Aggregate to the PDC, VDOT Construction District, and Statewide level.

   Estimate the future year (2045) percentage of STEM occupation employment by Virginia County.

4. Estimate the 2045 Employment by 2-digit NAICS industry by Virginia locality.

5. Use the 10-year employment growth rates for STEM occupation employment from BLS to determine 2019-2029 STEM growth rates as a percentage of jobs by NAICS 2-digit industry.

6. Apply this 10-year BLS growth rate again two times to estimate a 2049 STEM growth rates as a percentage of jobs by NAICS 2-digit industry.

7. Use the 2019-2049 growth rate to develop a proxy for a 2045 (2049) STEM percentage of jobs by NAICS 2-digit industry.

8. Using the 2045 employment estimated in Step 4 and the STEM percentage of jobs in step 7, estimate the number of STEM jobs in 2045 by Virginia locality.

9. Aggregate to the PDC, VDOT Construction District, and statewide levels.

Table 8: Forecasted Professional and Technical Services and STEM Jobs

	Base Year (2019)				Projected (2045)			
	P+TS Jobs	P+TS Share of Total Jobs in Region	STEM Jobs	STEM Share of Total Jobs in Region	P+TS Jobs	P+TS Share of Total Jobs in Region	STEM Jobs	STEM Share of Total Jobs in Region
STATEWIDE								
Total	587,145	11%	151,624	3%	1,021,230	14%	222,110	3%
VDOT CONSTRUCTION DISTRICTS								
Bristol	5,276	3%	3,484	2%	7,633	5%	3,955	2%
Culpeper	20,308	8%	6,039	2%	38,736	11%	9,380	3%
Fredericksburg	18,152	8%	5,003	2%	37,539	10%	8,743	2%
Hampton Roads	69,997	6%	25,667	2%	100,992	7%	32,361	2%
Lynchburg	8,701	4%	5,307	3%	12,154	5%	6,158	3%
Northern Virginia	366,553	20%	67,057	4%	657,425	24%	110,449	4%
Richmond	64,170	7%	21,274	2%	115,888	10%	29,650	2%
Salem	20,271	5%	9,597	2%	28,770	6%	11,171	2%
Staunton	13,717	4%	8,196	3%	22,093	5%	10,242	2%
PLANNING DISTRICT COMMISSIONS								
Accomack-Northampton	1,479	6%	677	3%	2,290	8%	834	3%
Central Shenandoah	7,065	4%	4,622	3%	11,284	5%	5,867	3%
Central Virginia	7,934	6%	3,918	3%	11,458	6%	4,768	3%
Commonwealth Regional Council	1,199	3%	756	2%	1,642	3%	921	2%
Crater	2,595	3%	1,870	2%	4,262	4%	2,111	2%
Cumberland Plateau	2,017	5%	947	2%	3,554	8%	1,121	3%
George Washington	15,375	9%	3,891	2%	33,805	11%	7,398	2%
Hampton Roads	68,078	6%	24,581	2%	97,927	7%	31,071	2%
Lenowisco	1,127	3%	616	2%	1,385	4%	736	2%
Middle Peninsula	1,636	4%	648	2%	2,129	5%	767	2%
Mount Rogers	2,586	3%	2,299	2%	3,376	3%	2,482	2%
New River Valley	4,983	5%	2,550	3%	7,105	6%	2,971	3%
Northern Neck	1,141	5%	464	2%	1,605	6%	577	2%
Northern Shenandoah	6,440	5%	3,312	2%	10,525	6%	4,123	2%
Northern Virginia	366,553	20%	67,057	4%	657,425	24%	110,449	4%
Rappahannock-Rapidan	6,243	7%	1,989	2%	9,864	8%	2,891	2%
Richmond Regional	60,629	8%	19,047	2%	110,243	10%	27,113	3%
Roanoke Valley-Alleghany	11,638	6%	5,232	2%	16,363	7%	6,201	3%
Southside	1,186	3%	775	2%	1,728	4%	824	2%
Thomas Jefferson	14,676	8%	4,238	2%	29,844	12%	6,787	3%
West Piedmont	2,565	3%	2,135	2%	3,416	4%	2,097	2%

For more details on how the above data was compiled, please see Appendix 5, Tables 5-1: Jurisdictions associated with each VDOT Construction District, and 5-2: Jurisdictions Associated with each Modified Planning District Commission.

3.1.8. VTrans Macrotrend # 8: Increase in Workplace Flexibility

Description: Remote working or telecommuting is the ability to work from home or from a location other than the employer office or jobsite through the use of the internet, email, telephone, and other communications technologies. The macrotrend estimates the number of workers that can potentially work from home based on industry in Virginia.

Significance: This trend will lead to greater flexibility in terms of where people choose to live and their commute and travel patterns. As job availability by industry and location change, it may affect the geographic distribution of where workers live and change travel demand on the Commonwealth's transportation system.

Drivers:

- Advancement of workplace communication technology[1] and collaboration tools
- Availability, reliability, and speed of broadband services[2]
- Growth in knowledge worker jobs[3]

Data Sources:

- Share of jobs that are work-from-home capable: Dey et al.[4]
- Share of jobs that are work-from-home capable; pre-COVID work-from-home take-up rates: Dingel and Neiman[5]
- Virginia Industry Projections: Virginia Employment Commission[6]
- Work-from-home Survey Report: Global Workplace Analytics[7]

[1] The State of Video Conferencing in 2020, Massive-uptick-in-collaboration-software-usage-in-2020

[2] Pew Research, Internet/Broadband Fact Sheet

[3] Wall Street Journal, The Rise of Knowledge Workers Is Accelerating Despite the Threat of Automation

[4] Dey, Matthew, Harley Frazis, Mark A. Loewenstein, and Hugette Sun (2020). "Ability to Work from Home: Evidence from Two Surveys and Implications for the Labor Market in the COVID-19 Pandemic : Monthly Labor Review: U.S. Bureau of Labor Statistics."

[5] Dingel, Jonathan I., and Brent Neiman. "How Many Jobs Can Be Done at Home?" Journal of Public Economics 189 (September 2020): 104235. Data tables found here.

[6] Virginia Employment Commission. "Industry Projections." Accessed February 1, 2021.

[7] Global Workplace Analytics (2020). "Global Work-from-Home Experience Survey Report." May 2020.

- Remote Work Survey: PricewaterhouseCoopers[1]
- Employment Data: US Census Bureau[2]

Calculations:

1. Estimate Virginia's share of workplace-flexible (WF) jobs at the two-digit NAICS industry level using occupational behavior survey results and methodology based on Dingel and Neiman[3] and Dey et al.[4] Results are shown below in Table 9 and based on the average rate between the two studies.
   % WF jobs = # of jobs that are remote work capable by NAICS industry/Total # of jobs in NAICS industry

2. Utilize the results from Dey et al. to estimate a pre-COVID "take-up rate" of flexible workplace arrangements by two-digit NAICS industry. Take-up rate refers to the percent of workplace-flexible (WF) job respondents that actually worked from home on the survey day. Results are shown below in Table 9.
   Pre COVID WF Takeup Rate is the number of workers that worked remotely prior to the COVID pandemic/ Total # of workers surveyed

3. Calculate the difference in workplace-flexible (WF) jobs between the pre-COVID take-up rate and full (100%) capability. The delta was again averaged between the two research sources (Dingel and Neiman and Dey et al). Results are shown below in Table 9.
   %WF Jobs, Delta = %WF jobs by industry x (1 – Pre-COVID WF takeup rate by industry)

   Where:
   - *%WF Jobs, Delta* is the number of additional workers who could potentially switch to remote work. Recall that the Pre-COVID WF takeup rate by industry indicates the percent of workers that could work from home that did already prior to COVID-19.
   - *%WF jobs by industry*[5] is from calculation step # 1.
   - *Pre-COVID WF takeup rate by industry*[6] is from calculation step # 2.

Table 9: Remote Work Capability and Utilization by Two-digit NAICS Industry Code

Two-Digit NAICS Code[7]	Industry Title	WF Jobs[8]	Pre-COVID WF take-up rate[9]	Additional Potential WF jobs[10]
11	Agriculture, Forestry, Fishing and Hunting	7.97%	20.40%	6.34%
21	Mining, Quarrying, and Oil and Gas Extraction	40.67%	26.30%	29.98%
22	Utilities	31.20%	22.20%	24.27%
23	Construction	17.93%	13.00%	15.60%

[1] PricewaterhouseCoopers (2021). "Business Needs a Tighter Strategy for Remote Work." Accessed January 19, 2021.

[2] U.S. Census Bureau. Longitudinal Employer-Household Dynamics (LEHD) Origin-Destination Employment Statistics (LODES).

[3] Dingel, Jonathan I., and Brent Neiman. "How Many Jobs Can Be Done at Home?" *Journal of Public Economics* 189 (September 2020): 104235.

[4] Dey, Matthew, Harley Frazis, Mark A. Loewenstein, and Hugette Sun. "Ability to Work from Home: Evidence from Two Surveys and Implications for the Labor Market in the COVID-19 Pandemic: Monthly Labor Review: U.S. Bureau of Labor Statistics." Accessed January 27, 2021.

[5] Dingel, Jonathan I., and Brent Neiman. "How Many Jobs Can Be Done at Home?" *Journal of Public Economics* 189 (September 2020): 104235

[6] Dey, Matthew, Harley Frazis, Mark A. Loewenstein, and Hugette Sun. "Ability to Work from Home: Evidence from Two Surveys and Implications for the Labor Market in the COVID-19 Pandemic: Monthly Labor Review: U.S. Bureau of Labor Statistics." Accessed January 27, 2021.

[7] Not all NAICS were available: if not available, defaulted to NLSY79 datapoint: "Industry missing - 30.4%"

[8] Averaged across calculations on two research sources: Dingel and Neiman and Dey et al.

[9] Dey, Matthew, Harley Frazis, Mark A. Loewenstein, and Hugette Sun. "Ability to Work from Home: Evidence from Two Surveys and Implications for the Labor Market in the COVID-19 Pandemic: Monthly Labor Review: U.S. Bureau of Labor Statistics." Accessed January 27, 2021.

[10] Averaged across calculations on two research sources: Dingel and Neiman and Dey et al.

Two-Digit NAICS Code	Industry Title	WF Jobs	Pre-COVID WF take-up rate	Additional Potential WF jobs
31-33	Manufacturing	29.44%	31.60%	20.14%
42	Wholesale Trade	39.33%	19.30%	31.74%
44-45	Retail Trade	20.62%	19.30%	16.64%
48-49	Transportation and Warehousing	22.01%	22.20%	17.12%
51	Information	71.45%	36.90%	45.09%
52	Finance and Insurance	77.05%	29.60%	54.24%
53	Real Estate and Rental and Leasing	41.81%	30.40%	29.10%
54	Professional, Scientific, and Technical Services	75.09%	40.80%	44.45%
55	Management of Companies and Enterprises	82.89%	29.70%	58.27%
56	Administrative and Support and Waste Management and Remediation Services	31.06%	30.40%	21.62%
61	Educational Services	65.77%	15.80%	55.38%
62	Health Care and Social Assistance	37.08%	15.80%	31.22%
71	Arts, Entertainment, and Recreation	29.75%	30.40%	20.71%
72	Accommodation and Food Services	8.27%	12.70%	7.22%
81	Other Services (except Public Administration)	31.12%	14.00%	26.76%
99	Federal, State, and Local Government, excluding state and local schools and hospitals and the U.S. Postal Service (OEWS Designation)	53.34%	16.50%	44.54%

4. Estimate base year (2018) jobs that are workplace-flexible by Virginia locality (counties and independent cities). Use the 2018 (LEHD/LODES)[1] job location data and apply the WF jobs percentage to each county in Virginia for the number of jobs in each two-digit industry.
   # of WF jobs$_{2018}$ *= %WF Jobs, Delta x LEHD/LODES jobs data by industry*

   Where:
   - *# of WF jobs*$_{2018}$ is the number of additional workplace flexible jobs in 2018.
   - *%WF Jobs, Delta* is the additional jobs that could potentially switch to remote work from calculation step # 3.
   - *LEHD/LODES jobs data by industry* is *the number of jobs by NAICS sector.*

[1] US Census Bureau. Longitudinal Employer-Household Dynamics

5. Develop future year (2045) estimations for WF jobs by county based on industry-specific job growth projections from the Virginia Employment Commission (VEC).[1]

   # of WF jobs$_{2045}$ *= # of WF jobs*$_{2018}$ *x VEC projected growth rate by industry*

   Where:

   - *# of WF jobs*$_{2045}$ is the number of additional workplace flexible jobs in 2045.
   - *# of WF jobs*$_{2018}$ is the number of additional workplace flexible jobs in 2018 from calculation step # 4.
   - *VEC projected growth rate by industry* is the percent growth rate estimated from the Virginia Employment Commission by NAICS industry extrapolated to project job growth between 2018 and 2045.

[1] Virginia Employment Commission. "Industry Projections." Accessed February 1, 2021.

3.1.9. VTrans Macrotrend # 9: Growth of the 65+ Cohort

Description: This trend refers to changes in the relative proportion of Virginia's population over age 65.

Drivers: The drivers of this macrotrend include:

- Migration patterns
- Location preferences of the population over the age of 65
- Overall population growth
- Natural increase (ratio of births to deaths)
- Historical births (Baby Boomer cohort)
- Advancements in medicine

Significance: Transportation infrastructure and services demand is influenced by household characteristics such as age of household occupants. Transportation systems may need to accommodate the changing needs of an aging population differently.

Data Sources:

- Historic and Forecast Population Estimates for Virginia: Weldon Cooper Center for Public Service[1]
- Historic and Forecast Population Estimates for Virginia: Woods & Poole[2]
- Population Estimates by Age and Sex (Virginia Localities): US Census Bureau[3]

The following table shows the base year (2017) and forecast (2045) population age 65 and older in Virginia.

[1] Weldon Cooper Center for Public Service, Annual Population Estimates and Population Projections

[2] Woods & Poole Economics, Inc. *Virginia, Maryland, and The District of Columbia, 2018 State Profile, State and County Projections to 2050.* 2018

[3] U.S. Census Bureau. *2017 Population Estimates: Age and Sex (Virginia Localities)*, Weldon Cooper Center for Public Service. 2018

Table 10: Population Forecast for Age 65+ Population (2045)

	Base Year (2017) Age 65+ Population		Projected (2045) Age 65+ Population		Projected (2045) Age 65+ Population Share		Change in Age 65+ Population (2017-2045)	
	Population	Share of Total Population in Region	WC	WP	WC	WP	WC	WP
STATEWIDE								
Total	1,271,428	15%	1,986,913	2,261,702	19%	20%	56%	78%
VDOT CONSTRUCTION DISTRICTS								
Bristol	73,301	21%	80,910	98,676	25%	27%	10%	35%
Culpeper	70,998	17%	116,113	122,943	21%	22%	64%	73%
Fredericksburg	78,451	16%	134,529	157,120	20%	20%	71%	100%
Hampton Roads	250,597	14%	383,636	416,934	19%	21%	53%	66%
Lynchburg	77,687	20%	93,552	91,327	22%	21%	20%	18%
Northern Virginia	282,142	11%	541,710	655,392	15%	17%	92%	132%
Richmond	202,690	15%	311,055	356,712	19%	21%	53%	76%
Salem	134,105	19%	174,397	199,815	23%	24%	30%	49%
Staunton	101,457	18%	146,755	165,389	22%	24%	45%	63%
PLANNING DISTRICT COMMISSIONS								
Accomack-Northampton	10,448	24%	10,166	11,318	29%	25%	-3%	8%
Central Shenandoah	54,481	18%	76,300	90,124	21%	24%	40%	65%
Central Virginia	48,177	18%	65,758	69,695	21%	21%	36%	45%
Commonwealth Regional Council	19,712	19%	26,431	23,965	23%	22%	34%	22%
Crater	28,370	16%	39,805	35,759	22%	21%	40%	26%
Cumberland Plateau	22,362	21%	22,579	31,403	25%	29%	1%	40%
George Washington	44,326	12%	93,360	116,626	17%	19%	111%	163%
Hampton Roads	234,046	14%	365,432	397,612	19%	20%	56%	70%
Lenowisco	17,511	20%	19,347	23,301	22%	25%	10%	33%
Middle Peninsula	19,541	21%	25,652	26,397	26%	24%	31%	35%
Mount Rogers	41,881	22%	48,914	55,383	27%	27%	17%	32%
New River Valley	28,400	16%	37,585	38,791	18%	19%	32%	37%
Northern Neck	14,584	29%	14,904	13,892	30%	25%	2%	-5%
Northern Shenandoah	42,127	18%	65,480	70,414	22%	23%	55%	67%
Northern Virginia	282,142	11%	541,710	655,392	15%	17%	92%	132%
Rappahannock-Rapidan	31,081	18%	51,080	60,220	22%	24%	64%	94%
Richmond Regional	161,285	15%	256,461	306,941	19%	20%	59%	90%
Roanoke Valley-Alleghany	66,761	20%	84,963	96,333	23%	25%	27%	44%
Southside	19,295	24%	20,311	22,529	28%	29%	5%	17%
Thomas Jefferson	43,860	17%	69,385	67,162	21%	21%	58%	53%
West Piedmont	41,038	22%	45,070	51,526	28%	27%	10%	26%

WC: Weldon Cooper Center
WP: Woods & Poole

3.1.10. VTrans Macrotrend # 10: Population and Employment Shift

Description: This trend refers to changes in the geographic distribution of population and the geographic and industry-level distribution of employment in Virginia.

Drivers:

- Macroeconomic factors such as industry agglomeration
- Location preferences of business
- Location preferences of households

Significance: Location preferences resulting from population and employment shifts cause change in demand for transportation infrastructure and services.

