VTRC
Virginia Transportation Research Council

We Bring Innovation to Transportation

Pilot Implementation of a Vehicle Occupancy Data Collection Program

https://vtrc.virginia.gov/media/vtrc/vtrc-pdf/vtrc-pdf/24-R9.pdf

YIQING XU. Ph.D.
Graduate Research Assistant

LANCE E. DOUGALD
Associate Principal Research Scientist

JOHN S. MILLER, Ph.D., P.E.
Associate Director

Final Report VTRC 24-R9

VIRGINIA TRANSPORTATION RESEARCH COUNCIL
530 Edgemont Road, Charlottesville, VA 22903-2454
vtrc.virginiadot.org

Standard Title Page—Report on State Project

<table>
<tr><td rowspan="2">Report No.:
VTRC 24-R9</td><td rowspan="2">Report Date:
January 2024</td><td rowspan="2">No. Pages:
46</td><td>Type Report:
Final</td><td>Project No.:
122189</td></tr>
<tr><td>Period Covered:
8/25/2022-11/01/2023</td><td>Contract No.:</td></tr>
<tr><td colspan="4">Title:
Pilot Implementation of a Vehicle Occupancy Data Collection Program</td><td rowspan="3">Key Words:
Vehicle occupancy, land use, crash data</td></tr>
<tr><td colspan="4">Author(s):
Yiqing Xu, Ph.D., Lance Dougald, and John S. Miller, Ph.D., P.E.</td></tr>
<tr><td colspan="4">Performing Organization Name and Address:
Virginia Transportation Research Council
530 Edgemont Road
Charlottesville, VA 22903</td></tr>
<tr><td colspan="5">Sponsoring Agencies' Name and Address:
Virginia Department of Transportation
1401 E. Broad Street
Richmond, VA 23219</td></tr>
<tr><td colspan="5">Supplementary Notes:</td></tr>
</table>

Abstract:

This study developed an approach for partially automating the extraction of vehicle occupancies from crash data. The approach can be implemented within 2 to 3 days based on a Tableau file available from the Virginia Department of Transportation's Traffic Operations Division, the execution of a Python script developed for this work, and the resultant creation of online maps showing occupancies by corridor, block group, jurisdiction (city or county), and district.

With additional effort, it is possible to reduce potential crash bias. One way of removing bias is heuristic: synthesize what are believed to be missing vehicles from the crash data. This Type 1 bias correction method was highly productive in that it took only about 2 hours and did not require field data collection; this approach is suitable for towns and small cities or counties. Although it had little impact for populous jurisdictions (e.g., it shifted the occupancy for Amelia County from 1.38 to 1.39), such correction had a substantial impact on small jurisdictions (changing the occupancy for Burkeville from 1.20 to 1.30).

Another way of removing crash bias is statistical and is more labor intensive. With Type 2 bias correction, there is a ground truth value: one measures occupancies in the field and then uses a regression model from these field estimates to adjust the crash occupancies for a specific corridor. This method requires considerable effort (e.g., 22 hours in the Richmond District) and is not always productive. Accordingly, guidance for when Type 1 and Type 2 bias correction should be performed is given herein; for instance, the research shows that Type 2 bias correction should be attempted only with sites where the occupancy for injury crashes is higher than the occupancy for property damage only crashes.

Historically, detailed occupancy data such as those developed in this study have not been available, and thus in consultation with the project's technical review panel, uses of these data to support planning decisions were explored. One application pertains to land development: how do various land use factors influence occupancy throughout Virginia? Geographically weighted regression showed that income, mean travel time, population density, and degree of land use mix explains about 40% of the variation in occupancy. For instance, for the urban state capital of Richmond, a 10% increase in households earning less than $15,000 annually was associated with an occupancy increase of 0.06. For rural southwest Virginia, occupancy increased by about 0.19 for areas having long travel times to work (compared to those having shorter commuting times). As these results suggest modest potential for regional variation to inform land development decisions, such findings can support more nuanced land development reviews for interested localities.

Supplemental files can be found at: https://library.virginiadot.org/vtrc/supplements.

FINAL REPORT

PILOT IMPLEMENTATION OF A VEHICLE OCCUPANCY DATA COLLECTION PROGRAM

Yiqing Xu, Ph.D.
Graduate Research Assistant

Lance E. Dougald
Associate Principal Research Scientist

John S. Miller, Ph.D., P.E.
Associate Director

Virginia Transportation Research Council
(A partnership of the Virginia Department of Transportation
and the University of Virginia since 1948)

Charlottesville, Virginia

January 2024
VTRC 24-R9

DISCLAIMER

The contents of this report reflect the views of the authors, who are responsible for the facts and the accuracy of the data presented herein. The contents do not necessarily reflect the official views or policies of the Virginia Department of Transportation, the Commonwealth Transportation Board, or the Federal Highway Administration. This report does not constitute a standard, specification, or regulation. Any inclusion of manufacturer names, trade names, or trademarks is for identification purposes only and is not to be considered an endorsement.

