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Feasibility of Adapting VisionEval for Scenario Planning

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16. Abstract:

Transportation investment decisions require consideration of uncontrolled events (e.g., changes in family size, vehicle technology, population, fuel prices, or societal norms such as telecommuting) along with possible policy responses to achieve desired goals. Although the possibility of these multiple alternative futures suggests one should explicitly consider them when making investment decisions, using more detailed models to support scenario planning is hampered by extensive data requirements and difficulty evaluating many different scenarios. One tool that has the potential to fill this gap is the VisionEval platform, which has less detail than an operational model with a transportation network but more detail than sketch approaches. VisionEval is an open-source scenario planning platform under development as part of a Federal Highway Administration–led pooled fund study in which Virginia is participating.

The purpose of this study was to determine the benefits, staff time requirements, and feasibility of applying VisionEval to explore 43 scenarios of interest to VDOT planning staff and planning partners with respect to their impact on vehicle miles traveled and carbon dioxide equivalent emissions. The primary benefit of this scenario planning tool is the rapid identification of which areas merit greater examination; in this case study region, telecommuting, truck electrification, and household vehicle electrification have relatively large potential impacts on emissions (on the order of 13%, 6%, and 4%, respectively) such that these areas merit greater study. By contrast, changes in household size, population, transit vehicle technology, and increased availability of carsharing vehicles had lesser impacts. Presently, VisionEval appears deployable with about 500 hours of staff time for a case study area with three localities, 1.43 million people, and 712 transportation analysis zones.

The tool addresses two key obstacles to enabling scenario planning in the VDOT environment: multiple potential inputs and substantial data requirements, although a limitation is that some scenarios, such as those relating to the density of pedestrian-friendly intersections, are not feasible with the current iteration of VisionEval. The study thus recommends the use of this platform for scenarios where sensitivity analyses show it is appropriate. The study further recommends changes to this platform in order to address these limitations. Two action items for putting these two recommendations into practice are given in the Implementation subsection of this report.

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FINAL REPORT

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DISCLAIMER

EXECUTIVE SUMMARY

Introduction

Transportation investment decisions require consideration of uncontrolled events along with possible policy responses to achieve desired goals. Capacity additions, such as increases in transit service or the addition of lane-miles, do not occur in a vacuum but rather in conjunction with sometimes unexpected demographic changes (family size, population growth); shifts in the price of fuel; evolution of societal norms such as telecommuting; alteration of the composition of the vehicle fleet; and the introduction, continuation, or deprecation of policy responses such as travel demand management. The possibility of these multiple alternative futures suggests one should explicitly consider them when making investment decisions.

Yet using more detailed models to support scenario planning is hampered by extensive data requirements and difficulty in evaluating many different scenarios. Elements of scenario planning can be performed with network-based regional travel demand models, for instance, where one can evaluate how the results of such models in terms of total travel demand are affected by changes in demographic inputs such as population and employment. Yet such packages are not necessarily designed for other scenarios (e.g., how emissions will change if some stationary plants use solar power) or multiple scenarios (e.g., run times on advanced computing systems are at least a dozen hours for one region [National Capital Region Transportation Planning Board, 2021]).

One tool that has the potential to fill this gap is the VisionEval platform—an elasticity-based "strategic model" (Raw and Flynn, 2020) having less detail than an operational model with a transportation network but having more detail than sketch approaches by incorporation of feedback loops between costs and behavior. VisionEval incorporates a variety of mathematical relationships among generators of travel demand (e.g., housing prices, employment locations); transportation service policies (e.g., transit availability and fares, roadway miles); and performance measures (e.g., vehicle miles traveled [VMT], emissions, transit use) and is designed to provide substantial flexibility in terms of the types of scenarios considered at the expense of providing precise impacts. Because VisionEval is modular, it is feasible to implement "new model features" (VisionEval, 2021a) within the platform. However, fully designing, implementing, and testing such features is a fairly extensive process that was not explored in this study. Wang (2018) provided such an example.

VisionEval is an open-source scenario planning platform under development as part of a transportation pooled fund (TPF) study led by the Federal Highway Administration in which Virginia is participating. Until this study, Virginia had not yet deployed VisionEval, so its benefits and limitations for scenario planning were not known to Virginia. Further, as VisionEval is still under development, the study described in this report has the possibility to inform future enhancements.

Study Purpose and Methodology

The purpose of this study was to determine the benefits, staff time (e.g., data preparation, model execution, and model interpretation), and feasibility of applying VisionEval to explore scenarios of interest to VDOT planning staff and planning partners. The focus was the VisionEval Regional Strategic Planning Model (VE-RSPM) in particular, hereinafter referred to as “VisionEval.”

A case study approach was used where the platform was used to inform policy-level discussions for a subset of VDOT’s Northern Virginia District, i.e., Fairfax City, Fairfax County, and Falls Church. For consistency with other VDOT modeling efforts, the case study used a 2019 base year and a 2045 forecast year. A technical report by the Northern Virginia Transportation Authority (NVTA) (NVTA, 2018), coupled with documents available from planning partners (e.g., Reynolds, 2020; Washington Metropolitan Area Transit Authority, 2019) and ideas suggested by the Virginia Transportation Research Council’s Transportation Planning Research Advisory Committee (Transportation Planning Research Advisory Committee, 2021), led to the development of alternative futures based on variations in development patterns, household size, aging in place, telecommuting habits, highway tax policy, transit service, highway construction, carsharing services, vehicle electrification, and fuel sources for vehicles and electric power generation.

A total of 43 alternative futures, or scenarios, were evaluated with VE-RSPM (accompanying R version 4.0.5 [VisionEval, 2021b]) with respect to their impact on VMT, energy use, carbon dioxide equivalent (CO_2e) emissions, and mode split across vehicles, transit, bicycles, and pedestrians. The study distinguished between scenarios that could be developed in a straightforward manner with a direct alteration to inputs (e.g., the platform allows one to specify what portion of trucks will be battery electric) versus scenarios that require more effort (e.g., the platform does not allow such a specification for household vehicles; rather, one must develop a synthetic carbon intensity and thus perform multiple scenario runs). Lessons learned regarding the execution of VisionEval for future scenario planning efforts were documented.

Results

Time Requirements

Over a 10-month period from December 2020-September 2021, 51 input files representing a baseline 2045 future in terms of demographic, economic, transportation, and industrial characteristics were developed for the case study region. An example of such a file is shown in Appendix A. A typical file required about 8 hours of staff time depending on the extent to which one sought to document the rationale, data availability, geoprocessing required, and level of geographical detail. Each file typically required between one and six attributes (e.g., a population-related file required age groups of less than or equal to 14 years, 15-19 years, and so forth). The attributes in a file required one of three possible levels of geographic level of detail for a given year: the entire region (hence just one row of attribute values), each city or county (hence three rows), or each transportation analysis zone (hence 712 rows). Each file had attribute values for the current year (chosen as 2019) and a future year (chosen as 2045). These attributes constituted the baseline case, or scenario 0.

Then, 10 different categories of scenarios were conceived by altering the input files; an example of a scenario is shown in Appendix B. Some scenario categories could be developed in a few hours (e.g., scenario 8b, change availability of carsharing services from low to high in low-income locations, or scenario 8c, have high levels of carsharing services everywhere). Other scenarios, however, could take 1 to 2 days to develop—not because of file complexity but because of the desire to ensure diverse but plausible futures. For instance, to envision a range of fuel and electricity prices for year 2045, several projections were examined—Macrotrends (2021), The World Bank (2021), U.S. Energy Information Administration (2020a, 2021)—but once these sources were understood, the coding of the inputs was fairly straightforward.

For the case study area (Fairfax City, Fairfax County, and Falls Church) of roughly 1.4 million people in 2045, execution of each scenario required slightly less than 20 minutes on a PC with about 5 additional minutes needed to write each output variable to a file. As VisionEval was new to Virginia, the final versions of the scenarios were executed one at a time; this also allowed the capturing of all results. However, a script developed by staff at the Volpe National Transportation Systems Center allows the analyst to execute scenarios in batch mode and to extract a subset of desired outputs.

Scenario Impacts

The case study suggested three strategies for reducing CO_2e emissions: (1) large-scale participation in telecommuting by two-fifths of the work force (12.9% reduction), heavy truck electrification (6.4% reduction), and household vehicle electrification (4.0% reduction). Logically, one would not expect these scenarios to be perfectly additive: one can eliminate a fossil fuel vehicle trip or convert the fuel source to electricity, but both emissions-reducing events cannot apply to the same vehicle trip. The results matched this anecdote: implementing all three scenarios reduced emissions by 19.6%. The study also suggested an almost 11.9% increase in emissions if none of these three actions occurred and population increased unexpectedly by 10% more than the value forecast by 2045. This 10% increase was not chosen randomly but rather reflected the long-term population forecast error at another metropolitan planning organization in Virginia where a retrospective study was performed (McCray et al., 2009). In short, the case study results showed that large-scale initiatives and unexpected events could swing regional CO_2e emissions by an absolute value as large as 31% (e.g., 19.6% reduction versus an 11.9% increase).

Figure ES1 shows that other strategies or events had a lesser impact (e.g., electrification of transit vehicles and large fuel tax increases affected emissions by less than 1%). The study also showed that population and employment forecast errors at the traffic analysis zone level, rather than the city or county level, had very little impact on emission estimates.

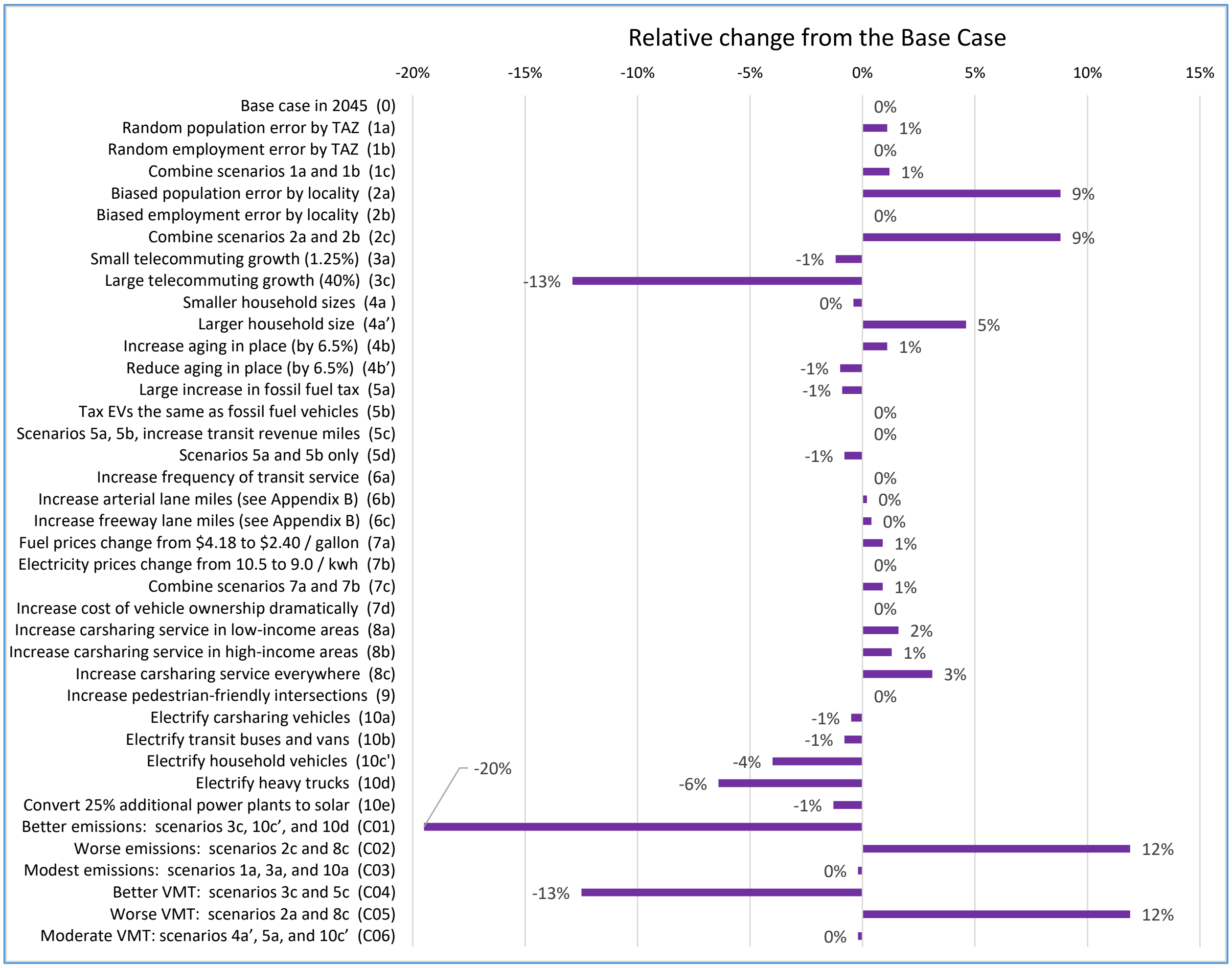

Figure ES1. Case Study Results: Percent CO_2e Emissions Change From the Base Case for 2045

Other items had an impact but less than the research team expected: conversion of one-fourth of power plant sources from natural gas to solar reduced emissions by slightly more than 1 percentage point. Notably, Figure ES1 affirms the relevance of uncontrolled events compared to conscious transportation investments. The larger impacts tend to result from external events (e.g., telecommuting, additional population growth, larger household sizes), whereas the smaller impacts result from transportation-related decisions (e.g., add lane-miles, modify taxation policies).

Lessons Learned for Future Users

The case study also revealed four key lessons for users of the current VisionEval platform. It is recognized that VisionEval is under development and may have additional functionality in future versions.

First, three input files do not appear to affect the output variables: frequency of transit service, density of pedestrian-friendly intersections, and cost of owning a vehicle whether levied as an annual flat fee or as a value-based tax. These three files are labeled bzone_transit_service, bzone_network_design, and azone_hh_veh_own_taxes, respectively. This lack of sensitivity was observed both with the real case study dataset and for the first two attributes with a hypothetical case study dataset in Appendix C. The cost of owning a vehicle did have a modest impact with the dataset in Appendix C but in a different way than what was expected: increasing the costs by an additional $2,000 raised household VMT by 0.4%. Thus, one best practice appears to be to deploy VisionEval very quickly—with hypothetical data—and then determine which variables appear to influence the outputs, as this knowledge can help one design scenarios.

Second, at least during an initial application of VisionEval, one should keep a record of the 158 variables that result from the disaggregate household output files (i.e., variables that reflect results for individual synthesized households) and Marea output files (i.e., variables that reflect results for the entire study region). Only some of these variables are true outputs that result from execution of the platform (e.g., total kilowatt hours consumed by electric vehicles from being recharged); many are closely related to inputs (e.g., number of workers in each household, which is synthesized based on population inputs provided by the user). In several cases, however, those detailed outputs were essential for interpreting the results and revising the design of the scenarios. Initially, for instance, examination of number of workers for each household showed that more than one-half of the total population was in the workforce, necessitating that an optional file (azone_relative_employment) be used to bring this ratio to a more realistic level. Examination of mode-specific results (e.g., number of transit trips) helped the research team understand when an input file had been used but had not had a large impact versus situations where an input file had no impact.

Third, some elements of calibration are useful for interpreting the results. Comparison of runs from the Northern Virginia regional model showed that household VMT could be replicated somewhat well—the totals from VisionEval (based on household VMT and commercial service VMT) were about 11% less than those from the 2045 regional model. Because VisionEval represents a smaller area than the Northern Virginia region, the commutes within the case study area will logically be shorter than those for the study area, suggesting that the telecommuting scenario may have a greater benefit than that shown here.

Fourth, a key decision one must make when applying VisionEval pertains to the size of the study area: how much of a particular region should one include in the model? Because VisionEval does not use external stations (i.e., zones that account for travel between the study area and areas outside the study area), this question of study area size is especially pertinent. For instance, for a location such as Northern Virginia, which has substantial interactions with the adjacent locations of Washington, D.C., and suburban Maryland, one might decide that an enlargement of the study area to include these two additional out-of-state locations is warranted. The use of probe-based datasets that show regional trip distribution, such as that provided by StreetLight Insight (Yang et al., 2020), can help one determine the extent to which a particular study area is affected by adjacent locations in terms of trip distribution.

Applicability to Planning Practice

In its current form, VisionEval facilitated quantitative investigation of some future scenarios through two mechanisms:

1. *VisionEval reduced data requirements compared to more detailed modeling approaches by not requiring the creation of a transportation network and extensive model calibration.* Roughly 400 person-hours were required by staff, some of whom were new to the platform, to develop the base input files; this development time should drop as data sources are acquired. For instance, one input file concerning the vehicle fleet was developed based on data provided by Lewis-Cheatham (2020) and Ponticello (2020); with this approach in place, replication for other geographic locations could be done considerably faster. The development of input files (and associated calibration steps) for regional models takes considerably longer; one estimate (Lorenzini et al., 2015) suggested that 2 years is reasonable.

2. *VisionEval allowed for effective representation of some policy alternatives and variations in future conditions.* This representation can be done individually (as was the case with the majority of scenarios considered here) or through the consideration of interacting effects. For instance, one can within 1 day develop a scenario that considers an increased availability of carsharing services, a reduced fuels tax, and the electrification of the vehicle fleet. In this manner, the exploration of VisionEval scenarios provides some ability to quantify potential impacts at two points in the planning process: (1) the trends component of the statewide long-range plan (Office of Intermodal Planning and Investment, 2021a, b), and (2) the time when a metropolitan planning organization is determining which inputs should be examined in detail with the regional model. Regarding the second point, the short execution time of VisionEval offers a way for the metropolitan planning organization to reduce the number of runs that might be performed for the regional model.

A limitation of the present version of VisionEval is that some scenarios do not appear to be feasible in the sense that the results suggest VisionEval does not adequately incorporate the elasticities involved. These scenarios are based on the aforementioned files concerning pedestrian-friendly intersection density, the cost of vehicle ownership, and the frequency of transit service. As discussed in the body of the report, the output variable "ExtraVmtTax," which determines the necessary revenues needed for roadway improvements, was always zero regardless of input values. For these reasons, experiments with a small network, such as that shown in Appendix C, can help one quickly determine what types of scenarios can be supported by this and future iterations of this platform. Such experiments can help one detect if a proposed scenario meets three key tests: (1) base conditions can be replicated; (2) outputs demonstrate sensitivity to inputs; and (3) methods exist to estimate possible input values for forecast years. An example of a scenario that meets this third criterion might be one based on fuel prices: although such 25-year forecasts are subject to great uncertainty, resources exist that help one estimate a potential range of such prices (e.g., Macrotrends, 2021; U.S. Energy Information Administration, 2020a, 2021; The World Bank, 2021).

Conclusions

VisionEval's Benefits

- *The primary benefit of the scenario planning tool is the rapid identification of which areas merit greater examination*. The platform sacrifices precision in favor of flexibility such that it highlights which areas should be studied in more depth. For instance, because telecommuting, truck electrification, and household vehicle electrification have much larger potential impacts (on the order of 13%, 6%, and 4%, respectively), these areas merit greater study.

- *Scenario planning, by design, allows for some relatively quick takeaways.* For instance, the case study showed that key insights practitioners can use are that the highest VMT increase results from an unforeseen population increase (8% VMT rise) but larger families than expected elevate household VMT by less than 1%.

- *VisionEval addresses at least two key obstacles to implementation of scenario planning in the VDOT environment: multiple potential inputs and substantial data requirements.* The platform allows one to consider multiple sets of inputs (e.g., different socioeconomic forecasts, fuel costs, taxing policies, and stationary and fixed fuel sources) and execute them fairly quickly, with roughly one-half hour required for a single run compared to more than a dozen hours for a regional model. This finding informs the study's first recommendation.

Costs

- *In its present form, VisionEval appears deployable in about 500 hours of staff time.* For an area with three localities, 1.43 million people, and 712 transportation analysis zones, the staff cost of applying this tool, including preparing the 51 required input files (example in Appendix A) and devising 10 scenario categories (example in Appendix B), is estimated as roughly 500 person-hours.

Suitability for Virginia

- *Execution requires examination of detailed outputs in order to distinguish between scenarios that have a modest impact and those where the platform cannot compute the impacts.* For example, increased transit revenue miles of service was correctly modeled but reduced household vehicle emissions were offset by increased transit vehicle revenue miles of service without a corresponding change in occupancy. By contrast, changing pedestrian intersection density had no impact in the model.

- *A limitation of the VisionEval platform at present is that some scenarios are infeasible.* Three key input files that relate to frequency of transit service, the density of pedestrian-friendly intersections, and the cost of owning a vehicle generally did not affect outputs. This finding informs the study's second recommendation.

- *Because some scenarios are infeasible in VisionEval, it may be more productive to run a scenario planning tool with fabricated values prior to developing realistic inputs.* In a few cases, it is more productive to devise a scenario quickly, review the results, and then decide whether to proceed with that scenario category.

Recommendations

1. *VDOT district planning staff and the Office of Intermodal Planning and Investment should consider using VisionEval for some types of scenario planning—those where the tool can be calibrated to base year conditions, shows sensitivity to inputs, and offers advantages compared to other methods.* The results herein suggest that the current version of VisionEval can help one evaluate unexpected consequences or policy options fairly quickly in some topical areas: population or employment changes, alterations to fuel types, changes in telecommuting, carsharing services, and additional highway capacity.

2. *The Federal Highway Administration should consider the results of this study with regard to future enhancements to VisionEval or its documentation.* As funds permit, enhancements to either the platform or its associated documentation that would allow one to render the outputs sensitive to pedestrian network density, transit frequency, and vehicle cost should help future users. It is possible that instead of modifying the platform, all that is needed is modifying the documentation. However, the research team could not fully determine how to use these input files effectively.

Implementation

Ways to put these recommendations into practice are discussed in the "Implementation and Benefits" section of the full report.

LIST OF TERMS

Azone	Geographical unit corresponding to a city or county
Azone_hh_loc_type_prop.csv	Input file indicating the proportion of households in each Azone that are a metropolitan, town, or rural area
Azone_hh_pop_by_age.csv	Input file indicating the population of each Azone stratified by age group
Azone_hh_veh_own_taxes.csv	Input file indicating two types of vehicle ownership taxes: annual flat fee and a vehicle value-based tax
Azone_lttrk_prop.csv	Input file indicating what proportion of household vehicles are light trucks versus sedans
Azone_relative_employment.csv	Input file indicating the proportion of persons in each of five age groups (15-19, 20-29, 30-54, 55-64, 65+) who are employed
Bzone	Geographical unit corresponding to a transportation analysis zone
Bzone_hh_inc_qrtl_prop.csv	Input file describing the relative wealth of households in a particular bzone (compared to other households who are in the same azone)
Bzone_network_design.csv	Input file containing the number of four (or more)–legged pedestrian-oriented intersections per square mile
Bzone_travel_demand_mgt.csv	Input file indicating the number of workers and households who participate in programs that encourage alternatives to driving alone (Appendix A)
Bzone_transit_service.csv	Input file describing frequency of transit service
Bzone_urban-mixed-use_prop.csv	Input file giving a “target proportion” of households living in “mixed-used neighborhoods” (VisionEval, 2021a)
Marea or Region	Geographical unit corresponding to the entire study area
Marea_transit_service.csv	Input file indicating the number of revenue miles of transit ridership

Region_ave_fuel_carbon_intensity.csv	Input file indicating the carbon intensities for various types of vehicles
Region_carsvc_powertrain_prop.csv	Input file indicating the proportion of carsharing vehicles that use combustion, hybrid electric, or battery electric powertrains
Region_2045.csv	Output file indicating an extra tax, if necessary, should user fees not cover the cost of roadway maintenance

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INTRODUCTION

The planning process entails trade-offs between choices offered to decision-makers. Yet the effects of actions are influenced by external events: a transportation investment may increase regional economic output, but so may lowered shipping prices. Community goals are usually targeted through several, not just one, initiatives. Such decisions may have multiplicative effects (e.g., increased fuel taxes may reduce travel to outlying areas but spur city core development, further reducing vehicle travel) or attenuating effects (perhaps resultant reduced congestion induces travel). For these two reasons—the complicating role of external events and the potential interaction effects of multiple decisions—stakeholders are sometimes interested in the impacts of diverse events—only some of which are explicitly chosen. This interest occurs within both the regional and statewide planning processes.

As a regional example, a technical report by the Northern Virginia Transportation Authority (NVTA) indicated an interest in improving outcomes (such as fewer transportation emissions) through deliberate decisions (e.g., build additional capacity in the Route 50 corridor in western Fairfax County) (NVTA, 2018). Yet this report, which supports the region's transportation plan, also noted that several trends outside such decisions "present a high degree of uncertainty" over a two-decade horizon, with one such trend being "development patterns" (NVTA, 2018). This uncertainty takes different forms; notably, metropolitan planning organization (MPO) 20-year forecasts of growth within specific census tracts or transportation analysis zones (TAZs) may be in error or the locality forecasts may be in error. Each error reflects different policy levers: for the former, a single county may within its borders use zoning or subdivision ordinances to encourage development in specific subareas. For the latter, mechanisms for regional cooperation are germane.