Data Sources:

- Historic and Forecast Population Estimates for Virginia and subgeographies: Weldon Cooper Center for Public Service[1]
- Historic and Forecast Population Estimates and Historic and Forecast Employment Estimates for Virginia: Woods & Poole[2]
- Forecast Employment Growth in Virginia: IHS Markit[3]
- Historical Employment for Virginia: US Bureau of Labor Statistics[4]
- Historical and Forecast Income for Virginia

Calculations:

For estimated changes in industry employment by location:

1. Gather historical employment trends from the Bureau of Labor Statistics as shown below in Table 11.
2. Gather 2018 employment by NAICS 2-digit industry classification by Virginia locality.[5]
3. Gather ten-year expected growth rates by NAICS 2-digit industry classification for Virginia Local Workforce Development Areas.[6]

[1] Weldon Cooper Center for Public Service, Annual Population Estimates and Population Projections

[2] Woods & Poole Economics, Inc. *Virginia, Maryland, and The District of Columbia, 2018 State Profile, State and County Projections to 2050.* 2018

[3] Jeafarqomi, K. *Email to John S. Miller.* December 13, 2018

[4] Bureau of Labor Statistics. *Quarterly Census of Employment and Wages,* Washington, D.C., undated. Accessed January 25, 2019

[5] US Census, Longitudinal Employer-Household Dynamics, Origin-Destination Employment Statistics

[6] Virginia Employment Commision, Long-term Projection by Industry, Virginia 2018-2028 Projections

Step 1: Macrotrend # 10: Population and Employment Shift Output

Table 11: Employment Forecast (2045)

	Base Year		Forecast		Statewide Share				Change (2017-2045)	
	2017 (IHS)[1]	2017 (WP)[2]	2045 (IHS)	2045 (WP)	2017 (IHS)	2017 (WP)	2045 (IHS)	2045 (WP)	IHS	WP
STATEWIDE										
Total	4,017,630	5,275,247	4,750,031	7,601,370	-	-	-	-	18%	44%
VDOT CONSTRUCTION DISTRICTS										
Bristol	137,963	160,837	133,790	190,791	3%	3%	3%	3%	-3%	19%
Culpeper	182,501	245,104	223,952	340,085	5%	5%	5%	4%	23%	39%
Fredericksburg	167,649	229,539	206,660	360,323	4%	4%	4%	5%	23%	57%
Hampton Roads	820,225	1,084,989	906,968	1,449,070	21%	20%	19%	19%	11%	34%
Lynchburg	169,564	211,032	175,139	277,339	4%	4%	4%	4%	3%	31%
Northern Virginia	1,293,486	1,756,035	1,690,425	2,746,961	32%	33%	36%	36%	31%	56%
Richmond	690,926	878,820	812,072	1,289,150	17%	17%	17%	17%	18%	47%
Salem	309,107	390,909	329,935	512,624	8%	7%	7%	7%	7%	31%
Staunton	246,209	317,982	271,090	435,027	6%	6%	6%	6%	10%	37%
MODIFIED PLANNING DISTRICT COMMISSIONS										
Accomack-Northampton	22,934	25,877	17,023	32,932	1%	0%	1%	0%	-26%	27%
Central Shenandoah	136,473	177,971	149,465	243,015	3%	3%	3%	3%	10%	37%
Central Virginia	108,254	140,329	116,201	197,168	3%	3%	2%	3%	7%	41%
Commonwealth Regional Council	33,539	41,709	32,476	51,888	1%	1%	1%	1%	-3%	24%
Crater	75,717	98,383	94,824	114,439	2%	2%	2%	2%	25%	16%
Cumberland Plateau	37,344	43,153	31,598	51,344	1%	1%	1%	1%	-15%	19%
George Washington	126,033	170,468	165,370	285,512	3%	3%	3%	4%	31%	68%
Hampton Roads	782,271	1,041,008	873,686	1,394,797	19%	20%	18%	18%	12%	34%
Lenowisco	30,099	34,745	30,691	42,769	1%	1%	1%	1%	2%	23%
Middle Peninsula	25,641	36,740	26,564	46,823	1%	1%	1%	1%	4%	27%
Mount Rogers	83,033	100,303	87,584	119,503	2%	2%	2%	2%	6%	19%
New River Valley	81,129	96,630	89,105	121,907	2%	2%	2%	2%	10%	26%
Northern Neck	15,975	22,331	14,726	27,988	0%	0%	0%	0%	-8%	25%
Northern Shenandoah	101,843	129,823	111,115	180,494	3%	2%	2%	2%	9%	39%
Northern Virginia	1,293,486	1,756,035	1,690,425	2,746,961	32%	33%	36%	36%	31%	56%
Rappahannock-Rapidan	61,922	86,185	69,782	126,907	2%	2%	1%	2%	13%	47%
Richmond Regional	598,022	759,909	706,346	1,150,963	15%	14%	15%	15%	18%	52%
Roanoke Valley-Alleghany	169,783	214,525	173,240	280,520	4%	4%	4%	4%	2%	31%
Southside	32,858	39,058	26,725	46,396	1%	1%	1%	1%	-19%	19%
Thomas Jefferson	125,463	166,318	158,984	222,628	3%	3%	3%	3%	27%	34%
West Piedmont	75,811	93,747	84,101	116,416	2%	2%	2%	2%	11%	24%

Notes: Cell shading indicates relative comparative values.

[1] IHS Markit, Jeafarqomi, K. Email to John S. Miller. December 13, 2018

[2] Woods & Poole Economics, Inc. Virginia, Maryland, and The District of Columbia, 2018 State Profile, State and County Projections to 2050. 2018

Table 12: Population Forecast (2045)

	Historic and Base Year Population		Forecast Population		Statewide Population Share				Change (2017-2045)	
	2000	2017	2045 (WC)[1]	2045 (WP)[2]	2000	2017	2045 (WC)	2045 (WP)	WC	WP
STATEWIDE										
Total	7,079,030	8,470,020	10,528,817	11,283,149	-	-	-	-	24%	33%
VDOT CONSTRUCTION DISTRICTS										
Bristol	363,236	345,314	325,987	364,412	5%	4%	3%	3%	-6%	6%
Culpeper	319,988	415,063	543,665	558,203	5%	5%	5%	5%	31%	35%
Fredericksburg	374,081	506,111	685,611	777,815	5%	6%	7%	7%	36%	54%
Hampton Roads	1,621,695	1,746,491	1,980,157	2,033,689	23%	21%	19%	18%	13%	16%
Lynchburg	380,728	396,872	423,421	425,827	5%	5%	4%	4%	7%	7%
Northern Virginia	1,815,197	2,501,308	3,546,256	3,870,499	26%	30%	34%	34%	42%	55%
Richmond	1,087,582	1,310,261	1,596,976	1,732,422	15%	15%	15%	15%	22%	32%
Salem	642,661	693,462	752,932	822,009	9%	8%	7%	7%	9%	19%
Staunton	467,563	555,138	673,812	698,273	7%	7%	6%	6%	21%	26%
MODIFIED PLANNING DISTRICT COMMISSIONS										
Accomack-Northampton	51,398	44,391	34,765	45,700	1%	1%	0%	0%	-22%	3%
Central Shenandoah	258,763	299,042	358,808	372,547	4%	4%	3%	3%	20%	25%
Central Virginia	222,317	261,254	306,881	325,873	3%	3%	3%	3%	18%	25%
Commonwealth Regional Council	97,102	102,387	112,874	111,130	1%	1%	1%	1%	10%	9%
Crater	167,129	173,092	181,355	174,268	2%	2%	2%	2%	5%	1%
Cumberland Plateau	117,229	104,439	90,196	108,534	2%	1%	1%	1%	-14%	4%
George Washington	241,044	364,840	535,363	613,297	3%	4%	5%	5%	47%	68%
Hampton Roads	1,533,739	1,667,226	1,910,793	1,953,027	22%	20%	18%	17%	15%	17%
Lenowisco	93,105	88,145	87,537	93,049	1%	1%	1%	1%	-1%	6%
Middle Peninsula	83,684	91,489	100,294	109,228	1%	1%	1%	1%	10%	19%
Mount Rogers	188,984	189,063	182,897	204,837	3%	2%	2%	2%	-3%	8%
New River Valley	165,146	182,993	208,993	202,913	2%	2%	2%	2%	14%	11%
Northern Neck	49,353	49,782	49,953	55,290	1%	1%	0%	0%	0%	11%
Northern Shenandoah	185,282	235,443	297,472	307,533	3%	3%	3%	3%	26%	31%
Northern Virginia	1,815,197	2,501,308	3,546,256	3,870,499	26%	30%	34%	34%	42%	55%
Rappahannock-Rapidan	134,785	177,418	228,219	251,646	2%	2%	2%	2%	29%	42%
Richmond Regional	865,941	1,084,424	1,366,353	1,503,263	12%	13%	13%	13%	26%	39%
Roanoke Valley-Alleghany	311,827	334,781	365,274	386,317	4%	4%	3%	3%	9%	15%
Southside	88,149	81,493	72,959	78,681	1%	1%	1%	1%	-11%	-4%
Thomas Jefferson	199,648	252,588	330,711	323,373	3%	3%	3%	3%	31%	28%
West Piedmont	202,909	184,422	160,864	192,144	3%	2%	2%	2%	-13%	4%

Notes: Cell shading indicates relative comparative values.

[1] Weldon Cooper Center for Public Service, Annual Population Estimates and Population Projections

[2] Woods & Poole Economics, Inc. Virginia, Maryland, and The District of Columbia, 2018 State Profile, State and County Projections to 2050. 2018

Table 13: Household Income Forecast (2045)[1]

	Household Income (Median)				Household Income (Mean)			
	2000	2017	2045	Change (2017-2045)	2000	2017	2045	Change (2017-2045)
STATEWIDE								
Total	$61,502	$68,351	$85,741	25%	$100,897	$120,910	$166,467	38%
VDOT CONSTRUCTION DISTRICTS								
Bristol	$33,247	$33,923	$43,039	27%	$59,247	$67,950	$91,147	34%
Culpeper	$57,700	$64,524	$84,411	31%	$99,285	$121,092	$155,098	28%
Fredericksburg	$62,479	$70,703	$90,336	28%	$90,439	$113,106	$152,346	35%
Hampton Roads	$52,610	$56,719	$68,287	20%	$87,128	$106,960	$146,272	37%
Lynchburg	$40,017	$37,297	$48,518	30%	$65,868	$73,571	$102,413	39%
Northern Virginia	$93,690	$104,225	$124,142	19%	$153,295	$172,388	$227,461	32%
Richmond	$56,646	$59,469	$72,087	21%	$95,393	$113,744	$156,125	37%
Salem	$44,073	$46,261	$57,443	24%	$71,712	$82,339	$109,938	34%
Staunton	$48,042	$50,053	$67,381	35%	$75,443	$90,182	$117,615	30%
MODIFIED PLANNING DISTRICT COMMISSIONS								
Accomack-Northampton	$35,900	$36,220	$52,930	46%	$60,596	$80,544	$111,527	38%
Central Shenandoah	$46,135	$44,286	$59,988	35%	$72,376	$84,524	$107,818	28%
Central Virginia	$45,863	$43,515	$53,778	24%	$75,293	$80,534	$109,342	36%
Commonwealth Regional Council	$37,658	$38,382	$51,926	35%	$60,624	$69,800	$92,374	32%
Crater	$45,244	$52,116	$57,065	9%	$73,345	$84,047	$113,054	35%
Cumberland Plateau	$30,220	$31,986	$39,061	22%	$58,806	$63,893	$86,968	36%
George Washington	$71,355	$80,235	$98,644	23%	$98,370	$123,298	$164,866	34%
Hampton Roads	$53,504	$57,641	$68,900	20%	$88,679	$108,505	$148,086	36%
Lenowisco	$30,386	$30,356	$40,856	35%	$53,519	$60,582	$82,469	36%
Middle Peninsula	$51,905	$53,696	$67,646	26%	$81,274	$95,167	$118,114	24%
Mount Rogers	$36,918	$36,139	$46,380	28%	$62,245	$73,164	$96,054	31%
New River Valley	$39,849	$46,208	$54,105	17%	$60,927	$74,194	$98,370	33%
Northern Neck	$42,508	$44,327	$66,535	50%	$72,252	$84,637	$109,504	29%
Northern Shenandoah	$51,470	$58,491	$77,388	32%	$80,905	$98,865	$130,661	32%
Northern Virginia	$93,690	$104,225	$124,142	19%	$153,295	$172,388	$227,461	32%
Rappahannock-Rapidan	$62,668	$68,849	$85,352	24%	$104,357	$119,278	$154,414	29%
Richmond Regional	$59,927	$61,807	$74,893	21%	$101,449	$120,482	$163,575	36%
Roanoke Valley-Alleghany	$47,633	$48,139	$57,262	19%	$78,026	$90,024	$123,882	38%
Southside	$36,656	$36,607	$51,905	42%	$59,716	$69,878	$97,414	39%
Thomas Jefferson	$53,514	$60,642	$82,982	37%	$94,282	$120,204	$153,176	27%
West Piedmont	$37,286	$34,612	$50,430	46%	$62,940	$70,094	$91,768	31%

Notes: Cell shading indicates relative comparative values.

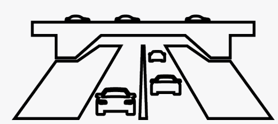
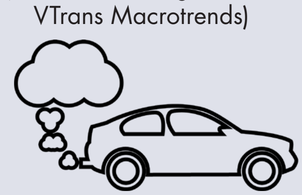
For more details on how the above data was compiled, please see Appendix 5, Tables 5-1: Jurisdictions associated with each VDOT Construction District, and 5-2: Jurisdictions Associated with each Modified Planning District Commission.

[1] Woods & Poole Economics, Inc. Virginia, Maryland, and The District of Columbia, 2018 State Profile, State and County Projections to 2050. 2018

3.2. Step 2: Develop Metrics for CTB Goals

Step 2 identifies metrics for the CTB's five Goals and associated Objectives[1] (Table 14). These metrics were established after an evaluation of availability of research, tools, and methods, and are considered fundamental blocks upon which a more comprehensive set of metrics can be developed in the future. Goal Metrics stand in for one or more aspects of the relevant goal and allow for progress toward the goal to be quantitatively tracked.

Table 14: Metrics for CTB Goals

Goals	Objectives	Metrics for CTB Goals and Objectives
Goal A Economic Competitiveness and Prosperity	A.1. Reduce the amount of travel that takes place in severe congestion	Vehicles Miles Traveled (VMT) Index (Estimated Change due to VTrans Macrotrends) 
	A.2. Reduce the number and severity of freight bottlenecks	
	A.3. Improve reliability on key corridors for all modes	
Goal B Accessible and Connected Places	B.1. Reduce average peak-period travel times in metropolitan areas	Shared Mobility Index (Switchable Urban Auto SOV VMT to Micromobility and TNC/Ridesourcing) 
	B.2. Reduce average daily trip lengths in metropolitan areas	
	B.3. Increase the accessibility to jobs via transit, walking, and driving in metropolitan areas	
Goal C Safety for All Users	C.1. Reduce the number and rate of motorized fatalities and serious injuries	Safety Index (Safety Index - Estimated Change in Number of Crashes with Fatalities + Serious Injuries Due to VTrans Macrotrends) 
	C.2. Reduce the number of non-motorized fatalities and serious injuries	
Goal D Proactive System Management	D.1. Improve the condition of all bridges based on deck area	Roadways at Risk from Flooding 
	D.2. Increase the lane miles of pavement in good or fair condition	
	D.3. Increase percent of transit vehicles and facilities in good or fair condition	
Goal E Healthy Communities and Sustainable Transportation Communities	E.1. Reduce per-capita vehicle miles traveled	Tailpipe Emissions Index (Estimated Change Due to VTrans Macrotrends) 
	E.2. Reduce transportation related NOX, VOC, PM, and CO emissions	
	E.3. Increase the number of trips traveled by active transportation (bicycling and walking)	

[1] Commonwealth Transportation Board, Actions to Approve the 2019 VTrans Vision, Goals, Objectives, Guiding Principles and the 2019 Mid-term Needs Identification Methodology and Accept the 2019 Mid-term Needs, January 15, 2020

3.3. Step 3: Estimate Impact of Macrotrends on Goal Metrics

Step 3 evaluates the cumulative impact of one or more of ten Macrotrends on each of the Goal Metrics (Table 15) and calculates a range of possible impacts on Virginia's transportation system performance for 2045. To account for interrelationships between Macrotrends, an order of influence is established to convey influence of one macrotrend on another. Order of influence ensures that the calculations respect the primary causal directions among Macrotrends, whereby Macrotrends that are early in the order of influence may influence those that are later in the order of influence, but not typically the reverse.

Table 15: Order of Influence of Macrotrends and Influence of Macrotrends on Goal Metrics

Order of Influence	Macrotrend (listed in order of influence)	VMT Index	Shared Mobility Index	Safety Index	Number of Directional Miles of Roadways at Risk from Flooding	Tailpipe Emissions Index
1	Macrotrend # 1: Increase in Flooding Risk				•	
	Macrotrend # 9: Growth of the 65+ Cohort	Included in the 2045 Business-as-usual Scenario				
2	Macrotrend # 8: Increase in Workplace Flexibility	•	•			•
	Macrotrend # 2: Adoption of Highly Autonomous Vehicles	•	•	•		•
	Macrotrend # 3: Adoption of Electric Vehicles	•	•			•
3	Macrotrend # 4: Growth in Shared Mobility	•	•			•
4	Macrotrend # 5: Growth in E-commerce	•				•
	Macrotrend # 6: Greater Automation of Goods and Services	•				•
5	Macrotrend # 7: Growth of Professional Services Industry Macrotrend # 10: Population and Employment Shift	Included in the 2045 Business-as-usual Scenario				
	Cumulative Impacts	•	•	•	•	•

• Quantified in Step 3

3.3.1. Impact of Step 1 Macrotrends on CTB Goal A Metrics

Description: The total mileage traveled for all vehicles in the state, typically reported daily and analyzed over a 1-year period.

Significance: Vehicle miles traveled (VMT) is a key indicator of total transportation system usage, measuring vehicle travel demand. VMT estimates also provide a fundamental input for estimating needs in other indicators used as metrics for CTB priorities, such as safety and tailpipe emissions. Estimates of future VMT changes are presented at the statewide and county level.

Data Sources:

- Share of jobs that are work-from-home capable: Dingel and Neiman[1]
- Share of jobs that are work-from-home capable: U.S. Bureau of Labor Statistics[2]
- Remote Work Survey: PricewaterhouseCoopers[3]
- Work-from-home Survey Report: Global Workplace Analytics[4]
- Virginia Industry Projections: Virginia Employment Commission[5]
- Employment Data: U.S. Census Bureau[6]
- Effect of AVs on Operating Cost and VMT: Compostella[7]
- Vehicle Cost Elasticities: Dong et al. (2012)[8]

[1] Dingel, Jonathan I., and Brent Neiman (2020). "How Many Jobs Can Be Done at Home?" Journal of Public Economics 189 (September 2020): 104235.

[2] Dey, Matthew, Harley Frazis, Mark A. Loewenstein, and Hugette Sun (2020). "Ability to Work from Home: Evidence from Two Surveys and Implications for the Labor Market in the COVID-19 Pandemic : Monthly Labor Review: U.S. Bureau of Labor Statistics." Accessed January 27, 2021.

[3] PricewaterhouseCoopers (2021). "Business Needs a Tighter Strategy for Remote Work." PwC. Accessed January 19, 2021.

[4] Global Workplace Analytics (2020). "Global Work-from-Home Experience Survey Report." May 2020.

[5] Virginia Employment Commission. "Industry Projections." Accessed February 1, 2021.

[6] U.S. Census Bureau. Longitudinal Employer-Household Dynamics (LEHD) Origin-Destination Employment Statistics (LODES).

[7] Compostella, Junia (2020). "Near- (2020) and Long-Term (2030-2035) Costs of Automated, Electrified, and Shared Mobility in the United States." Transport Policy, 2020, 14.

[8] Dong, Jing, Diane Davidson, Frank Southworth, and Tim Reuscher. "Analysis of Automobile Travel Demand Elasticities with Respect to Travel Cost." Oak Ridge National Laboratory, 2012.

- Virginia Daily Vehicle Miles Traveled: VDOT[1]
- Rate of return assumption of auto-based in-store purchases of retail trade: ATRI[2]
- Home delivery routes of e-commerce shipments stops per day: World Bank[3]
- Fare elasticity: Taiebat et al.[4] and Cohen et al.[5]
- Commute modes: FHWA[6]
- Percent non-work replacement VMT: Zhu and Mason[7]

Calculations:

Calculations to measure change in VMT in future year (2045) rely on outputs related to the following Macrotrends included in Section 3.1, Step 1. The Macrotrends' impact on VMT is estimated under the relevant headers before being combined to derive an overall range of estimates for VMT.

- Macrotrend # 2: Adoption of Highly Autonomous Vehicles
- Macrotrend # 3: Adoption of Electric Vehicles
- Macrotrend # 4: Growth in Shared Mobility
- Macrotrend # 5: Growth in E-commerce
- Macrotrend # 6: Greater Automation of Production and Services
- Macrotrend # 8: Increase in Workplace Flexibility

The combined impact of Macrotrend # 2: Adoption of Highly Autonomous Vehicles (AV), Macrotrend # 3: Adoption of Electric Vehicles, Macrotrend # 4: Growth in Shared Mobility (Ridesourcing only) on Vehicle Miles Traveled is calculated using the following steps.