ABSTRACT

This study developed an approach for partially automating the extraction of vehicle occupancies from crash data. The approach can be implemented within 2 to 3 days based on a Tableau file available from the Virginia Department of Transportation’s Traffic Operations Division, the execution of a Python script developed for this work, and the resultant creation of online maps showing occupancies by corridor, block group, jurisdiction (city or county), and district.

With additional effort, it is possible to reduce potential crash bias. One way of removing bias is heuristic: synthesize what are believed to be missing vehicles from the crash data. This Type 1 bias correction method was highly productive in that it took only about 2 hours and did not require field data collection; this approach is suitable for towns and small cities or counties. Although it had little impact for populous jurisdictions (e.g., it shifted the occupancy for Amelia County from 1.38 to 1.39), such correction had a substantial impact on small jurisdictions (changing the occupancy for Burkeville from 1.20 to 1.30).

Another way of removing crash bias is statistical and is more labor intensive. With Type 2 bias correction, there is a ground truth value: one measures occupancies in the field and then uses a regression model from these field estimates to adjust the crash occupancies for a specific corridor. This method requires considerable effort (e.g., 22 hours in the Richmond District) and is not always productive. Accordingly, guidance for when Type 1 and Type 2 bias correction should be performed is given herein; for instance, the research shows that Type 2 bias correction should be attempted only with sites where the occupancy for injury crashes is higher than the occupancy for property damage only crashes.

Historically, detailed occupancy data such as those developed in this study have not been available, and thus in consultation with the project’s technical review panel, uses of these data to support planning decisions were explored. One application pertains to land development: how do various land use factors influence occupancy throughout Virginia? Geographically weighted regression showed that income, mean travel time, population density, and degree of land use mix explains about 40% of the variation in occupancy. For instance, for the urban state capital of Richmond, a 10% increase in households earning less than $15,000 annually was associated with an occupancy increase of 0.06. For rural southwest Virginia, occupancy increased by about 0.19 for areas having long travel times to work (compared to those having shorter commuting times). As these results suggest modest potential for regional variation to inform land development decisions, such findings can support more nuanced land development reviews for interested localities.

FINAL REPORT

PILOT IMPLEMENTATION OF A VEHICLE OCCUPANCY DATA COLLECTION PROGRAM

Yiqing Xu, Ph.D.
Graduate Research Assistant

Lance E. Dougald
Associate Principal Research Scientist

John S. Miller, Ph.D., P.E.
Associate Director

INTRODUCTION

Both federal rules and state processes increasingly have the potential to require vehicle occupancy data—that is, some estimate of the total number of occupants in a passenger vehicle. Although the Intermodal Surface Transportation Efficiency Act (ISTEA) of 1991 required monitoring of congestion management strategies, the final rulemaking for the Moving Ahead for Progress in the 21st Century Act (MAP21) reauthorization entails vehicle occupancy for system performance measures such as "Percent of the Person-Miles Traveled on the Non-Interstate NHS That Are Reliable" (Federal Highway Administration [FHWA], 2017). When the rule was first implemented, the measure was needed only for urbanized areas with more than 1 million people but as of January 1, 2022, it includes urbanized areas with more than 200,000 people. Virginia has 14 urbanized areas, 3 of which exceed 1 million (Virginia Beach, Richmond, and Washington, DC-VA-MD) and a fourth, the Roanoke urbanized area, which exceeds 200,000 people, meaning the new requirements now apply to that location (Federal Transit Administration, 2022). Virginia's SMART SCALE program also uses vehicle occupancy where, depending on the location, congestion mitigation accounts for 10% to 45% of the project's benefits (Commonwealth Transportation Board, 2021). Congestion mitigation is computed using two performance measures: (1) the project's anticipated increase in person throughput, and (2) the project's anticipated reduction in person-hours of delay. In both cases, the performance measure can be computed by multiplying the change on a vehicular basis (e.g., increase in vehicle throughput and reduction in vehicle delay) by an average vehicle occupancy (AVO) rate.

In response to this increased emphasis on vehicle occupancy data, the Virginia Department of Transportation (VDOT) commissioned the Virginia Transportation Research Council (VTRC) to conduct a study titled "Development of Guidance for a Vehicle Occupancy Rate Data Collection Program." The study report (Xu et al., 2022a) described several approaches for routinely monitoring vehicle occupancy data, such as field collection and the use of probe-based datasets (e.g., StreetLight Insight), and culminated in two recommendations. The first recommendation was to extract crash data on a pilot basis to support an occupancy monitoring program, as the study found that because occupancies are now collected for all crashes (not just those with injuries), Virginia has a large dataset. The second recommendation was to apply methods to remove potential crash bias from occupancy estimates on a pilot basis in one VDOT district. One of these methods, Type 2 bias correction, requires the collection of field data if one is to estimate occupancy on a particular corridor.

There are two issues. First, VDOT does not have an established process for crash data extraction that is routine and that has been tested by someone other than the research team. Second, the time required to implement bias correction is not known. As a result, occupancy data have not historically been widely available, which leads to a potential opportunity: are there potential uses for occupancy data that have not been identified?