As a statewide example, Virginia's Office of Intermodal Planning and Investment (OIPI) *VTrans Policy Guide* (OIPI, 2021a), as part of its process for prioritizing mid-term needs (those over the next 10 years), explained key objectives that can be met through the "right" transportation system investments, such as reducing the severity of freight congestion and improving transportation reliability. Yet OIPI also noted the role of "uncertainty" with respect to expected future conditions. For example, one long-term trend that OIPI intends to monitor between the present and 2045 is the "adoption of highly autonomous vehicles," which would logically reduce crash risk. However, the accompanying technical document (OIPI, 2021b) noted that deviations in population growth could logically affect vehicle miles traveled (VMT) and therefore forecasts of safety impacts of this trend.

A Potential Benefit of Scenario Planning

Scenario planning can resemble the traditional long-range planning process with a focus on performance measures. The Federal Transit Administration (FTA) (2019) defined scenario planning as "a process that evaluates the effects of alternative policies" on a region where programs or plans may be evaluated against "performance indicators" and then steps may be taken to achieve a "preferred scenario." Such emphasis on performance measures is evident in the regional planning process—notably, the execution of a travel demand model to choose the set of projects that yield the lowest amount of delay. Yet scenario planning also concerns uncertainty associated with unforeseen futures such as "new technology, environmental patterns or global trade patterns" (Twaddell et al., 2016). In sum, scenario planning—the evaluation of potential impacts of unknown future conditions—enables stakeholders' consideration of potential policies by formalizing the role of uncertainty in the planning process (Zmud et al., 2014). This uncertainty manifests partly in the form of changes in exogenous variables such as sea level rise (Kalra et al., 2014) or oil price increases (Bauer et al., 2015). Yet uncertainty also reflects evolution in causal relationships (e.g., attitudes toward travel may shift in response to climate change [Bradley, 2014] and, crucially, interaction effects from multiple decisions [FTA, 2019]).

No single analytical technique defines scenario planning. Examples of techniques include interviews of experts (Bartholemew, 2005); the application of specific modeling packages (e.g., UrbanSim, which concerns land use, or TREDIS, which focuses on economic impacts [Twaddell et al., 2016]); and the adaptation of existing approaches such that multiple inputs are considered. For example, with network-based models, one may compare how greater-than-forecast employment increases affect delay compared to capacity additions. Meyer and Miller (2013) pointed out that in order to evaluate a wide range of potential futures, it is not uncommon for sketch planning techniques or other simplified methods to be implemented in practice (e.g., one example might be that the VMT per person at densities of 6,000 people per square mile is four-fifths the VMT per person at 3,000 people per square mile).

Scenario planning tools can also be developed for specific concerns: Williams et al. (2016) developed a spreadsheet-based tool for the Texas Department of Transportation (DOT) that forecasts changes in VMT as a function of population growth and jobs-housing balance estimates. Bauer et al. (2015) explained that scenario planning can be used for transportation system management and operations, envisioning responses to unforeseen situations such as an increase in driverless vehicles or changes in attitudes toward vehicle ownership. For example, in reference to transportation system maintenance and operations (TSMO), Bauer et al. (2015) noted that scenario planning could be used to identify "cost-effective TSMO strategies to support greenhouse gas emission targets given the potential impacts of a proposed new freight distribution center" or to decide investments in traffic management centers to strengthen resiliency given "uncertain technology trends." The common theme for scenario planning is consideration of factors controlled (taxation) and not controlled (advances in technology) by decision-makers.

The Challenge of Incorporating Scenario Planning in a DOT Environment

Transportation agencies—including VDOT and MPOs—have made large investments—staff, software, and institutional relationships—to maintain existing models, which is understandable given their regulatory uses such as air quality conformity. Given such earmarked resources, and the interagency consultation process (where participants devote long-term efforts to understand ongoing modeling), there is not a catalyst for agencies to explore the impacts of uncertainty.

In addition, network-based models are expensive in terms of data requirements and processing time, as they should be. If an agency is considering a [costly] bridge widening, one should carefully consider the impacts on travel patterns, and thus extensive short-term network shifts (such as localized rerouting) and longer-term land use impacts (such as development of newly accessible areas) matter. Yet such packages are not necessarily designed for a wide range of possible input values (e.g., what if population in the eastern part of a region grows at one-half the forecast rate over the next two decades?). With long run times for large regional models (e.g., for the Washington, D.C., region, run times on advanced computing systems are 12 to 17 hours [National Capital Region Transportation Planning Board, 2021]), the complexity associated with multiple model executions because of uncertain inputs is understandably best avoided.

Envisioning future scenarios is somewhat hampered by interaction effects. A starting point may be shifts in local key demographic variables, such as higher employment growth in certain TAZs; with historical analysis, reasonable upper and lower bounds for family sizes can be incorporated. Yet cascading effects of changes in technologies (e.g., use of alternative fuels), public sector responses (e.g., alterations to taxing policy for conventional and alternative fuels), and longer-term shifts (e.g., a change in VMT) are less straightforward to compute without some platform for their representation.

A Recent Tool for Performing Scenario Planning

A challenge of scenario planning is that it can become quite time-consuming, depending on how one balances the staff effort required with the sophistication of the modeling approach. For example, a previous effort that sought to examine potential impacts of driverless vehicles essentially required roughly 18 months to delve into the details of the regional planning model for one region and to consider ways to tweak the model to account for potential changes in capacity, land development, transit service characteristics, and new services such as mobility subscription services (Miller and Kang, 2019).

In response, over the past quarter century, a variety of analytical methods have been developed that can perform scenario planning. Examples include the Surface Transportation Efficiency Act Module (STEAM) (DeCorla-Souza et al., 1998), which runs as a post-processor to a regional model; UrbanSim, which can be integrated with the regional model (Meyer and Miller, 2013); CommunityViz (City Explained, Inc., 2020), a sketch tool that can help one determine total infrastructure needs given a certain level of growth and can be run independently of a regional model; and the National Public Health Assessment Model (Schoner et al., 2018), which is designed to run as an add-on after the user has executed other sketch tools. Avin et al. (2016) used a three-category taxonomy to characterize candidate scenario planning tools: (1) "sketch" level planning tools, which require limited data and are relatively quick to use (e.g., spreadsheet-based Envision Tomorrow Plus); (2) "heavyweight" tools, which require a substantial expertise for both data acquisition and calibration (e.g., Cube Land); and (3) "middleweight" tools, which have capabilities and processing requirements between these two (e.g., Impacts 2050). Table 1 lists a few of these tools along with sample scenarios that the tools might be able to tackle based on the research team's interpretation of the reference material.

Another parallel effort that also seeks to address scenario planning challenges (in terms of input file preparation time, data execution time, and the need to consider a broad level of scenarios) is a transportation pooled fund (TPF) study led by the Federal Highway Administration (FHWA) that seeks to enhance a decision tool known as VisionEval (Raw and Flynn, 2020; VisionEval, 2021a). This tool was discussed at the spring 2018 meeting of the Virginia Transportation Research Council (VTRC) Transportation Planning Research Advisory Committee (TPRAC). As a result of interest at that meeting, Virginia joined the TPF study (which was already underway). At the time of the meeting, the lead coordinator for the TPF study had described VisionEval as follows in materials that were distributed at the meeting:

Table 1. Examples of Analytical Methods That Can Facilitate Scenario Planning

Tool (Source)	Example Role	Example Scenario
STEAM (DeCorla-Souza et al., 1998)	Used as a post-processor for a regional travel demand model	If a toll is added to a freeway, what will the impact be on emissions, fuel consumption, and crashes?
Impacts 2050 (Avin et al., 2016)	Examine how demographic shifts will affect travel demand outside the modeling environment	How might changes in immigration affect travel demand?
UrbanCanvas Modeler (Avin et al., 2016; Waddell, n.d.)	Integrate land use impacts and inputs with a regional travel demand model	How will development affect water supply?
CommunityViz (Blandford et al., 2008; City Explained, Inc., 2020)	Show the community visualizations of potential development patterns and get feedback	Given this level of population growth, what additional levels of schools and roads are required?
Envision Tomorrow [ET+] (Wasatch Front Regional Council, n.d.)	Examine alternative scenarios for how a community might grow	To what extent will more mixed development shift trips to walking?
National Public Health Assessment Model (Schoner et al., 2018)	After using a sketch tool such as Community Viz or ET+, perform an add-on analysis to determine health impacts	For the scenario of mixed development, what proportion of residents would experience poor health impacts compared to the base case?

> VisionEval is an effort to respond to the emerging challenge faced by planning agencies to support rapid, well-informed decisions about how best to spend limited resources, in an environment where technology, travel needs, and public priorities are changing rapidly and becoming more and more complex. Today, planning agencies need to consider the combined effects of projects on many different performance measures ranging from congestion to job access to safety and health impacts, and to evaluate a range of innovative policies to improve the transportation system.
>
> New technologies, including shared mobility and vehicle automation, promise to radically alter how people meet their mobility needs, with a host of still unknown effects and needs. We don't know everything we need to do full predictive models, and consequently we also need to be able to test a wide range of assumptions (and not just extrapolate from the past). And because the range of things we need to consider is evolving very rapidly, the turnaround time on planning analysis is also shrinking, so we don't have time to build big new models for use in project or program screening.
>
> VisionEval is a state-of-the-art attempt to address these needs by creating a modeling system that can be enhanced rapidly to address new phenomena, that supports flexible and nuanced consideration of many dimensions of the transportation system, that enables agencies to find the best solution despite the complexities and uncertainties, and that makes it easy to explore our options against many possible future scenarios so that the decisions we have to make today can be effectively "future-proofed" (Raw, 2018).

VisionEval is an open-source scenario planning platform incorporating three models: the metropolitan area Regional Strategic Planning Model (VE-RSPM), the Rapid Policy Analysis Tool (VE-RPAT), and a statewide implementation (VE-State). After estimation of key parameters, the models act essentially as a large elasticity-based calculator with key transportation demand and supply inputs (e.g., population, employment, miles of highway, lines of transit service) and resultant outputs. The emphasis is on being able to examine a range of alternative futures fairly quickly, in terms of both computational time and data entry time.

If used without modification, VE-RSPM incorporates a variety of mathematical relationships between generators of travel demand (e.g., housing prices, employment locations); transportation service policies (e.g., transit availability and fares, roadway miles); and performance measures (e.g., VMT, emissions, and transit use), as shown in Figure 1. Each of these relationships is incorporated into 35 different modules. For instance, one module may be considered: the generation of household-related VMT. Table 2 replicates some of the values for one particular household in one TAZ in Virginia where socioeconomic variables (e.g., number of drivers, income, and vehicles); land use variables (e.g., population density and degree of mix); and supply variables (e.g., amount of freeway lane-miles), along with a transformation, yield an estimate of daily VMT for that household. Such an estimate is then "adjusted" through an iterative balancing process to account for factors such as VMT taxes and vehicle types (Wang et al., 2018); this balancing process does not affect land use or transport supply but does affect household level choices (VisionEval, 2021a).

VisionEval is a "strategic model" (Raw and Flynn, 2020) having less detail than an operational model with a transportation network but having more detail than sketch approaches by incorporating feedback loops between costs and behavior. This description is consistent with that of Avin et al. (2016) who described VisionEval as a "middleweight" tool: it is similar to the simpler sketch tools in that it has shorter run times; however, it entails the creation of synthetic households where the module balances household net travel and travel costs and the scenarios are not internal to the platform but rather are created externally by the user. For instance, vehicle types assigned to individual households are based partly on income; newer vehicles have lower emissions.

Inputs occur at three geographic levels: the region (a "Marea"), the locality (an "Azone"), and TAZs ("Bzones"). Figure 2 shows 1 Marea, 3 mutually exclusive Azones, and 712 Bzones.

Raw and Flynn (2020) concluded that this tool had both strengths and weaknesses: it is suitable for situations where there is substantial uncertainty (e.g., population growth, technologies) and allows one to evaluate a wide range of transportation policies (e.g., Intelligent Transportation System investments, travel demand management, and capacity improvements). A weakness is that because it does not represent a roadway network, it may not be suitable for project level analyses, especially given that congestion levels are aggregated at a wide level.

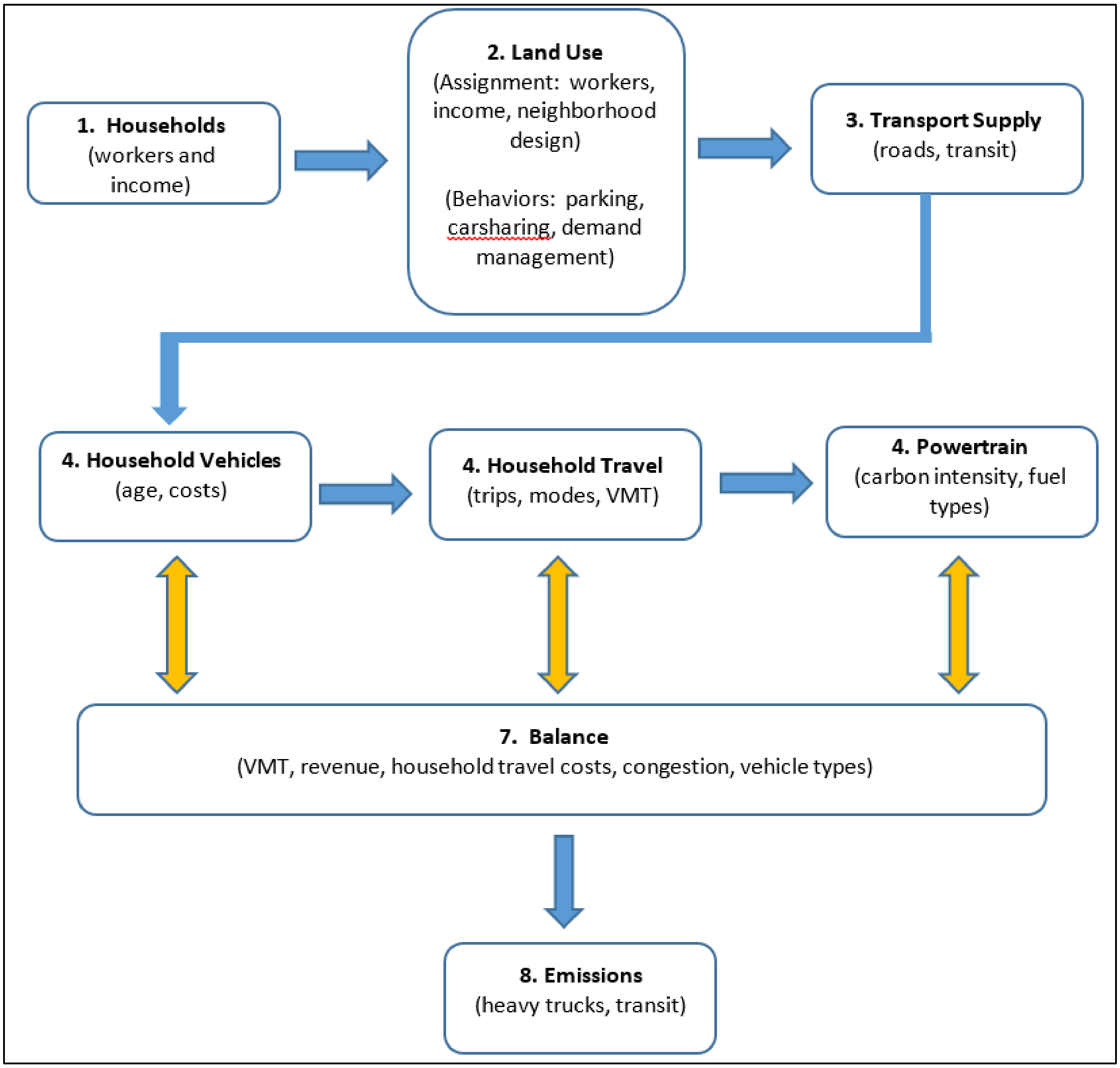

Figure 1. Overview of VisionEval. This overview was based on a review of program outputs and VisionEval (VisionEval, 2021a). VMT = vehicle miles traveled. Orange arrows indicate iterative feedback loops.

Table 2. Estimation of Household VMT for a Metropolitan Area (Zone-Specific Model)

Row	Variable	Coefficient Used in VisionEval	Value for a Household From the Household File	Product
1	Intercept	1.0850[a]	1[a]	1.085[b]
2	Drivers - number of drivers in the household	0.0866[a]	2[a]	0.17326[b]
3	LogIncome - natural log of annual household income ($2001)	0.0924[a]	12.16651[a]	1.12467[b]
4	Hbppopdn - density (pop/sq mi) of the census block group	-0.00000910[a]	13215.61[a]	-0.12022[b]
5	NumVeh - number of vehicles owned or leased by the household	0.0426[a]	2[a]	0.0852[b]
6	ZeroVeh - dummy variable identifying whether the household has no vehicles	-0.1269[a]	0[a]	0[b]
7	OneVeh - dummy variable identifying whether the household has only one vehicle	-0.0842[a]	0[a]	0[b]
8	Workers - number of workers in the household	0.1208[a]	2[a]	0.2416[b]
9	Age0to14 - number of persons in the 0-14 age group in the household	0.0725[a]	2[a]	0.145[b]
10	UrbanDev - whether the block group is urban mixed-use	-0.0602300[a]	1[a]	-0.06023[b]
11	FwyLaneMiPC - ratio of freeway lane-miles to urbanized area population	75.5400[a]	0.0004[a]	0.031667[b]
12	Total			2.70595[b]
13	Metropolitan Power Transform (given in the VisionEval Wiki accessible from VisionEval [2021])			0.24[a]
14	Initial estimated daily VMT for this household computed as $VMT = Total^{\left(\frac{1}{0.24}\right)} = 2.70595^{4.167}$			63.29[b, c]
15	Final estimated daily VMT for one particular household from VE-RSPM after balancing adjustments			20.26[a]

VMT = vehicle miles traveled.
[a] The value is directly observable in either the Wiki (VisionEval, 2021a) or the input or output file for this particular household.
[b] The result is not directly observable but was computed by the research team as an interim step.
[c] This transformation was explained by Gregor (2021) in response to a query regarding VisionEval (2021c).

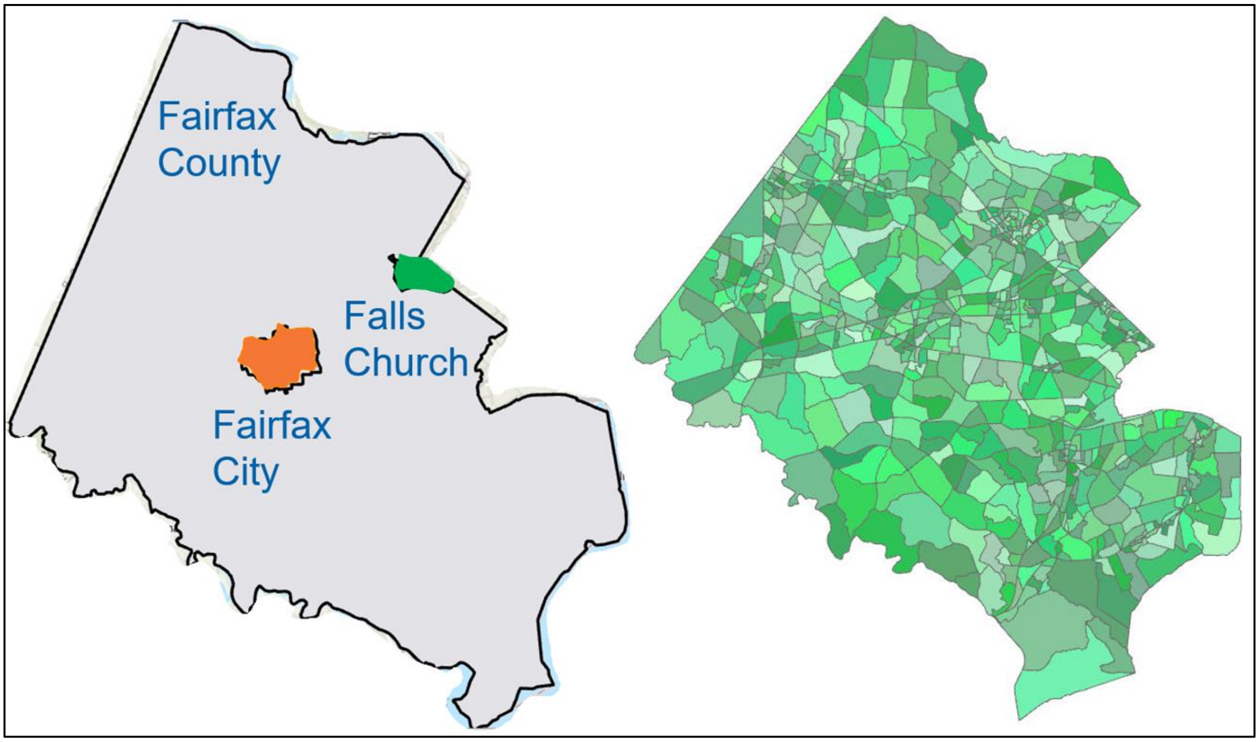

Figure 2. ***Left*: Study area with 3 Azones (Fairfax City [orange], Fairfax County [gray], and Falls Church City [green]).** ***Right*: 712 Bzones; colors serve only to differentiate zones. Figure 2 was created by the research team using ArcGIS® software by Esri. ArcGIS® and ArcMap™ are the intellectual property of Esri and are used herein under license. Copyright © Esri. All rights reserved.**

Problem Statement

The problem facing Virginia is that although VisionEval appears to offer an opportunity to perform scenario planning, the extent of this opportunity is not fully understood: staff have not yet executed the tool for a real scenario (so neither the time required to perform an analysis nor the types of results that can be produced are known); the full range of scenarios that can be addressed has not been determined; and although documentation is forthcoming, the specific mathematical relationships embedded in the feedback loops in Figure 1 are perhaps not as well understood by practitioners as would be desirable if the model were put into practice. A short course was held for Virginia users of VisionEval on May 18, 2020, where the consensus of the attendees was that the next step to understand the model is to use it.

PURPOSE AND SCOPE

The purpose of this study was to determine the benefits, costs, and suitability of applying VisionEval to scenario planning in Virginia. Benefits are defined as the insights obtained from deploying the model: the quantitative impacts on performance measures of interest as a function of policy, demographic, technological, or cost changes. Costs are defined as the staff time required for data preparation, model execution, and model explanation. Suitability is defined as the feasibility of adapting VisionEval to scenarios of interest to VDOT planning staff and planning partners, including any best practices needed to make the tool usable.

The scope of the study was limited in three ways:

1. The study focused on a case study in one location: a portion of VDOT's Northern Virginia District, where VisionEval is used to determine policies that would enable a substantial reduction in VMT and emissions. This case study was of interest to the technical review panel (TRP), and an accompanying document (NVTA, 2018) highlighted key ideas that helped generate potential scenarios.

2. The study used only VE-RSPM as available in late 2020 and early 2021 to focus on demographic trends, technological trends, and policy choices for the section of Northern Virginia shown in Figure 2 with a 2019 current year and a 2045 forecast year. Two other VisionEval models, the Rapid Policy Analysis Tool (VE-RPAT) (a simplified version of VE-RSPM) and a state-level model (VE-STATE) were not part of this study. Enhancements to VE-RSPM are underway and those made after March 31, 2021, were not part of this effort.

3. The study focused on one particular scenario planning tool, VE-RSPM within VisionEval, and did not examine other scenario planning tools such as those shown in Table 1.

METHODS

Five steps comprised the case study methodology:

1. Identify rough scenarios of interest to stakeholders.
2. Develop base input files.
3. Develop scenario input files.
4. Validate the model.
5. Execute scenarios.

Task 1. Identify Rough Scenarios of Interest to Stakeholders

NVTA (2018) highlighted multiple areas of uncertainty: population and employment forecasts; alterations in household size; development patterns; telecommuting; tax policy; the ability of older individuals to age in place; and possible emissions. Each of these areas was identified as a rough potential scenario. For instance, NVTA (2018) noted that a key item of interest is "demographic characteristics and preference (like family size)." Accordingly, a scenario was envisioned for year 2045 where family sizes would be larger than expected.

The research team took a fairly expansive view when defining potential scenarios. For example, NVTA (2018) noted that reducing transportation emissions is a key goal, citing options such as VMT reductions, slugging, carpooling, and reduced vehicle ownership. The research team added two other techniques for reducing emissions: alterations to the vehicle fleet (including heavy trucks) and the consideration of reducing emissions through altering fuel sources for power plants. Related literature from stakeholders was also examined to identify possible scenarios. For instance, Reynolds (2020) pointed out in a Fairfax County Board of Transportation meeting that the Fairfax County DOT "believes electric buses are the future," and the Washington Metropolitan Area Transit Authority (WMATA) (2019, 2021) has publicized efforts that reduce transit emissions (such as the use of compressed natural gas or clean diesel). Accordingly, the research team developed scenarios that looked at how electrification of transit buses and vans could reduce carbon dioxide equivalent (CO_2e) emissions.