1. Obtain change in total vehicle cost (accounts for fixed and variable costs) per mile for small and mid-size SUVs by vehicle type (unique combination of vehicle usage and fuel type) from Table A3 and A4 from Compostella et al.[8]

2. Given that total vehicle cost in calculation step # 1 has different impacts on personal usage vehicles and on ridesource vehicles, calculate two elasticities.
   - 2.1. Determine a change in travel demand elasticity of using an average of elasticities noted in various studies.[9]
   - 2.2. Determine a change in fare elasticity of using elasticities reported in Taiebat et al.[10] and Cohen et al. (2016).[11]

[1] Virginia Department of Transportation. "2019 Traffic Data Daily Vehicle Miles Traveled."

[2] ATRI, E-Commerce impacts on the trucking industry, February 2019. Last accessed on April 8, 2021.

[3] The World Bank, Facilitating Trade and Logistics for E-Commerce: Building Blocks, Challenges and Ways Forward, December 2019. Last accessed on April 8, 2021.

[4] Taiebat, Morteza, Samuel Stolper, and Ming Xu (2019). "Forecasting the Impact of Connected and Automated Vehicles on Energy Use: A Microeconomic Study of Induced Travel and Energy Rebound." Applied Energy 247 (August 2019): 297–308.

[5] Cohen, Peter, Robert Hahn, Jonathan Hall, Steven Levitt, and Robert Metcalfe (2016). "Using Big Data to Estimate Consumer Surplus: The Case of Uber." Cambridge, MA: National Bureau of Economic Research, September 2016.

[6] Federal Highway Administration (2017). 2017 National Household Travel Survey.

[7] Zhu, P., & Mason, S. G. (2014). The impact of telecommuting on personal vehicle usage and environmental sustainability. *International Journal of Environmental Science and Technology,* 11(8), 2185-2200.

[8] Compostella, Junia, Lewis M. Fulton, Robert de Kleine, Chul Kim Hyung, and Timothy J. Wallington. "Near- (2020) and Long-Term Costs of Automated, Electrified, and Shared Mobility in the United States." Transport Policy, 2020, 14.

[9] Average demand elasticity calculated based on a review of the following studies: Hagemann, et al 2011 (Draft), Li, et al, 20112, Gillingham, 2010, Hymel , et al (2010), Karpus, 2010, Barla et al , 2009, Brand, 2009, McMullen & Zhang, 2008, Austin, 2008, Dargay, 2007, Small & Van Dender, 2007a, Small & Van Dender, 2007b, Feng et al, 2005, Goodwin, et al 2004*, Graham & Glaister 2002,2004*, de Jong & Gun, 2002* (shares), Brons, et al ,2002*, Goodwin , 2002*, Greene et al, 1999, TRACE, 1999 (Travel shares)*, Johannson & Shipper, 1997, Schimek, 1996a, Blundell et al, 2011, Souche, 2010, Bento et al, 2009, Salon (2009), Ingram and Liu, 1999, Small and Winston, 1999, Oum et al, 1992

[10] Taiebat, Morteza, Samuel Stolper, and Ming Xu. "Forecasting the Impact of Connected and Automated Vehicles on Energy Use: A Microeconomic Study of Induced Travel and Energy Rebound." Applied Energy 247 (August 2019): 297–308.

[11] Cohen, Peter, Robert Hahn, Jonathan Hall, Steven Levitt, and Robert Metcalfe. "Using Big Data to Estimate Consumer Surplus: The Case of Uber." Cambridge, MA: National Bureau of Economic Research, September 2016.

3. Utilizing outputs from calculation steps # 1 and # 2, calculate VMT change due to AV[1] for three scenarios (low, medium, high) using the following formula.[2]

4. $b_v = p_v \times e$

   Where:

   - v is a vehicle type v out of all vehicle types V.
   - b_v is the estimated VMT increase by vehicle type v.
   - p_v is the change in total vehicle cost by vehicle type (calculation step # 1)
   - e is the change in travel demand or fare elasticities (calculation step # 2)

5. Utilizing outputs from Section 3.1.4, VTrans Macrotrend # 4: Growth in Shared Mobility, estimate mix of personal-use and ridesource vehicles for three scenarios (low, medium, high). Retain ridesourcing VMT shares for low, medium, and high scenarios from Section 3.1.4, calculation step # 9. Convert to percentage of all VMT for each scenario by dividing by 2045 Virginia VMT calculated in section 3.1.4 from StreetLight Data.

6. Utilizing outputs from Section 3.1.3, VTrans Macrotrend # 3: Adoption of Electric Vehicles, estimate vehicle fuel type (internal combustion engine, electric, and hybrid) for each of the personal-use and ridesource vehicle mix for all three scenarios (low, medium, high) derived from calculation step # 4. Retain internal combustion engine (ICE) vehicle, plug-in hybrid electric vehicle (PHEV), and electric vehicle (EV) Virginia fleet shares for the Business as Usual and Accelerated Electrification scenarios, which became the low and high scenarios respectively in this analysis. These fleet shares are from Section 3.1.3 calculation step # 1. ICE and EV Virginia fleet shares for the medium scenario are the average of the low and the high, and Virginia's medium scenario PHEV fleet share is set so that PHEV, ICE, and EV fleet shares add to 100 percent.

7. Estimate the VMT increase or *VMT change (d)* for personal-use and ridesource vehicles using the formula below:

   $c_v = b \times a_v$

   $MT\_2\_3\_4\ (d) = AV\ Market\ Penetration \times \sum_{v\,V} c_v$

   Where:

   - v is a vehicle type out of all vehicle types V.
   - a_v is the estimated share of fleet for vehicle type v.[3]
   - b is the estimated VMT increase from calculation step # 4.
   - c_v is the product of the share of fleet and VMT increase for vehicle type v.
   - *AV Market Penetration* is total market penetration percentages for vehicles with automation levels 3 or 4.

Impact of Macrotrend # 4: Growth in Shared Mobility (Micromobility only) on Vehicle Miles Traveled is calculated using the following steps.

8. Reduction in VMT due to increases in micromobility is estimated for each scenario (low, medium, high) using the following equation based on data from from Section 3.1.4, calculation step # 9.

   $MT\_4 = new\ 2045\ micromobility\ mileage / 2045\ automobile\ VMT$

[1] Note that Compostella (2020) does not specifically call out levels of automation but uses the more generic term Automated Vehicles (AVs) which is typically used for higher levels of automation (level 3 and level 4)

[2] Note that VMT is inversely proportional to the cost and fare elasticities. A negative elasticity implies a unit decrease in price will lead to an increase in miles.

[3] To calculate the estimated fleet share for each vehicle type, combine retained ridesourcing VMT shares (calculation step # 5) and Virginia fleet shares (calculation step # 6) for low, medium, and high scenarios to estimate fleet share for the following vehicle types: private ICEV, private HEV, private PHEV40, private BEV200, private BEV300, ridesource ICEV, ridesource HEV, ridesource BEV200, and ridesource BEV300. BEV fleet shares are split evenly between 200- and 300-miles ranges.

Where:

- new 2045 micromobility mileage is the auto VMT that is expected to switch to micromobility by 2045. For the medium scenario, this is the micromobility switchable VMT for 2045 as calculated in step 1 for Macrotrend #4: Growth in Shared Mobility. Scenarios are defined such that 50% of the VMT that is expected to switch to micromobility in the medium scenario also switches in the low scenario, and 150% of the VMT that is expected to switch in the medium scenario also switches in the high scenario.

Impact of Macrotrend # 5: Growth in E-commerce on Vehicle Miles Traveled is calculated using the following steps.

Estimate annual automobile VMT avoided in future year (2045) due to e-commerce for each scenario (low, medium, high).

9. Determine the ratio between value per ton for B2C e-commerce commodity and value per ton for average goods-movement-dependent industry commodity at the state level. Use US BTS and FHWA's Freight Analysis Framework Version 5 (FAF5)[1] database, based on which the value per ton for "mixed freight" goods traveling within Virginia was estimated as $5,575 per ton, which was assumed to be a typical value per ton for retail trade or B2C e-commerce commodities. Using the same data, the overall value per ton of goods traveling to/from/within Virginia was estimated as $1,096 per ton. The value per ton ratio between retail trade or B2C e-commerce commodities and all goods movement dependent industry commodities was estimated as 5.1.

10. Estimate future year (2045) non-commercial auto VMT avoided over base year (2019) at the Virginia MSA level.
    $\textit{Auto VMT Avoided}^{\,Region}$
    $= (\textit{Future B2C Output}^{\,Region} \times \textit{Future B2C E-Com }\%^{Region} - \textit{Base B2C Output }\%^{Region} \times \textit{Base B2C E-Com }\%^{Region}) \times (1+ARR) \times \textit{Value per Ton Ratio}^{B2C\ E\text{-}Com} \times (1/AGVW) \times ATD^{\,Region}$

    Where:
    - $\textit{VMT Avoided}^{\,Region}$: Estimated regional daily auto VMT avoided by 2045 due to growth in B2C e-commerce
    - *ARR*: Rate of return assumption of auto-based in-store purchases of retail trade or B2C goods
    - *AGVW*: Auto average gross vehicle weight assumption
    - $ATD^{\,Region}$: Average auto-based shopping travel distance assumption by region size

    According to an ATRI study,[2] around 8 percent of all in-store purchases are returned, hence the value of 8 percent was used as ARR. AGVW was assumed as 2.7 tons/vehicle. $ATD^{\,Region}$ was assumed as average shopping round-trip length by region size in Virginia based on the 2017 National Household Travel Survey.

11. Estimate annual automobile VMT avoided in future year (2045) due to e-commerce and e-commerce delivery methods for three scenarios (low, medium, high) using the following equation. Automobile VMT is avoided due to replacement of shopping trips with e-commerce.
    $\%\Delta \textit{ Auto VMT} = \textit{Daily 2045 Auto VMT Avoided/Daily Auto 2019 VMT} \times \textit{2019 VMT/2045 VMT} \times -1 \times (1-\textit{Truck VMT Share})$

[1] FHWA. Freight Analysis Framework Version 5.

[2] ATRI, E-Commerce impacts on the trucking industry, February 2019, Available at: https://truckingresearch.org/wp-content/uploads/2019/02/ATRI-Impacts-of-E-Commerce-on-Trucking-02-2019.pdf (last accessed on April 8, 2021)

Where:

- *Daily Auto VMT Avoided* is the calculated number of automobile VMT avoided due to e-commerce, as calculated in calculation step # 10 above.
- *Daily Auto VMT* is the 2019 number of daily auto VMT on Virginia roads as reported by VDOT.[1]
- *2019 VMT* is the annual 2019 VMT estimated by StreetLight Data.
- *2045 VMT* is the annual 2045 VMT estimated by StreetLight Data.
- *Truck VMT Share* is the 2019 truck daily VMT share as reported by VDOT.[2]

Estimate annual additional truck VMT avoided in future year (2045) due to e-commerce.

12. Estimate future year (2045) Gross truck tons added over base year (2019) (due to cargo re-allocation from auto to truck) at the MSA level and Truck Class. Define MSAs by size:
    - Large MSAs: Richmond, Virginia Beach-Norfolk-Newport News and Northern Virginia
    - Medium MSAs: Charlottesville, Lynchburg, Roanoke
    - Rest of State: Small MSAs + Rural Areas

    $\text{Gross Truck Tons Added}_k^{Region} = (\text{Future B2C Output}^{Region} \times \text{Future B2C E-Com }\%^{Region} - \text{Base B2C Output}^{Region} \times \text{Base B2C E-Com }\%^{Region}) \times (1+TRR) \times \text{Value per Ton Ratio}^{B2C\ E\text{-}Com} \times T\ \%_k^{B2C\ E\text{-}Com}$

    Where:
    - $\text{Gross Truck Tons Added}_k^{Region}$: Estimated 2045 regional daily gross truck tons added by 2045 for truck type k due to growth in B2C e-commerce
    - $\text{Future B2C Output}^{Region}$: Output of calculation Steps 19-21 for 3.1.5. VTrans Macrotrend #5: Growth in E-commerce
    - $\text{Base B2C Output}^{Region}$: Output of calculation Steps 19-21 for 3.1.5. VTrans Macrotrend #5: Growth in E-commerce
    - $\text{Future B2C E-Com }\%^{Region}$: Output of calculation steps 6-9 for 3.1.5. VTrans Macrotrend #5: Growth in E-commerce
    - $\text{Base B2C E-Com }\%^{Region}$: Output of calculation steps 6-9 for 3.1.5. VTrans Macrotrend #5: Growth in E-commerce
    - *TRR*: Rate of return assumption of truck-based retail trade or B2C e-commerce goods
    - $\text{Value per Ton Ratio}^{B2C\ E\text{-}Com}$: Output of calculation step 9 above
    - $T\ \%_k^{B2C\ E\text{-}Com}$: Truck tonnage share for truck type k assumption used in retail trade or B2C e-commerce goods

    According to an ATRI study,[2] between 13 and 30 percent of all online orders result are returned, hence an average value of 22 percent was assumed as TRR. Depending on the size of the region, different truck class distributions, $T\ \%_k^{B2C\ E\text{-}Com}$, were assumed for retail trade or B2C e-commerce goods

13. For each scenario (low, medium, high), the following equation is used to estimate the increase in truck VMT in the future year (2045) due to growth in e-commerce accounting for commercial drone delivery services.

    $\%\Delta\ \text{Truck VMT} = \%\Delta\ \text{Truck VMT}_c \times \text{Truck VMT Share}$

    Where:
    - *%Δ Truck VMT* is the change in the share of truck VMT incurred due to e-commerce after accounting for commercial drone delivery service, from calculation step # 12.
    - *Truck VMT Share* is the 2019 truck daily VMT share as reported by VDOT.[3]
    - *c* represents the geographic level being analyzed

[1] Virginia Department of Transportation (2019). Traffic Data Daily Vehicle Miles Traveled. 20 – DVMT by Federal Vehicle Class 2019. Accessed May 25, 2021.

[2] ATRI, E-Commerce impacts on the trucking industry, February 2019, Available at: https://truckingresearch.org/wp-content/uploads/2019/02/ATRI-Impacts-of-E-Commerce-on-Trucking-02-2019.pdf (last accessed on April 8, 2021)

[3] Virginia Department of Transportation (2019). Traffic Data Daily Vehicle Miles Traveled. 20 – DVMT by Federal Vehicle Class 2019. Accessed May 25, 2021.

14. Estimate future year (2045) Truck VMT added over Baseline by Virginia MSAs and Truck Class

$$Truck\ VMT\ Added_k^{Region} = Gross\ Truck\ Tons\ Added_k^{Region} \times [(T\ \%_k^{B2C\ E\text{-}Com})\ /\ \sum_k (TGVW_k \times T\ \%_k^{B2C\ E\text{-}Com})] \times TTD^{\ Region}$$

Where:

- $Truck\ VMT\ Added_k^{Region}$: Estimated regional daily truck VMT added by 2045 for truck type k due to growth in B2C e-commerce
- $TGVW_k$: Truck average gross vehicle weight assumption for truck type *k*
- $TTD^{\ Region}$: Average truck travel distance per unit B2C e-commerce shipment assumption by region size

$TGVW_k$ for truck classes used in B2C e-commerce are as shown in Table 16.

Table 16: B2C E-Commerce related Average Gross Vehicle Weight by Truck Class

Truck Class	Average Gross Vehicle Weight (tons/vehicle)
Class 6/7 Urban Delivery	14.8
Class 4/5 Urban Delivery	9.3
Class 3 Walk-in/Delivery	6.0
Class 2b Van	4.0
Other Modes (Passenger Cars, Bike, Trike, Walk, etc.)	2.7

According to a World Bank Report,[1] home delivery routes of e-commerce shipments typically consist of 50 to 150 stops per day, depending on the type of vehicle. $TTD^{\ Region}$ was calculated using an equation and assumptions as follows:

$$TTD\ Region = 30{,}000\ miles\ traveled\ per\ year\ /\ 300\ days\ per\ year\ /\ Stops\ per\ day^{Region}$$

Where:

- $Stops\ per\ day^{Region}$: Number of stops made per day by a truck for B2C e-commerce delivery was assumed to vary by region size: 100 stops for large MSA, 50 for medium size MSA and 25 for rest of the State.

Impact of Macrotrend # 6: Greater Automation of Production and Services on Vehicle Miles Traveled is calculated using the following steps.

Estimate Truck VMT added over base year (2019) by Truck Class for Virginia MSA's and rural areas for future year (2045) for each scenario (low, medium, high).

15. $Truck\ VMT\ Change_k^{Region} = Gross\ Truck\ Tons\ Change_k^{Region} \times (Baseline\ Gross\ Truck\ VMT_k^{Region})\ /\ (Baseline\ Gross\ Truck\ Tons_k^{Region})$

Where:

- $Truck\ VMT\ Change_k^{Region}$: Estimated regional daily truck VMT added over base year (2019) by 2045 for truck type k due to growth in 3D printing
- $Gross\ Truck\ Tons\ Change_k^{Region}$: Output of calculation step 14 for 3.1.6. VTrans Macrotrend #6: Greater Automation of Production and Services
- $Baseline\ Gross\ Truck\ VMT_k^{Region}$: Total gross truck tons (Baseline) for Large and Medium MSAs and Rest of State (Small MSAs + Rural Areas) and Truck Class
- $Baseline\ Gross\ Truck\ Tons_k^{Region}$: Total truck VMT (Baseline) for Large and Medium MSAs and Rest of State (Small MSAs + Rural Areas) and Truck Class

[1] The World Bank, Facilitating Trade and Logistics for E-Commerce: Building Blocks, Challenges and Ways Forward, December 2019. Available at: https://openknowledge.worldbank.org/bitstream/handle/10986/33174/Facilitating-Trade-and-Logistics-for-E-Commerce-Building-Blocks-Challenges-and-Ways-Forward.pdf (last accessed on April 8, 2021)

Table 17: 3D Printing-related Daily Truck VMT Change by Truck Type, 2045

Truck Type	2045 Daily Gross Truck Tons (000s) Change Over Base Year (2019)		
	Low Estimate	Medium Estimate	High Estimate
Class 8 Tractor Long-Haul	-47.1	-363.4	-649.6
Class 8 Tractor Short-Haul	2.8	21.9	39.1
Class 8 Tractor Drayage	-4.8	-37.0	-66.1
Class 6/7 Regional Haul	27.3	211.0	377.3
TOTAL	-21.7	-167.4	-299.3

Table 18: 3D Printing-related Daily Truck VMT Change by Region, 2045

Region	2045 Daily Gross Truck Tons (000s) Change Over Base Year (2019)		
	Low Estimate	Medium Estimate	High Estimate
Charlottesville, VA	-0.2	-1.7	-3.0
Lynchburg, VA	0.0	0.3	0.6
Roanoke, VA	-1.8	-14.3	-25.5
Richmond, VA	-1.3	-9.7	-17.3
Virginia Beach-Norfolk-Newport News, VA-NC	-4.6	-35.9	-64.2
Northern Virginia, VA	-1.0	-7.9	-14.1
Rest of State	-12.7	-98.3	-175.7
TOTAL	-21.7	-167.4	-299.3

For each scenario, estimate the change in truck VMT due production automation including 3D printing.

$MT\_6 = \%\ Truck\ VMT_c \times Truck\ VMT\ Share$

Where:

- *% Truck VMT* is the change in the share of truck VMT incurred due to production automation and 3D printing, as calculated in step 1 for Macrotrend # 6: Greater Automation of Goods and Services.
- *Truck VMT Share* is the 2019 truck daily VMT share as reported by VDOT.
- *c* represents the geographic level being analyzed

Estimate the increase in truck VMT in the future year (2045) due to growth in e-commerce accounting for commercial drone delivery services.

$Truck\ VMT\ Avoided_k^{Region} = Gross\ Truck\ Tons\ Avoided_k^{Region} \times (1 / TGVW_k) \times TTD^{Region}$

Where:

- $Truck\ VMT\ Avoided_k^{Region}$: Estimated regional daily truck VMT avoided by 2045 for Class 2b van due to growth in short-range drone delivery service
- $TGVW_k$: Truck average gross vehicle weight assumption for Class 2b van
- TTD^{Region}: Average truck travel distance per unit short-range drone shipment assumption by region size
- *TGVW* for Class 2b van used in short-range drone suited shipments is assumed as 4.0 tons/vehicle

% VMT = % Truck VMT × Truck VMT Share

Where:

- *% Truck VMT* is the change in the share of truck VMT incurred due to e-commerce after accounting for commercial drone delivery service, as calculated in step 13 above.
- *Truck VMT Share* is the 2019 truck daily VMT share as reported by VDOT.[1]

16. For each scenario, estimate the change in 2045 truck VMT due to greater automation of production and services.
MT_6 = %Δ Truck VMT × Truck VMT Share

Where:

- *%Δ Truck VMT* is the change in the share of truck VMT incurred due to production automation and 3D printing, as calculated in Calculation Step 15 above.
- *Truck VMT Share* is the 2019 truck daily VMT share as reported by VDOT.[2]

Impact of VTrans Macrotrend # 8: Increase in Workplace Flexibility on Vehicle Miles traveled is calculated using the following steps.[3]

17. Calculate number of workers by industry for each county in Virginia.
$\#\ of\ workers_{2045} = \#\ of\ workers_{2018} \times projected\ industry\ growth\ rate$

Where:

- $\#\ of\ workers_{2018}$ is the number of workers at the two-digit NAICS industry level in the base year (2018)[4]
- *projected industry growth rate* is the growth rate by 2-digit NAICS codes[5]

18. Utilize the following formula to calculate WF capacity in the future year (2045).
$WF\ capacity\ count = \sum_{i=industry} \%WF\ Capable\ Jobs_i \times \#of\ workers_i$

Where:

- $\%WF\ Capable\ Jobs_i$ is the share of workplace flexible jobs in industry i,as calculated in Section 3.1.8.

$\times\ \#of\ workers_i$ is the number of workers in industry i, as calculated in Section 3.1.8.

19. Calculate number of home-based commute round trips reduced due to VTrans Macrotrend # 8: Increase in Workplace Flexibility for three scenarios[6,7]: Low (2-days remote work), medium (3.5-days remote work), and high (5-days remote work) in the future year (2045).

[1] Virginia Department of Transportation (2019). Traffic Data Daily Vehicle Miles Traveled. 220 – DVMT by Federal Vehicle Class 2019. Accessed May 25, 2021.

[2] Virginia Department of Transportation (2019). Traffic Data Daily Vehicle Miles Traveled. 220 – DVMT by Federal Vehicle Class 2019. Accessed May 25, 2021.

[3] Assumptions:

- Distribution of commute mode is the same for all North American Industry Classification System (NAICS) occupations.
- Morning peak period average trip length is the same for all trip type (e.g., HBW, HBO, NHB) because it is not split out by mode purpose in available datasets.
- Zero carpooling is assumed.
- The peak AM period is defined as 6AM to 9PM.
- VMT is assigned to the county where the trip ends.
- Discount factor is the percent increase in non-work VMT by telecommuters compared to non-telecommuters with respect to non-telecommuters' daily work VMT from the 2009 NHTS, as reported by Zhu & Mason (2014).

[4] US Census Bureau. Longitudinal Employer-Household Dynamics

[5] Virginia Employment Commission. "Industry Projections." Accessed February 1, 2021.

[6] PricewaterhouseCoopers. "Business Needs a Tighter Strategy for Remote Work." PwC. Accessed January 19, 2021.

[7] Global Workplace Analytics and flexjobs. "2017 State of Telecommuting in the U.S. Employee Workforce," 2017.

20. Convert reduction in home-based commute round trips to VMT reduction in the base year (2019) due to VTrans Macrotrend # 8: Increase in Workplace Flexibility for AM peak hours for each scenario (low, medium, high).
$VMT\ reduction\ rate_c = trip\ ends_c \times \%HBW_c - reductPotential \times \%autoCommute \times \%AM\ Peak_c \times avg\ trip\ length_c \times (1 - discount\ factor) \times 2$

Where:
- *trip ends*$_c$ if the number of vehicle trips per county *c* during the morning peak period[1]
- *%HBW*$_c$ is the percent of trips per county *c* that are home-based work (HBW)[2]
- *reductPotential* is the output of calculation step # 19.
- *%autoCommute* is the share of workers that use private automobile as primary mode to workplaces in Virginia (91.43%).[3]
- *%AM Peak*$_c$ is the percent of StreetLight Data trips per county in peak morning peak period on weekdays (Mon-Thurs in 2019).[4]
- *avg trip length*$_c$ is the average trip length in miles (assigned to destination by county).[5]
- *discount factor* is the percent non-work replacement VMT (discount factor)[6]

21. Calculate annualized VMT reduction using the following formula: VMT reduction was annualized by multiplying by 261 workdays per year. The total can be multiplied by 2 to account for both morning and evening peak periods.
$MT_7 = VMT\ reduction\ rate_c \times Number\ of\ Annual\ Weekdays \times Number\ of\ Daily\ Weekday\ Peak\ Periods$

Where:
- *Annualized VMT reduction*$_c$ is the estimated reduction in VMT over a calendar year for each subgeography *c*
- *VMT reduction rate*$_c$ is the output from calculation step # 20
- *Number of Annual Weekdays* equals 261 weekdays in a calendar year
- *Number of Daily Weekday Peak Periods* is estimated two (morning and afternoon) peak periods on a typical weekday

Calculate the combined effect of the Macrotrends on vehicle miles traveled.

22. Combine the independent effects of each macrotrend on VMT (calculation steps # 7, # 8, # 16, and # 21) by multiplying the independent effects of each macrotrend using the following equation:

$$Total\ Impact_{VMT} = VMT_{start} \times (1 + MT_7) \times (1 + MT_{2\ 3\ 4}) \times (1 + MT_5) \times (1 + MT_6) \times (1 + MT_4)$$

23. Combine the macrotrend effects on Truck VMT (calculation steps #14 and #16) to calculate the truck index using the following equation:

$$Truck\ Index = (1 + \%\Delta VMT_{M-5}) * (1 + \%\Delta VMT_{M-6}) * DVMT_M + (1 + \%\Delta VMT_{H-5}) * (1 + \%\Delta VMT_{H-6}) * DVMT_H / DVMT_M + DVMT_H$$

Where:
- $\%\Delta VMT_{M-5}$: Percent change in medium truck VMT due to growth in E-commerce accounting for commercial drone delivery services, from calculation step # 13
- $\%\Delta VMT_{M-6}$: Percent change in medium truck VMT due to production automation including 3D printing, from calculation step # 15

[1] Streetlight Data
[2] Streetlight Data
[3] Federal Highway Administration 2017 National Household Travel Survey.
[4] Streetlight Data
[5] Streetlight Data
[6] Zhu, P., & Mason, S. G. (2014). The impact of telecommuting on personal vehicle usage and environmental sustainability. *International Journal of Environmental Science and Technology,* 11(8), 2185-2200.

- $\%\Delta VMT_{H-5}$: Percent change in heavy truck VMT due to growth in E-commerce accounting for commercial drone delivery services, from calculation step # 13
- $\%\Delta VMT_{H-6}$: Percent change in heavy truck VMT due to production automation including 3D printing, from calculation step # 15
- $DVMT_M$: Daily VMT of medium trucks
- $DVMT_H$: Daily VMT of heavy trucks

Step 3: Impact of VTrans Macrotrends on CTB Goal A in the Year 2045

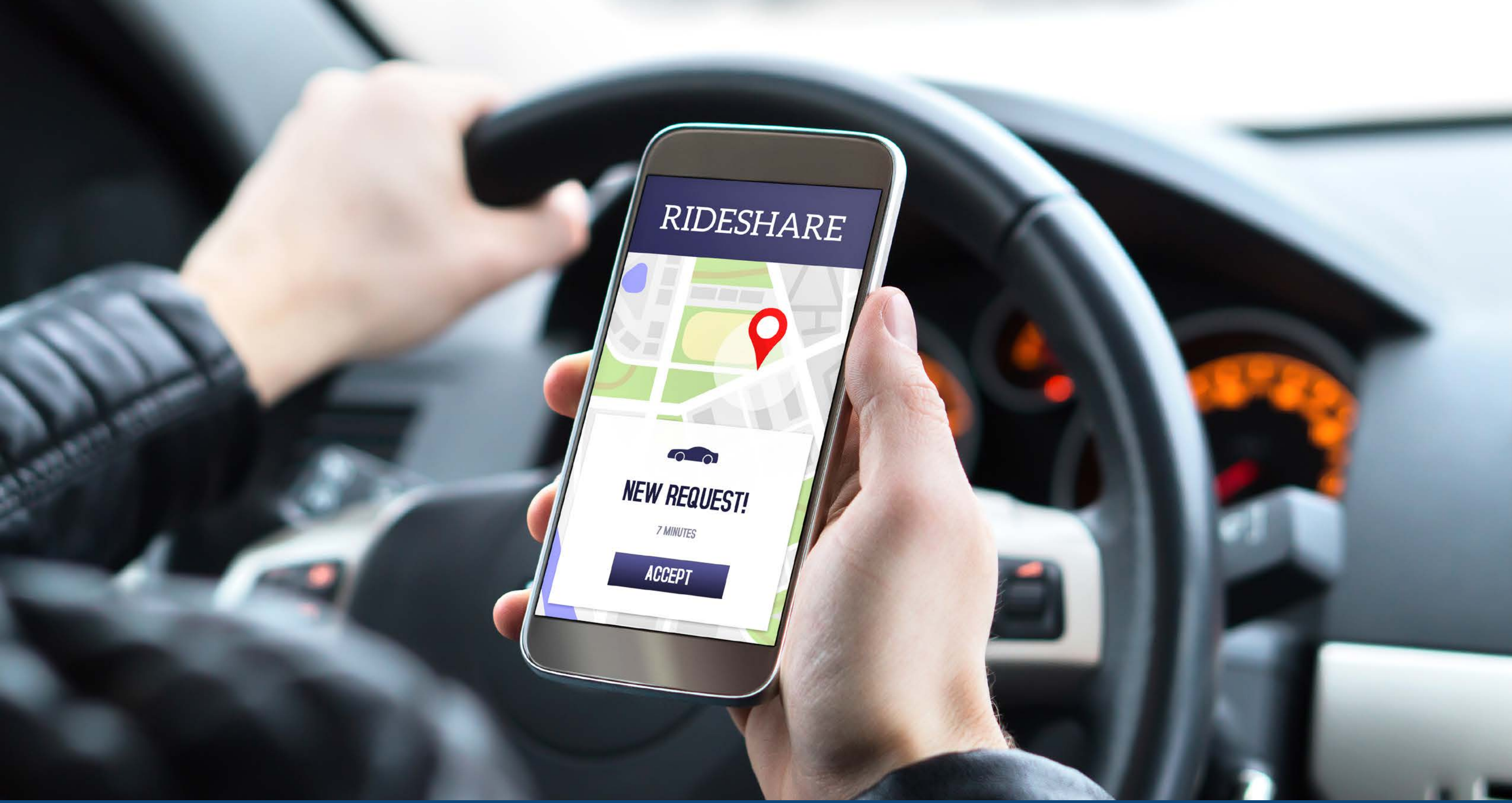
The results of calculation step # 23 are included in Table 19 and should be interpreted as follows:

- **Low-impact Scenario:** Overall number of vehicle miles traveled in Virginia is estimated to increase by 4 percent and the truck VMT is expected to decrease by 0.5 percent compared to the 2045 no-build scenario (absence of VTrans Macrotrends (Step 1)).
- **Medium-impact Scenario:** Overall number of vehicle miles traveled in Virginia is estimated to increase by 8 percent and the truck VMT is expected to decrease by 4 percent compared to the 2045 no-build scenario (absence of VTrans Macrotrends (Step 1)).
- **High-impact Scenario:** Overall number of vehicle miles traveled in Virginia is estimated to increase by 17 percent and the truck VMT is expected to decrease by 7.1 percent compared to the 2045 no-build scenario (absence of VTrans Macrotrends (Step 1)).

Table 19: Estimated Impact of VTrans Macrotrends on CTB Goal A in Year 2045

CTB Goal	Metric for CTB Goal	Low Estimate	Medium Estimate	High Estimate
Goal A: Economic Competitiveness and Prosperity	Vehicle Miles Traveled Index (All)	1.04	1.08	1.17
	Vehicle Miles Traveled Index (Truck Only)	0.995	0.960	0.929

Where 1.0 is 2045 business-as-usual scenario where VTrans Macrotrends have no impacts.



3.3.2. Impact of Step 1 Macrotrends on CTB Goal B Metrics

Description: Share of Urban Area Single-Occupant-Vehicle VMT switchable to shared mobility

Significance: A change in the share of trips switchable to shared mobility can indicate progress toward attaining CTB Goal B: Accessible and Connected Places

Data Sources:

- Percentage of VMT switchable to TNC at the statewide level and the county level[1]
- Percentage of VMT switchable to micromobility at the statewide level and the county level[2]

Calculations:

Calculations to measure change in share of VMT switchable to shared mobility in future year (2045) rely on outputs related to the following macrotrends included in Section 3.1, Step 1. The calculation relative to the baseline is as follows.

1. Calculate the shared mobility index (ridesourcing), which represents the change in share of VMT switchable to ridesourcing compared to no-build scenario, using the following equation.
   *shared mobility index (Ridesourcing) = 1 + a *(% VMT switchable to TNC)*
2. Calculate the shared mobility index (micromobility), which represents the change in share of VMT switchable to micromobility compared to no-build scenario, using the following equation.
   *shared mobility index (Micromobility) = 1 + a * (% VMT switchable to Micromobility)*
3. Calculate the shared mobility index (micromobility), which represents the change in share of VMT switchable to shared mobility compared to no-build scenario, using the following equation.
   *shared mobility index = 1 + a * (% VMT switchable to TNC + % VMT switchable to Micromobility)*

   Where:
   a = 0.5 ➔ low scenario; a = 1 ➔ medium scenario; a = 1.5 ➔ high scenario

[1] See Section 3.4, Step 9 (page 25 of this document)
[2] See Section 3.4, Step 9 (page 25 of this document)

Step 3: Impact of VTrans Macrotrends on CTB Goal B in Year 2045

The results of the change in share of VMT switchable to ridesourcing, micromobility, and shared mobility calculations are included in Table 20. Statewide results should be interpreted as follows:

- Low estimate: The change in share of VMT switchable to ridesourcing, micromobility, and shared mobility are estimated to be 8.98 percent, 0.05 percent, and 9 percent higher than the 2045 no-build scenario, respectively.
- Medium estimate: The change in share of VMT switchable to ridesourcing, micromobility, and shared mobility are estimated to be 17.97 percent, 0.09 percent, and 18 percent higher than the 2045 no-build scenario, respectively.
- High estimate: The change in share of VMT switchable to ridesourcing, micromobility, and shared mobility are estimated to be 26.95 percent, 0.14 percent, and 27 percent higher than the 2045 no-build scenario, respectively.

Table 20: Change in share of VMT switchable to shared mobility

CTB Goal	Metric for CTB Goal	Low Estimate	Medium Estimate	High Estimate
Goal B: Accessible and Connected Places	Shared Mobility Index (Ridesourcing and Micromobility Combined)	1.09	1.18	1.27
	Shared Mobility Index (Ridesourcing Only)	1.0898	1.1797	1.2695
	Shared Mobility Index (Micromobility Only)	1.0005	1.0009	1.0014

Limitations:

Due to the lack of reliable available and applicable research, the method does not account for the following factors.

- Changes in walking, bicycling, carpooling/average vehicle occupancy, or transit usage.
- Shared mobility beyond micromobility and ridesourcing.
- Changes in energy prices.
- Public or private investment into transportation infrastructure or technologies.

3.3.3. Impact of Step 1 Macrotrends on CTB Goal C Metrics

Description: As outlined in Section 3.2, estimated change in number of crashes involving fatalities and serious injuries is used as a metric to assess impact of VTrans Macrotrends on CTB Goal C: Proactive System Management.

Significance: A change in the number of crashes involving fatalities and serious injuries can impact CTB Goal C which has an objective of reducing the number of fatalities and serious injuries.

Data Sources:

- Crash modification factors associated with AV technologies: Li and Kockelman[1]
- Crash statistics for Virginia: VDOT[2]
- Number of fatal and serious injury crashes in Virginia: FHWA[3]
- Adoption of AV technologies between levels 1 and 4: Bansal and Kockelman[4]
- Safety benefit to market penetration of AVs: Marler et al. (2018)[5]

Calculations:

Calculations to measure change in the number of crashes involving fatalities and serious injuries in future year (2045) rely on outputs related to the following macrotrends included in Section 3.1, Step 1. The Macrotrend's impact on safety along with the impact of changing VMT calculated in Section 3.3.1 are estimated in this section under the relevant headers before being combined to derive an overall range of estimates for safety changes.

- Macrotrend # 2: Adoption of Highly Autonomous Vehicles

[1] Li, T., & Kockelman, K. M. (2016, January). Valuing the safety benefits of connected and automated vehicle technologies. In Transportation Research Board 95th Annual Meeting (Vol. 1).

[2] Virginia Department of Transportation (2019). Virginia Crashes.

[3] Federal Highway Administration (2019). State Highway Safety Report (2019) – Virginia.

[4] Bansal, P., & Kockelman, K. M. (2017). Forecasting Americans' long-term adoption of connected and autonomous vehicle technologies. Transportation Research Part A: Policy and Practice, 95, 49-63.

[5] Marler, S., Hofer, B., Sharp, W., & Markt, J. (2018). Interstate 80 Automated Corridor (No. 18-04176).

Impact of Macrotrend # 2: Adoption of Highly Autonomous Vehicles Number of Crashes Involving Fatalities and Serious Injuries is calculated using the following steps:

1. Utilize estimated market penetration[1] of automation (Vehicle Automation Levels 1 through 4) for "low impact", "medium impact", and "high impact" scenarios for 2045 VTrans Macrotrend # 2: Adoption of Highly Autonomous Vehicles.

2. Utilize Table 2 in Li and Kockleman[3] to establish a crosswalk between vehicle automation features (e.g. Forward Collision Warning or FCW) and vehicle collision type (e.g. rear end).

3. Create three different scenarios based on three different mixes of vehicle automation. Utilize market penetration of Level 4 vehicles (Table 21) to estimate the remaining penetration with Levels 1 and 2, keeping overall automation at 90 percent.

Table 21: Scaled Market Penetration of Highly Automated Vehicles by Vehicle Automation Levels

	Low Estimate[4]	Medium Estimate[5]	High Estimate[6]
Assumed Market Penetration of Vehicles with Level 1 through 4 technologies[7]	90%	90%	90%
Level 4 (calculation step # 1, Table 3)	25%	45%	87%
Remaining Vehicles with Levels 1 and 2 Technologies only	65%	45%	3%

4. Utilize the crash modification factors (CMFs) reported in Li and Kockleman[8] using the KABCO Scale to derive crash modification factors by scenario (Table 22).

[1] Assumption: The maximum market share is taken rather than the sum because many vehicles are expected to be equipped with multiple automation technologies.

[2] Bansal, P., & Kockelman, K. M. (2017). Forecasting Americans' long-term adoption of connected and autonomous vehicle technologies. Transportation Research Part A: Policy and Practice, 95, 49-63.