Task 2. Develop Base Input Files

The final version of VE-RSPM executed by the team requires 51 current and forecast year input files spanning the areas of demographics, economy, transportation supply, vehicles fleet, network design, and pricing. As shown in Figure 2, these input files may reflect the entire study area, each city or county (known as an Azone), or each transportation analysis zone (known as a Bzone). For each input file, the research team used publicly or privately available data to estimate plausible values; although there were several situations where a range of values was feasible, in all cases the research team sought to avoid arbitrary inputs. For example, one required input was per capita income for the present and forecast years at the city (e.g., Azone) level; these were obtained from public sources for 2019 (U.S. Census Bureau, 2020a, b, c) and then adjusted based on privately purchased sources for 2045 (Moody's Analytics, 2019; Woods & Poole Economics, Inc. [Woods & Poole], 2018a, b). Generally, one can obtain from public sector sources all of the data for the base year. However, for Virginia, there were no forecast year publicly available data sources for income or employment, especially at the Bzone (e.g., TAZ) level of geography.

In several instances it was necessary to consult non-traditional data sources to obtain appropriate input values for the base (2019) year. For instance, VisionEval requires the proportion of household vehicles that are sedans as opposed to pickup trucks or SUVs. This file is azone_lttrk_prop. An approximation was developed using vehicle populations periodically developed by the Virginia Department of Environmental Quality (Lewis-Cheatham, 2020) as part of the National Emissions Inventory. These populations are used with the U.S. Environmental Protection Agency (U.S. EPA) MOVES model, and the proportion can be determined from 2 of the 13 MOVES vehicle types: passenger car (type 21) and passenger truck (31), the latter of which includes "many SUVs and minivans" (U.S. EPA, 2019). This approach is an approximation: some vehicles in this inventory may reflect commercial rather than household uses and there is not a perfect alignment between U.S. EPA vehicle classifications and FHWA vehicle classifications (Ponticello, 2020), with the U.S. EPA (2019) defining "light duty vehicles" based on weight and emissions. That said, this approach can give base year proportions, as shown in the top of Table 3.

Table 3. Base Year and Forecast Year Values for Proportion of Vehicles That Are Light Trucks

Geo (Name of city or county)	Year	LtTrkProp (Proportion of household vehicles that are light trucks)
Fairfax County	2019	0.44
Fairfax City	2019	0.42
Falls Church	2019	0.39
Fairfax County	2045	0.50
Fairfax City	2045	0.48
Falls Church	2045	0.45

[a] Table 3 reflects the contents of file azone_lttrk_prop.csv except the material inside the parentheses was added for clarity.

It was also necessary to adapt national or regional forecasts to the case study area. For instance, referring to the aforementioned ratio of sedans to passenger SUVs or trucks, the research team was not aware of Virginia-specific forecasts for 2045. However, forecasts for other locations suggested this ratio may not remain constant. Voelk (2020) quoted an interviewee from IHS Markit who stated that in 2025, the "light-truck segment" (inclusive of SUVs and pickup trucks) was expected to increase from 72% to 78%. A graphic in Schuster (2018) forecast that the share of SUVs sold in the United States would increase from 50% in 2020 to 53% in 2025. The International Energy Agency (2019) noted that worldwide use of oil attributed to the growing popularity of SUVs could reduce the benefit of electrification between the present and 2040, although this worldwide forecast included other countries where SUV use was lower than in the United States at present and thus has more room to increase (Schuster, 2018). Accordingly, forecast values for 2045 were developed for Fairfax County, Fairfax City, and Falls Church on the presumption that they might mirror U.S. trends forecast through 2025 and worldwide trends through 2040 such that one might expect some increase in the light truck proportion. In recognition that vehicle sales is not synonymous with vehicle fleet, one forecast is that a 6% increase in the light truck proportion of sales by 2025 (Voelk, 2020) could translate into a 6% increase in light truck proportion of household vehicles by 2045. Thus, for each jurisdiction, the 2045 values were increased by 6 percentage points (e.g., Fairfax County was increased from 43.8% in 2017 to 49.8% in 2045). Such values, rounded to whole percentages, are shown at the bottom of Table 3.

Task 3. Develop Scenario Input Files

For each rough scenario identified as part of Task 1, one or more input files (Figure 3) were modified as appropriate. Again, the research team sought never to pick a value for an input arbitrarily; rather, a candidate input value was chosen based on the available literature. For instance, one scenario entails the use of increased taxes for fossil fuels. The question arises: what is a realistic upper bound? One answer may be found by reviewing past proposals relative to past fuel prices. More than three decades ago, The Road Information Program (1989) reported that some proposals included a $0.50 fuel tax when fuel cost $1.00 per gallon—hence, as an upper bound, a fuel tax of 50% of the purchase price was used for that scenario.

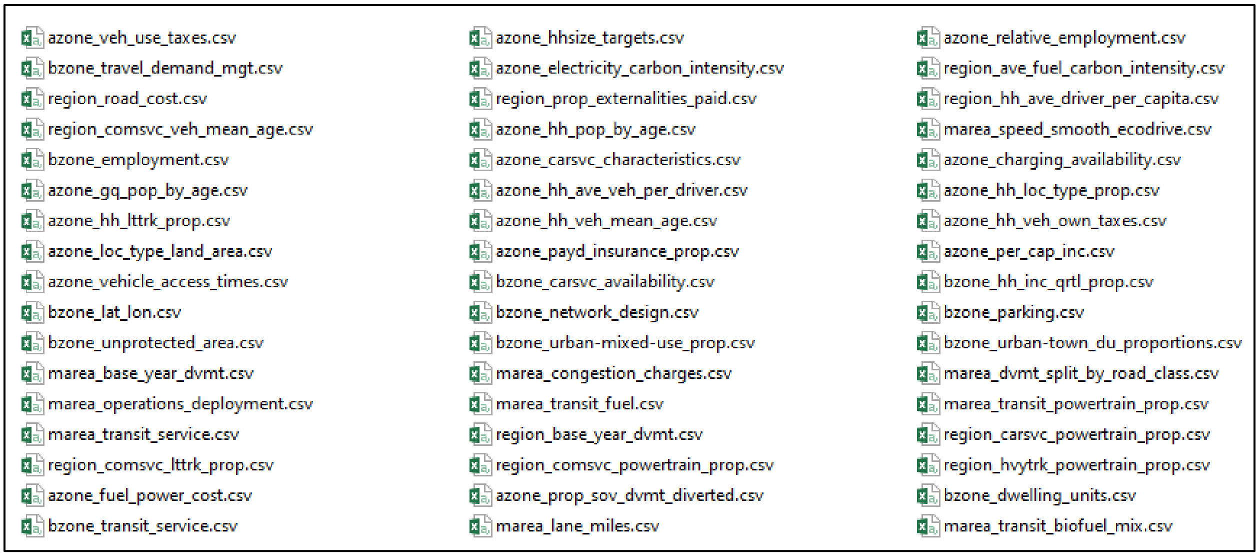

Figure 3. Input Files Required for the Case Study Application of VisionEval. Those that begin with the letter "a" have a different input for each city or county; those that begin with "b" have a different input for each transportation analysis zone; and all others have a single input for the entire region.

Care was taken to relate the conceptual scenarios from Task 1 to realistic input values in Task 3. For example, one scenario concerned forecast errors for population and employment. In Virginia, city and county population forecasts are the responsibility of the Virginia Employment Commission, but the sub-allocation of these forecasts to individual TAZs is the responsibility of the MPO. Rather than arbitrarily pick a forecast error, the research team consulted previous work, which showed that over 20 years for an MPO in central Virginia, the number of households had yielded a 48% error (at the TAZ level) but that at the regional level, a smaller error of 10% had resulted for total population. Thus, one scenario consists of accurate locality forecasts but an average absolute percent error of 48% for TAZ-level forecasts (to represent deviations from expected MPO forecasts) and another scenario includes 10% population errors for Fairfax City, Fairfax County, and Falls Church (to represent deviations from expected Virginia Employment Commission forecasts).

Additional literature was sought to estimate benefits. For instance, one scenario entailed the conversion of power plants to solar power. Relative carbon intensities provided by Helman (2021) for solar and natural gas were thus used to determine the emissions reductions associated with increased use of solar power.

Task 4. Validate the Model

Validation took two forms. First, the 2045 outputs in terms of VMT were compared from the base case of VisionEval and the Fairfax County portion of the regional model. This allowed detection of whether the total amount of estimated travel demand for VisionEval (from its household file) and a more detailed method were similar, where one could examine passenger and truck travel demand separately. Ratios of workforce to population based on national data and those in VisionEval were also examined.

Second, the scenarios were used: to what extent are the relationships between travel demand and factors that influence that demand reasonable? For example, to what extent does a large increase in the fuel tax lead to a reasonable decrease in household VMT as found in the literature (e.g., McMullen and Eckstein, 2013)? This second validation form was also used with a hypothetical area where, because some scenario results were surprising, VisionEval was re-executed. VisionEval's internal adjustments were not always apparent, such as the manner in which estimated initial estimated daily VMT (second to the last row of Table 2) is adjusted to yield a final estimated VMT (last row of Table 2). Accordingly, an artificial five-TAZ system (Figure 4) allowed for quick experimentation to examine VMT elasticity with respect to income and fuel taxes.

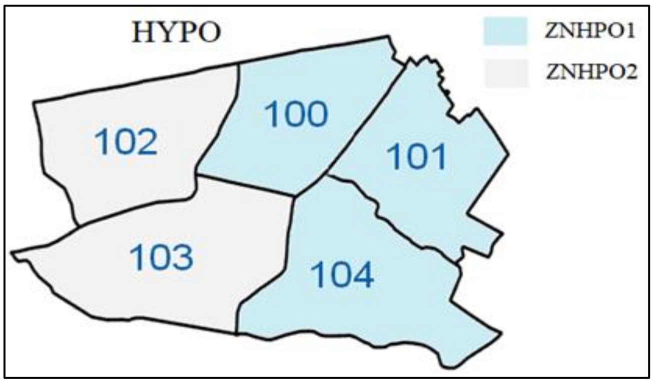

Figure 4. Five-Zone Hypothetical Model Marea (HYPO), Azones (ZNHPO1 and ZNHPO2), and Bzones

Task 5. Execute Scenarios

Scenarios were executed using the version of VisionEval that accompanies R version 4.0.5 (VisionEval, 2021b) in two ways. First, a script in R that is publicly available allows one to execute the scenarios one at a time with minimal programming. The VisionEval Wiki (VisionEval, 2021a) provides instructions, but for one-at-a-time execution, the simplest instructions are those that accompany the software download (VisionEval, 2021b). This approach was used with the aforementioned theoretical model. Second, a script that executes scenarios simultaneously was developed by staff at the Volpe National Transportation Systems Center (Volpe) and used to execute groups of scenarios. Then, after revisions to input files were made, the scenarios were executed a final time individually in order to have a record of all output variables.

Scenario results focused on performance metrics of interest to stakeholders from step 1: household and heavy truck VMT; delays for vehicle light duty vehicles; CO_2e emissions (for households and the region); total energy use (gasoline gallon equivalents from fossil fuel vehicles and kilowatt hours for electric vehicles); and mode split (trips by vehicle, transit, pedestrian, and bicycle). Scenarios were run in two phases: first as individual changes in order to understand impacts at an order of magnitude level, and second as combinations of steps in order to understand potential extreme effects.

Collaborative Efforts

Development of the input files, model execution, and debugging was a collaborative effort: over a period of 10 months, video meetings were held with representatives from FHWA, Volpe, VDOT's Northern Virginia District, and VTRC (see Table 4). Insights were also received in the course of a presentation on this work made at the VisionEval summit in 2021 (Adel et al., 2021).

Table 4. Collaborative Element With U.S. DOT and Other Users

Date	Topic	Example of a Result
October 13, 2020	Proposed idea of how to collaborate among FHWA, Volpe, and VDOT	Case study will be the area of Northern Virginia; NVTA (2018) has some scenario planning topics.
October 20 and 26	Roughly 54 input files are required depending on how VisionEval is run. Some files are optional, and later just 51 were used.	Google Drive allows sharing data input files, but because of VDOT/VITA security policies, UVA rather than VDOT logins will be used.
November 10	Volpe identified promising sources based on the Atlanta Regional Commission, and these will be divided among the group for the study area. One TRP member noted the importance of being consistent with existing VDOT modeling efforts in Fairfax.	The case study area should include 3 jurisdictions: Fairfax County, Fairfax City, and Falls Church. TAZs that are part of the Northern Virginia regional model will be used for consistency.
November 17	Documentation of development of input files, such as Census data, is essential.	Additional data sources include the public sector (e.g., Weldon Cooper Center for Public Service) and the private sector (e.g., Moody's and Woods & Poole).
November 24	Non-traditional data sources for planners are needed (e.g., emissions information for passenger cars and trucks).	Data from the National Emissions Inventory, provided by the Virginia Department of Environmental Quality to VDOT's Environmental Division, were essential.
December 2	Geographic data from the U.S. Census Bureau, such as tracts and block groups, do not necessarily align with TAZs from the Northern Virginia portion of the regional model.	Volpe developed a customized tool in R for aligning these (using group homes as an example), and VTRC presented the use of the Summarize Within tool in ArcGIS Pro (for transit service frequency).
December 10	Volpe identified an error that VTRC could not solve (incorrect folder name and missing subfolder) for running the R customized script.	Individuals running the models learned that spacing, capitalization, and folder names are essential.
December 17	Computation of two input files: bzone_parking, and marea_transit_service.	For bzones, TAZ_N is the unique identifier and the attribute PkgSpacesPerGQ should not have a systemwide average of 0.17 but rather should have higher values for GMU and zero values for group quarters.
January 28, 2021	Volpe presented computation of income percentiles, and VDOT presented intersection density and revised parking. Discussion concerned how to get 2045 values for intersection density and how to interpret parking costs from MWCOG, which are detailed.	Keep income quartiles allotted by Azones. For intersection density, use a different method (forecast of pedestrian-friendly areas developed for WMATA and provided by a TRP member) for 2045 values.
February 4	When the hypothetical model was executed, an unexplained error resulted.	Examination of the source code by Volpe showed that Azones (e.g., cities and counties) must have a certain number or else the software will crash (e.g., 1,000 people in an Azone is acceptable but 10 is not).

February 18	In some cases, the meaning of the data elements is not clear, and in other cases, the manner in which Census tract data should be converted to TAZs is not clear.	The proper manner of aggregation varies between count-based attributes and mean-based attributes; e.g., if 2 Census block groups corresponded to 1 TAZ and each block contained a count of jobs, one should sum them. If each block contained a population density, one should compute their mean.
March 11	For setting location types, the VisionEval Wiki refers users to Claritas (2011) for understanding land use types, and these types explicitly do not use Census designations.	Categorize land uses as metro, town, or rural based on a methodology suggested by BTS (2015) and applied to a special tabulation provided by the U.S. Census Bureau (2012).
April 15 and 21	How to develop scenarios apart from the base input files	Input files appear twice: (1) in subfolder 1 (original case), and (2) modified in subfolder 2 (modified case for a scenario).
May 10	Discussion of the general structure of VisionEval scenarios and outputs for reasonableness testing	One TRP member noted that scenario 10 (electrification of vehicles) has a higher priority than other scenarios given local interest; thus, this scenario was developed next.
May 27	How to represent telecommuting as a scenario given that modification of the employee commute options attribute did not materially affect VMT	Represent telecommuting using the optional input file azone_relative_employment.csv.
June 10	VisionEval can provide a variety of outputs	The most critical outputs are VMT, delay, emissions, and mode split.
June 28	Initial set of 19 scenarios completed	Additional scenarios should be developed pertaining to combined population and employment errors.
August 3[a]	Meet with representatives of Fehr & Pers to discuss a future enhancement to VisionEval regarding connected autonomous vehicles	Any analysis should clarify that the case study area (focused on Northern Virginia) by itself does not account for external traffic passing through the region.
August 25[b]	Invited TRP to an overview of the project and developed slides explaining the development of input files for the base case and scenarios, initial results, and initial surprises	VisionEval is not limited to the regional model; it can be a separate public involvement tool. Tailor 1 recommendation to the needs of the VTrans development of risks (OIPI, 2021a, b), and ensure the methodology behind the platform (such as Table 2) is explained.
Sept 23[a]	Meet to discuss a proposed enhancement to VisionEval regarding equity	Equity can be computed in a variety of ways, and perhaps the new module should include diverse methods—including one relevant to Virginia (see OIPI, 2020).

FHWA = Federal Highway Administration; Volpe = Volpe National Transportation Systems Center; NVTA = Northern Virginia Transportation Authority; VITA = Virginia Information Technology Agency; UVA = University of Virginia; TRP = technical review panel; TAZ = transportation analysis zone; VTRC = Virginia Transportation Research Council; GMU = George Mason University; MWCOG = Metropolitan Washington Council of Governments; WMATA = Washington Metropolitan Area Transit Authority; BTS = Bureau of Transportation Statistics; VMT = vehicle miles traveled; OIPI = Office of Intermodal Planning and Investment.

[a] Topics went beyond the case study into proposed enhancements to VisionEval under consideration by FHWA.

[b] This was a meeting with the TRP.

In addition, as VisionEval is still under development, there are elements of the platform that were not fully understood by the research team. When two specific questions arose regarding unexpected outputs, the research team submitted these questions to the development site as issues 147 and 148 (VisionEval, 2021c). One concerned the transformation used in the second to the last row in Table 2 and the subsequent calculation in the final row of Table 2 where VMT is estimated. The second question concerned the platform's balancing of roadway costs and revenues, as the outputs were not sensitive to changes in maintenance costs per lane-mile, which was surprising.

The research team also submitted a more general form of these questions to the VisionEval section of the Travel Model Improvement Program, asking if there was a better way to link input files to specific outputs given the various modules shown in Figure 1 (FHWA, 2021).

RESULTS

Development of Scenarios Based on Stakeholder Interest

Table 5 shows 10 categories of scenarios developed based on stakeholder interest: (1) unexpected development patterns (errors in 26-year population and employment forecasts by TAZ); (2) socioeconomic forecast errors by locality; (3) changes in telecommuting; (4) unexpected changes in household size; (5) alterations to tax policy for highway travel; (6) increases in roadway and transit supply; (7) changes in travel and electricity costs; (8) increases in carsharing services; (9) changes in the number of pedestrian-friendly intersections; and (10) electrification of transit and highway vehicles, including altering fuel sources for fixed source power plants. Scenarios were based on stakeholder concerns; for instance, as transportation emissions reduction was a key goal (NVTA, 2018), household vehicle electrification was identified as a scenario. Because stakeholder literature suggested alternative fuels for transit vehicles (Reynolds, 2020; WMATA, 2019*)*, scenario 10b was added.

Each scenario reflects a policy change enacted by decision-makers (e.g., electrification of transit vehicles) or an unanticipated change wrought by external events beyond the control of the decision-maker (e.g., a change in fuel prices). Some scenarios were envisioned because of competing forecasts. For example, the base 2045 forecast for fuel prices is $4.18 per gallon (U.S. Energy Information Administration [U.S. EIA], 2020a). However, since 1950, oil prices have fluctuated such that the highest price (adjusted for inflation) in 2007 is roughly 8 times the lowest price in 1998 (Macrotrends, 2021) such that there should be considerable uncertainty in this forecast. The World Bank (2021) forecast a decrease in crude oil prices (in constant U.S. dollars) from $61.70 to $59.00 for year 2035. If this same value were to hold for 2045 ($59 per barrel), and if the cost of a gallon of fuel were to be similarly affected, then the 2045 forecast price of fuel should fall slightly from the 2019 value of $2.51 to a new forecast of $2.40 (e.g., $59/$61.70*$2.51). This discrepancy formed the basis of scenario 7a.

Table 5. Summary of Northern Virginia Scenarios

No.	Changes From the Base Case	Stakeholder Question or Topic
0	None.	Baseline 2045 result.
1a	*Presume random forecast population error by TAZ.* Maintain accurate locality control totals but modify distribution of households by transportation analysis zone (TAZ) to obtain a 48% forecast error as observed elsewhere (McCray et al., 2009).	Within a given locality, what if population or employment is distributed in a manner different than expected?
1b	*Presume random forecast employment error by TAZ.* Similar to 1a, maintain a 136% employment error as observed elsewhere (McCray et al., 2009).	
1c	*Presume both random population and employment forecast errors at the TAZ level*. (Combine scenarios 1a and 1b.)	
2a	*Presume biased forecast population error by locality.* Increase population and households by 10%, an error observed elsewhere (McCray et al., 2009).	What if total locality population or employment is higher than what has been expected?
2b	*Presume biased forecast employment error by locality level*. Increase employment by 12%, an error observed elsewhere (McCray et al., 2009).	
2c	*Presume biased population and employment forecast errors by locality*. (Combine scenarios 2a and 2b.)	
3a	*Increase telecommuting slightly* (by 1.25%)	What if telecommuting shifts?
3c	*Increase telecommuting substantially* (by 40%).	
4a	*Reduce household size* by altering the number of one-person households, mean household size, and number of children in various age categories.	What if "demographic characteristics" (Northern Virginia Transportation Authority [NVTA], 2018) (e.g., family size) differ from assumptions?
4a'	*Increase household size* in a manner comparable to scenario 4a.	
4b	*Increase aging in place by 6.5%.* Seniors who live in institutionalized group quarters now move to households.	What are the impacts of aging in place?
4b'	*Reduce aging in place by 6.5%.* (A variant of scenario 4b where 6.5% of seniors leave households because of a lack of aging-in-place facilities.)	
5a	*Increase the fuel tax on vehicles that use gasoline to be one-half the price of fuel.* Thus, the fuel tax shifts from $0.52 to $2.09 per gallon.	What are the impacts of changes in tax policy?
5b	*Increase the fuel tax on electric vehicles* to match the current 2045 base scenario. (Presently, the surcharge levied by the Department of Motor Vehicles on electric vehicles is $88.20, which is about 1.4% of the fuel taxes generated by a conventional vehicle; scenario 5b increases that percentage to 100%.)	
5c	*Increase taxes and shift funds to transit.* Increase fuel taxes to one-half the price of fuel, apply the same increase to electric vehicles, calculate the increase in transit supply that could be provided by this tax increase, and increase transit revenue miles of service (marea_transit_service.csv).	
5d	*Increase taxes only.* (Similar to scenario 5c, increase the fuels tax for all vehicles types, but, unlike scenario 5c, do not divert the extra funds to transit.)	
6a	*Increase transit frequency* (e.g., the aggregate frequency of transit service is increased in certain locations). (This is attribute D4c within bzone_transit_service.csv.)	Transit crowding relief is needed at specific locations, especially inside the beltway and along the I-66/ Orange/Silver Line.
6b	*Increase arterial lane-miles supply* in the form of HOV lanes on Route 28, the Fairfax County Parkway, and the Franconia-Springfield Parkway.	Improvements are needed for some roadway facilities shown on a map (NVTA, 2018).
6c	*Increase freeway lane-miles supply* in the form of HOV lanes in scenario 6b where those lanes function as freeways rather than arterials.	
7a	*Change highway fuel costs* from a 2045 forecast of $4.18 per gallon (U.S. Energy Information Administration, 2020a) to a forecast (for 2035) of $2.40 (derived from The World Bank [2021] forecast for oil prices in year 2035).	NVTA (2018) noted that about one-fifth of survey respondents indicated that higher travel costs are key to concentrating development and that "economics" is uncertain.
7b	*Change electricity costs.* The U.S. Energy Information Administration (2021) noted that electricity could fall from a 2020 price of 10.5 cents per kwh to a price of 9.0 cents per kwh under a scenario of larger availability of oil and gas.	
7c	*Change both highway fuel and electricity costs* (scenarios 7a and 7b).	
7d [a]	*Increase car ownership costs dramatically* (add $2,000 to the annual cost of owning a vehicle and increase the ad valorem tax rate)[b]	

8a	*Change car service availability from low to high in high income zones*.	The impact of connected autonomous vehicles on vehicle miles traveled (VMT) is unknown. (They cannot be reflected in VisionEval but may be combined with other car sharing services.)
8b	*Change car service availability from low to high in low income zones*.	
8c	*Change car service availability from low to high in all zones*. In all three scenarios, the attribute car service availability is explicitly set to low, medium, or high for each TAZ (Bzone) in the region.	
9a	*Develop alternative base case values* (for pedestrian intersection density).	NVTA (2018) noted that one initiative is to improve "the street grid . . . and pedestrian environment in Tysons and Reston."
9b	*Increase intersection density in areas where parking supply is dropping*.	
9c	*Increase intersection density in Tysons and Reston*.	
9d	*Increase intersection density in the 55 zones with the highest forecast dwelling units*.	
9e	*Increase intersection density by 50%*.	
9f	*Increase intersection density by 100%*.	
10a	*Replace the 44.1% of carsharing vehicles that are internal combustion engines, making one-half hybrid and one-half battery electric*.	What kinds of fleet strategies and power plant policies can support reducing transportation and stationary source emissions?
10b	*Electrify transit buses and vans, making one-half hybrid and one-half battery electric*.	
10c'	*Electrify household vehicles, making one-half hybrid and one-half battery electric*.	
10d	*Convert one-half of trucks to hybrid and one-half to battery electric*.	
10e	*Enable an additional 25% of Virginia's power to be solar in 2045 than would be the case under the business as usual scenario*.	
C01	*Better emissions impact*: electrification of household vehicles (10c'), electrification of trucks (10d), and increased telecommuting (3c).	More than one policy may be enacted. What are examples of combinations that yield better, worse, and moderate emissions impacts and VMT impacts?
C02	*Worse emissions impact*: increased locality population (2c) and increased carsharing (8c).	
C03	*Modest emissions impact*: small amount of telecommuting (3a), random population forecast errors at the TAZ level (1a), and electrification of carsharing (10a).	
C04	*Better VMT impact*: large telecommuting growth (3c) and increased fuel tax (with commensurate tax on EVs) with extra funds diverted to transit (5c).	
C05	*Worse VMT impact*: population increased for localities (2a) and increased carsharing such as Uber, Lyft, or autonomous vehicles (8c).	
C06	*Moderate VMT impact*: larger families (4a'), increased electrification of household vehicles (10c'), and a fuel tax increase (5a).	