[3] Li, T., & Kockelman, K. M. (2016, January). Valuing the safety benefits of connected and automated vehicle technologies. In Transportation Research Board 95th Annual Meeting (Vol. 1).

[4] Corresponds to "conservative" scenario (More ADAS and less ADS in fleet) in Li and Kockleman. The split across vehicle automation levels is assumed to account for more ADAS and less ADS such that the total total market share of vehicles with some level of automation is at 90%, consistent with Li and Kockelman.

[5] Corresponds to "moderate" scenario (Middle of road ADAS and ADS in fleet) in Li and Kockleman. The equal distribution of across ADAS and ADS such that the total total market share of vehicles with some level of automation is at 90%, consistent with Li and Kockelman.

[6] Corresponds to" aggressive" scenario (More ADS than ADAS in fleet) in Li and Kockleman. The split across vehicle automation levels is assumed to account for less ADAS and almost entirety with ADS such that the total total market share of vehicles with some level of automation is at 90%, consistent with Li and Kockelman.

[7] Li, T., and Kockelan, K,., *Valuing the Safety Benefits for Connected and Automated Vehicle Technologies*, In Transportation Research Board 95th Annual Meeting (Vol. 1).

[8] Li, T., and Kockelan, K,., *Valuing the Safety Benefits for Connected and Automated Vehicle Technologies*, In Transportation Research Board 95th Annual Meeting (Vol. 1).

Table 22: Crash Modification Factors due to Vehicle Automation

Crash Severity	Crash Modification Factors by Scenario		
	Low Estimate	Medium Estimate	High Estimate
Fatal Injury – K	45%	51%	63%
Severe Injury – A	56%	62%	74%
Visible Injury – B	70%	74%	84%
Non Visible Injury – C	79%	81%	87%
Property Damage Only – O	81%	83%	87%

5. Utilize crash modification factors (CMF) from Table 3 in Li and Kockelman[1] to calculate expected number of crashes using the following formula:
   $EC_s^c = RC_s^c \times CMF$

   Where:
   - EC_s^c is the number of expected crashes by collision type c[2] and severity type s[3] from Calculation Step # 4
   - RC_s^c is the number of reported VDOT crashes by collision type c and severity s in 2019
   - *CMF* is the crash modification factor by scenario

6. Calculate number of expected crashes by collision severity using the following formula:
   $EC^s = \sum_{(c=1)}^{C} EC_s^c$

   Where:
   - EC^s is the expected number of crashes summed across the severity types
   - EC_s^c is the expected number of crashes by collision type c and severity type s

7. Calculate crash reduction rate for the three scenarios (low, medium, high) using the formula below:
   $\text{Crash Reduction Rate}^s = EC^s / RC^s$

   Where:
   - EC^s is the expected number of crashes summed across the severity type *s*
   - *Crash Reduction Rate*^{s} is the crash reduction rate by collision severity type *s*
   - *RC* is reported VDOT crashes by severity type *s*

8. Assuming a linear relation of safety benefit to the market penetration of AVs from Marler et al,[4] estimate crash reduction by crash severity based on AV market penetration in Table 23 and the expected crash reduction rate in step #5.

[1] Li, T., & Kockelman, K. M. (2016, January). Valuing the safety benefits of connected and automated vehicle technologies. In Transportation Research Board 95th Annual Meeting (Vol. 1).

[2] Table 2 in Li, T., and Kockelman, K,., *Valuing the Safety Benefits for Connected and Automated Vehicle Technologies*, In Transportation Research Board 95th Annual Meeting (Vol. 1).

[3] KABCO Scale

[4] Marler, S., Hofer, B., Sharp, W., & Markt, J. (2018). *Interstate 80 Automated Corridor* (No. 18-04176).

9. Interpolate crash reductions corresponding with the low, medium, and high estimates of AV market penetration.

   potential crash rate reduction = lower crash red + (upper crash red – lower crash red/upper market pen – lower market pen) × (market pen – lower market pen)

   Where:
   - *lower crash red* and *upper crash red* are respectively the lower and upper crash rate reductions between which the actual crash reduction is being interpolated.
   - *lower market pen* and *upper market pen* are respectively the lower and upper market penetrations corresponding with the lower and upper crash reductions.
   - *market pen* is the AV market penetration for which the potential crash reduction is being interpolated.

Table 23: Potential Crash Rate Reductions by AV Market Penetration

Crash Rate Reduction	Low Estimate	Medium Estimate	High Estimate
Fatal Injury - K	23%	38%	62%
Severe Injury - A	29%	43%	73%
Moderate Injury - B	36%	56%	83%
Minor Injury - C	41%	62%	85%
Property Damage Only - O	42%	63%	86%

Estimate the impact of change in vehicle miles traveled (2045) derived from Section 3.3.1 on safety

10. Account for ΔVMT (2045). Estimated crashes compared with baseline are calculated for each 'KABCO' crash severity level and the low, medium, and high scenarios by multiplying the forecasted "low," "medium," and "high" VMT growth from Section 3.3.1 by the potential crash rate reductions, as shown in the equation below. For crash types other than K and A, crashes compared with baseline are considered the safety index.

    crashes compared to baseline = Safety Index =ΔVMT × (1 – potential crash rate reductions)

    $Safety\ index_s = \Delta VMT * (1 - potential\ crash\ reductions_s)$

    Where:
    - *Safety index*$_s$ is the safety index for crash type (s)
    - *ΔVMT* is the change in VMT calculated for the low, medium, and high scenarios in Section 3.3.1 calculation step # 22 and shown in Table 24.
    - *potential crash rate reductions* is the estimate for the change in crash rate shown in the calculation step # 9, Table 25.

Table 24: VMT Increases Compared to Baseline by Scenario

Low Estimate	Medium Estimate	High Estimate
4%	8%	17%

Table 25: Crashes Compared to Baseline by Scenario

Crashes	Low Estimate	Medium Estimate	High Estimate
Fatal Injury - K	80%	66%	44%
Severe Injury - A	74%	62%	31%
Visible Injury - B	66%	47%	20%
Non Visible Injury - C	62%	41%	17%
Property Damage Only - O	60%	40%	16%

11. For fatal and serious injury crashes, the combined safety index is calculated by creating a weighted safety index based on the proportional split in Virginia between K and A crashes using 2019 5-year average crash counts.[1] For the statewide analysis, this translates to the following weights: 9.4 percent (K) and 90.6 percent (A).

$$\Delta SafetyIndex\ (2045) = K\ crashes \times (K\ counts)/(K\ counts + A\ counts) + A\ crashes \times (A\ counts)/(K\ counts + A\ counts)$$

Where:

- *K crashes* is the estimated fatal crashes compared with baseline shown in the table above ("crashes compared to baseline" from calculation step # 10).
- *A crashes* is the estimated serious injury crashes compared with baseline shown in the table above ("crashes compared to baseline" from calculation step # 10).
- *K counts* is the 2019 5-year fatal injury crash count in Virginia.[2]
- *A counts* is the 2019 5-year serious injury crash count in Virginia.[3]

Step 3: Impact of VTrans Macrotrends on CTB Goal C in the Year 2045

The results of calculation step # 11 for the statewide analysis are included in Table 26 and should be interpreted as follows:

- **Low-impact Scenario:** Number of crashes involving fatalities and serious injuries is estimated to decrease by 26 percent over the 2045 no-build scenario (absence of VTrans Macrotrends (Step 1))
- **Medium-impact Scenario:** Number of crashes involving fatalities and serious injuries is estimated to decrease by 38 percent over the 2045 no-build scenario (absence of VTrans Macrotrends (Step 1))
- **High-impact scenario:** Number of crashes involving fatalities and serious injuries is estimated to decrease by 67 percent over the 2045 no-build scenario (absence of VTrans Macrotrends (Step 1))

Table 26: Estimated Impact of VTrans Macrotrends on CTB Goal C in Year 2045

CTB Goal	Metrics for CTB Goal	Low Estimate	Medium Estimate	High Estimate
Goal C: Safety for All Users	Safety Index$_{K+A}$ (Estimated Change in Number of Crashes with Fatalities + Serious Injuries Due to VTrans Macrotrends)	0.74	0.62	0.33
	Safety Index$_{B}$ (Estimated Change in Number of Crashes with Visible Injuries Due to VTrans Macrotrends)	0.66	0.47	0.20
	Safety Index$_{C}$ (Estimated Change in Number of Crashes with Non Visible Injuries Due to VTrans Macrotrends)	0.62	0.41	0.17
	Safety Index$_{O}$ (Estimated Change in Number of Property Damage Only Crashes Due to VTrans Macrotrends)	0.60	0.40	0.16

Where 1.0 is 2045 business-as-usual scenario where VTrans Macrotrends have no impact.

[1] Federal Highway Administration (2019). State Highway Safety Report (2019) – Virginia. Accessed June 24, 2021.
[2] Federal Highway Administration (2019). State Highway Safety Report (2019) – Virginia. Accessed June 24, 2021.
[3] Federal Highway Administration (2019). State Highway Safety Report (2019) – Virginia. Accessed June 24, 2021.

Limitations and Opportunities for Continuous Improvement

There are several known and unknown uncertainties as well as limitations of the method described above. Some of the known uncertainties and limitations include:

- Uncertainties around baseline assumptions not captured since the outputs are over the 2045 no-build scenario which assume absence of VTrans Macrotrends. Therefore, this method does not capture the impacts of ongoing education and awareness campaigns and physical infrastructure improvements.
- Statewide perspective conceals localized performance impacts. For example, market penetration of vehicle automation level 4 technologies could be unevenly distributed across Virginia likely resulting in uneven realization in the safety benefits.
- Effects of alternative population growth and migration patterns that impact VMT and therefore safety estimations are not considered.
- Change in pedestrian or bicycle exposure to collisions is not considered. For example, propensity to walk and bike, among other factors, could change exposure of pedestrians and bicyclists.
- Future changes in vehicle composition (size, speed, acceleration, deceleration characteristics) are not considered.
- This method does not account for mode shift or differentiation of relative VMT change of personal and commercial vehicles.

3.3.4. Impact of Step 1 Macrotrends on CTB Goal D Metrics

Description: For the purposes of calculations, this is defined as increase in flooding risk due to: (1) sea level rise; (2) storm surge; and, (3) inland and riverine flooding.

Data Sources:

Table 27: Data Sources by Scenario for Estimating Risk from Flooding Events

Hazard	Data Source of Estimated Hazard	Low Scenario	Medium Scenario	High Scenario
Sea Level Rise	Virginia Institute of Marine Sciences (VIMS)	Intermediate sea level rise scenario (Year 2040)	Intermediate-High sea level rise scenario (Year 2040)	Extreme sea level rise scenario (Year 2040)
Storm Surge	National Hurricane Center (NHC)	Category 2 hurricane storm surge	Category 3 hurricane storm surge	Category 4 hurricane storm surge
Inland/Riverine Flooding[1]	Federal Emergency Management Agency (FEMA) VDOT	100-year flood zone AND Historical Weather-Related Damages or Closures	500-yr flood zone AND Historical Weather-Related Damages or Closures	FEMA 500-yr flood zone with varying width buffer (10-200ft) based on floodplain width AND Historical Weather-Related Damages or Closures (Appendix 2)

[1] Please refer to Appendix 3 for the creation of the Extreme Inland/Riverine Flooding Scenario.

Source of Methodology: The methodology is based on Federal Highway Administration's FHWA Vulnerability Assessment Scoring Tool (VAST) for each of the three scenarios. This approach uses data on asset location and other key attributes as indicators of each of the three components of vulnerability: (1) Exposure; (2) Sensitivity; and, (3) Adaptive Capacity.

- **Exposure:** whether the asset or system is located in an area experiencing direct effects of climate variables. For example, a road that could experience flooding and inundation due to its location in a low-lying area. The nature and degree to which an asset is exposed to significant climate variations (i.e., asset location relative to a stressor).
- **Sensitivity:** how the asset or system fares when exposed to a climate variable. For example, a tunnel could be more sensitive to flooding due to challenges removing water. (i.e., if all assets were equally exposed, which assets would experience the greatest damage?).
- **Adaptive capacity:** the asset or system's ability to adjust to or cope with existing climate variability or future climate impacts. For example, redundant or alternative routes that could be used to reach the same location would increase adaptive capacity compared to a route that is the only source of access. The ability of a system or asset to adjust to the impacts of climate change to moderate potential damages, to take advantage of opportunities, or to cope with consequences.

Calculations: The VTrans Vulnerability Assessment uses a point-based system to determine an asset's level of vulnerability. Similar to FHWA's VAST tool, the VTrans Vulnerability Assessment relies on an indicator-based approach. Indicators are representative elements such as location, existing flood protection, and projected climate stressors that can be used as proxy measurements for the exposure, sensitivity, or adaptive capacity of a specific asset. Indicators within each of the three main component categories (Exposure, Sensitivity, and Adaptive Capacity) were weighted within their respective category. Then each of the three main components are also given a weighting.

Two sets of indicators were developed - one for roadways and one for structures because: (a) structures, as an asset type, have different characteristics and therefore different sensitivity; and, (2) generally, more precise and complete datasets are available for structures. Tables 28 and 29 list component and indicator weights for roadway segments and structures, respectively. If an asset is exposed to inundation, a three-point score is developed for each indicator which is then weighted and summed per the weighting in Tables 28 and 29 to calculate a vulnerability score for each asset by hazard type.

Step 3: Impact of VTrans Macrotrends on CTB Goal C in Year 2045

Table 28: Estimated Impact of VTrans Macrotrends on CTB Goal D in Year 2045[1]

CTB Goal	Metric for CTB Goal	Low Estimate	Medium Estimate	High Estimate
Goal D: Proactive System Management	Number of Directional Miles at Risk from Flooding (in miles) by Hazard	SLR - 935 SS - 7,706 IRF - 17,475	SLR - 1,101 SS - 13,095 IRF - 17,829	SLR - 1,424 SS - 17,092 IRF - 18,250

[1] SLR: Sea level rise; SS: Storm surge; IRF: Inland and riverine flooding

Table 29: Component and Indicator Weightings for Roadway Segments

Component	Component Weight	Indicator	Indicator Weight by Hazard Type		
			Sea Level Rise	Storm Surge	Inland/Riverine Flooding
Exposure	40%	Inundation from Sea Level Rise OR Storm Surge OR Inland/Riverine Flooding	100.0%	100.0%	100.0%
Sensitivity[1]	20%	Pavement Condition	5.0%	5.0%	5.0%
		Pavement Type	10.0%	10.0%	10.0%
		Historical Weather-Related Damages or Closures	85.0%	85.0%	85.0%
Adaptive Capacity[1]	40%	Functional Class	10.0%	10.0%	10.0%
		Hurricane Evacuation Route	15.0%	50.0%	0.0%
		Annual Average Daily Traffic (AADT)	20.0%	20.0%	20.0%
		Corridors of Statewide Significance (CoSS)	55.0%	20.0%	70.0%
Vulnerability Score	100%				

Table 30: Component and Indicator Weightings for Structures

Component	Component Weight	Indicator	Indicator Weight by Hazard Type		
			Sea Level Rise	Storm Surge	Inland/Riverine Flooding
Exposure	40%	If Exposure to Sea Level Rise	100.0%	100.0%	100.0%
Sensitivity[1]	20%	*If Bridge:*			
		–Deck Rating	2.5%	2.5%	2.5%
		–Superstructure Rating	2.5%	2.5%	2.5%
		–Substructure Rating	5.0%	5.0%	5.0%
		If Culvert:			
		–Culvert Rating	10.0%	10.0%	10.0%
		Scour Criticality	20.0%	20.0%	35.0%
		Channel and Channel Protection	0.0%	10.0%	15.0%
		Waterway Adequacy	50.0%	40.0%	20.0%
		Historical Weather-Related Damages or Closures	20.0%	20.0%	20.0%
Adaptive Capacity[1]	40%	Hurricane Evacuation Route	15.0%	50.0%	0.0%
		Navigable Waterway	25.0%	10.0%	0.0%
		Importance Factor	60.0%	40.0%	100.0%
Vulnerability Score[1]	100%				

[1] Scores for Sensitivity, Adaptive Capacity, and Vulnerability are only developed if Exposure component indicates risk of inundation.

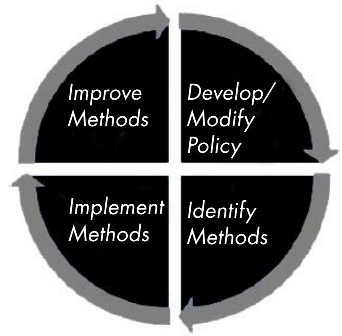
Table 31: Miles at Risk of Flooding by VDOT District and Planning District Commission

	Inland-Riverine Flooding (Roadway Segment Miles affected)			Storm Surge (Roadway Segment Miles affected)			Sea Level Rise (Roadway Segment Miles affected)		
	Low	Medium	High	Low	Medium	High	Low	Medium	High
STATEWIDE									
Total	17,474	17,829	18,250	7,706	13,094	17,091	935	1,100	1,423
VDOT CONSTRUCTION DISTRICTS									
Bristol	2,966	3,049	3,165	-	-	-	-	-	-
Culpeper	1,314	1,320	1,344	-	-	-	-	-	-
Fredericksburg	1,260	1,291	1,332	2,056	2,790	3,326	270	329	471
Hampton Roads	1,270	1,343	1,376	5,386	9,763	12,945	617	723	887
Lynchburg	3,377	3,400	3,477	-	-	-	-	-	-
Northern Virginia	616	635	656	82	144	260	12	12	14
Richmond	2,415	2,442	2,473	177	393	552	37	37	52
Salem	2,771	2,837	2,896	-	-	-	-	-	-
Staunton	1,485	1,511	1,532	-	-	-	-	-	-
PLANNING DISTRICT COMMISSIONS									
Accomack-Northampton	151	181	183	1,276	1,540	1,771	197	266	368
Central Shenandoah	597	615	618	-	-	-	-	-	-
Central Virginia	1,237	1,258	1,285	-	-	-	-	-	-
Commonwealth Regional Council	1,304	1,306	1,331	-	-	-	-	-	-
Crater	901	906	920	96	167	213	18	18	19
Cumberland Plateau	795	820	840	-	-	-	-	-	-
George Washington	606	609	630	47	85	149	4	6	12
Hampton Roads	641	682	700	4,050	8,141	11,082	407	444	505
Lenowisco	801	842	895	-	-	-	-	-	-
Middle Peninsula	408	426	440	1,338	1,601	1,780	191	238	330
Mount Rogers	1,549	1,565	1,611	-	-	-	-	-	-
New River Valley	783	813	831	-	-	-	-	-	-
Northern Neck	246	257	262	671	1,104	1,397	75	84	129
Northern Shenandoah	799	806	816	-	-	-	-	-	-
Northern Virginia	616	635	656	82	144	260	12	12	14
Rappahannock-Rapidan	839	839	850	-	-	-	-	-	-
Richmond Regional	921	944	958	142	306	431	32	32	45
Roanoke Valley-Alleghany	599	615	629	-	-	-	-	-	-
Southside	1,010	1,012	1,026	-	-	-	-	-	-
Thomas Jefferson	861	868	891	-	-	-	-	-	-
West Piedmont	1,811	1,831	1,878	-	-	-	-	-	-

Limitations and Opportunities for Continuous Improvement

The execution of the methodology outlined in this technical memorandum relies on data and computations to ensure transparent, data-driven, and replicable methods. The following should be noted:

Figure 4: Opportunities for Continuous Improvement



- **Data:** The execution relies on data from state and national sources. Each of these sources relies on various methods, techniques, and technologies to develop its datasets and, therefore, has its own limitations such as:
  - Lack of readily usable data: There are instances in which the current completeness and accuracy of datasets makes it unsuitable used to execute the methodology outlined in this technical memorandum. For example, more information on roadway horizontal and vertical geometry will significantly improve quality and accuracy of the vulnerability assessment results. Similarly, availability of alternative routes will help provide more relevant data to determine the Adaptive Capacity of a facility (more details in Section 2) and thereby improve accuracy of the VTrans Vulnerability Assessment. Therefore, application of transportation planning or engineering judgment is recommended prior to developing solutions.
  - Scope of the task: The availability of data largely governed the scope of the task. For example, more precise information on transit and rail assets can help make the VTrans Vulnerability Assessment more multimodal in nature.
- **Computations:** The sheer size and magnitude of the effort relies on complex computations to perform an analysis on more than one million roadway segments. The effort requires synthesis, format conversions, and computations, such as in the following examples, that could result in inadvertent errors.
  - Units: Different data sources have different units. Some datasets are available by directional segment, whereas other datasets are available at the area or sub-area level.
  - Levels of aggregations: Some datasets are more aggregated than others. For example, historical weather data are available as point data and were aggregated and assigned to roadway segments (See Appendix 2).
  - Frequency of data collection: Some datasets are collected in real time, whereas other datasets are updated once per year or even less frequently.
  - Frequency of data reporting: In addition to the variations in data collection schedule, some datasets are reported in real time, where other datasets are reported once a year.
  - Data formats: Transportation assets are currently available in vector formats primarily as line or points features where weather related datasets are primarily in raster formats. One of the significant limitations of vector formats is that they are not ideal for data on continuous scales such as those available for weather, precipitation, etc. This limitation results in less accuracy (refer to Appendix 4) and should be a higher priority for any future work.

The Statewide Transportation Planning Team at OIPI sees these considerations as opportunities for continuous improvement. Methods and techniques outlined in this memorandum can continue to evolve and improve based on advances in technology, data quality, data collection, and reporting tools.

3.3.5. Impact of Step 1 Macrotrends on CTB Goal E Metrics

Description: As outlined in Section 3.2, estimated change in tailpipe emissions for the future year (2045) is used as the metric to assess the impact of the VTrans Macrotrends (outlined in Section 3.1) on CTB Goal E: Healthy Communities and Sustainable Transportation Communities.

Significance: Tailpipe emissions can impact CTB Goal E.[1]

Data Sources:

- Long-term VMT forecasts: Federal Highway Administration[2]
- VMT in Virginia in 2019 by functional system: Federal Highway Administration[3]
- VMT in Virginia in 2019 by vehicle type: VDOT[4]
- Forecasted shares of vehicles in 2045 by energy source: Section 3.1.3, VTrans Macrotrend # 3: Adoption of Electric Vehicles
- Impact on CO2e emissions due to electrification of transportation: Section 3.1.3, VTrans Macrotrend # 3: Adoption of Electric Vehicles
- Real-world fuel economy: EPA[5]

[1] U.S. Environmental Protection Agency (2020). Smog, Soot, and Other Air Pollution from Transportation. Last updated November 20, 2020. Accessed June 10, 2021.

[2] Federal Highway Administration (2020). FHWA Forecasts of Vehicle Miles Traveled (VMT): Spring 2020.

[3] Federal Highway Administration (2020). "Functional System Travel – 2019 Annual Vehicle-Miles." Highway Statistics 2019.

[4] Virginia Department of Transportation (2019). Daily Vehicle Miles Traveled (DVMT) by FHWA Vehicle Class. VDOT Report ID – VMT 2020.

[5] U.S. Environmental Protection Agency (2019). "Table 2.1. Production, Estimated Real-World CO2, and Fuel Economy for Model Year 1975–2019." 2019 EPA Automotive Trends Report.

- Emissions tonnage by vehicle weight class: EPA[1]
- Change in emissions due to electrification: Energy Innovations[2]
- Change in truck VMT due to e-commerce: Section 3.1.5., VTrans Macrotrend #5: Growth in E-commerce
- Change in truck VMT due to automation: Section 3.1.6., VTrans Macrotrend #6: Greater Automation of Goods and Services

Calculations:

These calculations rely on research conducted for Step 1. The following six (6) macrotrends are expected to influence Tailpipe Emissions. The Macrotrends' impact on tailpipe emissions is estimated under the relevant headers before being combined to derive a cumulative range of estimates for tailpipe emissions.

- Macrotrend # 2: Adoption of Highly Autonomous Vehicles
- Macrotrend # 3: Adoption of Electric Vehicles
- Macrotrend # 4: Growth in Shared Mobility
- Macrotrend # 5: Growth in E-commerce
- Macrotrend # 6: Greater Automation of Automation and Services
- Macrotrend # 8: Increase in Workplace Flexibility

The combined impacts of Macrotrend # 2: Adoption of Highly Autonomous Vehicles (AV), Macrotrend # 3: Adoption of Electric Vehicles, Macrotrend # 4: Growth in Shared Mobility (Micromobility only) on Tailpipe Emissions is calculated using the following steps:

1. Utilize light vehicles VMT increase estimates calculated in calculation step # 7 from Section 3.3.1.

Impact of Macrotrend # 4: Growth in Shared Mobility is calculated using the following steps:

2. Utilize calculation step output to obtain the reduction in VMT due to switching light vehicle trips to micromobility. The following equation is used for each scenario to account for the change in the light vehicle VMT due to shared mobility.
   Δlight vehicles = ΔVMT from Shared Mobility × 2019 DVMT all classes/2019 DVMT light

   Where:
   - *ΔVMT from Shared Mobility* is the percentage change in all VMT due to growth in shared mobility. This accounts for micromobility only since ridesourcing is not expected to reduce the number of automobile miles. Micromobiilty is assumed to be emissions-free.
   - 2019 *DVMT all classes* is the daily VMT in 2019 from all vehicle classes in Virginia. This is used to scale the change in VMT to make it account for light vehicles only.[3]
   - 2019 *DVMT light* is the daily VMT in 2019 from motorcycles, passenger cars, and two-axle 4-tire single unit vehicles.[4]

Impact of Macrotrend # 5: Growth in E-Commerce on Tailpipe Emissions is calculated using the following steps:

3. Utilize calculation step # 13 output from Section 3.3.1 to estimate light vehicle VMT avoided due to e-commerce,
4. Utilize calculation step # 14 output from Section 3.3.1 to estimate the increase in medium and heavy trucks VMT in the future year 2045 due to growth in e-commerce.

[1] U.S. Environmental Protection Agency (2017). National Emissions Inventory Data - Virginia.

[2] Energy Innovations (n.d.). Virginia Energy Policy Simulator (EPS) Summary Documentation.

[3] Virginia Department of Transportation (2019). Daily Vehicle Miles Traveled (DVMT) by FHWA Vehicle Class. Series 220 – DVMT by Federal Vehicle Class. Last updated May 13, 2020.

[4] Virginia Department of Transportation (2019). Daily Vehicle Miles Traveled (DVMT) by FHWA Vehicle Class. Series 220 – DVMT by Federal Vehicle Class. Last updated May 13, 2020.

Impact of Macrotrend # 6: Greater Automation of Production and Services on Tailpipe Emissions is calculated using the following steps:

5. Utilize calculation step # 16 output from Section 3.3.1 to calculate the change in medium and heavy vehicles VMT due to greater production automation and 3D printing.

Impact of Macrotrend # 8: Increase in Workplace Flexibility on Tailpipe Emissions is calculated using the following steps:

6. Utilize estimated reduction in light vehicles VMT due to VTrans Macrotrend # 8: Increase in Workplace Flexibility calculated in calculation step # 20 from section 3.3.1

Estimate the cumulative impacts of the previous Macrotrends:

7. Combine the independent effects of each macrotrends' effect on that vehicle class's VMT using the following equation for the "low," "medium," and "high" scenarios for different vehicle weight classes.
   $\textit{combined effect} = \prod_{m \in M} (1 + \textit{effect on } VMT_m)$

   Where:
   - *m* is a Macrotrend out of all applicable macrotrends *M*.
   - *effect on* VMT_m is the percentage change in that vehicle class's VMT that is expected due to macrotrend *m*.
   - $\prod_{m \in M}$ refers to the product operator, meaning that it multiplies the sequence of Macrotrends *m* out of all relevant Macrotrends *M*.

Table 32: Cumulative Net Impact of Macrotrends on VMT Relevant for Tailpipe Emissions by Vehicle Weight Class

Macrotrend #	Light-duty Vehicle			Medium-duty Vehicle			Heavy-duty Vehicle		
	Low Impact	Medium Impact	High Impact	Low Impact	Medium Impact	High Impact	Low Impact	Medium Impact	High Impact
Adoption of Highly Autonomous Vehicles Adoption of Electric Vehicles	5.6%	10.5%	21.7%						
Growth in Shared Mobility	0.0%	-0.1%	-0.2%						
Growth in E-commerce	-0.1%	-0.3%	-0.4%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Greater Automation of Automation and Services				0.0%	0.1%	0.2%	-0.7%	-5.7%	-10.2%
Increase in Workplace Flexibility	-1.3%	-2.3%	-3.2%						
Net Impact of Macrotrends	4.0%	7.6%	17.1%	0%	0.1%	0.2%	-0.7%	-5.7%	-10.2%

[1] Assumption: Annual emissions tonnage is not available therefore an average of heavy-duty and light-duty vehicles emission tonnage is utilized.

8. Calculate tons per mile by converting annual emission tonnage to daily emission tonnage and dividing by daily VMT called "Per VMT" in Table 33.

Table 33: Emissions by Vehicle Weight Class

Vehicle type	Emission tonnage		
	Annual	Daily	Per VMT
Heavy-duty Vehicles	9,123,663	24,996	0.002355
Medium-duty Vehicles[1]	Not available	Not available	0.001412
Light-duty Vehicles	37,366,768	102,375	0.000468

9. Calculate internal combustion engine (ICE) emissions reduction estimated reduction in tailpipe emissions due to improvements ICE vehicles' fuel efficiency or between 2017 (which is the year for which emissions tons per mile were calculated) and 2045. Data for fuel efficiency is from the Environmental Protection Agency's (EPA) real-world fuel economy between 1990 and 2019 and extrapolated to 2045 using linear trends. The resulting decrease in fuel consumption (called "ICE emissions reduction") is 13.4 percent.

10. Estimate base year (2019) tailpipe emissions[2] in tons per mile[3] utilizing annual emission tonnage by vehicle weight class.[4]
    Baseline emissions= $\sum_{v\ V} VMT_v \times \textit{tons per mile}_v \times \textit{ICE emissions reduction}$

    Where:
    - VMT_v is annual VMT for vehicle class *v*
    - *v* is a vehicle class out of all vehicle weight classes *V*
    - *tons per mile*$_v$ is the emissions of vehicle class v in tons shown in calculation step # *7.*
    - *ICE emissions reduction* from calculation step # 9

11. Calculate *EV effect* which is the percent of emissions that are expected to be reduced due to VTrans Macrotrend # 3: Adoption of Electric Vehicles (more details regarding this Macrotrend in calculation step # 2 of Section 3.1.3).

12. Calculate *EV share* which is the percentage of vehicles of each vehicle type that are expected to be electric in 2045 in each scenario based on Section 3.1.3, output of calculation step # 1.

13. Estimate the expected emission tonnage of each vehicle type in the low, medium, and high scenarios by multiplying their combined effect by 2019 VMT for that vehicle type, the vehicle type's emissions per mile, and the expected reduction in tailpipe emissions due to adoption of electric vehicles (formula below).
    Expected emissions tonnage = combined effect × tons per mile × VMT × (EV share × (1–EV effect) + (1–EV share) × (1-ICE emissions reduction))

[1] U.S. Environmental Protection Agency (2019). "Table 2.1. Production, Estimated Real-World CO2, and Fuel Economy for Model Year 1975–2019." 2019 EPA Automotive Trends Report.

[2] Note: The following emissions types are included: Criteria and/or Hazardous Air Pollutant: NH3, CO, NOX, PM2.5 and PM10, SO2, VOC, CO2, CH4, N2O, SF6

[3] Assumption: VMT shares of light, medium, and heavy vehicles will remain roughly constant through 2045.

[4] U.S. Environmental Protection Agency (2017). *National Emissions Inventory Data - Virginia.*

Where:

- *combined effect* was calculated for each scenario and vehicle type from Table 32 after calculation step # 6.
- *tons per mile* was calculated for each light-, medium-, and heavy-duty vehicles, from calculation step # 7.
- *VMT* was calculated for each vehicle type based on the 2019 VMT by federal vehicle class from VDOT for all Virginia roads.[1]
- *EV effect* (refer to calculation step # 10)
- *EV share* (refer to calculation step # 11)
- ICE emissions reduction is the estimated reduction in ICE vehicles' tailpipe emissions due to improvements in ICE vehicles' fuel efficiency, as calculated in calculation step # 8)

14. Calculate Emissions (%) for each scenario (low, medium, high), which is the net change in tailpipe emissions due to VTrans Macrotrends (Step 1) using the following formula.
    Emissions (%) = 1 – Expected emissions/Baseline Emissions

Where:

- *Baseline emissions are the emissions without the effects of any Macrotrends.*
- *Expected emissions for each scenario are from calculation step # 12.*

Step 3: Impact of VTrans Macrotrends on CTB Goal E

The results of calculation step # 15 for the statewide analysis are included in Table 34 and should be interpreted as follows:

- Low-impact Scenario: Tailpipe emissions are estimated to decrease by 3 percent (equivalent to 1 – 0.97) over the 2045 no-build scenario (absence of VTrans Macrotrends (Step 1)
- Medium-impact Scenario: Tailpipe emissions are estimated to decrease by 17 percent (equivalent to 1 – 0.83) over the 2045 no-build scenario (absence of VTrans Macrotrends (Step 1)
- High-impact scenario: Tailpipe emissions are estimated to decrease by 69 percent (equivalent to 1 – 0.31) over the 2045 no-build scenario (absence of VTrans Macrotrends (Step 1)

Table 34: Estimated Impact of VTrans Macrotrends on CTB Goal E in Year 2045

CTB Goal	Metric for CTB Goal	Low Estimate	Medium Estimate	High Estimate
Goal E: Healthy Communities and Sustainable Transportation Communities	Tailpipe Emissions Index	0.97	0.83	0.31

Where 1.0 is 2045 business-as-usual scenario where VTrans Macrotrends have no impact.

[1] Virginia Department of Transportation (2019). Daily Vehicle Miles Traveled (DVMT) by FHWA Vehicle Class. Series 220 – DVMT by Federal Vehicle Class. Last updated May 13, 2020.

3.4. Step 4: Develop VTrans Long-term Risk & Opportunity Register

Step 4 is utilized to develop the VTrans Long-term Risk & Opportunity Register to allow for systematic and methodical identification of risks[1] and opportunities.[2] The Register documents and highlights areas requiring attention from the Commonwealth and helps organize and communicate the identified risks and opportunities across different agencies and departments to ensure a common direction and strategy to meeting the CTB Goals.

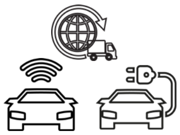
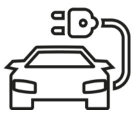
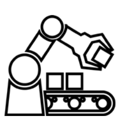
The register takes into account the work completed in Steps 1 through 3, including the order of influence established for the ten macrotrends and the magnitude of impact established in Step 3. Additionally, discussions with OIPI, VDOT and DRPT leadership, and direction from the CTB, guide the creation of the register.

Table 35: VTrans Long-term Risk & Opportunity Register

Macrotrend	Characterization	Description
		1. A large number of the state's roadways are at risk of flooding 2. Several unknown and unquantified flooding risks are present 3. Impacts of increased flooding risk are disproportionately higher for certain geographic areas and populations
		4. Proactively eliminate or mitigate identified flooding risks 5. Increase the state's preparedness to address other macrotrends associated with climate change megatrend

Uncertainty with negative impacts on CTB Goals in Step 3 Uncertainty with a positive impact on CTB Goals in Step 3

[1] The term risk is defined as a situation or scenario wherein there is some uncertainty and at least some probability of a negative outcome or result.
[2] The term opportunity is defined as a situation or scenario wherein there is some uncertainty and at least some probability of a positive outcome or result.

Macrotrend	Characterization	Description
	⚠	6. Greater wear-and-tear on the transportation system due to increased vehicle miles traveled (VMT) and increase in average vehicle weight
	☀	7. Improve the state's ability to manage a transportation system with a high number of highly autonomous vehicles 8. Maximize safety benefits offered by highly autonomous vehicles, especially those with Automated Driving System
	⚠	9. Higher vehicle miles traveled (VMT) for each unit of economic activity compared to the present fleet
	☀	10. Minimize environmental impacts of the transportation system development
	⚠	11. Increased curb access conflicts in urbanized areas
	⚠	12. Projected growth in shared mobility (micromobility and TNC/ridesourcing) does not provide measurable transportation system benefits 13. Benefits of growth in shared mobility are not equally accessible by all areas and population segments
	☀	14. Utilize shared mobility services to improve accessibility 15. Improve the state's ability to manage a transportation system with a high number of shared mobility vehicles
	☀	16. Proactively eliminate or mitigate transportation impacts associated with e-commerce including those related to large warehouse and distribution centers
	☀	17. Improve state's ability to proactively manage transportation impacts associated with greater automation of production and services
	☀	18. Maximize utilization of workplace flexibility for telework capable jobs
	⚠	19. Transportation system and services are unable to meet mobility needs of Virginians age 65 and older

⚠ Uncertainty with negative impacts on CTB Goals in Step 3 ☀ Uncertainty with a positive impact on CTB Goals in Step 3

3.5. Step 5: Track Macrotrends

OIPI shall provide updates to the CTB on the VTrans Mega- and Macrotrends and any changes to items in the 2021 Long-term Risk & Opportunity Register once per calendar year based on a monitoring of the macrotrends and the Trend Trackers identified in Table 36.

Table 36: VTrans Trend Trackers

VTrans Macrotrend	VTrans Trend Trackers	Expected Data Source
1. Increase in Flooding Risk	▪ Number of directional miles at risk from sea level rise ▪ Number of directional miles at risk from storm surge ▪ Number of directional miles at risk from inland/riverine flooding ▪ Annual cost of transportation repair due to flooding events	VTrans Vulnerability Assessment
2. Adoption of Highly Autonomous Vehicles	▪ Market Penetration of Semi-Autonomous (Levels 1 and 2) Vehicles ▪ Attitude and Preferences for Adoption of Semi-Autonomous (Levels 1 and 2) Vehicles[1] ▪ Market Penetration of Highly Autonomous (Levels 3 and 4) Vehicles[1] ▪ Attitude and Preferences for Adoption of Highly Autonomous (Levels 3 and 4)[1] Vehicles	VTrans State of Transportation Biennial Survey
3. Adoption of Electric Vehicles	▪ Number of Electric Vehicles ▪ Market Penetration of Electric Vehicles ▪ Attitude and Preferences for Adoption of Electric Vehicles[1] ▪ Transportation Revenue by Revenue Source	Virginia Department of Motor Vehicles VTrans State of Transportation Biennial Survey
4. Growth in Shared Mobility	▪ Access to Shared Mobility Services[1] ▪ Utilization of Shared Mobility Services by Type[1]	VTrans State of Transportation Biennial Survey
5. Growth in E-Commerce	▪ Number of Warehouse and Distribution Centers ▪ Square Footage of Warehouse and Distribution Centers ▪ Share of E-commerce Sales (Business-to-business, business-to-customers) ▪ Number of Jobs in Goods Movement Dependent Industries	Transearch US Census Quarterly E-Commerce Report US Census Annual Report for Wholesale Trade US Bureau of Labor Statistics State Occupational Employment and Wage Estimates for Virginia
6. Greater Automation of Production and Services	▪ Number of short-range drone deliveries ▪ Number of long-range drone deliveries	

[1] OIPI shall conduct a biennial statistically valid survey to measure these trend trackers.