[a] Scenario was not based on any stakeholder input but rather was introduced to understand the sensitivity of VisionEval.

Realistic inputs were used; for instance, scenarios 4b and 4b' examine the impact of accessory dwelling units by altering the age 65+ population by 6.5%. This percentage was chosen based on Wellman (2010), who reported that 6.5% of Americans age 65+ live in a nursing home or assisted living facility. An accessory dwelling unit is a smaller self-contained living area on a lot that already has a separate primary residence; the accessory unit may be physically attached to the primary residence (as in a garage converted such that it has a kitchen, restroom, and bedroom) or a detached structure (AARP, 2021).

The rationale was that with accessory dwelling units being encouraged, 6.5% of persons age 65+ could be in an accessory dwelling unit and thus affect household vehicle trip generation; otherwise, these persons would be in an assisted living facility and not affect household vehicle trip generation.

In a couple of cases, scenarios were included to test the sensitivity of the model. For instance, for scenario 9, it appears that the use of two different geospatial approaches—R and ArcGIS Pro—gave slightly different values where the number of pedestrian-friendly intersections differed by about 1%. Scenario 9a therefore sought to determine if this alteration would have a meaningful impact on the resultant performance measures.

Development of Base Input Files

A total of 51 base input files were ultimately developed, corresponding to those shown in Figure 3. Each file required the identification of source data, conversion of these data to a format suitable for use in VisionEval, and then development of forecast year values. Input files covered topics such as age, income, transit vehicle fuels (e.g., compressed natural gas, diesel, hybrid, biodiesel), pedestrian network density, transit service frequency, and vehicle fleets; in some cases, default values could be used and in other cases, additional processing was needed. In all cases, the research team sought to have a defensible, rather than an arbitrary, input value. Three examples of input file development are presented here: one that requires additional processing, one that requires outreach to other users, and one where additional research is needed to understand the variable definitions.

Example of an Input File Where Additional Processing Is Needed

One input file requires an estimate of the revenue miles of transit ridership for the region. This file is marea_transit_service.csv. FTA (2020) reported revenue miles in the National Transit Database by system (e.g., Fairfax County Connector), which is problematic for the regional system WMATA since such revenue miles would include areas outside the case study area (e.g., Washington, D.C.). The National Transit Database indicated that for local systems in Fairfax City and Fairfax County there were 10.4 million revenue miles (Falls Church's system was not shown), but for WMATA, only a regional figure (for DC/MD/VA) of 37.4 million revenue miles was given. However, the Northern Virginia Regional Model Version 2.3.75 (Shahpar, 2020) has an attribute called MILES that refers to local bus systems, and it shows a value of 0.261 M for systems in Fairfax County, Fairfax City, and Falls Church, with the model showing 1.846 M for the entire region of DC/MD/VA. Accordingly, Equation 1 was used to estimate that the WMATA portion attributed to Fairfax County, Fairfax City, and Falls Church is (0.261/1.846)(37.413) = 5.3 M revenue miles. Thus, the total 2019 revenue miles in 2019 was 5.3 M (from WMATA) plus 10.4 M (from local systems) = 15.7 M revenue miles.

$$\frac{\text{Local revenue miles for case study area} = 0.261}{\text{Total local revenue miles} = 1.846} = \frac{\text{WMATA revenue miles for case study area}}{\text{Total WMATA revenue miles} = 37.413} \qquad \text{[Eq. 1]}$$

Example of an Input File Requiring Outreach to Other Users

In some cases, additional research was needed to determine the meaning of data elements. For example, one attribute known as ImpProp is the number of households that participate in an individualized marketing (IM) program—but no further information is given. A veteran user of VisionEval provided two critical insights that were then used by the research team to develop values for the case study region (see Appendix A).

First, the attribute is based on a "Smart Trips" case study developed by Boddy and Kassirer (2013) where in Portland (Oregon) staff directly appealed to new residents using three techniques: “individualized marketing,” “customized, personal communication,” and “reinforcement and encouragement.” New residents received multiple mailings encouraging them to order materials that would help them use alternative modes, and then these were delivered (by bicycle) to their homes; examples were transit system maps, local coupons, and a pledge to reduce vehicle use. Residents were also contacted afterward by phone and email and subsequently provided newsletters about changing their trip behavior.

Second, this attribute is based on the work of Gregor (2015) where such programs are feasible only in areas of sufficient density and “an urban mixed-use urban form.” Gregor (2015) suggested that a minimum threshold of 4,000 people per square mile be used to determine feasibility (although other thresholds could be used). Weidner (2021) also noted that the program (along with the EcoProp program) must be “pretty rigorous” in order to justify the reduction of 5% to 9% in VMT that is incorporated into VisionEval. Thus, as shown in Appendix A, the 2045 population density, along with information about the county’s travel demand management efforts, was used to develop this input file.

Example of Obtaining Values by Reviewing Additional Literature

VisionEval requires the proportion of Azone households (e.g., Fairfax City, Fairfax County, and Falls Church) by three different location types: metro, town, and rural. The VisionEval Wiki (VisionEval, 2021a) does not explicitly define the meaning of these attributes but instead refers to a “2001 National Household Travel Survey (NHTS) measure of the tract level urban/rural indicator,” which was “developed by Claritas” and which uses the “density of the tract and surrounding tracts to identify the urban/rural context of the tract.” Elsewhere, the Wiki explains that there are three possible categories, i.e., rural, town, and urban, but does not state how these categories are defined.

Understanding the Meaning of Metro, Town, and Rural

Both Claritas (2011) and the *2009 National Household Travel Survey User’s Guide* (U.S. DOT, 2011) referred to the role of these variables for describing these census tracts. Claritas (2011) explained that persons per square mile was converted to a centile (e.g., a score from 0 to 99) and indicated that substantial GIS processing was done to categorize zones in one of four categories: urban, town/rural (which are used in VisionEval), suburban, and second city (which are not used in VisionEval).

In describing the methodology for the NHTS, the Bureau of Transportation Statistics (BTS) (2015) noted that these Claritas data can be purchased; however, given that VisionEval is designed to be an open-source tool, the research team sought an alternative approach for defining tracts. To be clear, Claritas (2011) specifically warned that how it defines urban versus rural should not be “confused with . . . the Census defined urban area status.” However, Claritas also clarified that although these categories of urban, town, and rural are based on multiple factors, the following observations can be made based on block groups:

- Most (94%) of urban block groups have a population density centile of 75-99.
- Most (98%) of town block groups have a density centile of 20-40.
- All rural block groups have a density centile of 0-20.

Categorizing Case Study Tracts Based on Population Densities

BTS (2015) noted that these labels of urban, town, and rural "cannot be extracted from the NHTS" for all block groups (without purchasing these data). Accordingly, BTS (2015) used the population density of each census tract (not block group), where BTS (2015) sorted these densities by percentile.

A similar approach was adopted for the case study region. Surprisingly, the research team could not obtain a pre-made distribution of U.S. population densities by Census tract; however, a special tabulation done for the 2010 decennial census (U.S. Census Bureau, 2012) provided the population and land area for each census tract. The 74,002 tracts were downloaded, and the population densities were computed and sorted; then, the 20th, 40th, and 75th percentiles were determined and were found to be 161, 1,241, and 5,260 people per square mile.

Then, for the 712 TAZs, population densities were estimated for 2019 and 2045. For 2019, populations were obtained from the attribute SUB_POP15 (from the regional model), and for 2045, forecast populations were obtained from the attribute SUB_POP40. Areas were estimated from the attribute SQMI_FXTAZ, which was tabulated in ArcGIS; this was total area, not land area, but was a reasonable estimate (for these three jurisdictions, total area was about 4% higher than land area). Summing these land areas by jurisdiction and type gave Table 6, with the presumption that metro should be the land area defined as urban and suburban. Figure 5 shows the 2019 and 2045 areas.

Table 6. Proportion of Households by Area Type[a]

Azone	Year	Metro	Town	Rural
Fairfax County[b]	2019	0.946	0.051	0.002
Fairfax City	2019	0.997	0.003	0
Falls Church	2019	1	0	0
Fairfax County	2045	0.936	0.039	0.025
Fairfax City	2045	0.991	0.009	0
Falls Church	2045	1	0	0

[a] Input file is azone_hh_loc_type_prop.csv, and attributes are PropMetroHh, PropTownHh, and PropRuralHh.
[b] These values unintentionally do not sum to 1.0 due to rounding.

Summary of the Location Types Input File

The rural areas shown in Figure 5 generally are not truly rural but rather appear to reflect locations where individuals cannot reside. For example, the rural area to the far west is rural because it includes Dulles International Airport (and hence no residents); the rural area to the south includes Potomac Shoreline Regional Park; and the area circled in red includes Fairfax Hospital. For these reasons, the proportions shown in Table 6 are much lower than would be inferred from reviewing Figure 5. That is, at present, although "rural" areas are clearly noticeable in Fairfax County, Table 6 shows that in practice they represent one-fifth of 1% of households.

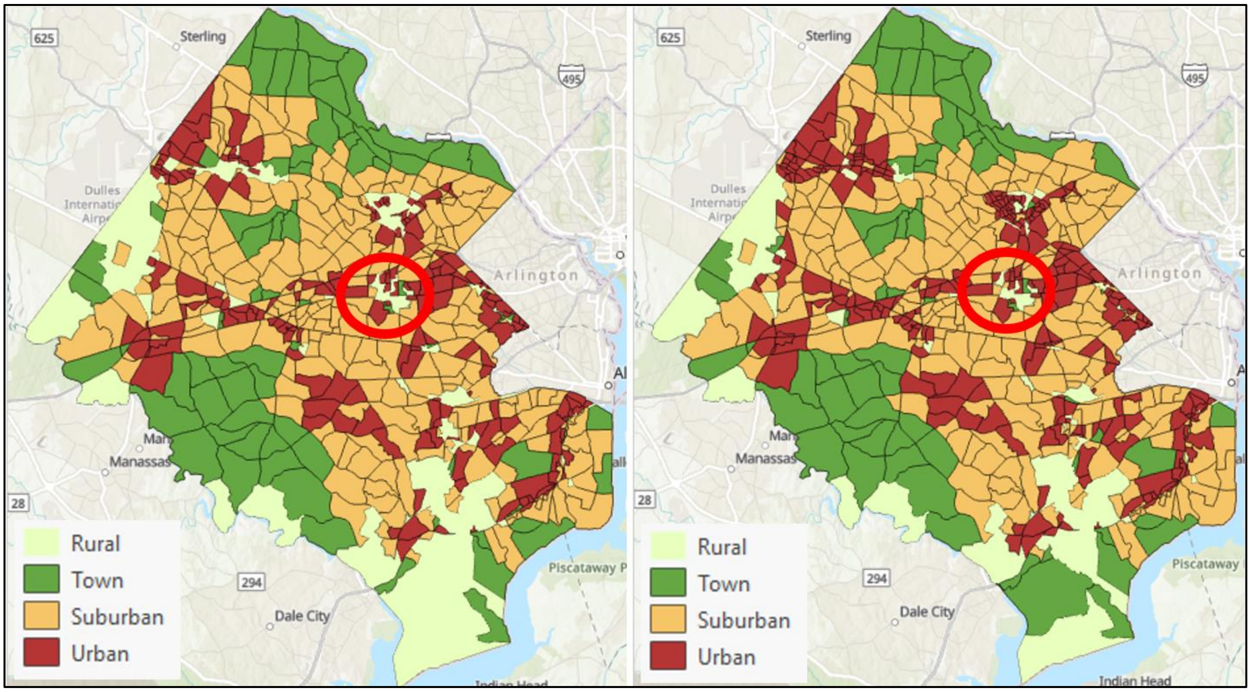

Figure 5. Location Types for the Case Study Area for 2019 (*left*) and 2045 (*right*). Very few households are located in the "rural" areas (0.2% in 2015 and 2.5% in 2045) as much of these areas reflect infrastructure such as Dulles International Airport (left portion of each map), parks (such as those in the lower portion of each map), or Fairfax Hospital (circled in red) in the center of the map. Figure 5 was created by the research team using ArcGIS® software by Esri. ArcGIS® and ArcMap™ are the intellectual property of Esri and are used herein under license. Copyright © Esri. All rights reserved. Attributions provided by Esri for the basemap underlying Figure 5 are "Fairfax County, VA, M-NCHPPC, VITA, Esri, HERE, Garmin, INCREMENT P, NGA, USGS."

Summary of Input File Preparation

The aforementioned steps are specific to the use of VisionEval. When one considers only the input files that are explicitly related to transportation supply and demand, VisionEval—as is the case with other sketch-level or "middleweight" models (Avin et al., 2016) —requires considerably less data than more detailed models. As is the case with the latter, VisionEval requires some indication of residences and employment by TAZ; however, the employment is split into just three groups (total, retail, and service) rather than the more detailed North American Industrial Classification System codes. VisionEval does require an aggregate measure of transit service but not a detailed transit or highway network; survey files (e.g., transit on-board surveys, home-based surveys) are not required. Yet, consistent with other sketch-level models, VisionEval does require some additional inputs not explicitly required in a network-based model (e.g., forecasts of fuel prices, parking supply, and travel demand management practices) that relate to the types of scenarios employed.

Development of Scenario Input Files

Input files were devised to match the 43 scenarios shown in Table 5, with judicious consideration of which attributes should be modified and the resultant values. In all cases, realistic input values were sought. Four examples of deriving such input values, chosen because they illustrate the range of rationales for such derivations, are as follows:

1. Scenario 1a asks: What if locality totals are accurate but Bzone (TAZ) forecasts differ from the correct value by an average absolute percent error of 48%, as observed elsewhere? Scenario 1a thus presumes that total population by city or county in 2045 is accurate but uses an average error of 48% for the 712 TAZs. Figure 6 illustrates this approach with just five zones: the year 2045 population totals are identical, but the households are redistributed such that on average, with the base taken as ground truth, there is an average absolute percent error by TAZ of 48%.

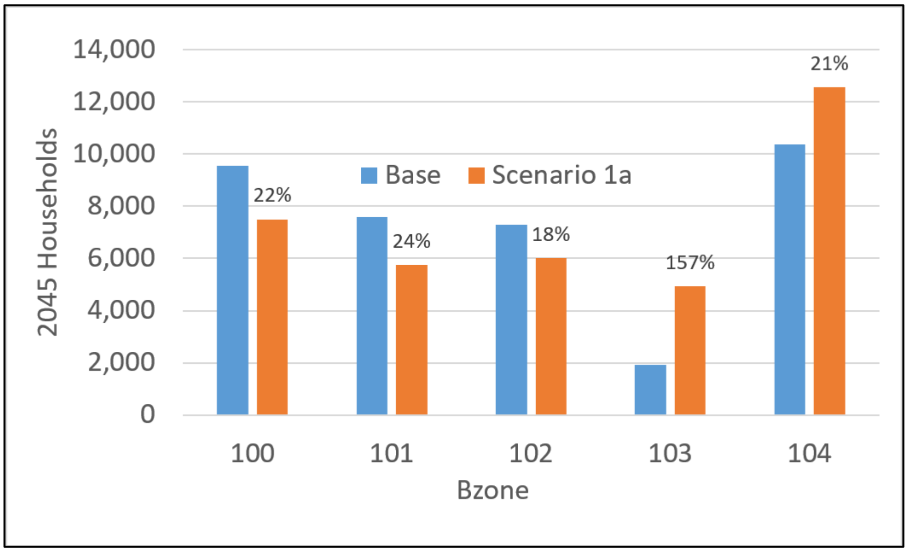

Figure 6. Example of Redistributing Households for Scenario 1a. Total households are unchanged for scenario 1a, but differences exist for each Bzone (traffic analysis zone), shown also as absolute percent errors.

2. Two different scenarios—4a and 4a'—ask: What if household sizes shrink or grow from what is forecast for year 2045? The smallest and largest possible mean household sizes for year 2045 were determined by reviewing mean household sizes for 1947-2020 (U.S. Census Bureau, 2020b) and, since 2019-2045 represents a 26-year period, choosing the mean 26-year change in household size (0.40) and then decreasing and increasing the 2019 value by that amount.

3. Scenario 5b recognized that there is not the equivalent of a fossil fuels tax on electric vehicles. However, VisionEval has an attribute PevSurchgTaxProp that represents a surcharge on electric vehicles designed to capture this fuels tax. The base scenario assumes that the Virginia Department of Motor Vehicles will maintain only an $88.20 fee on electric vehicles that it will periodically adjust for inflation. Thus, for year 2045, the taxes of $0.522 per gallon (in 2019 dollars) generates $6,458 in revenue based on FHWA (2018a) reporting that Virginia vehicles travel an average of 12,372 miles per year. Thus, for the base scenario, the $88.20/$6,458 gives a low value for PevSurchgTaxProp of 0.0137. For scenario 5b, one raises PevSurchgTaxProp from 0.0137 to 1.000, such that electric vehicles are taxed at the same rate as gasoline-powered vehicles.

4. Scenario 8 examined what might happen if carsharing services shifted. NVTA (2018) observed the following: "Short-term car rental services, including ZipCar, Car2Go, and Enterprise CarShare, offer users the opportunity to rent a car for specific, short trips and errands." VisionEval requires an input file (Figure 7) that shows the proportion of households in each bzone that are in the lowest, second lowest, second highest, or highest income quartiles for the given azone. For instance, Figure 7 shows that 13.3% of the households in bzone 1614 are in the highest income quartile for Fairfax County whereas almost one-half (47.7%) of the households in bzone 1615 are in the highest income quartile for Fairfax County, suggesting bzone 1615 is wealthier than bzone 1614.

Geo	Year	HhPropIncQ1	HhPropIncQ2	HhPropIncQ3	HhPropIncQ4	Average
1614	2019	28.4%	34.3%	24.0%	13.3%	0.430532
1615	2019	9.6%	20.9%	21.9%	47.7%	0.644153

Figure 7. Excerpt of an Input File Describing Household Proportion by Income. For instance, 28.4% of households in bzone 1614 are in the bottom quartile of incomes for Fairfax County whereas just 9.6% of households in bzone 1615 are in the bottom quartile of incomes for Fairfax County. The "Average" column at the far right is not part of the input file but indicates that zone 1615 is wealthier than zone 1614. The input file is bzone_hh_inc_qrtl_prop.csv.

Figure 7 shows a weighted average that was computed based the midpoint of the four quartiles such that wealthier bzones had a higher average (see Eqs. 2 and 3). Bzones were then classified as high or low income based on whether their value was above the median value.

$$\begin{aligned}\text{Average} = \; & 0.125 \text{ (Percent households in the lowest income quartile)} \\ + \; & 0.375 \text{ (Percent households in the second lowest income quartile)} \\ + \; & 0.625 \text{ (Percent households in the second highest income quartile)} \\ + \; & 0.875 \text{ (Percent households in the highest income quartile)} \end{aligned} \quad \text{[Eq. 2]}$$

$$\begin{aligned}\text{Average} = \; & 0.125 \text{ (HhPropIncQ1)} + 0.375\text{(HhPropIncQ2)} \\ + \; & 0.625 \text{ (HhPropIncQ3)} + 0.875\text{(HhPropIncQ4)} \end{aligned} \quad \text{[Eq. 3]}$$

Directly Implementable Scenarios

All scenarios required the development of one or more input files. For most scenarios, the process was fairly straightforward in terms of how to make a modification but required judgment about what constituted a reasonable value. For instance, as shown in Appendix B, for the development of scenarios 6b and 6c—increased lane-miles supply—one could argue that the additional HOV lanes envisioned by NVTA (2018), even though they would be placed on the arterial system, might function more similarly to freeways rather than arterials given these two classes of roadways in VisionEval. Further, as shown in the first portion of Appendix B, some additional processing was required to ensure that modifications were made to the appropriate Bzones.

In some cases, default inputs provided by VisionEval were used as a starting point but then customized for the development of an input file for a scenario. This is illustrated with scenario 10a, which looked at electrification of the carsharing fleet. Scenario 10a alters the proportion of hybrid vehicles used by carsharing services (e.g. Uber, Lyft, or autonomous vehicles). The input file (Figure 8) indicates the powertrain for shared vehicles, and the research team used the default values, which seemed plausible. One 2040 forecast is that electric vehicles may represent 58% of global market share (Collins, 2021), so a 2045 forecast of 52.8% for hybrid electric plus 3.1% for battery electric is a plausible estimate. For the base case, in year 2045, 44.1% of carsharing vehicles have an internal combustion engine, as shown by the “0.441” near the left side of Figure 8.

Scenario 10a converts one-half of these vehicles to hybrid and one-half to battery electric, as shown by the yellow portion near the bottom of Figure 8. The use of “one-half” can be debated, but Wood Mackenzie (2021) suggested that battery electric vehicles could be 48% of all vehicles sold in 2050. (The remaining 52% of vehicles are mostly internal combustion engine vehicles with smaller percentages for fuel cell vehicles and plug in hybrid electric vehicles). The result is that about three-fourths (74.85%) of carsharing vehicles are hybrid and roughly one-fourth (25.15%) are battery electric.

CarSvcAutoPropHev	CarSvcAutoPropBev	CarSvcLtTrkPropIcev	CarSvcLtTrkPropHev	CarSvcLtTrkPropBev
0.01	0	1	0	0
0.528	0.031	0.5335	0.4572	0.0093
CarSvcAutoPropHev	CarSvcAutoPropBev	CarSvcLtTrkPropIcev	CarSvcLtTrkPropHev	CarSvcLtTrkPropBev
0.01	0	1	0	0
0.7485	0.2515	0	0.72395	0.27605

Figure 8. Powertrain Input File for the Base Case (Top 2045 Row) and Scenario 10a (Bottom 2045 Row). The figure shows the proportion of carsharing service autos that use internal combustion, hybrid electric, or battery electric powertrains and the proportion of carsharing service light trucks that have these three powertrains. The figure shows the input file region_carsvc_powertrain_prop.csv. The yellow highlighting indicates values that were changed in order to execute scenario 10a.

Indirectly Implementable Scenarios

Unlike the previous scenarios, for some scenarios the concept could not be implemented exactly in VisionEval but rather had to be implemented indirectly and thus required some experimentation. Two such examples are telecommuting and electrification of household vehicles.

Telecommuting

Scenario category 3 reflects the impacts of telecommuting. The research team initially sought to modify an input file showing the number of commuters who participate in a program that provides an alternative method of traveling to work rather than driving alone. This input file is bzone_travel_demand_mgt.csv, and the attribute indicating the number of commuters is EcoProp.

Because VisionEval does not include an internal transportation network, persons who choose to telecommute would be equivalent to persons who choose to walk or bike in that neither group contributes to key metrics such as emissions, VMT, and delay. However, modification of the EcoProp attribute resulted in, at most, a telecommuting rate of slightly more than 1%; that is, as shown in Table 7, raising the attribute EcoProp from its base value to the maximum value can reflect, at most, a 1.25% reduction in work trips. Presumably, therefore, this would reflect a maximum telecommuting rate of about 1.25%, assuming the eliminated work trips were not replaced by newly induced work trips.

Table 7 raised two other concerns. First, although there are 778,350 workers, which would suggest a total of 2*778,350 = 1,556,700 work trips, the total number of trips is roughly double that figure. In other words, in Table 7, work trips are about 44% of total trips—more than twice the national average. Second, there is not a one-to-one correspondence between the reduction in vehicle trips and the increase in walk, bike, and transit trips: the elimination of 38,470 vehicle trips yields an increase of only 1,950 + 212 + 2,490 = 4,652 transit trips.