VTrans Macrotrend	VTrans Trend Trackers	Expected Data Source
7. Growth of Professional Services Industry	▪ Share of Professional Services Industry Jobs ▪ Number of STEM Jobs	IHS Markit, Woods & Poole, Employment Estimates by NAICS 2-digit code
8. Increase in Workplace Flexibility	▪ Number of Workers with Workplace Flexibility[1] ▪ Utilization of Workplace Flexibility[1]	VTrans State of Transportation Biennial Survey Bureau of Labor Statistics, Current Population Survey
9. Growth of the Age 65+ Cohort	▪ Number of Virginians with Age 65 or higher ▪ Share of Age 65+ Cohort	US Census Decennial reports and American Community Survey, Population by Age
10. Population and Employment Shift	▪ VTrans Land Use Vitality (LUV) Index ▪ Population ▪ Employment ▪ Income	Weldon Cooper Center for Public Service, Annual Population Estimates Bureau of Labor Statistics Quarterly Census of Employment and Wages Woods & Poole, Moody's Analytics, Income Estimates

[1] OIPI shall conduct a biennial statistically valid survey to measure these trend trackers.

APPENDIX 1: SEA LEVEL RISE SCENARIOS

The VTrans Vulnerability Assessment makes use of Year 2040 Intermediate, Intermediate High, and Extreme Scenario from NOAA. The sea level rise scenarios and their associated values are included as Figure 1-1 and Table 1-1 .

Figure 1-1: Relative Sea Level Rise Scenarios Curves[1]

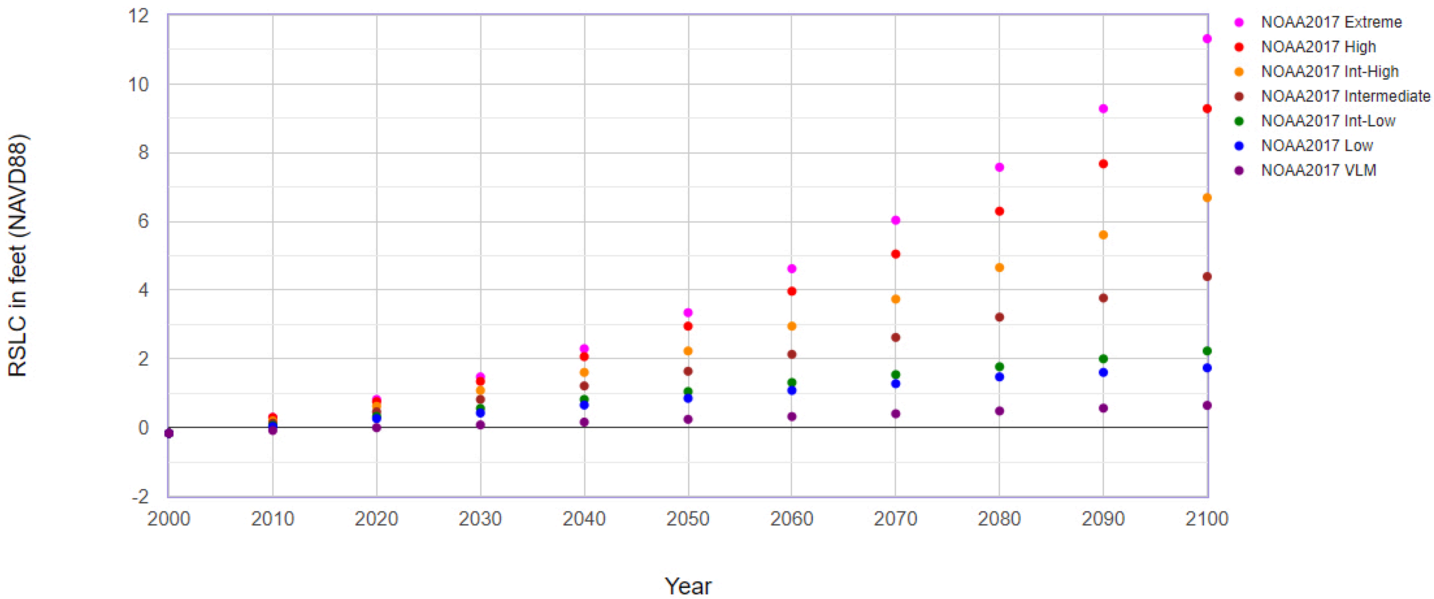


Table 1-1: Relative Sea Level Rise Scenario Values for Global Sea Level Rise[1]

Year	Scenarios for Sewells Point – NOAA 2017 (feet)						
	VLM	Low	Int-Low	Intermed.	Int-High	High	Extreme
2000	-0.17	-0.17	-0.17	-0.17	-0.17	-0.17	-0.17
2010	-0.09	0.03	0.06	0.13	0.19	0.29	0.29
2020	0	0.26	0.33	0.46	0.62	0.75	0.82
2030	0.08	0.42	0.56	0.82	1.08	1.34	1.47
2040	0.16	0.65	0.82	1.21	1.61	2.06	2.29
2050	0.16	0.65	0.82	1.21	1.61	2.06	2.29
2060	0.32	1.08	1.31	2.13	2.95	3.97	4.62
2070	0.4	1.28	1.54	2.62	3.74	5.05	6.03
2080	0.48	1.47	1.77	3.21	4.66	6.3	7.58
2090	0.56	1.61	2	3.77	5.61	7.67	9.28
2100	0.64	1.74	2.23	4.39	6.69	9.28	11.32

[1] USACE's Sea-level Change Curve Calculator (Version 2021.12)

APPENDIX 2: UTILIZING HISTORICAL WEATHER EVENTS FOR INLAND/RIVERINE FLOODING EXPOSURE AND SENSITIVITY

The data for historic weather events was provided by the VDOT Traffic Operations Division via the VaTraffic (Virginia 511) reporting database. The weather data, including both "Traffic Incidents" and "Road Conditions" were queried from the reporting database by the unique identifier "WX_". All spatial points (latitude/longitude) with prefix "WX" were collected for the time period January 2015 to December 2020.

For the purposes of the VTrans Vulnerability Assessment, only "Traffic Incidents" or "Road Conditions" of the 'Event Type' shown below in Table 2-1 were retained for the analysis:

Table 2-1: Utilization of the VDOT Historical Weather Event Dataset

Category	Event Types (from data)
Flooding	'flood', 'Flood', 'Flooded', 'Flooding', 'Flooding / High Water'
High Tide	'Heavy fog & High Tide', 'High Tide', 'High tides', 'High Tides', 'Wind and High Tide', 'Wind and High Tides'
High Water	'High water', 'High Water', 'High Wind and Water'
Hurricane	'Coastal Storm', 'Hurricane', 'Hurricane Earl', 'Hurricane Irene'
Mudslide	'Mud', 'Mud in the road.', 'Mud Slide', 'Mudslide'
Washout	'Washout', 'Bridge Washout', 'Road Wash Out', 'Road washed out', 'Road Washed Out', 'Road Washed out/ pipe collapsed', 'Road Washout', 'Roadway is cracked and washing away', 'Roadway washout', 'wash out', 'Wash out', 'Wash Out', 'Washed out', 'Washed Out', 'Washed out bridge', 'washout', 'Washout'
Standing Water	'Standing water', 'Standing Water', 'Standing Water (Ponding)', 'Standing water and trees down'

The weather data described above was formatted as a GIS point layer. A 400-foot buffer was developed for each point. Any roadway segments that intersect with any portion of a buffer were considered to be exposed to that historic weather-related event.

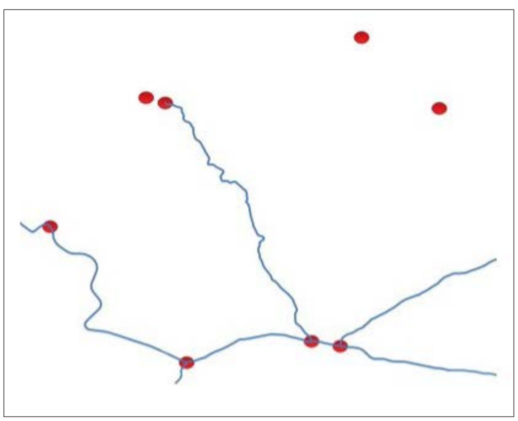
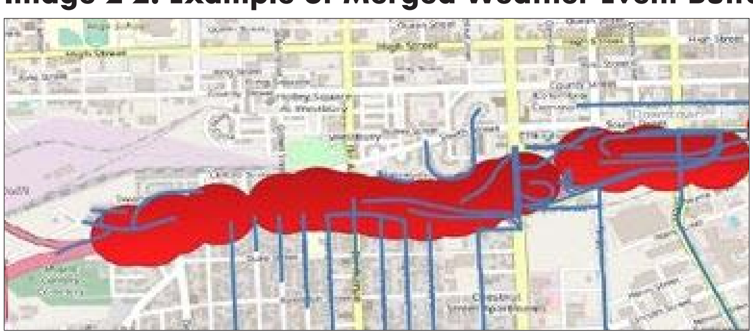


Image 2-1: Example of Roadway Segments overlapping with Historical Weather Event Buffers

This layer was also used in the Sensitivity component development. The buffers were merged in order to determine the frequency of weather-related events in a single location, defined as any cluster of overlapping buffers dissolved into one GIS polygon feature. Each polygon was assigned the sum of the overlapping events as the frequency. This frequency was then assigned to the roadway segments that intersected with the merged polygon feature.

Image 2-2: Example of Merged Weather Event Buffers Used to Determine Sensitivity

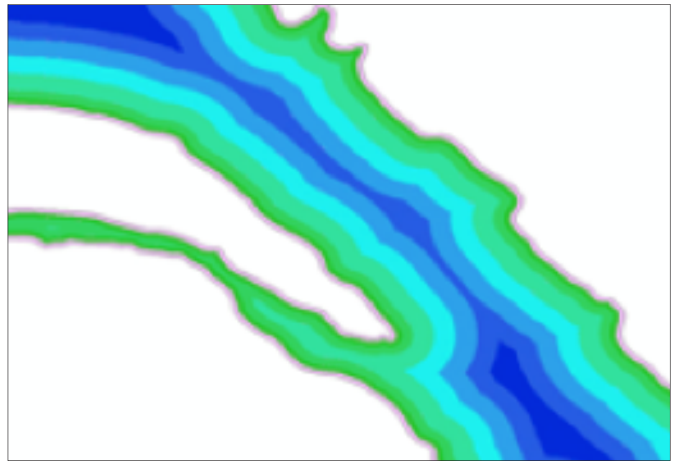


APPENDIX 3: METHODOLOGY FOR CREATION OF THE EXTREME INLAND/ RIVERINE FLOODING SCENARIO

One of the three scenarios for inland/riverine flooding relied on 500 year floodplain data and applied an additional buffer to create a scenario equivalent of extreme sea level rise, while limiting this buffer based on the width of the floodplain. This was done using the following GIS steps resulting in an additional buffer of 10-200 feet depending on width of the flood plain.

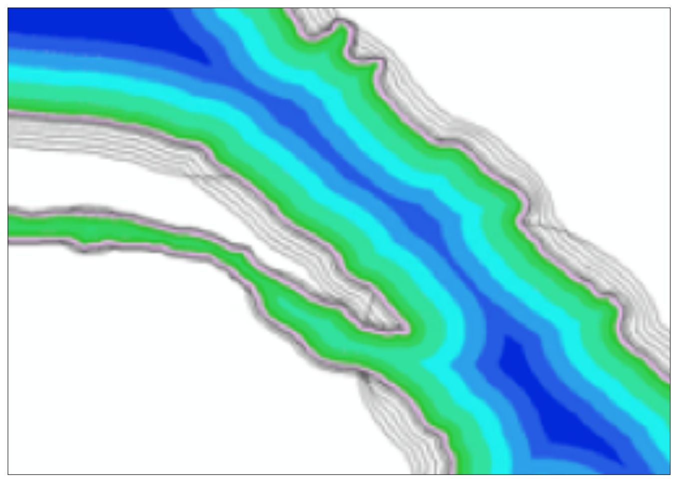
1. Generate negative-distance buffers at varying distances (25, 50, 100, 200, 300, 400, 500 feet) within the combined 100-year and 500-year floodplain area (Figure 3-1). This is intended to capture areas that are more than 1,000 feet wide (see the dark blue below) all the way to 50 feet or less.

Figure 3-1: Generate Negative-distance Buffers



2. Apply buffers to these inner rings equivalent to the distance needed to get back out to the edge of the floodplain + 20 percent of width (Figure 3-2). This is as follows:
   - More than 1,000 feet wide areas (500 feet dark blue inner rings) get buffered at 500 + 200 feet
   - 800 feet wide areas (400 feet inner rings) get buffered at 400 + 160 feet
   - 600 feet wide areas (300 feet inner rings) get buffered at 300 + 120 feet
   - (continue the same method)
   - 50 feet wide areas (or less) get a minimum buffer of 10 feet from edge of floodplain

Figure 3-2: Apply Buffers



3. Merge the buffers into one (Figures 3-3 and 3-4)

Figure 3-3: Merge Buffers (Sample 1)

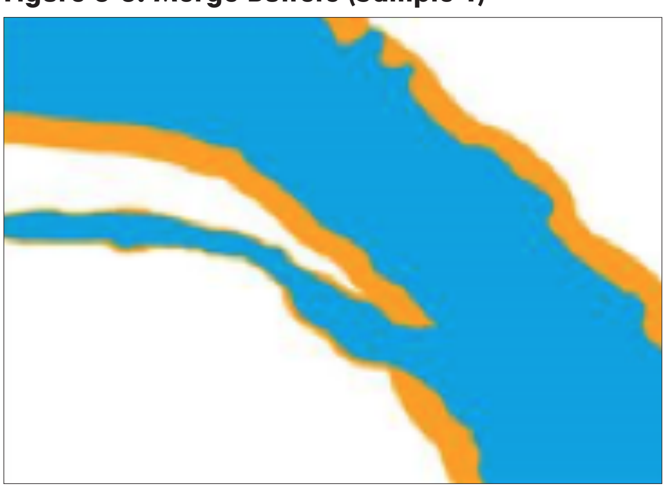


Figure 3-4: Merge Buffers (Sample 2)

Buffer around 500 year floodplain

APPENDIX 4: METHODOLOGY TO ASSIGN EXPOSURE VALUES TO ROADWAY SEGMENTS

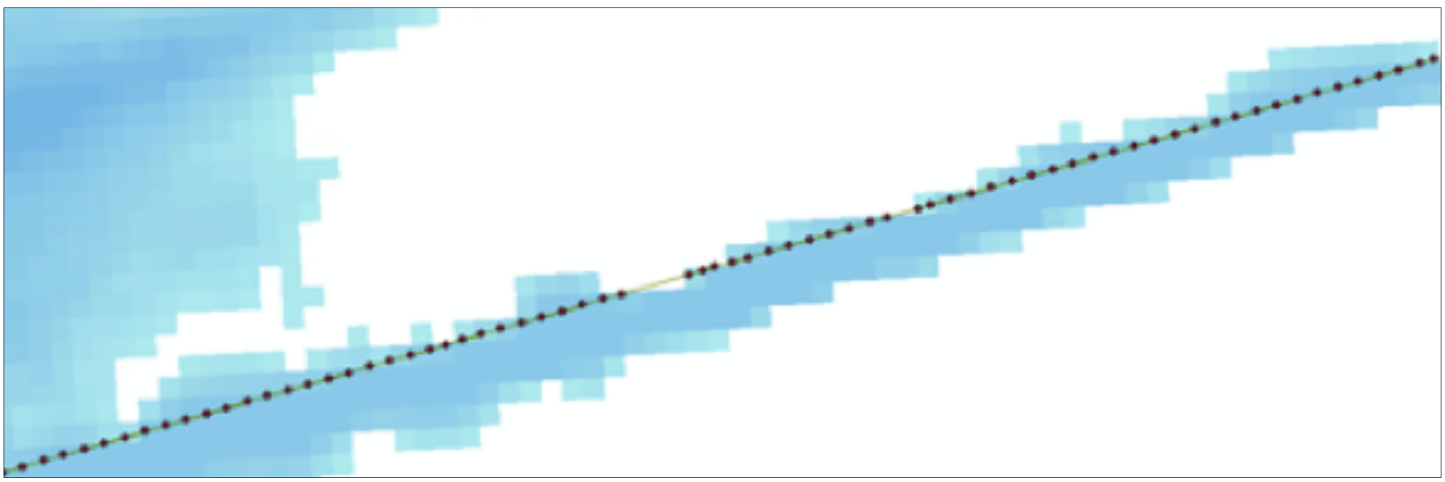
Exposure Assessment Methodology

This appendix outlines the GIS steps performed to assess statewide exposure to sea level rise, storm surge, and inland/riverine flooding for the Commonwealth of Virginia. As noted in Section 1.5, this method does not account for roadway vertical geometry which might be different than ground surface elevations.

- Sea Level Rise
  The following steps were performed to assess the maximum depth of sea level rise experienced by a roadway for a given scenario. Initially the "Zonal Statistics" GIS tool was considered for this analysis, however, it was discovered that this tool had limitations for processing overlapping lines or "zones" resulting in missing values. The following approach was used as an alternate:

  1. Conversion of sea level raster data to vector data
  2. Intersection of roadway network (VDOT LRS 19.1) with sea level rise vector data to capture only the roadways exposed
  3. Develop nodes along the exposed roadways at 1 meter internal (same resolution as raster cells)
  4. Sample the sea level rise raster data at each point on roadway network (VDOT LRS 19.1) by extracting values to points (Figure 4-1).
  5. Summarize the result to obtain the maximum depth for each roadway segment in VDOT LRS 19.1.

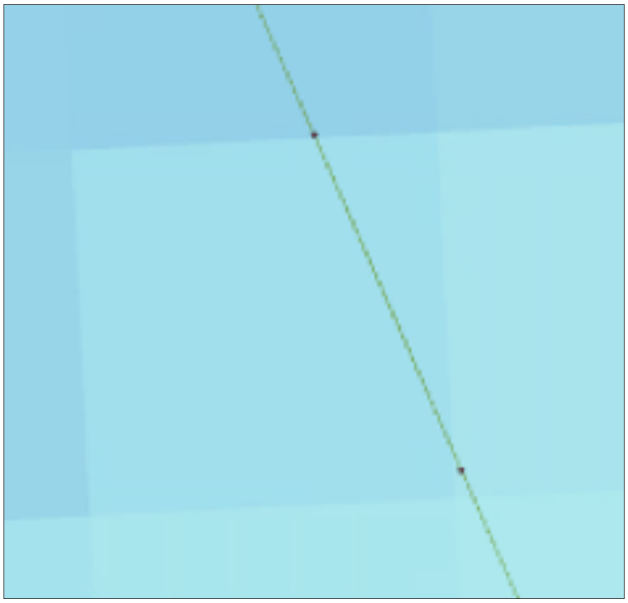
Figure 4-1: Sampling of Sea Level Rise Data



- Storm Surge
  The following steps were performed to assess the maximum depth of storm surge experienced by a roadway segment for a given scenario. Initially the "Zonal Statistics" GIS tool was considered for this analysis, however, it was discovered that this tool had limitations for processing overlapping lines or "zones" resulting in missing values. The following approach was used as an alternate:

  1. Conversion of storm surge raster data to vector data
  2. Intersection of roadway network (VDOT LRS 19.1) with storm surge vector data to capture only the exposed roadway segments.
  3. Develop nodes along the exposed roadways at 30 meter internal (same resolution as raster cells)
  4. Sample the storm surge raster data at each point on roadway network (VDOT LRS 19.1) by extracting values to points (Figure 4-2).
  5. Summarize the result to obtain the maximum depth for each roadway segment in VDOT LRS 19.1.