Accordingly, an alternative approach to reflect telecommuting is to reduce the number of workers by using an optional file in VisionEval. Table 2 showed that the number of workers is a factor in household-related VMT, and thus reducing the number of workers should be a way to reflect telecommuting. The input file shown in Table 8 was thus used where the number of workers was decreased. For instance, a value of 0.9 for the attribute RelEmp20to29 suggests 0.9 workers for each person in the age group of 20 to 29—in theory. Thus, to reflect telecommuting, one reduces this proportion. This approach worked with a test case: for 2045, it reduced the number of workers by 10% for year 2045 from 778,350 (when all 1s were used for Table 8) to 700,516 and reduced the household DVMT (daily vehicle miles traveled) by 6% from 26,930,212 to 25,413,862.

Table 7. Example of Extracting Data on Telecommuting

Case	EcoProp	Walk Trips	Bike Trips	Transit Trips	Vehicle Trips	Workers	Possible Work Trips	DVMT
Base	0.003	650,148	50,106	404,845	3,078,253	778,350	1,556,700	26,930,212
Middle	0.3	650,734	50,169	405,600	3,066,778	778,350	1,556,700	26,827,088
High	1.0	652,098	50,318	407,335	3,039,783	778,350	1,556,700	26,584,497
Difference between the high and base case		1,950	212	2,490	-38,470	0	0	-345,715
Explanation		These are off the network.		These are undesired.	Reduction in vehicle trips of 1.25%.	Should be 0, which it is.	Should be 0, which it is.	Reduction in DVMT of 1.28%.

DVMT = daily vehicle miles traveled.

Table 8. Sample Data for a New Input File Showing the Proportion of Each Age Group in the Labor Force[a]

Geo	Year	RelEmp 15to19[b]	RelEmp 20to29[b]	RelEmp 30to54[b]	RelEmp 55to64[b]	RelEmp 65Plus[b]
Fairfax	2019	1	1	1	1	1
Fairfax City	2019	1	1	1	1	1
Falls Church	2019	1	1	1	1	1
Fairfax	2045	0.9	0.9	0.9	0.9	0.9
Fairfax City	2045	0.9	0.9	0.9	0.9	0.9
Falls Church	2045	0.9	0.9	0.9	0.9	0.9

[a] This is input file azone_relative_employment.csv.

[b] Proportion of persons in each age group who are in the labor force. For instance, the table suggests that in 2045, 90% of all persons age 15 and above would be in the labor force.

The final version of the telecommuting scenario entailed determining the actual proportions in the labor force and reducing those accordingly. For instance, in reality, roughly 82% of persons age 30 to 54 are presently in the labor force. Thus, Table 8 showed a value of 0.82 for RelEmp30to54 for the base case. Then, telecommuting scenario 3c used an input file where this attribute value was dropped by 40%, such that 0.49 replaced 0.82.

Electrification of Household Vehicles

Scenario 10c sought to determine the benefits of household vehicle electrification. Unlike inputs for other vehicles, such as buses, carsharing vehicles, and trucks, VisionEval does not have a direct input for indicating what proportion of household vehicles are battery electric or hybrid. The workaround developed by the research team was to adjust another attribute: the carbon intensity of household fuels. Normally, such an attribute is not used: the VisionEval default is that one includes “NA” for the carbon intensity. Accordingly, the team sought first to develop a “default” household vehicle carbon intensity for the base 2045 scenario (scenario 10c) and then to develop a household vehicle carbon intensity that reflected electrification of household vehicles (scenario 10c’).

Scenario 10c was executed by first presuming that for a fuel that is 10% ethanol, the emissions from both the gasoline and the ethanol is 18.95 lb of CO_2 (or 8,596 g of CO_2) per gallon (U.S. EIA, 2014) where such a gallon generates 111,836 BTUs (Spellman, 2012) such that the energy content is 8,596 g of CO_2/111,836 BTUs or 72.85 g CO_2/MJ. Then, for scenario 10c’—a simulated new case in 2045—the research team presumed 25.15% battery electric vehicles and 74.85% hybrid electric vehicles. The carbon intensity of the battery electric vehicles was estimated as the carbon intensity of electricity (65.21 g CO_2/MJ in 2045 based on a review of U.S. EIA [2020b]). The carbon intensity of the hybrid electric vehicles was estimated as 69 g CO_2/MJ—midway between the carbon intensity of gasoline (72.85) and electricity (65.21) with the weighted average (25.15*65.21 + 74.85*69) = 68.08 g CO_2/MJ (Figure 9).

The difference between scenario 10c and the baseline scenario gives a rough estimate of how well the calibration procedure performed. The difference between scenario 10c’ and scenario 10c gives a rough estimate of the effects of telecommuting.

Year	HhFuelCI	CarSvcFuelCI	ComSvcFuelCI	HvyTrkFuelCI	TransitVanFuelCI	TransitBusFuelCI	TransitRailFuelCI
2019	NA	NA	NA	NA	NA	NA	NA
2045	NA	NA	NA	NA	NA	NA	NA
Year	HhFuelCI	CarSvcFuelCI	ComSvcFuelCI	HvyTrkFuelCI	TransitVanFuelCI	TransitBusFuelCI	TransitRailFuelCI
2019	72.85	NA	NA	NA	NA	NA	NA
2045	72.85	NA	NA	NA	NA	NA	NA
Year	HhFuelCI	CarSvcFuelCI	ComSvcFuelCI	HvyTrkFuelCI	TransitVanFuelCI	TransitBusFuelCI	TransitRailFuelCI
2019	72.85	NA	NA	NA	NA	NA	NA
2045	68.08	NA	NA	NA	NA	NA	NA

Figure 9. Example of Modifying Carbon Intensity for Scenario 10c. The seven attributes refer to carbon intensities for fuels used by household vehicles, carsharing vehicles, commercial service vehicles, heavy trucks, transit vans, transit bus, and heavy rail vehicles. The input file is region_ave_fuel_carbon_intensity.csv. The yellow highlighting signifies values that were changed to execute scenario 10c.

Model Validation

There were four elements considered in the validation of VisionEval. The first three (VMT, percentage of the population that is employed, and emissions) concerned replication of base year conditions. The fourth—sensitivity of VMT to travel cost—concerned elasticity of outputs to inputs. VisionEval does not require a "calibration" step per se—there is not an explicit point at which one always has the option of adjusting certain inputs or parameters either to replicate base conditions or to achieve a desired sensitivity of outputs to inputs. However, the results of this validation could help one determine how to adjust some of the input values and which scenarios could plausibly be considered in VisionEval.

Replication of Forecast Year VMT

One element of the validation was to compare the VMT generated by VisionEval for year 2045 with the VMT generated by the regional model (Table 9). The regional model characterizes VMT as either car or truck based, whereas VisionEval attributes VMT to three sources: households, heavy truck, and commercial service (e.g., plumbers, architects, and other groups that provide such services). When using the default values for relative employment by age group, VisionEval and the regional model were relatively close in terms of the sum of auto-oriented and commercial service VMT (from VisionEval) and car VMT from the regional model; these values differed by just 1.4%. This was not the case, however, for truck VMT, where VisionEval captured slightly more than only one-fifth of the regional model heavy truck VMT. This may be partly explained by the regional model's inclusion of through truck travel.

The research team initially thought commercial service VMT could include some passenger vehicles and some heavy trucks. However, later execution of one of the scenarios (10d) that altered the fuel type for heavy vehicles showed that the emissions reductions came from heavy vehicles and not at all from commercial service vehicles.

Table 9. Comparison of VisionEval Results and the Northern Virginia Regional Model

VisionEval Platform			Northern Virginia Regional Model	
Variable	**Value (54.4% of population working)[a]**	**Value (40.2% of population working)[b]**	**Variable**	**Value**
2045 Household VMT	27,004,817	23,630,769	2045 Car VMT	28,358,311
2045 Commercial Service VMT	1,745,039	1,520,859		
2045 Heavy Truck VMT	1,214,243	1,214,541	2045 Heavy Truck VMT	5,690,723
Total	29,964,099	26,366,169	Total	34,049,034

[a] Default value for relative employment, where the user indicates 100% of each age group is employed in the file azone_relative_employment.csv.
[b] Modified values for relative employment.

Replication of Current Year Percentage of the Population That Is Employed

Before inclusion of the relative employment input file, examination of the household output file showed that VisionEval had synthesized, from 1,430,377 households, a total of

777,431 workers—that is, 54.4% of the total population was working. The research team cannot fully explain this result. The same answer is obtained if one includes the optional file (azone_relative_employment), which allows the user to indicate the percentage of each age group (15 and over) that is a worker. The research team initially populated this file with values of 1.0, such that each person age 15 and over would hypothetically be working. With 282,091 persons in the age group of 0 to 14, it should have been the case that VisionEval placed the remaining 1,148,286 individuals (80.3%) of the total population aged 15 and older in the workforce.

Instead of using all 1s or omitting the file, the research team sought to populate it using baseline labor force participation data from two sources. For four age groups (15-19, 20-29, 30-54, and 55-64), data from the U.S. Bureau of Labor Statistics (2020) were used; for the age group 65+, data from the AARP Public Policy Institute (2018) were used. This gave a baseline result of 40.2% of the total population of all ages (in VisionEval) being in the workforce (e.g., 575,351 workers of 1,430,377 people). This gave a comparable value to the nation as a whole where in 2019 (prior to the COVID-19 pandemic), there were 130.6 million full-time U.S. workers (Statista. Inc., 2021) of a population of 328.2 million (U.S. Census Bureau, 2021) for a ratio of 39.8% (see Figure 10). That said, Desilver (2019) pointed out that the labor force in the United States is more than 157 million when all jobs are included, which would suggest a ratio of workers to total population of about 48%. Then, these percentages were reduced by 40% for scenario 3c (telecommuting).

Scenario	Geo	Year	RelEmp 15to19	RelEmp 20to29	RelEmp 30to54	RelEmp 55to64	RelEmp 65Plus
0 (Base Case)	Fairfax	2045	0.35	0.78	0.82	0.65	0.2
	Fairfax City	2045	0.35	0.78	0.82	0.65	0.2
	Falls Church	2045	0.35	0.78	0.82	0.65	0.2
3c (Telecommuting)	Fairfax	2045	0.21	0.47	0.49	0.39	0.12
	Fairfax City	2045	0.21	0.47	0.49	0.39	0.12
	Falls Church	2045	0.21	0.47	0.49	0.39	0.12

Figure 10. Baseline and Scenario 3c Relative Employment. The file is azone_relative_employment.csv.

Comparison of 2045 Household Vehicle Emissions With an Optional Input

Scenario 10c sought to estimate a carbon intensity of gasoline-powered vehicles that would align with the internal value used by VisionEval, where the research team computed an initial carbon intensity of 72.85 g CO_2/MJ for household vehicles using fossil fuels. The user is not required to enter a carbon intensity; the research team executed VisionEval without this input.

With no other changes, one would expect household CO_2 emissions ideally to be identical in scenario 10c and the base scenario. Instead, whereas for the base scenario CO_2e emissions were 5,965,726 kg/day, for scenario 10c they were 4,511,767 kg/day—about 75% of the initial value.

Sensitivity of VMT to Per-Mile Travel Costs

The fact that a large increase in the fuels tax led to only a 1% decrease in VMT (scenario 5a) and/or that an increase in the VMT tax on electric vehicles from 2% of the fossil fuels tax rate to 100% led to no reduction in VMT seems unlikely for most locations. McMullen and Eckstein (2013) suggested a long-run elasticity of roughly -0.15 (e.g., a 50% increase in the fuel price would reduce VMT by 7.5%). Earlier figures by Goodwin et al. (2004) suggested an even larger long-run elasticity of -0.29 such that a 50% increase in fuel price should reduce VMT by almost 14.5%.

The research team initially suspected the cause was the fairly high per capita (not household) income of roughly $58,000. Accordingly, an artificial five-TAZ system allowed for quick experimentation to examine VMT elasticity with respect to income and fuel taxes. Table 10 shows a modest response of household VMT to income: as per capita income (not household income) dropped from $32,000 to $10,000, household VMT dropped about 25%. Truck VMT dropped much more—almost identical to the drop in income. However, when income was kept constant, Table 10 shows a surprising inelasticity of VMT with respect to fuel price: a quadrupling of the fuel tax (in order for the fuel tax to be one-half the fuel price) showed an almost imperceptible change in household VMT and no change in truck VMT. Thus, the relative inelasticity of household VMT with respect to fuel price may be an artifact of the platform; it is important to note that truck VMT but not the fuel tax is based on income.

Another experiment with the artificial five-TAZ system in Appendix C was to increase the tax for owning a vehicle from $70 to $2,070 (scenario 7d in Table C6). In this instance, household VMT increased, rather than decreased, slightly by 0.4%. By contrast, with the Northern Virginia case study, such an increase (coupled with a doubling of the ad valorem tax rate) had no effect on household VMT or any other output variables except the cost of vehicle ownership.

Table 10. Summary of Five-Zone Hypothetical Model Scenario Results

Fuel Tax	Per Capita Income	Household VMT	Heavy Truck VMT
$0.484	$32,000	1.000	1.000
$1.936	$32,000	0.992	1.000
$0.484	$10,000	0.750	0.301
$1.936	$10,000	0.744	0.301
$0.484	$7,000	0.675	0.212
$1.936	$7,000	0.671	0.212

VMT = vehicle miles traveled.

Implications of the Validation Step

The validation suggested one key change to the base input files: one must adjust azone relative employment in order to have a reasonable ratio of workers to population. The validation also showed that for a scenario where one seeks to estimate how electrification of household vehicles affects emissions, one should execute the scenario in two steps: (1) determine a baseline scenario based on the research team's estimate of carbon intensity (if household vehicles use fossil fuels, which is designated as scenario 10c), and (2) reduce the carbon intensity to account for electrification (which the research team designated as scenario 10c'). The difference between these two steps—10c and 10c'—is the resultant impact of electrification of household vehicles.

The validation also showed how one should interpret one of the scenarios, i.e., scenario 10d, which is the electrification of heavy trucks. Heavy truck VMT is considerably less (in VisionEval) than it is in the Northern Virginia regional model. One plausible explanation is that as the case study region (used for VisionEval) is smaller than the Northern Virginia / Washington, D.C. / suburban Maryland area (used for the regional model), through truck trip lengths are much greater in the regional model. Accordingly, it is probably the case that the impacts of scenario 10d, as they are based on reducing truck VMT emissions, are underreported.

Scenario Results

Table 11 shows the impacts for year 2045 for the region, with all values normalized to 1.00 for the base case. For example, total CO_2e emissions from six regional categories (urban commercial service vehicles, nonurban commercial service vehicles, urban heavy trucks, buses, rail, and transit vans) plus the CO_2e emissions for the 564,202 households yielded 7,229,084 kg per day for the base scenario. If, as per scenario 1a, the population forecasts at the TAZ level are off by an average of 48% (but the county and city total populations are accurate), then daily emissions rose to 7,312,216 kg. The second row of Table 11 shows this slight 1.1% increase as 1.011 for scenario 1a.

For scenarios 10c', C01, and C06, the results shown in Table 11 should be compared to scenario 10c, rather than scenario 0, as the baseline because those scenarios require a default household carbon intensity. For instance, scenario 10c as executed showed a value of CO_2 that was 0.784 of the baseline value and scenario 10c' showed a value of CO_2 that was 0.744 of the baseline value. Because scenario 10c was intended to represent the equivalent carbon intensity of household vehicles using fossil fuels, scenario 10c'—electrification of household vehicles—reduced the CO_2 emissions by 4% (e.g., 0.784 − 0.744).

Table 12 shows the relative change in trips by mode for each scenario. For instance, scenario 1a cut the number of transit trips from 494,001 to 454,953. This 7.9% drop in transit trips is shown as 1.000 − 0.079, or 0.921, under the transit column for Table 12.

Table 11 revealed several surprises that once placed in context offered insights. At first glance, the aggregate metrics were not highly sensitive to the specific policies tested in the scenarios, although a deeper examination of the model's details suggested these were reflective of the model design. Scenario 3c entailed a 40% reduction in the number of persons who travel to work across the various age groups to represent 40% of all workers telecommuting. FHWA (2013) reported that typically about 28% of VMT is work related, so the 16.1% reduction, although small, is somewhat reasonable. It is also possibly a product of the case study region being smaller than the area in the regional model, as was the case with truck-based scenario 10d.

Table 11. Summary of Scenario Results (Key Performance Measures)

No.	Summary	VMT (HH)	VMT (Trucks)	Delay (LDV)	GGE (All)	kwh (All)	CO_2e (All)
0	Base case in 2045	1.000	1.000	1.000	1.000	1.000	1.000
1a	Random population error by TAZ	1.017	0.995	1.018	1.011	1.011	1.011
1b	Random employment error by TAZ	1.001	1.000	1.001	1.001	1.000	1.000
1c	Combine scenarios 1a and 1b	1.017	0.995	1.019	1.012	1.011	1.012
2a	Biased population error by locality	1.079	1.099	1.121	1.088	1.071	1.088
2b	Biased employment error by locality	1.000	1.000	1.000	1.000	1.000	1.000
2c	Combine scenarios 2a and 2b	1.079	1.099	1.121	1.088	1.072	1.088
3a	Small telecommuting growth (1.25%)	0.990	1.000	1.001	0.988	0.995	0.988
3c	Large telecommuting growth (40%)	0.839	0.999	0.781	0.870	0.910	0.871
4a	Smaller household sizes	1.003	0.962	0.995	0.996	0.992	0.996
4a'	Larger household size	0.991	1.278	1.057	1.045	1.080	1.046
4b	Increase aging in place (by 6.5%)	1.009	1.011	1.013	1.011	1.009	1.011
4b'	Reduce aging in place (by 6.5%)	0.991	0.987	0.984	0.990	0.991	0.990
5a	Large increase in fossil fuel tax	0.992	1.000	0.989	0.990	1.007	0.991
5b	Tax EVs the same as fossil fuel vehicles	1.000	1.000	1.000	1.001	0.997	1.000
5c	Scenarios 5a, 5b, increase transit revenue miles	0.985	1.000	0.981	1.001	0.988	1.000
5d	Scenarios 5a and 5b only	0.991	1.000	0.988	0.992	0.995	0.992
6a	Increase frequency of transit service	1.000	1.000	1.000	1.000	1.000	1.000
6b	Increase arterial lane-miles (see Appendix B)	1.001	1.000	0.964	1.002	1.003	1.002
6c	Increase freeway lane-miles (see Appendix B)	1.007	1.000	0.984	1.003	1.005	1.004
7a	Fuel prices change from $4.18 to $2.40/gal	1.007	1.000	1.009	1.010	0.991	1.009
7b	Electricity prices change from 10.5 to 9.0/kwh	1.000	1.000	1.000	1.000	1.001	1.000
7c	Combine scenarios 7a and 7b	1.007	1.000	1.009	1.010	0.993	1.009
7d	Increase cost of vehicle ownership dramatically	1.000	1.000	1.000	1.000	1.000	1.000
8a	Increase carsharing service in low-income areas	1.022	1.000	1.029	1.018	0.993	1.016
8b	Increase carsharing service in high-income areas	1.020	1.000	1.023	1.012	1.012	1.013
8c	Increase carsharing service everywhere	1.042	1.000	1.051	1.032	1.005	1.031
9[b]	Increase pedestrian-friendly intersections	1.000	1.000	1.000	1.000	1.000	1.000
10a	Electrify carsharing vehicles	1.000	1.000	1.000	0.994	1.021	0.995
10b	Electrify transit buses and vans	1.000	1.000	1.000	0.990	1.012	0.992
10c	Base case in 2045 (default HH carbon intensity)	1.000	1.000	1.000	1.000	1.000	0.784 [a]

10c'	Electrify household vehicles	1.000	1.000	1.000	1.000	1.000	0.744 [a]
10d	Electrify heavy trucks	1.000	1.000	1.000	0.915	1.236	0.936
10e	Convert 25% additional power plants to solar	1.000	1.000	1.000	1.000	1.000	0.987
C01	Better emissions: scenarios 3c, 10c', and 10d	0.839	0.999	0.781	0.785	1.146	0.589 [a]
C02	Worse emissions: scenarios 2c and 8c	1.124	1.099	1.173	1.121	1.079	1.119
C03	Modest emissions: scenarios 1a, 3a, and 10a	1.007	0.995	1.018	0.996	1.026	0.998
C04	Better VMT: scenarios 3c and 5c	0.828	0.999	0.767	0.875	0.901	0.875
C05	Worse VMT: scenarios 2a and 8c	1.124	1.099	1.173	1.121	1.079	1.119
C06	Moderate VMT: scenarios 4a', 5a, and 10c'	0.988	1.278	1.046	1.039	1.090	0.782[a]

HH = household; TAZ = transportation analysis zone; EV = electric vehicle; VMT = daily vehicle miles traveled; LDV = light duty vehicle; GGE = gasoline gallon equivalents; CO_2e = carbon dioxide equivalents.
[a] For scenarios 10c', C01, and C06, the results shown here for CO_2 should be compared to scenario 10c rather than scenario 0.
[b] All variations of scenario 9 (9a, 9b, 9c, 9d, 9e, and 9f) showed the same result.

Simple spreadsheet-based experiments with calculation of household VMT showed that the number of workers (Table 2) has a modest influence: a household with one worker increased the dependent variable in Table 2 (before transformation) by less than 10%. At the jurisdiction level, having a population forecast that is 10% larger than expected (scenario 2a) raised household VMT by almost 8% with a comparable increase in VMT for heavy trucks (almost 10%). Such large-scale forecast errors had a greater impact than distribution errors (e.g., scenario 1a, which redistributes households but does not increase them, had only a modest household VMT impact of less than 2%). Changes in household size (scenarios 4a and 4a' where changes were based on the mean 26-year shift observed between 1947-2020 inclusive) altered VMT modestly by 0.3% and 0.9%, although the direction of the shift was surprising. Most relationships within the variables moved in the direction one might expect: emissions rose as VMT rose (although the relation was not perfectly linear), and examination of some of the subvariables not reported in Table 11 seemed appropriate (e.g., electrification of trucks greatly cut truck emissions).

For most scenarios, the mode splits in Table 12 were expected based on the results in Table 11 and the fact that the number of vehicle trips was more than two-thirds of the total. For instance, the 8.8% increase in emissions of scenario 2a from Table 11 aligns with the 9% increase in vehicle trips from Table 12. The 4.2% growth in household VMT for scenario 8c (increase carsharing availability throughout the region from low to high) matches the 4.0% increase in vehicle trips. The 68.6% increase in bike trips for larger families (scenario 4a' in Table 12) is indeed striking and would not be evident from a review of the 4.5% increase in gasoline gallon equivalents of the corresponding row in Table 11. However, although this is indeed a large shift in relative terms, the large percentage is logically due to the more than doubling of persons age 0-19, such that bike trips increased from 1.4% of total trips in the base scenario to 2.1% of total trips in scenario 4a'. That said, Table 12 offers an insight in the sense that telecommuting may allow for an increase in other types of trips such that possibly one may need to examine how to encourage other modes closer to the home end.

Table 12. Summary of Scenario Results (Mode Split)

No.	Summary	Walk Trips	Bike Trips	Transit Trips	Vehicle Trips
0	Base case in 2045	1.000	1.000	1.000	1.000
1a	Random population error by TAZ	0.941	0.875	0.921	1.017
1b	Random employment error by TAZ	1.000	0.999	0.999	1.001
1c	Combine scenarios 1a and 1b	0.940	0.874	0.920	1.018
2a	Biased population error by locality	1.136	1.206	1.135	1.090
2b	Biased employment error by locality	1.000	1.000	1.000	1.000
2c	Combine scenarios 2a and 2b	1.136	1.206	1.135	1.090
3a	Small telecommuting growth (1.25%)	1.002	1.003	1.004	0.991
3c	Large telecommuting growth (40%)	1.038	1.412	1.239	0.848
4a	Smaller household sizes	0.971	0.900	0.936	0.998
4a’	Larger household size	1.114	1.686	1.400	1.026
4b	Increase aging in place (by 6.5%)	1.011	0.984	1.007	1.011
4b’	Reduce aging in place (by 6.5%)	0.974	0.963	0.981	0.990
5a	Large increase in fossil fuel tax	1.002	1.003	1.006	0.991
5b	Tax EVs the same as fossil fuel vehicles	1.000	1.000	1.000	1.000
5c	Scenarios 5a, 5b, and increase transit frequency	1.016	0.964	1.071	0.984
5d	Scenarios 5a and 5b only	1.002	1.004	1.006	0.990
6a	Increase frequency of transit service	1.000	1.000	1.000	1.000
6b	Increase arterial lane-miles (see Appendix B)	1.000	0.999	0.999	1.001
6c	Increase freeway lane-miles (see Appendix B)	0.997	0.997	0.996	1.000
7a	Fuel prices change from $4.18 to $2.40/gal	0.998	0.995	0.994	1.008
7b	Electricity prices change from 10.5 to 9.0/kwh	1.000	1.000	1.000	1.000
7c	Combine scenarios 7a and 7b	0.998	0.995	0.994	1.008
7d	Increase cost of vehicle ownership dramatically	1.000	1.000	1.000	1.000
8a	Increase carsharing service in low-income areas	0.965	0.929	0.930	1.021
8b	Increase carsharing service in high-income areas	0.963	0.919	0.913	1.021
8c	Increase carsharing service everywhere	0.925	0.809	0.841	1.041
9f	Increase pedestrian-friendly intersections	1.000	1.000	1.000	1.000
10a	Electrify carsharing vehicles	1.000	0.999	1.000	1.000
10b	Electrify transit buses and vans	1.000	1.000	1.000	1.000
10c	Base case in 2045 (default HH carbon intensity)	1.000	1.000	1.000	1.000
10c'	Electrify household vehicles	1.000	1.000	1.000	1.000
10d	Electrify heavy trucks	1.000	1.000	1.000	1.000
10e	Convert 25% additional power plants to solar	1.000	1.000	1.000	1.000
C01	Better emissions: scenarios 3c, 10c’, and 10d	1.038	1.412	1.239	0.848
C02	Worse emissions: scenarios 2c and 8c	1.042	0.945	0.954	1.134
C03	Modest emissions: scenarios 1a, 3a, and 10a	0.943	0.876	0.925	1.008
C04	Better VMT: scenarios 3c and 5c	1.057	1.384	1.317	0.836
C05	Worse VMT: scenarios 2a and 8c	1.042	0.945	0.954	1.134
C06	Moderate VMT: scenarios 4a’, 5a, and 10c’	1.115	1.688	1.402	1.022

TAZ = transportation analysis zone; EV = electric vehicle; HH = household; VMT = vehicle miles traveled.

These results offered three types of policy insights, which help to reduce the number of model runs required for future more detailed analyses.

1. *Areas to ignore.* Table 11 suggests areas that may not require further study. One concern of stakeholders has been forecasting at both the TAZ and county levels. Scenarios 1a and 1b suggested that random errors in TAZ forecasts (the responsibility of MPOs) are not problematic, affecting fuel consumption and emissions by roughly

1% for population and 0.1% or less for employment. Supporting (or not supporting) aging in place also had a fairly modest effect on VMT and emissions of about 1 percentage point: the 65+ population is 15% of the total population, and only about 6.5%, at most, might require some form of assisted living (scenarios 4b and 4b').

2. *Areas of importance.* Table 11 suggests areas that might yield the greatest impact for achieving some policy objective. In this instance, for reducing greenhouse gas emissions, the largest benefit came from telecommuting (12.9% reduction, scenario 3c), electrification of heavy trucks (6.4% reduction, scenario 10d), and electrification of household vehicles (4% based on the difference between scenarios 10c and 10c'). Surprisingly (to the research team), the conversion of one-fourth of power plant sources from natural gas to solar had only a modest impact on CO_2e of slightly more than 1% (scenario 10e). Thus, although electrification of transit vehicles offers public appeal, scenario 6b suggested that other types of electrification may yield a greater benefit. That said, a limitation of the scenarios analysis is that the scenarios do not incorporate costs. It may be the case that public sector dollars spent electrifying transit buses are so much less than public sector dollars supporting electrification of trucks (e.g., subsidies of charging stations) that the benefit-cost ratio of scenario 6b is higher than implied in Table 11.

3. *Agreement on outputs.* One can formulate two different opinions on the role of combined scenarios depending on one's choice of output. First, if one is concerned with household VMT, then only telecommuting matters; the combined scenarios with other factors have no effect. Second, if one is concerned with not just households but also all vehicles including commercial service and trucks, Table 11 shows that a package of policies matters more. These calculations can be displayed graphically, such as in Figure ES1, which illustrates the role of the "better future emissions" scenario compared to the telecommuting scenario.

In sum, the value of the scenario planning exercise is to inform the policy discussion early, especially for clarifying the importance of politically difficult actions. For instance, scenario 10d—truck electrification—showed a reduction in total energy sources (electrical and fossil fuels) demanded by trucks, yielding a 71% reduction in truck emissions. Scenario 10b—electrification of transit buses and vans—showed a 39% reduction in transit vehicle emissions. Both percentages are impressive, but in relative terms scenario 10d yielded a 6.4% overall emissions reduction whereas the reduction in scenario 10b was much smaller. Stakeholders can thus weigh the importance of these initiatives in light of their total costs (capital and political) and make decisions accordingly.

DISCUSSION

Potential Advantages of Using VisionEval for Early Scenario Planning

The platform offers some benefits for Virginia in terms of quick performance of scenario planning in some situations. Four key observations are noted with respect to this platform.

1. Scenario planning supports later implementation of detailed models.
2. Fast representation of policy alternatives enables understanding of impacts.
3. Exchange of precision for flexibility allows for wide-ranging alternatives.
4. Location-specific information can be used to quantify scenario impacts.

Scenario Planning Supports Later Implementation of Detailed Models

It is tempting to emphasize the observation that with the right combinations of policy choices and circumstances, one can potentially reduce household VMT by more than 17% (scenario C04) or aggregate emissions by almost 20% (scenario C01)—examples of the right circumstantial and policy levers necessary to achieve a particular goal (FTA, 2019). Strong support of telecommuting coupled with electrification of household vehicles and trucks (to reduce emissions) or increased VMT taxes for all vehicles with funds diverted to transit (to reduce VMT) is what the case study suggests as "to do" items. If none of these initiatives is pursued and there is unexpected population growth, then emissions and VMT will increase (scenarios C02 and C05) by around 12%.

Yet a crucial takeaway is that most events or policies have a moderate impact: one might expect as part of a "business as usual" situation modest growth in telecommuting, electrification of carsharing vehicles with a reduction in carbon intensity, and perhaps population forecast errors at the TAZ level. Scenario C03 showed that one would then see an almost imperceptible drop in emissions—about 0.2%. Table 11 shows that such modest impacts are in fact the result of most scenarios when policies are considered individually: the number of higher impact events was relatively small compared to the number of low impact events. Thus, if certain goals are of elevated importance, one contribution of scenario planning is the identification of which of the relatively few actions can lead to meaningful improvement. Because many scenario combinations have modest impacts, more detailed methods may be used to focus on those relatively few, but more promising, scenarios.

These results also show that the choice of output affects interpretation of results—that is, the scenario planning exercise can help one determine the critical scope of future work. For instance, if one is focused on household VMT, then this particular case study showed that the only policy that materially matters is telecommuting. If one is focused on total emissions, then the better choice is a combination of policies that include telecommuting with vehicle electrification. Generally, scenario analyses have the potential to identify quickly which outputs are most critical early in the planning process.

Fast Representation of Policy Alternatives Enables Understanding of Impacts

Veteran planners may argue that some results can be inferred without modeling. Persons familiar with mode split are likely not surprised that electrifying transit trips had a lesser impact than eliminating commute trips given the larger VMT share of the latter. As natural gas (not coal) accounts for most power plants in the region, specialists may envision the conversion of one-fourth of plants to solar as having a lesser impact than locations with more coal-fired plants. Regional modelers may point out that random errors (provided city and county control totals are accurate) only modestly affect regional VMT and thus not be surprised by scenario 1.

Yet Table 11 highlights quantitative impacts that otherwise might be discussed only qualitatively. Getting accurate TAZ population forecasts certainly affects the value of total gasoline consumed. Errors lead to an increase in fuel consumption of 1.1%, or about 6,560 extra gallons of fuel per day (scenario 1a). This impact, however, is less than one-sixth the impact of making an error in the control total for regional population (scenario 2a), which in turn is roughly one-half the impact of having 40% of the population telecommute (scenario 3c).

A middle position is that this platform helps quantify insights that careful consideration of inputs might lead an observer to suspect. Insights arise from examination of results (Table 11) but also through preparation of the input files. For instance, based on the period 1947-2020, the mean number of persons per household shifted over any 26-year period by about 0.40. Thus, although it is possible that a household size could grow from the 2019 value of 2.8 to, say, 4.0, such a shift seems unlikely unless the change from 2019 to 2045 was larger than what had been observed over any 26-year period since 1947. Other findings in the preparation of the input files, such as the current vehicle fuel sources, the proportion of the population in the labor force, and the number of pedestrian-friendly intersections, help the analyst better consider potential impacts prior to executing the tool. In short, additional insights are gained in the preparation of inputs such as longer-term trends.

Exchange of Precision for Flexibility Allows for Wide-Ranging Alternatives

The platform sacrifices some precision (e.g., an ability to forecast, say, changes in delay as a function of an intersection improvement) in order to be able to encompass a wider range of inputs (e.g., to consider both improving transportation supply and changing fuel sources for stationary power plants) and to have faster execution times than a more detailed package. This trade-off appears to serve the scenario process well in that for a large region, one can quickly determine key areas of interest, but the process is not exact. One may consider, for instance, the role of carbon intensity. Unlike for buses, carsharing vehicles, and trucks, VisionEval does not have a direct input for indicating what proportion of household vehicles are battery electric; rather, one adjusts the carbon intensity of household fuels—and the default is that the carbon intensity is not needed. The research team intended scenario 10c to yield results identical to those of the base scenario after calculating a default carbon intensity for household vehicles and then intended scenario 10c' to provide a new carbon intensity based on an increase in the share of hybrid and battery electric vehicles based on derived carbon intensities from the literature (Spellman, 2012; U.S. EIA, 2020b). Because of the difference between scenario 10c and scenario 0, the result of scenario 10c' is only an approximation, but the key finding is that household vehicle electrification can reduce emissions. Similarly, the platform offers some flexibility in that one can create new scenarios, such as telecommuting, that were not part of the original design but that can be devised based on labor force participation rates for 2019 and 2045 (AARP Public Policy Institute, 2018; U.S. Bureau of Labor Statistics, 2020).

Part of this trade-off between exactness and flexibility can be seen in a comparison of required input files. Both VisionEval and a more detailed travel demand model require some estimate of TAZ-level households and employment. However, because VisionEval does not require a transportation network per se (but only more aggregate measures of service such as transit miles of service or highway lane-miles), the time associated with creating such detailed networks is eliminated (Cambridge Systematics et al., 2012). Although a household travel survey is not required for execution of a travel demand model, such a survey is a good practice for model calibration (Cambridge Systematics, 2014); one example of a detailed survey for a large region was a 2-year process (Brown et al., 2018). Because one estimate of the time required for developing input files and performing the calibration process is 2 years, Lorenzini et al. (2015) characterized one of the predecessors of VisionEval (known as "GreenSTEP") as an example of why strategic planning models can be advantageous in some situations: because they have a less disaggregate focus, they can help address some "challenges" such as a lack of resources for developing more detailed models or performing quality control for data inputs.

Location-Specific Information Can Be Used to Quantify Scenario Impacts

When the results of an earlier version of some of these scenarios were included in a paper submitted to the Transportation Research Board, an anonymous reviewer asked whether this platform provided insights into specific locations, asking, for example, if one might see differences between two areas chosen at random such as Chicago and Dallas. If such differences were not observed, the reviewer suggested that one might not need to run the model more than once.

Because VisionEval is largely an elasticity-based tool, the reviewer's concern is on target in that the relationships that are defined internal to the platform will logically drive the results. For instance, one may contrast the results of scenarios executed in Northern Virginia with those in the hypothetical location in Appendix C. Certainly, some scenarios showed no changes: for the hypothetical location, scenarios 2b, 6a, and 9f had no change, as was the case with the real-world location. Further, the direction of impacts for the scenarios was similar: in scenario 5c, which entailed an increase in a tax on fossil fuels and an increase in transit frequency, vehicle trips were reduced in both the real-world location of Northern Virginia and the hypothetical location.

However, the magnitude of these changes is somewhat location dependent. For instance, in the hypothetical case, scenario 5c decreased household vehicle trips by 5% compared to a bit less than 2% in Northern Virginia. Scenario 4a'—increased family sizes—increased heavy truck VMT by 71% in the hypothetical case compared to 28% in Northern Virginia; not surprisingly, the increase in total CO_2e emissions was much greater in the hypothetical scenario (21% as shown in Table C6) compared to just under 5% in Northern Virginia, as shown in Table 11.

Returning to the explicit question of Dallas versus Chicago, data from the FHWA Office of Policy Information (2018b) indicated that the Chicago urbanized area has approximately 75% of the lane-miles as the Dallas urbanized area while having about 68% more in population. Accordingly, scenario 6c was re-executed; however, the respective base cases for freeway lane-miles were adjusted to reflect areas, in terms of freeway lane-miles versus population, that were similar to Chicago and Dallas (Northern Virginia is much more similar to the former than the latter). In response to scenario 6c, which expanded freeway lane-miles by 18%, household VMT in both locations expanded but more so in Dallas (1.4%) than Chicago (0.6%). The amount of VMT on the freeway system grew in both locations but, not surprisingly, by more in Chicago (14.0%) than in Dallas (5.2%). The percentage of freeway VMT that was either severely or extremely congested fell slightly in Chicago (from 61% to 58%) but more so in Dallas (26% to 16%). These results indicate that VisionEval will give different results for different geographic locations because it is based on attributes, such as the ratio of roadway lane-miles to population, that vary by location.

That said, location in terms of geographical coordinates does not have a large impact. A simple experiment was conducted where the 712 bzone centroids (Figure 11 in blue) were then spread based on doubling their distance from the centroid (green) such that the new centroids were more dispersed (red). There were slight numerical changes in some attributes, but all were less than 0.001; for instance, household VMT shrank by about 1,800 per day (of a total of 23.6 million).

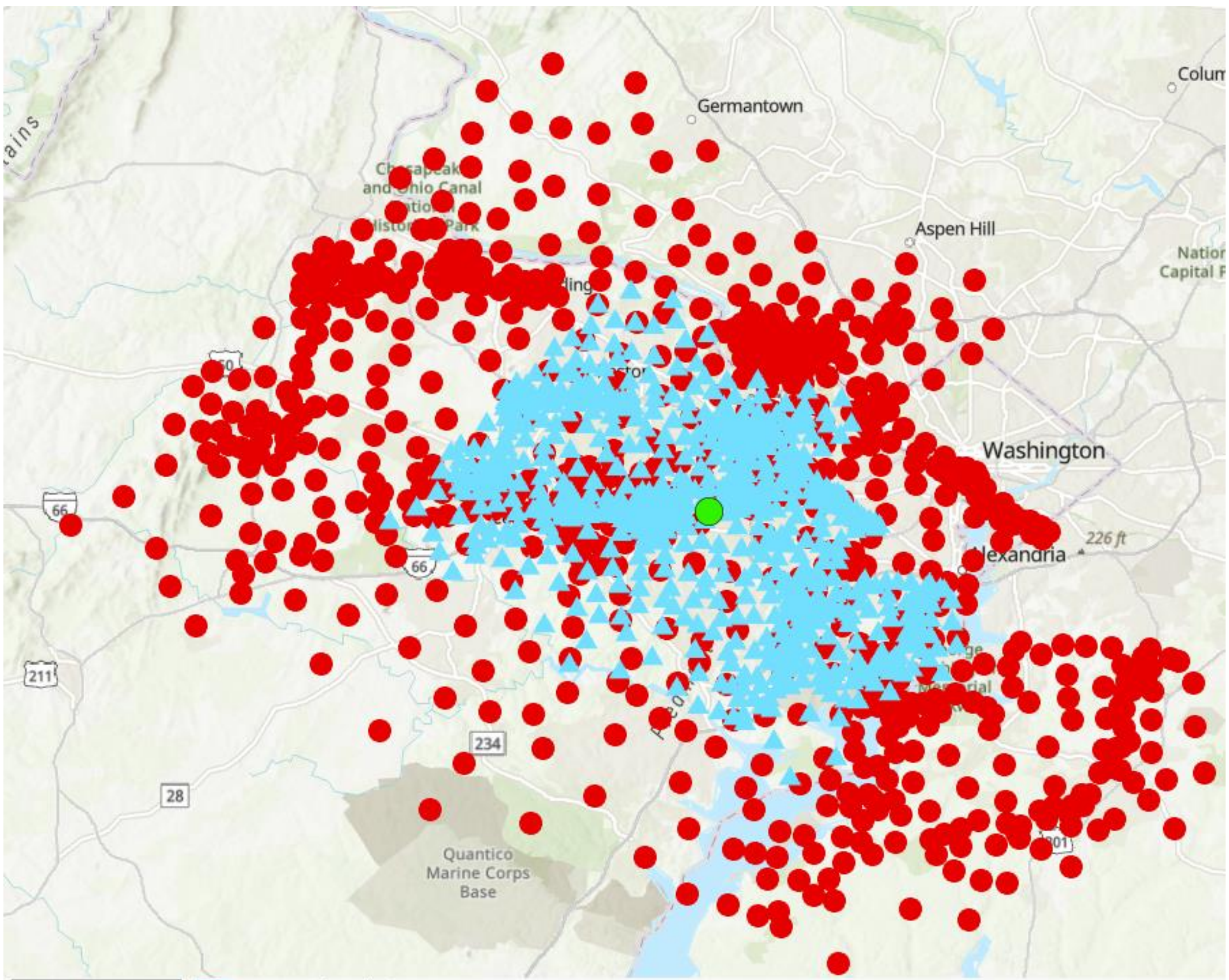

Figure 11. Expansion of Bzones in VisionEval. Blue triangles are the centroids of the original bzones, and red circles are the new locations. Figure 11 was created by the research team using ArcGIS® software by Esri. ArcGIS® and ArcMap™ are the intellectual property of Esri and are used herein under license. Copyright © Esri. All rights reserved. Attributions provided by Esri for the basemap underlying Figure 11 are "Fairfax County, VA, M-NCHPPC, VITA, Esri, HERE, Garmin, INCREMENT P, NGA, USGS."

Lessons Learned About the VisionEval Platform

Three lessons were learned that may be of interest to others using the VisionEval platform: (1) execute scenarios iteratively, (2) distinguish global from relative outputs, and (3) identify incompatible scenarios through trial and error.

Execute Scenarios Iteratively

Each scenario was executed at least 3 times: (1) once in a stand-alone mode where results were quickly reviewed and discarded; (2) once as part of a batch process where all scenarios were executed simultaneously as part of an R script designed by Volpe staff where a few key measures (e.g., VMT, emissions) were recorded; and (3) once in a stand-alone mode after input files were corrected and where all output variables were retained. This process proved helpful: the first step enabled one to determine if files were executable (e.g., in one case certain .csv files looked correct but had become corrupted such that they could not be used); the second step gave an early indication of the types of results that would be expected; and the third step allowed one to correct some logical errors in the input files and to query additional outputs in order to better understand some of the results that were surprising.

The identification of logical errors in the input files was accomplished through careful consideration of the context of each scenario. For instance, one initial scenario conceived by the team was to combine an unexpected population increase (scenario 2a) and larger-than-expected family sizes (scenario 4a'). However, these two scenarios each require a modification to the same input file: scenario 2a and scenario 4a' both made use of a file showing household populations stratified by age such that one could not simply run these files simultaneously—rather, one had to devise a new input file that accommodated both scenarios. This particular input file was azone_hh_pop_by_age.csv.

Examples of surprising results were scenarios 8a, 8b, and 8c, which led to an increase in VMT. VisionEval (2021a) suggested: "For households that substitute car service vehicle(s) for owned vehicle(s), the annual ownership cost savings (calculated by the AdjustVehicleOwnership module) are added to household income." VisionEval produces in its detailed output three attributes for each household that the user can then sum. Table 13 shows, for each scenario, the number of vehicles with high car service, the cost savings relative to total ownership costs (e.g., insurance, depreciation, taxes, and residential parking), and the change in VMT.

Table 13. Impact of High Carsharing on Cost Savings and VMT

Scenario (Location of High Carsharing Services)	No. of High Car Sharing Service Vehicles (Relative to Total Base Case Household Vehicles)	Cost Savings	VMT Change Relative to the Base Scenario
Base (no zones)	0 (0%)	0%	0%
8a (high income zones)	122,763 (11.4%)	4.7%	2.2%
8b (low income zones)	186,873 (17.4%)	11.1%	2.0%
8c (all zones)	309,941 (28.8%)	17.0%	4.2%

VMT = vehicle miles traveled.

The results were expected in that high car services increase access to vehicles and in that the cost savings are greater (relative to costs) for lower income zones (scenario 8b) than for higher income zones (scenario 8a). The results also suggest a modest inelasticity of VMT to travel costs: when there are high service carsharing vehicles everywhere—such that these vehicles are almost 30% of the size of the household fleet in the base case—a 17% cost savings overall yields a VMT increase of about 4.2%.

Distinguish Global From Relative Outputs

The focus on aggregate VMT and emissions can mask smaller substantial changes at the modal level owing to the fact that mode use varies by an order of magnitude—e.g., in the base case, there are 7 times as many vehicle trips as there are transit trips, and the ratio is 63 for vehicle trips to bike trips. Scenario 5c increased the fuel tax dramatically and shifted the funds to increase transit service supply (in the form of bus revenue miles from a 2045 baseline value of 21 million to almost 36 million). Globally, scenario 5c had no effect on CO_2e emissions and reduced household VMT by 1.5% (and household vehicle trips by 1.6%). However, this scenario did affect transit use—increasing transit trips by 7.1%. Scenario 5c also reduced household CO_2e by 1.6%. Thus, transit use was affected (the research team had been concerned that this scenario was like that of scenario 10b). However, the sensitivity of emissions to increased transit use was less than initially expected.

This difference between modal and global outputs also explains a minute difference between the aforementioned scenario 5c versus scenario 5d, where the latter was identical except that the increased fuel taxes were not used to increase transit revenue miles of service. In Table 11, scenario 5d reduced total emissions by about 1% whereas scenario 5c had no effect on total emissions. This was surprising at an aggregate level because in addition to more transit trips, scenario 5c has more bike and walk trips (and fewer vehicle trips) than scenario 5d. The explanation is that scenario 5c indeed showed 0.6% lower household emissions than scenario 5d; however, scenario 5c includes about 1.7 times the level of transit emissions than scenario 5d. Thus, an implication is that if the policy were to increase transit dramatically to reduce emissions, one would have to combine scenario 5c and scenario 10b: reduce transit vehicle emissions only in conjunction with increasing transit ridership.

With a deeper exploration of some of the outputs, one can better understand the results in Table 11 or at least how they are modeled. For instance, the model suggests that a plausible value of larger family sizes based on a review of historical data from the U.S. Census Bureau (2020b) could increase emissions by 4.6%, as shown in scenario 4a'. Within the model, much of these increased emissions is attributed to the impact of increased emissions from commercial service vehicles, whose VMT is about 28% higher than the base case. The decrease in household VMT (associated with larger families) is on its face surprising; however, what the model is doing is presuming that larger households will lead to shorter trip lengths (by about 4.4%).

Identify Incompatible Scenarios Through Trial and Error

Although surprising, scenarios 5c and 5d appear to be at least plausible in that the model used the inputs as intended by the research team; e.g., increased vehicle taxes materially affected

VMT, albeit to a lesser degree than expected. Scenario 5b was similar in that raising the surcharge for electric vehicles such that they provide a similar amount of tax revenue as fossil fuel vehicles did not have any immediate effect in Table 11, but upon closer examination, this scenario had been developed properly: vehicle trips dropped slightly (by 0.021%), daily kilowatt hours dropped by a noticeable amount (0.5%), and average road user costs per mile rose by 2.51%.

For four scenarios, however, it appears that the situation as envisioned by the research team was not the situation as reflected by the model:

1. changes in employment (scenario 2b)
2. changes in transit frequency (scenario 6a)
3. changes in the pedestrian network (scenario 9)
4. changes in vehicle ownership costs (scenario 7d).

Changes in Employment (Scenario 2b)

Scenario 2b increased employment without any population change. To reflect this situation, the employment values in each bzone had been increased by 12%. Examination of the detailed outputs showed that the number of workers did not change at all from the base scenario. One explanation was that perhaps this was because the decision to include the bzone_relative_relative employment file, an optional file, had constrained total workers. However, removal of this optional file did not affect the results—the number of workers remained unchanged. Scenario 2b did show a few modest changes in terms of travel, but these were fractional increases of 1 percentage point: VMT and walk trips increased by 0.001%, transit and vehicle trips increased by 0.002%, and bike trips increased by 0.008%. These very small increases affected congestion levels also by an almost immeasurable amount (e.g., light duty vehicle delay increased by 0.001%).

In retrospect, this scenario by itself was not necessarily realistic in the sense that if population and the number of workers are both fixed, there cannot be a change in employment without importing workers from elsewhere. The solution appears to be to devise two scenarios. For scenario B, one establishes another zone (which was placed in the distant location of Leesburg in Loudoun County), populates this zone with virtually no employment but with people, and then adds the jobs to the original case study area. Then, one compares this to scenario A, where one places the same number of jobs and people (as scenario B) in the original case study area. These cases are shown in Table 14. This approach worked in the sense that the scenario increased VMT by 8.0% compared to an alternative that increased VMT by only 5.6%. This result is not reported in Tables 11 and 12 as this was simply an experiment, but the approach may have merit for examining how the expansion of the size of the community affects VMT and other performance measures.