Figure 4-2: Sampling of Storm Surge Data



The primary limitation of the method used for assigning storm surge exposure values to roadway segments is that using the same resolution for the line splits as the raster cells leads to the potential of a raster grid cell getting skipped depending on where it is crossed (Figures 4-1 and 4-2). This could result in a high value raster cell not being reflected in the maximum depth for a given segment, however this issue was not found to be widespread. This error could be reconciled on a subsequent run by shortening the line splits to less than the raster resolution. For example, the sea level rise analysis could be performed with segments of half a meter and the storm surge analysis could be shorted considerably.

This assessment defines exposure to inland/riverine flooding as meeting two conditions:

1. Being within a Location Relative to FEMA Flood Zone or buffer as outlined in Appendix 3.

2. Exposed to a historical flood event as outlined in Appendix 2.

- Inland/Riverine Flooding (IRF)
  This assessment assigned roadways as being either in or out of the floodplain as well as exposure to a historical weather-related event by means of a direct spatial intersect. Distance of flooded area was not considered at this time. All roadways that touch the floodplain and historical weather-related event buffer were scored a 1 and the rest 0.

APPENDIX 5: SOCIO-DEMOGRAPHIC TRENDS RELATED ASSUMPTIONS AND OPPORTUNITIES FOR CONTINUOUS IMPROVEMENT

Table 5-1: Jurisdictions Associated with Each VDOT Construction District

Construction District	Jurisdictions
Bristol	Bland, Buchanan, Dickenson, Grayson, Lee, Russell, Scott, Smyth, Tazewell, Washington, Wise, Wythe, Bristol, Norton
Salem	Bedford, Botetourt, Carroll, Craig, Floyd, Franklin, Giles, Henry, Montgomery, Patrick, Pulaski, Roanoke County, Galax, Martinsville, Radford, Roanoke City, Salem City
Lynchburg	Amherst, Appomattox, Buckingham, Campbell, Charlotte, Cumberland, Halifax, Nelson, Pittsylvania, Prince Edward, Danville, Lynchburg
Richmond	Amelia, Brunswick, Charles City, Chesterfield, Dinwiddie, Goochland, Hanover, Henrico, Lunenburg, Mecklenburg, New Kent, Nottoway, Powhatan, Prince George, Colonial Heights, Hopewell, Petersburg, Richmond City
Hampton Roads	Accomack, Isle of Wight, James City, Northampton, Southampton, Surry, Sussex, York, Greensville, Chesapeake, Emporia, Franklin, Hampton, Newport News, Norfolk, Poquoson, Portsmouth, Suffolk, Virginia Beach, Williamsburg
Fredericksburg	Caroline, Essex, Gloucester, King and Queen, King George, King William, Lancaster, Mathews, Middlesex, Northumberland, Richmond County, Spotsylvania, Stafford, Westmoreland, Fredericksburg
Culpeper	Albemarle, Culpeper, Fauquier, Fluvanna, Greene, Louisa, Madison, Orange, Rappahannock, Charlottesville
Staunton	Alleghany, Augusta, Bath, Clarke, Frederick, Highland, Page, Rockbridge, Rockingham, Shenandoah, Warren, Buena Vista, Covington, Harrisonburg, Lexington, Staunton, Waynesboro, Winchester
Northern Virginia	Arlington, Fairfax County, Loudoun County, Prince William, Alexandria, Fairfax City, Falls Church, Manassas, Manassas Park

Table 5-2: Jurisdictions Associated with each Modified Planning District Commission

Modified Planning District Commission	Jurisdictions
Lenowisco	Lee, Norton, Scott, Wise
Cumberland Plateau	Buchanan, Dickenson, Russell, Tazewell
Mount Rogers	Bland, Bristol, Carroll, Galax, Grayson, Smyth, Washington, Wythe
New River Valley	Floyd, Giles, Montgomery, Pulaski, Radford
Roanoke Valley-Alleghany	Alleghany, Botetourt, Covington, Craig, Franklin County , Roanoke City , Roanoke County , Salem
Central Shenandoah	Augusta, Bath, Buena Vista, Harrisonburg, Highland, Lexington, Rockbridge, Rockingham, Staunton, Waynesboro
Northern Shenandoah	Clarke, Frederick, Page, Shenandoah, Warren, Winchester
Northern Virginia	Alexandria, Arlington, Fairfax City, Fairfax County, Falls Church, Loudoun, Manassas, Manassas Park, Prince William
Rappahannock-Rapidan	Culpeper, Fauquier, Madison, Orange, Rappahannock
Thomas Jefferson	Albemarle, Charlottesville, Fluvanna, Greene, Louisa, Nelson
Central Virginia	Amherst, Appomattox, Bedford, Campbell, Lynchburg
West Piedmont	Danville, Henry, Martinsville, Patrick, Pittsylvania
Southside	Brunswick, Halifax, Mecklenburg

Modified Planning District Commission	Jurisdictions
Commonwealth Regional Council	Amelia, Buckingham, Charlotte, Cumberland, Lunenburg, Nottoway, Prince Edward
Richmond Regional	Charles City, Chesterfield, Goochland, Hanover, Henrico, New Kent, Powhatan, Richmond City
George Washington	Caroline, Fredericksburg, King George, Spotsylvania, Stafford
Northern Neck	Lancaster, Northumberland, Richmond County , Westmoreland
Middle Peninsula	Essex, Gloucester, King and Queen, King William, Mathews, Middlesex
Crater	Colonial Heights, Dinwiddie, Emporia, Greensville, Hopewell, Petersburg, Prince George, Surry, Sussex
Accomack-Northampton	Accomack, Northampton
Hampton Roads	Chesapeake, Franklin City, Hampton, Isle of Wight, James City, Newport News, Norfolk, Poquoson, Portsmouth, Southampton, Suffolk, Virginia Beach, Williamsburg, York

Adjustments for Income Forecasts

The following adjustments for income forecasts were made:

- As is the case with employment, the household income reported by Woods & Poole is typically higher than that of other sources such as the U.S. Census Bureau. Formally, the Woods & Poole income includes not only wages and salaries but also “proprietors’ income, rental income of persons, dividend income, personal interest income, and transfer payments less personal contributions for social insurance.” Woods & Poole reports that income as reported by the U.S. Census Bureau excludes certain items such as the value of food stamps, the value of medical payments, and the “imputed rental value of owner-occupied housing.” Another factor is that whereas Woods & Poole reports the mean household income, other sources may report the median household income. For these reasons, it is not surprising that the mean household income in Virginia for 2017 ($120,910) is considerably higher than the median household income reported by the U.S. Census ($68,766)—even though the former is in 2009 dollars and the latter is in 2017 dollars.[1]
- For household incomes reported by Moody’s Analytics, there are four methodological differences that affect how these data are interpreted with respect to incomes reported by Woods & Poole. First, although Virginia has 133 independent cities and counties in total, Moody’s only reports data for 105 geographical areas in Virginia, which in total represent the entire Commonwealth. Most (82) of Moody’s areas correspond directly with a Virginia jurisdiction; for example, Moody’s provides an income for the independent city of Virginia Beach. However, about one-fifth (23) of Moody’s 105 areas are an aggregation of two or more Virginia jurisdictions. For example, Moody’s provides a single income for the combined area of Roanoke County plus the City of Salem (but the City of Roanoke is reported separately); another example is that the cities of Colonial Heights and Petersburg, along with Dinwiddie County, are reported as a single area. As shown in Table 5-2, the county that represented these combined areas was used to assign the area to the appropriate VDOT Construction District. For instance, because Prince George County is in the VDOT Richmond Construction District, the City of Hopewell is also placed in this same Construction District.

[1] U.S. Census Bureau, Woods and Poole

Table 5-3: Correspondence Between Moody's Areas and the Assigned Jurisdiction

Moody's Combined Area	Assigning Jurisdiction
Albemarle + Charlottesville (VA)	Albemarle County, Va
Alleghany, Clifton Forge + Covington (VA)	Alleghany County, Va
Augusta, Staunton + Waynesboro (VA)	Augusta County, Va
Campbell + Lynchburg (VA)	Campbell County, Va
Carroll + Galax (VA)	Carroll County, Va
Dinwiddie + Col. Hts + Peters (VA)	Dinwiddie County, Va
Fairfax County, Fairfax City + Falls Church (VA)	Fairfax County, Va
Frederick + Winchester (VA)	Frederick County, Va
Greensville + Emporia (VA)	Greensville County, Va
Henry + Martinsville (VA)	Henry County, Va
James City + Williamsburg (VA)	James City County, Va
Montgomery + Radford (VA)	Montgomery County, Va
Pittsylvania + Danville (VA)	Pittsylvania County, Va
Prince George + Hopewell (VA)	Prince George County, Va
Prince William, Manassas + Manassas Park (VA)	Prince William County, Va
Roanoke County + Salem (VA)	Roanoke County, Va
Rockbridge, Buena Vista + Lexington (VA)	Rockbridge County, Va
Rockingham + Harrisonburg (VA)	Rockingham County, Va
Southampton + Franklin City (VA)	Southampton County, Va
Spotsylvania + Fredericksburg (VA)	Spotsylvania County, Va
Washington + Bristol (VA)	Washington County, Va
Wise + Norton (VA)	Wise County, Va
York + Poquoson (VA)	York County, Va

- Moody's reports forecast incomes in current year dollars. For example, Moody's forecasts the 2045 median income for Appomattox County to be $109,710—in year 2045 dollars. Accordingly, a customized Virginia-specific statewide deflator table was provided by Moody's staff[1] for a base year of 2009, where one multiplies dollars reported in any other year by the deflator to obtain forecast income in 2009 dollars. Because the deflator for year 2045 is 0.5229, the Appomattox County median income of $109,710 (in 2045 dollars) is multiplied by 0.5229 to obtain a 2045 forecast median income of $57,367 (in 2009 dollars). The value of 2009 dollars was chosen because the incomes provided by Woods & Poole[2] are also in 2009 dollars. The statewide deflator is an estimate in that one could also purchase deflators that are specific to certain metropolitan areas.
- Woods & Poole reports the mean household income, whereas Moody's reports the median household income. In locations where there were a few households with very large or very small household incomes, there could be a difference between the mean and the median incomes. Mean values are more influenced by extreme values in a distribution than median values.
- Moody's and Woods & Poole do not define income in the same manner. Moody's indicates that for a definition of income, one should examine the corresponding "driver" of this income, which Moody's[3] then notes, is based on four sources: "the U.S. Census Bureau's (BOC) annual American Community Survey (ACS), Decennial Census, the Current Population Survey, and the Small Area Income and Poverty Estimates from the BOC." The U.S. Census Bureau then

[1] Kamins, A. Email to John S. Miller. January 10, 2019.

[2] Woods & Poole Economics, Inc. 2018 State Profile, District Of Columbia, Maryland, and Virginia, CD-ROM Technical Documentation. Washington, DC, 2018.

[3] Moody's Analytics. U.S. County Forecast Database, New York, NY, 2019.

reports that personal income includes eight categories of income, abbreviated here as salaries, self-employment, interest/royalties/net rental income, social security income, disability income, public assistance income, retirement income, and all other income (e.g., child support). To be clear, the U.S. Census Bureau includes social security retirement income (e.g., income for individuals who have reached a certain age of 62 or older and have elected to start receiving such income), supplemental security income (abbreviated as "SSI") which "guarantees a minimum level of income for needy aged, blind, or disabled individuals", and public assistance income (which is Temporary Assistance to Needy Families ("TANF"); this last program was colloquially described as "welfare" until 1996 when TANF replaced a program in place from 1935 to 1996 known as Aid to Families with Dependent Children (Center on Budget and Policy Priorities, 2018). While the U.S. Census Bureau (2018c) does not explicitly state whether it includes social security disability income (SSDI), the Bureau notes that it includes in its income "permanent disability insurance payments made by the Social Security Administration prior to deductions for medical insurance" which, based on a review of how the Social Security Administration (2018) defines SSDI, suggests that SSDI is included in incomes from the U.S. Census Bureau and hence would be part of the Moody's[1] data set.

- Although these categories are numerous, note that as suggested by Woods & Poole, the incomes based on the U.S. Census (such as Moody's) tend to be smaller than those of Woods & Poole. Examination of incomes for one county in Virginia supports this viewpoint. For Appomattox County, in 2009 dollars, an approximate 2018 household income was approximately $45,105 (Moody's Analytics), $48,069 (U.S. Census Bureau), and $78,468 (Woods & Poole) as shown in the right column of Table 5-4.

Table 5-4: Current Household Incomes for Appomattox County

Source	Period	Type	Income (year $)	Income (2009 $)
Woods & Poole	2017	Mean	$78,468 (2009 $)	$78,468
U.S. Census Bureau (2018d)	2013-2017[2]	Median	$54,875 (2017 $)	$48,069
Moody's Analytics	2017	Median	$50,851 (2017 $)	$45,105

- Woods & Poole reports incomes in 2009 dollars, this is not the case for the other two sources, thus, the Moody's income in 2017 dollars was deflated using the value provided by staff and the American Community Survey data was deflated using the consumer price index (U.S. Bureau of Labor Statistics) so that 2009 income would be available for all three data sources.
- For each modified PDC, a weighted median household income was computed in a manner similar to that used for the Woods & Poole data. After the incomes for each Moody's area were converted to 2009 dollars, for each area in the PDC, the product of the area's households and income was summed and then divided by the number of households in the PDC as provided by Moody's Analytics. A similar process was followed for aggregating incomes by VDOT Construction Districts. Moody's Analytics frequently updates these data; the household data in this report were updated December 21, 2018 and the income data were updated January 4, 2019. The authors have reported the estimated statewide median income in this manner, where the median household income (by jurisdiction) is multiplied by the number of households for each jurisdiction and then the total is divided by all households in the Commonwealth.

(This estimated median was chosen for consistency with the geography used for obtaining specific Construction District and PDC values. It is also possible to obtain, from a separate data series, what Moody's reports as a statewide median, which is not disaggregated by jurisdiction. The statewide median from this statewide series differs from the estimated median (based on the county series) by approximately 7 percent for year 2017 and 4 percent for year 2045. Possible reasons for the difference include the fact that the statewide deflator provided by Moody's to the researchers is an estimate (e.g., different deflators could be used for different urban areas) and the fact that the household weighted estimate for a median is not identical to computing a true median value.)

[1] Moody's Analytics. U.S. County Forecast Database, New York, NY, 2019.

[2] For jurisdictions under 20,000 people, the American Community Survey obtains data over a 5 year period.

Feasibility of Comparing Employment Forecasts from Different Sources

The employment data are based on the VDOT Construction District where the job is located and include wage and salary workers, proprietors, private household employees, and "miscellaneous workers"; because proprietors and military workers are included [as well as both full and part-time jobs], employment may be higher from this database than from other sources.[1] Such disparities in employment definitions are not unusual; for example total 2016 jobs in the U.S. obtained from the Bureau of Economic Analysis (almost 150 million) is about 6 percent higher than jobs obtained from the Bureau of Labor Statistics (almost 142 million) because the latter does not include (or fully include) certain types of employment such as religious organizations, rail transportation, some nonprofits with fewer than four employees, and military employees.[2]

Woods & Poole defines households as occupied housing units and excludes persons in "group quarters" such as university dormitories, prisons, or "military barracks." Because Woods & Poole reports a "mean household income" which is the "total personal income less estimated income of group quarters population divided by the number of households", the authors computed a weighted mean household income for each PDC or Construction District. This weighted mean household income was computed by multiplying the number of households for each city or county by the mean household income for each such jurisdiction to get a total household income by jurisdiction, summing these total income values by PDC or Construction District, and then dividing by the corresponding number of households for the PDC or Construction District.

Explanation of Differences in Employment Forecasts

While it is not possible to know which employment forecast will prove to be most accurate in 2045, it is possible to examine the reasons for the disparity in employment forecasts. Both Woods & Poole[3] and IHS Markit[4] forecast an increase in employment statewide (44.1 percent and 18.2 percent), respectively—but within professions, some forecasts differ substantially. While there is a difference of 26 percentage points between these statewide forecasts, there are some industrial classifications where these two sources are more similar: arts, entertainment, and recreation (45 percent and 30 percent); manufacturing (decreases of 4 percent and 6 percent); and government (24 percent and 10 percent). (The Woods & Poole government category includes the three categories of state and local, federal civilian, and federal military; IHS Markit government is a single category of public administration.) Notable differences include health care and social assistance (increases of 90 percent and 33 percent for forecast), professional and technical services (61 percent and 31 percent), retail trade (46 percent and 5 percent), other services (examples of which are churches, dry cleaning, pet care, dating services, machinery repairing, and advocacy[5] (56 percent and 2 percent), and real estate & rental & leasing (97 percent and 55 percent). If these last five differences were eliminated, then overall the percentage difference for these two sources for statewide employment would be between 7 and 9 percentage points depending on the exact manner of tabulation, rather than 26 percentage points.

The two biggest contributors to these different statewide forecasts in total employment are health care and retail trade. These are then followed by five employment categories that are much closer to each other (in terms of their importance to the difference in statewide employment as forecast by Woods & Poole and IHS Markit): professional and technical services; other services (e.g., churches, dry cleaning, pet care, dating services, machinery repairing, and advocacy [Woods & Poole]); accommodation & food services; government; and administrative & waste services.

[1] Woods & Poole Economics, Inc. Virginia, Maryland, and The District of Columbia, 2018. State Profile, State and County Projections to 2050. Washington, 2018.

[2] Bureau of Economic Analysis. Local Area Personal Income and Employment Methodology, Washington, DC, 2017. Accessed December 12, 2018.

[3] Woods & Poole Economics, Inc. Virginia, Maryland, and The District of Columbia, 2018 State Profile, State and County Projections to 2050. Washington, DC, 2018.

[4] Jeafarqomi, K. Email to John S. Miller. December 13, 2018.

[5] Woods & Poole Economics, Inc. 2018 State Profile, District Of Columbia, Maryland, and Virginia, CD-ROM Technical Documentation. Washington, DC, 2018.

Differences in employment forecasts by sector can be magnified in PDCs with relatively small employment totals. For example, consider Accomack-Northampton, which showed a 27 percent increase in employment (Woods & Poole) and a 26 percent decrease in employment by IHS Markit for the period 2017-2045. The latter 26 percent decrease in employment would change to an 8 percent increase in employment if differences in just four employment categories were eliminated: health care (which more than doubles according to Woods & Poole but shrinks by 18 percent based on IHS Markit), government employment (a 16 percent increase versus a 34 percent decrease, manufacturing (a 5 percent increase versus a 32 percent decrease), and other services (a 32 percent increase versus a 50 percent decrease).

ADDENDA AND ERRATA

Date	Version	Long-term Policy Step	Description
September, 2021	v1		Draft technical guide available for public and agency review
November, 2021	v2	Step 1	Tables previously found in appendices placed on page 42 (Table 8), page 48 (Table 10), page 50 (Table 11), page 51 (Table 12), and page 52 (Table 13).
		Step 3	Added additional new Indices developed and associated calculations: ▪ Goal A - added Index for Truck only VMT ▪ Goal B - added Indices for Ridesourcing only and Micromobility only ▪ Goal C - added Indices for Visible Injuries, Non-visible Injuries, and Property Damage only crashes
		Step 4	Added draft VTrans Long-term Risk & Opportunity Register
		Step 4	Added additional trend trackers
			Reorganized Appendices: removed full technical memos and replaced with only information relevant to this document.
December, 2021	v3		Additional edits for clarification and consistency.

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