Table 14. Example of How to Design a VisionEval Scenario That Accounts for New Jobs

Scenario	Population Change	Employment Change	Change in VMT
Base	None	None	None
A	Add 100,000 people and 30,000 dwelling units to the original case study area.	Add 40,000 jobs to the original case study area.[a]	5.6%
B	Add 100,000 people and 30,000 dwelling units to a new Azone and Bzone in Loudoun County.	Add 40,000 jobs to the original case study area.[a]	8.0%

VMT = vehicle miles traveled.
[a] In addition to these new jobs, VisionEval requires that an Azone have at least some jobs. Thus, an additional 1,000 total jobs were added to Loudoun County (in scenario B) or to Fairfax (in scenario A).

Changes in Transit Frequency (Scenario 6a), the Pedestrian Network (Scenario 9), and Vehicle Ownership Costs (Scenario 7d)

For three other scenarios, the research team could determine if there was an error in their conception of the scenario, but the platform did not appear to be sensitive to input values.

1. *Scenario 6a (increasing transit supply) did not change any of the 158 output variables.* Scenario 6a entailed increasing the frequency of transit service via attribute D4c within the file bzone_transit_service.csv. VisionEval (2021a) defined attribute D4c as the "aggregate frequency of transit service within 0.25 miles of block group boundary per hour during evening peak period (Ref: EPA 2010 Smart Location Database)." By contrast, VisionEval is at least moderately sensitive to the bus revenue miles attribute within marea_transit_service.csv, which was part of scenario 5c.

2. *Scenario 9 (increasing the network density of pedestrian-friendly intersections) did not change any of the 158 output values.* VisionEval (2021a) defined this quantity as "the intersection density measured by the number of pedestrian-oriented intersections having four or more legs per square mile." This quantity refers to the file bzone_network_design.csv where attribute D3bpo4 indicates the network density for each of the 712 bzones.

3. *Scenario 7d showed that the ad valorem tax rate affected only 1 output variable.* NVTA (2018) noted that for about one-fifth of survey respondents, higher travel costs are key to concentrating development. Scenario 7d added a $2,000 flat fee to each vehicle and doubled the valorem tax rate. The latter includes the percentage of the vehicle value that one pays in taxes such that more expensive vehicles cost more in taxes. Neither situation was realistic but simply described the sensitivity of VisionEval to travel given the earlier results where a large increase in the fuel tax did not show a large change in VMT. Of the 158 variables available from the output files, only 1 showed a change: the cost of owning a vehicle increased dramatically (by 67%)—but this did not affect any other behavior.

The research team also experimented with a separate input file, bzone_urban-mixed-use_prop.csv, which includes an attribute that defines the "target proportion of households located in mixed-use neighborhoods" (VisionEval, 2021a). In the base case, there was no target specified. Based on the VisionEval Wiki, the probability of a household being in a mixed-use neighborhood tends to increase if the bzone has higher density or fewer single family homes. In practice, some experiments with setting this proportion for all zones with values of 0.1, 0.2, 0.3, and 0.4 showed some expected impacts: with a proportion of 0.4, VMT was 1.8% lower than was the case when the proportion was 0.1, with that reduction being attributable to fewer vehicle trips (drop of 0.5%); a shorter trip length (drop of 0.7%); and an increase in walk, pedestrian, and bicycle trips (on the order of 1.2% to 2.9%). However, inexplicably, an increase in this proportion to a value of 0.5 for Northern Virginia resulted in some nonsensical results: some households showed negative VMT. Thus, this particular attribute was not used further.

That said, this attribute may have use in other datasets; for instance, for the dataset in Appendix C, a change in this target probability of a household being in a mixed-use neighborhood reduced household VMT in what appears to be a reasonable manner: e.g., setting the proportion of households located in mixed-use neighborhoods to values of 0.2, 0.5, and 0.8 reduced household VMT by amounts of 1.9%, 4.9%, and 7.9% compared to the base case of setting this equal to 0.0. In the dataset for Appendix C, the 2045 household VMT is slightly affected by the 2019 proportion. For instance, if the 2045 proportion is always set to 0.4, then the 2045 household VMT shifts by about 0.1% depending on whether the 2019 proportion is set to 0.4 or NA.

Changes in Roadway Maintenance and Construction Costs

Finally, one unexplained result may inform the development of future scenarios. An essential input file pertains to roadway maintenance costs. This file (region_road_cost.csv) is not described in the Wiki (VisionEval, 2021a), but the corresponding R script, titled BalanceRoadCostsAndRevenues.R, is available within the installation platform (VisionEval, 2021b). The script explains key attributes therein such as those excerpted in Table 15: for each light duty VMT, that vehicle exerts a cost of about 1 cent in terms of preservation, operations, and maintenance. Then, to build a new lane-mile for an arterial facility, the cost is estimated as $1.8 million in 2005 dollars. These latter values seem reasonable given figures published by the American Road and Transportation Builders Association (2021) of $1.0 million to $2.5 million in 2021 dollars per arterial lane-mile. The script further explains that if user fees are not large enough to cover the cost of roadway maintenance, then an extra tax will be levied to make up the shortfall. That resultant extra tax is called ExtraVmtTax and is an attribute in the Region_2045.csv output file.

Table 15. Excerpt of Attributes for the Input File Region_Road_Cost.csv

Attribute	RoadPresOpMaintCost.2005	ArtLnMiCost.2005.1e3
Value	0.01	1,800
Meaning	One cent (in 2005 dollars) per light-duty vehicle mile traveled	$1.8 million (in 2005 dollars) per lane-mile constructed

The value of ExtraVmtTax is always zero—even when all attributes in the region_road_cost input file were multiplied by 100. However, a surprise was that the increase in these road maintenance costs did affect mode split: the 100-fold increase reduced VMT and vehicle trips by 84% but increased walk trips, bike trips, and transit trips by only 42%, 44%, and 112%, respectively. Given that the latter three modes accounted for only a fraction of total trips, this meant the 100-fold increase simply eliminated trips entirely—the total number of trips dropped by about 36%.

The implication is that a dramatic increase in costs to the supplier (e.g., in this case the transportation agency) affects demand from the user (in the form of the mode splits). Such causality is logical in the long run; were such an increase in costs to occur, the increase would logically be passed on to consumers. However, this change does not manifest in the way expected by the research team (where ExtraVmtTax would change); rather, it directly affects the number of users for each mode. Thus, there may be an opportunity to use this relationship in future iterations of VisionEval to connect more strongly travel demand to costs borne by the user. In other words, in retrospect, a different way of executing scenarios 5a, 5b, 7a, 7b, and 7d—all of which entailed some type of change in the cost to travel (whether in the form of owning a vehicle, higher energy costs, or higher cost per VMT)—might be to adjust the values in the input file region_road_cost. This possibility is tempered, however, by the fact that increasing the values in region_road_cost by a more modest amount (4.18/2.40, or 74%, which is the increase sought in scenario 7a) had no effect on any of the output variables.

Summary of Incompatible Scenarios

On balance, it appears that VisionEval was not sensitive to three input files when entered in the manner as done in this case study: bzone_transit_service.csv (for scenario 6a); bzone_network_design.csv (for scenario 9); and except for the cost of vehicle ownership, azone_hh_veh_own_taxes.csv (for scenario 7d). For a fourth input file, region_road_cost.csv, VisionEval's mode split is affected by these values but not in the manner expected: a modest increase has no effect on any of the output variables, and a dramatic (100 fold) increase does not affect the ExtraVmtTax attribute but does have an impact on mode split.

In theory, this finding points to a larger lesson in that ideally scenarios should be developed in tandem with an understanding of the analytical tools VisionEval implements (e.g., Figure 1 and Table 2). However, in practice, the documentation alone (e.g., VisionEval, 2021a) may not fully explain why certain scenarios are not appropriate with this platform. Thus, a good best practice would be to perform some experimentation with a small network to understand fully the potential limitations of the framework (e.g., including insensitivity to certain parameters) or of the available data (e.g., in some cases some of the bzone data elements have a large degree of uncertainty).

Applicability to Virginia

The results in Table 11 suggest that the present version of VisionEval can help one evaluate unexpected consequences or policy options fairly quickly in some topical areas:

population or employment changes, alterations to fuel types, changes in telecommuting, carsharing services, and additional highway capacity. However, the present version of VisionEval is not suitable for other topics, notably, changes in pedestrian intersection density and fuel costs. Further, as shown in Table 1, there are in addition to VisionEval other types of sketch planning tools that were not investigated as part of this study.

Since future improvements to VisionEval may enhance its capabilities, it does not appear appropriate to decide in advance which topical areas can be considered. Rather, as shown in Tables 10 and 11—and in the development of inputs as per Table 5—three key criteria appear relevant for using this tool: (1) can VisionEval be executed such that base conditions are replicated, (2) do changes in key inputs result in expected changes in key outputs, and (3) are there documented ways of estimating the values of the input files or the ranges of possible values for the input files.

An example of a topical area that meets criterion 1 is the proportion of the total population that is employed. With the inclusion of an additional input file (azone_relative_employment), one can ensure that the proportion of total population working in VisionEval approaches the proportion of total population employed in reality. An example of a topical area that fails to meet criterion 2 is the increase in fuel tax, given that the increases shown in Tables 10 and 11 are considerably less that the elasticity suggested by the literature (Goodwin et al., 2004; McMullen and Eckstein, 2013). An example of a topic that meets criterion 3 is household income in 2045. Income is of course highly uncertain: one cannot know if, for instance, a recession will occur in a given year or what new technologies will be available in 2045 that may affect productivity. However, published sources exist that provide income estimates (e.g., Moody's Analytics, 2019; Woods & Poole, 2018a, b; IHS Markit [Jeafarqomi, 2018]) such that one can at least have a basis for developing a forecast.

CONCLUSIONS

VisionEval's Benefits

1. *The primary benefit of the scenario planning tool is the rapid identification of which areas merit greater examination*. The platform sacrifices precision in favor of flexibility such that it highlights which variables or factors should be studied in more depth. The case study, for instance, suggests that 20-year population and employment forecasts, which historically have had errors of 48% and 136%, respectively (McCray et al., 2009), have only a modest impact provided city and county projections are accurate, meaning less emphasis should be placed on getting highly accurate TAZ level projections. Similarly, electrification of transit vehicles altered greenhouse gas emissions by less than 1%. Because telecommuting, truck electrification, and household vehicle electrification have much larger potential impacts (on the order of 13%, 6%, and 4%, respectively), these areas merit greater study. Scenario planning tools such as VisionEval may become part of routine use as a preliminary exercise prior to execution of more detailed models with a smaller number of scenarios.

2. *Scenario planning, by design, allows for some relatively quick takeaways*. For instance, the case study showed key insights practitioners can use, including that the highest VMT increase results from an unforeseen population increase (8% VMT rise) but larger families than expected elevate household VMT by less than 1%. Increasing telecommuting resulted in the largest drops in emissions and VMT. In terms of emissions, the scenario that combined telecommuting, electrification of trucks, and electrification of household vehicles demonstrated that effects are not always additive—meaning interaction effects can be critical when multiple events are considered.

3. *VisionEval addresses at least two key obstacles to implementation of scenario planning in the VDOT environment: multiple potential inputs, and substantial data requirements*. The platform allows one to consider multiple sets of inputs (e.g., different socioeconomic forecasts, fuel costs, taxing policies, and stationary and fixed fuel sources) and execute them fairly quickly, with roughly one-half hour required for a single run compared to more than a dozen hours for a regional model. Although data requirements require resources (e.g., 51 input files, some of which are specific to each TAZ), the time to compile these data is a fraction of what a regional model requires. This finding informed Recommendation 1 of this study.

Costs

4. *In its present form, VisionEval appears deployable with about 500 hours of staff time.* For an area with three localities, 1.43 million people, and 712 TAZs, the staff cost of applying this tool is estimated as roughly 500 person-hours. The larger portion of this time is spent preparing the 51 required input files, with a rough estimate of 8 hours per file (see Appendix A), and part of this time is spent devising 10 scenario categories (again, 8 hours is a rough estimate as per Appendix B), with some effort needed to interpret results. Logically, some of these time components should decrease as VDOT attains greater familiarity with data sources, processing methods, and model scope.

Suitability for Virginia

5. *Execution requires examination of detailed outputs in order to distinguish between scenarios that have a modest impact and those where the platform cannot compute the impacts*. Table 11 suggests two actions: (1) increasing transit revenue miles of service, and (2) increasing pedestrian-friendly intersections; these will not affect greenhouse gas emissions. The reasons for each action not affecting greenhouse gas emissions are very different. For action 1, the increased transit revenue miles did lower emissions produced at the household level, but for this particular case, these emissions were offset by transit vehicle revenue miles of service. For action 2, changing pedestrian intersection density had no impact in the model: none of the 158 detailed output variables (e.g., number of household walking trips, average vehicle trip length, miles of travel on the freeway under various congestion levels) showed any difference from the base scenario.

6. *A limitation of the VisionEval platform at present is that some scenarios are infeasible*. Three key input files that relate to frequency of transit service, density of pedestrian-friendly intersections, and cost of owning a vehicle generally did not affect outputs. For the first two attributes, this held in the case study area and in the hypothetical scenario in Appendix C. Cost of owning a vehicle did have a modest impact in Appendix C but in a different way than what was expected: increasing the cost by an additional $2,000 raised household VMT by 0.4%. Further, the elasticity of travel demand with respect to fuel cost was lower than that in the literature (Goodwin et al., 2004; McMullen and Eckstein, 2013). This finding informed Recommendation 2 of this study.

7. *Because some scenarios are infeasible in VisionEval, it may be more productive to run a scenario planning tool with fabricated values prior to developing realistic inputs*. The research team sought to develop realistic input values for all 51 required input files prior to executing the model. The team later learned that for some cases, the input file does not have an impact on the results. In the case of scenario 9, the team had developed several other related scenarios that also affected the pedestrian network density; for instance, one such scenario was to increase density where parking supply is forecast to drop (Fairfax County Land Development Services, 2018). These other related scenarios took roughly 40 hours to develop based on various types of geoprocessing. In retrospect, it would have been more productive to run just one scenario and then review the results.

RECOMMENDATIONS

1. *VDOT district planning staff and OIPI should consider using VisionEval for some types of scenario planning—those where the tool can be calibrated to base year conditions, shows sensitivity to inputs, and offers advantages compared to other methods.* Generally, the present version of VisionEval (available as of March 31, 2021) appears useful for scenarios that concern changes in population, teleworking, alternative fuel sources, vehicle sharing, and the addition of highway infrastructure. Unless customization is pursued, the basic platform does not appear appropriate for scenarios that involve pedestrian infrastructure, vehicle ownership costs, and changes in transit frequency. However, VisionEval is being enhanced, so readers should consult the appropriate technical documentation (VisionEval, 2021a) as these improvements are made.

2. *FHWA should consider the results of this study in future enhancements to VisionEval or to its documentation.* VisionEval is being modified as part of the TPF effort (Transportation Pooled Fund Program, 2020) with enhancements in areas such as connected and autonomous vehicles (Wallace, 2021). As funds permit, enhancements to the platform or associated documentation that would allow one to render the outputs sensitive to the elements noted in conclusion 6—pedestrian network density, transit frequency, and vehicle cost—should help future users. Further, either the "Balance Road Costs and Revenues" script or the associated documentation may merit some tweaking so that increased construction or operations costs affect model outputs in the way intended by the model developers.

IMPLEMENTATION AND BENEFITS

Researchers and the technical review panel (listed in the Acknowledgments) for the project collaborate to craft a plan to implement the study recommendations and to determine the benefits of doing so. This is to ensure that the implementation plan is developed and approved with the participation and support of those involved with VDOT operations. The implementation plan and the accompanying benefits are provided here.

Implementation

Action Items

Implementation of Recommendations 1 and 2 will be facilitated by two action items:

1. Within 1 year of the publication of this report, VTRC, in coordination with VDOT and the U.S. DOT, will schedule a webinar with Virginia planning partners to share the findings of this study and to encourage the use of VisionEval where appropriate. Part of this webinar may include the material under the section titled "Example VisionEval Application in Support of Recommendation 1."

2. Within 1 year of the publication of this report, a meeting will be held between VTRC and FHWA to consider the proposed enhancements described in Recommendation 2. The TPF study in which Virginia is currently participating may provide one such opportunity.

Example VisionEval Application in Support of Recommendation 1

For some types of scenarios, VisionEval may be used to support situations facing Virginia where risk determination is needed. One such example is the development of the "VTrans Long-term Risk & Opportunity Register" (OIPI, 2021a), which occurs after the development of mid-term (typically 10-year) needs and prior to recommended actions; OIPI (2021a) referred to this register as a "major component" of the VTrans long-range statewide plan. The register itself can be visualized as a matrix that lists for each risk or opportunity six key attributes: the name of the risk or opportunity, a description, the probability of this event occurring, the impact, the priority, and the proximity (e.g., length of time until the event transpires). A corresponding technical guide (OIPI, 2021b) explained that these values can be ordinal rather than numeric (e.g., probability may be Very High, High, Medium, or Low).

For some regions and some risks/opportunities in Virginia, VisionEval may enable one to provide this information. For example, two risks can be considered: (1) the forecast population at the city or county level shifts in an unexpected manner, and (2) the availability of carsharing services increases from low to high. The following information can be used to populate the register using information developed in the course of the VisionEval case study in Northern Virginia. It should be noted that the raw data—that is, the input files—provide information for four key attributes whereas execution of the VisionEval platform was suitable for the "Impact" category and decision-makers are presumably responsible for the "Priority" category.

Risk 1. Forecast population at the city/county level shifts in an unexpected manner.

- *Risk.* This is characterized as a risk in Table 16 because the change in population might affect forecast VMT, which in turn could affect emissions in the region.

- *Description.* The long-term (in this case, 26 years from 2019 to 2045) population at the city/county level shifts in an unexpected manner.

- *Probability.* The probability is set to high as Virginia has one location where population forecast accuracy was examined at the regional level: in central Virginia, the forecast made in 1980 for the year 2000 population differed from the observed population (in year 2000) by about 10% (McCray et al., 2009).

- *Proximity*. The proximity is set to long-term because this 26-year period exceeds the long-term threshold of 20 years. Although population changes can occur rapidly, they have in the past tended to be more gradual.

- *Impact*. This scenario can affect VMT and emissions. Table 11, a quick scenario planning exercise with VisionEval in a portion of Northern Virginia (Fairfax County, Fairfax City, and Falls Church City), showed that a 10% population increase (beyond what was expected) increased VMT by 8% and CO_2 emissions by 8.4%.

Risk 2. Availability of Carsharing Services Increases

VisionEval (2021a) defined the attribute CarSvcLevel as the level of availability of "car services," which are "taxis, car sharing services (e.g., Car-To-Go, Zipcar), and future automated taxi services." Three levels are possible: low, medium, and high, with VisionEval (2021a) explaining: "High level of car service is considered to increase household car availability similar to owning a car. Low level of car service does not have competitive access time and is not considered as increasing household car availability." NVTA (2018) alluded to various forms of carsharing, notably ride hailing and specific providers such as Zipcar, the use of autonomous vehicles, and "short-term car rental services, including ZipCar, Car2Go, and Enterprise CarShare," which allow one to rent a vehicle for a short trip. NVTA (2018) specifically noted that that this market was "emerging." The following information may be obtained from the case study:

- *Risk.* This is characterized as a risk in Table 16 because the change in carsharing could lead to increased vehicle use.

- *Description.* Carsharing services, some of which may be automated and some of which may be existing, increases from low to high such that they become competitive with the private auto.

- *Probability.* The probability is unknown.

- *Proximity.* The proximity is set to medium as a conservative estimate. There is no definitive forecast information about the rise of competitiveness of carsharing services; however, nationwide, Schmidt and Deryckere (2020) forecast a doubling of vehicles used for peer-to-peer carsharing over the next 5 years. Given that 2015 is a relatively low level, this suggests that the medium to long term, rather than the short term (5 years or less), is a relevant horizon.

- *Impact.* This scenario can affect VMT and emissions. Table 11, a quick scenario planning exercise with VisionEval in a portion of Northern Virginia (Fairfax County, Fairfax City, and Falls Church City) showed that increasing carsharing levels from low to high increased VMT by 4.2% and CO_2e emissions by 3.2%.

Summary

These two risks are shown in Table 16. It should be noted that for the priority, until more information is available, one cannot know if this impact on emissions is worse or greater than all other impacts. However, one can compare their relative impacts as shown in the second column from the right.

Benefits

As stated in conclusions 1, 2, and 3, the primary benefit of VisionEval is that one can fairly rapidly identify which topical areas should be studied in depth for a particular region—that is, the use of VisionEval may help one better focus more detailed planning work. This case study suggested that for a region of 1.4 million people, about 500 person-hours are needed to prepare and execute the platform for a wide variety of topical areas: demographics (population, proportion of persons who are employed, age, income, and household size); vehicle use (including fuel types, telecommuting, and carsharing); and additional highway capacity. Thus, the primary benefit of Recommendation 1 is an ability to determine which planning areas should be studied in greater detail—and to make this determination relatively quickly.

Recommendation 2 pertains to potential changes in either the platform or the documentation. Such enhancements could enable VisionEval to support more strongly scenarios in terms of transit, pedestrian infrastructure, and taxation policy.

Table 16. Example of Applying Step 4 of the Policy Guide (OIPI, 2021a) Using VisionEval

No.	Risk or Opportunity	Description	Probability	Impact	Priority	Proximity
1	Risk	Forecast population at the city/county level shifts in an unexpected manner	High: in the past, a study in one MPO suggested that at the county level, population could be off by 10%	VMT and emissions could be higher than expected	Higher than item 2 as emissions increase by 8.4%	Long term
2	Risk	Availability of carsharing services increases dramatically	Unknown, although Schmidt and Deryckere (2020) suggested that in 2025 one form of carsharing (peer to peer) will be almost 5 times the 2015 level	VMT and emissions could be higher than expected	Lower than item 1 as emissions increase by 4.2%	Medium to long term

MPO = metropolitan planning organization; VMT = vehicle miles traveled.

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APPENDIX A

EXAMPLE OF DEVELOPING A BASE INPUT FILE

Summary

The input file bzone_travel_demand_mgt.csv refers to workers participating in an "employee commute options program" and households participating in a "strong individualized marketing program" with attributes shown in Figure A1. For the former, designated by attribute EcoProp, a value of 0.003 is used for 2019 and 2045 as a baseline case; this is the small number of employers who actively promote alternative modes. For the latter, designated by attribute ImpProp, a value of 0.009 is used as a baseline case but only where density exceeds the threshold suggested by Gregor (2015) of 4,000 people per square mile. For these parameters, the intended meaning—a robust program that strongly markets alternative modes of travel—is evident after reviewing the VisionEval documentation (for EcoProp) and the earlier GreenStep documentation (for ImpProv) and consulting a veteran user of VisionEval.

Geo	Year	EcoProp	ImpProp
1611	2019	0.003	0
1611	2045	0.003	0
1612	2019	0.003	0
1612	2045	0.003	0
1613	2019	0.003	0.009
1613	2045	0.003	0.009

Figure A1. Example Data for bzone_travel_demand_mgt.csv

Key Attributes

The VisionEval Wiki (VisionEval, 2021) defines the two variables that are included in bzone_travel_demand_mgt.csv as follows, with one relating to workers and one relating to households:

1. EcoProp: proportion of workers working in Bzone who participate in strong employee commute options program.

2. ImpProp: proportion of households residing in Bzone who participate in strong IM program.

The meaning of these terms is not immediately obvious; in fact, notes from an agency that had used VisionEval previously included the statement: "More description and example of Individualized marketing programs might help user understand."

Meaning of EcoProp

A file within the VisionEval platform, however, clarifies the source EcoProp: "The rate of reduction for ECO programs on commute VMT is taken from the 'Moving Cooler' technical appendix (Table 5.13, p. B-54) for medium size urban areas, 5.4%." The document containing this appendix (Cambridge Systematics, 2009) explained that the source of the 5.4% VMT reduction is "Level 3" support where "employers promote alternative modes @ high level." Cambridge Systematics (2009) indicated the following elements for this high level of support:

- Carpooling: "in-house carpool matching and information services plus preferential (reserved, inside, and/or especially convenient) parking for carpools, a policy of flexible work schedules to accommodate carpools, and a half-time transportation coordinator."

- Vanpooling: "vanpool development and operating assistance, including financial assistance, such as vanpool purchase loan guarantees, consolidated purchase of insurance, and a startup subsidy."

- Bicycling: "secure bicycle parking and shower and locker facilities."

Meaning of ImpProp

Although ImpProp is not defined within VisionEval beyond the description of an IM program, a veteran user of VisionEval in Oregon provided two critical insights. First, the IM program is based on a "Smart Trips" case study developed by Boddy and Kassirer (2013) where in Portland (Oregon) staff directly appealed to new residents using three techniques: "individualized marketing," "customized, personal communication," and "reinforcement and encouragement." New residents received multiple mailings encouraging them to order materials that would help them use alternative modes, and then these were delivered (by bicycle) to their home; examples were transit system maps, local coupons, and a pledge to reduce vehicle use. Residents were also contacted afterward by phone and email and subsequently provided newsletters about changing their trip behavior.

Second, Weidner (2021) pointed out that the IM program is based on the work of Gregor (2015) where such programs are feasible only in areas of sufficient density and "an urban mixed-use urban form." Gregor (2015) suggested that a minimum threshold of 4,000 people per square mile be used to determine feasibility (although other thresholds could be used). Weidner (2021) also noted that the program (along with the EcoProp program) must be "pretty rigorous" in order to justify the reduction of 5% to 9% in VMT that is incorporated into VisionEval.

Baseline Value of EcoWork Used Elsewhere

When Oregon executed VisionEval with 210 bzones, all values had a value of 0 for both EcoProp and ImpProp for the base year. Then, for the forecast year (2038 in Oregon's case), most (197) of the values also had a value 0 for both of these variables; just 13 zones (6%) of the total had a nonzero value. For those 13 zones, Oregon assigned a value of 0.2 for EcoProp and 0.4 for ImpProp. Thus, this execution reflected no participation in either program in year 2010. For year 2038, this execution reflected a relatively small amount of participation.

Baseline Value of EcoWork for Fairfax County

For EcoWork in Fairfax County, a value of 0.003 appears to be a reasonable base year estimate. An internet search revealed that Fairfax County has 36,948 total employers, of which 109 meet the criterion of being a "Best Workplace for Commuters," which includes several benefits such as a card for using Metrobus or MetroRail (which may have been provided "on a pre-tax basis through payroll deduction or a direct funding benefit to employees up to the maximum allowed by the IRS [Internal Revenue Service])," teleworking, an emergency ride home program, bicycle parking (with locker rooms and showers), and electric vehicle charging stations (Fairfax County DOT, 2019a). Thus, for the county as a whole, it appears that 109/36498, or 0.3% (e.g., a proportion of 0.00295), currently offers a program. If it were the case that such employers were more numerous than other employers, then of course this proportion could be raised, but a value closer to 0.00 (in this case 0.003) appears reasonable and in line with Oregon's. This value was assigned throughout all zones of Fairfax and left unchanged for the forecast year.

Baseline Value of ImpProv for Fairfax County

For ImpProp, two other documents provided an estimate not of population but of communities, which can be used to infer the baseline value.

1. Fairfax County (n.d.) indicated several communities in the bronze, silver, gold, and platinum categories. For the bronze level, a community must have a "residential transportation coordinator" who works with the county to promote alternative modes or a brochure holder that displays information about such modes; the silver level requires attainment of the bronze level plus two of four specific initiatives (bike racks for residents, pedestrian walking paths, a designated carpool site, or welcome packages with transit information); the gold level requires attainment of the silver level plus one of four additional initiatives (an alternative commute day, an alternative commute table event, alternative commute information on a digital display, or the distribution of SmartTrip cards); and the platinum level requires attainment of the gold level plus a shuttle service, an annual commuter fair, or a commuter survey. There are 18 communities: 4 each in bronze, silver, and gold and 6 in platinum.

2. The county’s recent transportation report (Fairfax County DOT, 2019b) stated that in 2019, the county had “either identified or implemented trip reduction TDM [travel demand management] programs” at 285 communities, with 45 being designated as one of the four aforementioned levels (bronze, silver, gold, or platinum). If one presumes that only platinum level commuter-friendly communities could meet the standard for Individualized Marketing (IM) based on Boddy and Kassirer (2013), Gregor (2015), and Weidner (2021), then as of 2018 there were an estimated 15 IM communities in Fairfax County.

The total number of communities in Fairfax County is not known. However, an appendix in Khaja (2019) showed when only apartments were considered, in 2018 there were at least 314 rental communities representing 79,521 units. In the county as a whole, in 2018 there were 409,600 households. Thus, a very rough estimate of the number of “communities” in Fairfax County is (409,600/79,521)*314 = 1,617. With 15 meeting the IM standard, the proportion became 15/1,617 = 0.009.

This proportion was assigned, however, only for zones where the population density was at least 4,000. These zones are shown in red in Figure A2 for 2019 and 2045.

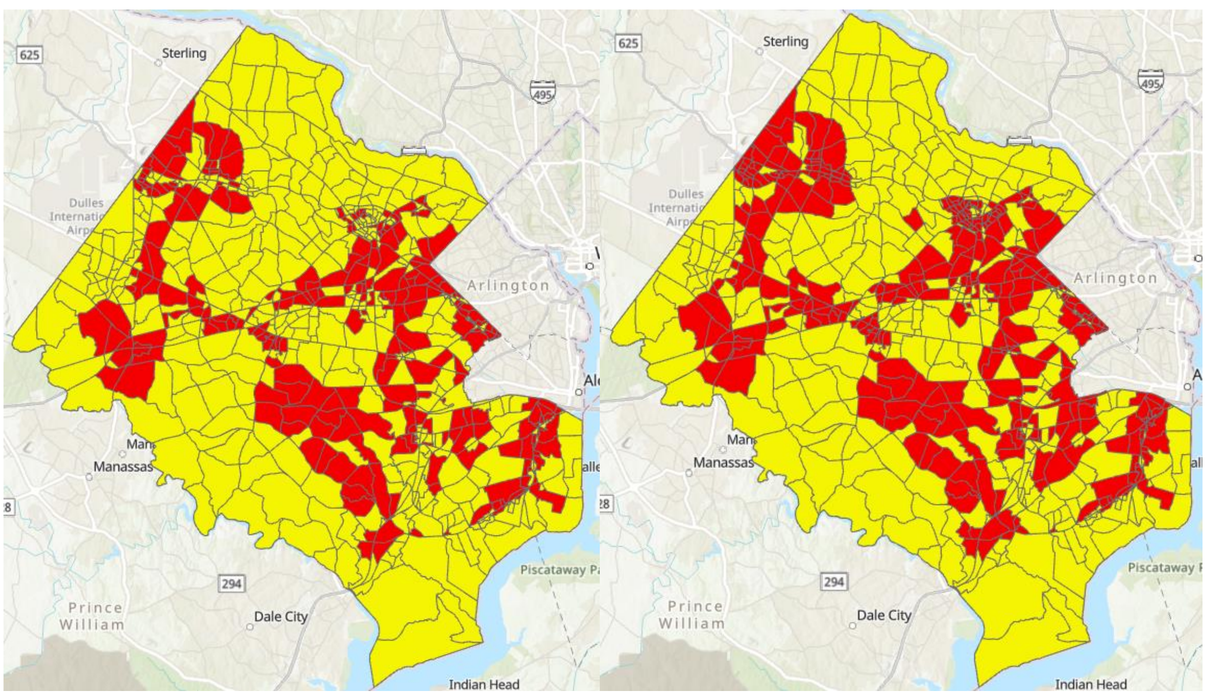

Figure A2. Zones With Population Densities Above 4,000 People per Square Mile (red) for 2019 (left) and 2045 (right). For such zones, the value of ImpProv is set to 0.009 rather than zero. Figure A2 was created by the research team using ArcGIS® software by Esri. ArcGIS® and ArcMap™ are the intellectual property of Esri and are used herein under license. Copyright © Esri. All rights reserved. Attributions provided by Esri for the basemap underlying Figure A2 are “Fairfax County, VA, M-NCHPPC, VITA, Esri, HERE, Garmin, INCREMENT P, NGA, USGS.”

APPENDIX B

EXAMPLE OF DEVELOPING A SCENARIO INPUT FILE

Increase Transit Supply (Scenario 6a)

Scenario 6a entails increasing transit supply to address crowding. NVTA (2018) provided a figure where "individuals experiencing crowding" was defined as all seats filled on local buses, 90% of seats filled on express buses and Virginia Railway Express trains, and Metrorail trains having at least 100 passengers per car. These locations are inside the beltway (notably the City of Falls Church) and along the I-66/Orange/Silver Lines. The map from NVTA (2018) showed deep red and purple that corresponded to large crowding (Figure B1, left). The map was georeferenced as an RGB raster; raster algebra was performed (subtracting green and blue pixel values from red pixel values); the resultant one-band raster was converted to points; and then points with a grid cell above zero were identified as indicative of crowding (Figure B1, middle). Then, the number of such points within each TAZ was tabulated such that the zones with any crowding (124 of 712) were identified (Figure B1, right). These values ranged from 1 to 67 with a mean value of almost 11.

Then, for these 124 zones, the attribute D4c within bzone_transit_service.csv was increased. Attribute D4c is defined as the "aggregate frequency of transit service within 0.25 miles of block group boundary per hour during evening peak period (Ref: EPA 2010 Smart Location Database)" and for the base year reflected smart location groups obtained from the U.S. EPA (2020). For the forecast year, no change in transit service is the base case. For the zones with crowding, the attribute D4c was then increased in a manner proportionate to the amount of crowding with a scale factor of 2. For instance, for one zone, the attribute D4c had a value of 20.4 and there were 4 points indicating crowding, so the new value because 20.4 + 2(4) = 28.4.

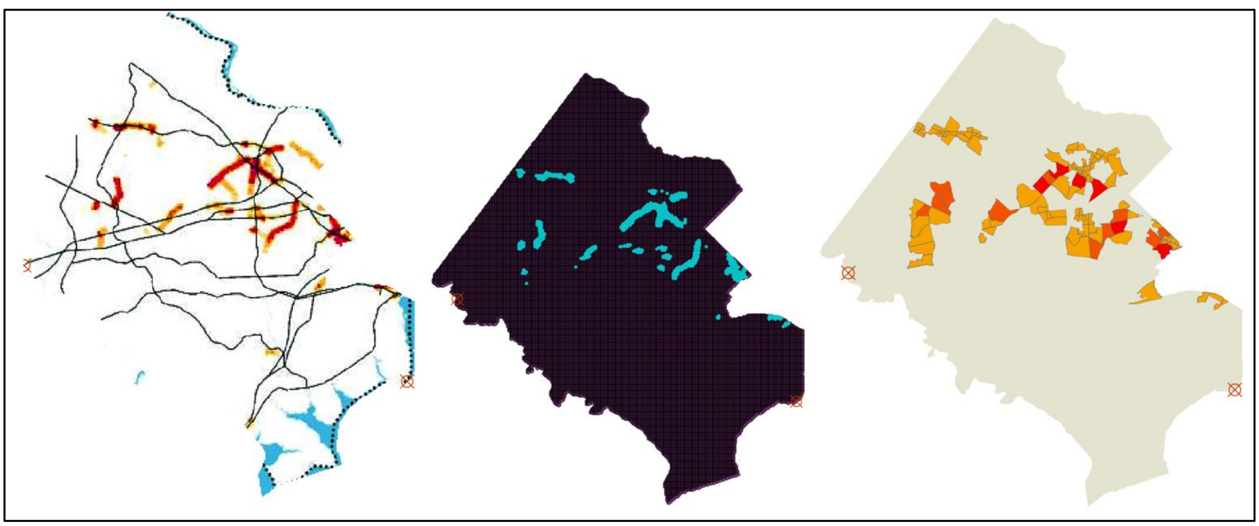

Figure B1. Determination of Crowded Transit Locations. The far right panel of Figure B1 was created by the research team using ArcGIS® software by Esri. ArcGIS® and ArcMap™ are the intellectual property of Esri and are used herein under license. Copyright © Esri. All rights reserved.

The choice of scale factor (e.g., 2 as opposed to 1 or 3) was indeed arbitrary except that the use of 2 ensured that for most zones the new value of D4c remained below a reasonable threshold. This reasonable threshold was determined by examining D4c for the 712 zones for the base case and picking the largest value, which the research team believed could be indicative of the largest possible aggregate frequency. With the scale factor of 2, the increased value of D4c nonetheless was below the threshold for all 708 of the 712 zones. For those remaining four zones, D4c was then revised to be equal to the threshold. Figure B2 shows an excerpt of bzone_transit_service.csv.

Original Data			Scenario Data		
Geo	Year	D4c	Geo	Year	D4c
1960	2045	34.40169	1960	2045	70.40169
1961	2045	27.60436	1961	2045	97.60436
1962	2045	39.30196	1962	2045	141.302
1963	2045	33.49682	1963	2045	33.49682

Figure B2. Original and Scenario 6a Versions of bzone_transit_service.csv Where There Is Crowding in Zones 1960, 1961, and 1962 But Not Zone 1963

Increase Lane-Miles Supply (Scenarios 6b and 6c)

Two new scenarios were developed for the supply of lane-miles. NVTA (2018) noted the addition of HOV lanes on Route 28, the Fairfax County Parkway, and Franconia-Springfield Parkway, which within the county give lengths of 14, 31.8, and 3 centerline miles. Based on the presumption of one HOV lane per direction, this would translate into an additional 97.6 lane-miles beyond the 2045 base case of about 930 miles. Thus, this value of 97.6 was added to the base case for a total of 1,028 lane arterial lane-miles (level 2).

It is conceivable that these HOV additions could represent facilities, however, that function as an interstate rather than an arterial facility. Thus, the next new scenario (level 3) was to add these 97.6 additional miles to the freeway system rather than the arterial system as shown in Figure B3.

Geo	Year	FwyLaneMi	ArtLaneMi	Base
NVTA	2019	517.38	845.86	
NVTA	2045	534.45354	930.446	
Geo	Year	FwyLaneMi	ArtLaneMi	Expansion of Arterial
NVTA	2019	517.38	845.86	
NVTA	2045	534.45354	1028.046	
Geo	Year	FwyLaneMi	ArtLaneMi	Expansion of Freeway
NVTA	2019	517.38	845.86	
NVTA	2045	632.05354	930.446	

Figure B3. Original and Scenario 6a Versions of marea_lane_miles.csv. The yellow highlighting indicates the values that were changed to execute scenarios 6b and 6c.

APPENDIX C

EXECUTE VISIONEVAL FOR A SMALL HYPOTHETICAL REGION

To better understand the results of Tables 10 and 11 for Northern Virginia, VisionEval was executed on a five-zone hypothetical region to better understand its sensitivity to inputs. As shown in Figure 4 and Table C1, this hypothetical region consisted of two A zones (ZNHPO1 and ZNHPO2) and five B zones (100-104).

Then, as was the case with Northern Virginia, VisionEval was executed to determine household VMT, heavy truck VMT, light duty vehicle trips, and trips by mode (bike, walk, transit, and vehicle).

Table C1. Geographic Relationship Between the Zones and the Region

Azone	Bzone	Marea
ZNHPO1	100	HYPO
ZNHPO1	101	HYPO
ZNHPO1	104	HYPO
ZNHPO2	102	HYPO
ZNHPO2	103	HYPO

Creation of Base Input Files

All values in the input files are hypothetical, but they are in an appropriate ratio with both the VisionEval default Oregon model and the Northern Virginia (NOVA) model. Attributes such as azone_vehicle_use_taxes; bzone_lat_lon.csv; bzone_parking.csv; marea_congestion_charges; marea_operations_deployment.csv; marea_transit_ave_fuel_carbon_intensity.csv; marea_congestion_charges.csv; region_road_cost; region_com_svc_vehicle_mena_age.csv; and the region_base_year_dvmt were added in accordance with the default Oregon model, but other attributes that are related to travel demand were based on appropriate ratios with the NOVA model. For example, the total employment, total single family and multifamily dwelling units (but not group quarters), total population (excluding group quarters), and total lane-miles were 29,548 jobs, 50,220 people, 21,384 households, and 59 miles, respectively. These suggest an average of 1.69 people per job and 2.35 people per household. Table C2 represents the comparison of the total employment, total population and total dwelling units of the three VisionEval Regional Strategic Planning Model regions: Oregon, NOVA, and HYPO (hypothetical).

Table C2. Comparison of Inputs in Three Different VisionEval Regions

Model	Total Employment	Household Population	Single-Family and Multi-Family Dwelling Units
Oregon Model	198,111	247,198	178,777
NOVA Model (year 2045)	818,486	1,425,487	559,724
HYPO Model	29,548	50,220	21,384

[a] Based on the input files bzone_dwelling_units.csv, bzone_employment.csv, and azone_hh_pop_by_age.csv.

Creation of Scenario Input Files

Table C3 summarizes the new scenarios. For the category 5 scenarios, the fuel tax was increased to 50% of the current fuel price ($3.872), meaning the new fuel tax became $1.936. Tables C4 and C5 list the input files and attributes for scenarios 5a, 5e, 5f, 5g, 5h, 7d, and 9f. Scenario 9f refers to the attribute D3bpo4, which is the intersection density measured by the number of pedestrian-oriented intersections having four or more legs per square mile.

Table C3. Modifications of the Input Files for Different Scenarios

Scenario	Description
2b	Increased employment by 12%
4a’	Increase the household target size for the two Azones by 65% and 27%, and double the household population in the age categories of 0 to 14 and 15 to 19 years.
5a	Increase fuel tax (from $0.48 per gallon to $1.936 per gallon).
5b	Tax EVs the same as fossil fuel vehicles
5c	Scenarios 5a, 5b, and increase transit frequency
5d	Scenarios 5a and 5b only
5e[a]	Decrease per capita income to $10,000
5f[a]	Decrease per capita income to $10,000 and increase fuel tax from $1.936 per gallon
5g[a]	Decrease per capita income to $7,000
5h[a]	Decrease per capita income to $7,000 and increase fuel tax from to $1.936 per gallon
6a	Increase frequency of transit service
7a	Fuel prices change to 57% of base price
7b	Electricity prices change to 85.6% of the base price
7d	Increase cost of vehicle ownership dramatically (from $50 to $2,050)
9f	Increase pedestrian-friendly intersections

[a] These scenarios were run only with the hypothetical region and not with the Northern Virginia region.

Table C4. Base Input Files and Modified Input Files for Scenarios 5a, 5e-5h, and 7d

Input File	Base Value	Scenario					
		5a	5e	5f	5g	5h	7d
azone_veh_use_tax.csv	$0.484	$1.936	$0.484	$1.936	$0.484	$1.936	0.484
azone_per_cap_inc.csv	$32,000	$32,000	$10,000	$10,000	$7,000	$7,000	$32,000
azone_hh_veh_own_taxes	50	50	50	50	50	50	2,050

Table C5. Input File Values for Base Case and Scenario 9f

bzone_network_design value	D3bpo4 in Bzone (TAZs)				
	100	101	102	103	104
Base Case	8.44	0.587	0.738	0.41	0.286
Scenario 9f	16.88	1.175	1.461	0.821	0.572

Results of Scenario Execution

Table C6 summarizes the results with respect to the base case; the version of VisionEval that accompanied R 4.1.0 was used for these results. For instance, a drop in per capita income from $32,000 (base case) to $10,000 (scenario 5e) reduces household VMT by 25% and CO_2e from all vehicles by 34.8%. Most results were expected, but surprises are noted in scenarios 4a’ and 7d.

Table C6. Summary of Scenarios Using the Hypothetical Zones

No.	Summary	VMT (HH)	VMT (Trucks)	Delay (LDV)	GGE (All Veh)	KWH (All Veh)	CO_2e (All Veh)
0	Base case in 2045	1.000	1.000	1.000	1.000	1.000	1.000
2b	Biased employment error by locality	1.000	1.000	1.000	1.000	1.000	1.000
4a'	Larger household size	0.915[a]	1.709	0.964	1.194	1.441	1.209
5a	Large increase in fossil fuel tax	0.992	1.000	0.992	0.994	1.003	0.995
5b	Tax EVs the same as fossil fuel vehicles	1.000	1.000	1.000	1.000	0.998	1.000
5c	Scenarios 5a, 5b, and increase transit frequency	0.951	1.000	0.954	1.077	0.970	1.055
5d	Scenarios 5a and 5b only	0.991	1.000	0.991	0.995	0.996	0.995
5e	Decreased the income to 10000	0.750	0.301	0.768	0.671	0.448	0.652
5f	Scenario 5e+ Scenario 5a	0.744	0.301	0.757	0.666	0.452	0.648
5g	Decreased the income to 7000	0.675	0.212	0.700	0.608	0.360	0.586
5h	Scenario 5g+Scenario 5a	0.671	0.212	0.688	0.604	0.365	0.582
6a	Increase frequency of transit service	1.000	1.000	1.000	1.000	1.000	1.000
7a	Fuel prices change to 57% of base price	1.007	1.000	1.007	1.006	0.996	1.005
7b	Electricity prices change to 85.6% of the base price	1.000	1.000	1.000	1.000	1.002	1.000
7c	Combine scenarios 7a and 7b	1.008	1.000	1.007	1.005	0.998	1.005
7d	Increase cost of vehicle ownership dramatically	1.004[a]	1.000	1.003	1.011	0.964	1.008
9f	Increase pedestrian-friendly intersections	1.000	1.000	1.000	1.000	1.000	1.000

GGE = gasoline equivalent gallons; CO_2e = grams of carbon-dioxide equivalents; KWH = kilowatt-hours consumed per day; Veh = vehicles. Base income = $32,000. Base fuel tax = $0.484.
[a] These results were unexpected by the research team.

The larger household size in scenario 4a' led to fewer, not more, vehicle trips. As was the case with scenario 4a' one would assume a larger household size would result in more vehicle trips (although, if one accepts the premise of fewer vehicle trips, reduced delay is logical). Further, although not shown in Table C6, scenario 4a' decreased average vehicle trip length by almost 40% (in Northern Virginia, scenario 4a' also decreased vehicle trip length but only by 4.4%).

Scenario 7d (which increases the cost of the vehicle ownership dramatically) showed a slight increase in household VMT. Scenario 2b can be explained by the fact that, as discussed in the report, a change in employment does not seem to have a substantial impact to the extent that the supply of workers and the supply of people remains fixed.

Table C7 shows changes in trips by mode. For instance, scenario 5a shows that an increase in fossil fuel taxes reduced vehicle trips by less than a percentage point (0.8%), but scenario 5c shows that in conjunction with increased transit frequency, vehicle trips were reduced by 5%.

Table C7. Summary of Scenarios Using the Hypothetical Location

No.	Summary	Walk Trips	Bike Trips	Transit Trips	Vehicle Trips
0	Base case in 2045	1.000	1.000	1.000	1.000
2b	Biased employment error by locality	1.000	1.000	1.000	1.000
4a’	Larger household size	1.675	8.694	2.527	0.856[a]
5a	Large increase in fossil fuel tax	1.004	1.003	1.007	0.992
5b	Tax EVs the same as fossil fuel vehicles	1.000	1.000	1.000	1.000
5c	Scenarios 5a, 5b, and increase transit frequency	1.040	0.828	1.348	0.950
5d	Scenarios 5a and 5b only	1.004	1.003	1.008	0.990
5e	Decrease the income to $10000	0.911[a]	0.971[a]	1.155	0.828
5f	Scenario 5e and Scenario 5a	0.914	0.973	1.160	0.821
5g	Decrease the income to $7000	0.891	0.978	1.229	0.768
5h	Scenario 5g and Scenario 5a	0.893	0.979	1.233	0.763
6a	Increase frequency of transit service	1.000	1.000	1.000	1.000
7a	Fuel prices change to 57% of base price	0.996	0.997	0.993	1.008
7b	Electricity prices change to 85.6% of the base price	0.999	0.999	0.999	1.000
7c	Combine scenarios 7a and 7b	0.996	0.997	0.992	1.008
7d	Increase cost of vehicle ownership dramatically	0.995[a]	0.995[a]	0.986[a]	1.007[a]
9f	Increase pedestrian-friendly intersections	1.000	1.000	1.000	1.000

[a] These results were unexpected by the research team.

Most results in Table C7 were expected, but surprises are noted in scenarios 4a’, 5e, 7d, and 9f. In the NOVA model, scenario 4a’ (larger household size) had generated 2.6% more vehicle trips; by contrast, vehicle trips dropped by almost 15% in Table 8. Scenario 5e (reducing household income) reduced vehicle trips and increased transit trips as expected but the drop in bicycle and walk trips was not expected (in the sense that these modes tend to be cheaper than vehicle trips). In scenario 7d, a dramatic increase in vehicle ownership costs slightly increased vehicle trips and, surprisingly, the cheaper bike trips, walk trips, and transit modes were not substituted for vehicle trips. Changing the number of pedestrian intersections (scenario 9f) also had no impact on mode split.

The hypothetical model also showed that improper ratios between input files can skew the results. For instance, in an initial version of the runs not reported here, the research team inadvertently had created a region with one job per 10 households. This may have explained why scenarios 5a, 5e, and 5h showed an initial reduction in VMT (by increasing the fuel tax). After these errors were identified, the input files were modified and the results were more reasonable as shown in Table C6.