PURPOSE AND SCOPE

The purpose of this study was to demonstrate how to implement a vehicle occupancy data collection program at the district level using crash data with an eye toward documenting the approach so that it could be replicated in other VDOT districts as necessary. The study had three objectives.

First, the study focused on developing a systematic process for mapping crash occupancies derived from crash data, including building a specialized workflow designed to partially automate this process and having others test this workflow. Second, the study quantified the benefits (in terms of potential improved accuracy) and costs (in terms of labor) associated with removing potential crash bias from occupancy estimates. Third, the study demonstrated the practical implications of site-specific occupancy estimates (e.g., census tracts in the Bristol District and cities and counties in Northern Virginia) by applying them to two specific decisions of interest to planners.

Unless otherwise mentioned in this report, "occupancy" refers to the number of occupants, including the driver, in a passenger vehicle.

METHODS

Three tasks were performed to accomplish the study objectives:

1. Develop a workflow for extracting vehicle occupancies from crash data.
2. Quantify the benefits and processing costs of removing potential crash bias.
3. Examine the relationship between land development and occupancy.

Develop a Workflow for Extracting Vehicle Occupancies From Crash Data

A workflow was developed in a GIS environment that could be adapted to four different geographic levels: VDOT districts, Virginia cities and counties, census block groups, and specific roadway segments. Key steps included (1) developing a stand-alone Python script for extracting these data from Tableau; (2) obtaining relevant shapefiles, such as a map of roadways, for use in the analysis; (3) joining data spatially to the appropriate roadway, block group, city/county, or district; and (4) customizing each map, such as setting labels with the vehicle occupancy.

The supplemental material for this report shows the detailed documentation necessary to replicate this workflow. For instance, the source of occupancy data is a yearly Tableau table (Simmons, 2022) where the key data element is the number of passengers (plus one for the driver) for each vehicle involved in a crash. Because the occupancy data from the Tableau table have duplicative vehicle information and need to be cleaned, this process is described in the documentation. The workflow therein leads the user through the process of downloading all required files, establishing a working environment for running Python scripts in ArcGIS Pro; running the Python script for obtaining clean crash data that can be directly used for mapping; and automatically performing Type 1 bias correction at the jurisdiction level based on the clean crash data obtained through the Python processing.

In February 2023, the workflow was tested by VDOT's Transportation Mobility and Planning Division (TMPD), particularly focusing on Python processing and occupancy mapping. TMPD staff (Jun, 2023) later reported that the testing had been successful, noting that the Python script worked for the specific tabular dataset provided, and creating occupancy maps using ArcGIS Pro followed the instructions provided. The communication (Jun, 2023) also indicated key changes necessary, including the need for clearer instructions on crash data sources and GIS output panel refreshing. Additional clarifications then were incorporated into the instructions by the research team. The revised workflow was then tested by two more individuals at VTRC (who were not affiliated with the project) in June and August, respectively, and additional revisions based on their feedback were made.

Toward the conclusion of the study, the technical review panel (TRP) for the study suggested it would be beneficial to provide additional information regarding how analysts should interpret vehicle occupancy maps that were derived from this workflow. Through discussions with the TRP, the research team documented the relative strengths and limitations of these occupancy maps, which were developed for four different geographic levels: corridor, block group, locality, and VDOT district. Then, these interpretations were used to provide four types of guidance for how the maps might be used in various VDOT applications.

Quantify the Benefits and Labor Costs of Removing Potential Crash Bias

Four steps were followed to determine the value of performing bias correction and when it should be undertaken: (1) determine sample sizes requiring bias correction; (2) quantify the impact of Type 1 bias correction; (3) quantify the impact of Type 2 bias correction; and (4) establish guidance for bias correction. The motivation was that if bias correction is not necessary—a real possibility given Virginia's large number of vehicle crashes—then VDOT's workload for developing occupancies could be reduced considerably.

Determine Sample Sizes Requiring Bias Correction

Larger sample sizes tend to require less bias correction than smaller sample sizes. To quantify how sample size affects the need for bias correction, an association test based on the eta-squared value was conducted for five variables: crash severity, driver age, driver gender, vehicle year, and collision type. This eta-squared value was calculated for each variable and was determined by dividing the sum of squares for subgroups by the total sum of squares. If eta-squared is larger than 0.01, the variable is considered correlated with occupancy in the crash data. The existence of such a correlation signifies that bias correction is needed, and such correlation tends to occur with smaller samples. For example, in the case of larger samples, no variables were found to be associated with occupancy; therefore, bias correction was not needed. Conversely, in smaller samples, most of the variables were tested and shown to be correlated with occupancy, indicating the necessity for bias correction.

Quantify the Impact of Type 1 Bias Correction

The impact of bias correction is the mean |difference| between the original occupancy and the bias-corrected occupancy, where the dataset is 1 year of crash data. For example, occupancies were generated for all counties, cities, and towns in the Richmond District for four time periods: 24-hour, AM peak, PM peak, and off-peak. The purpose of Type 1 bias correction is to address missing data for vehicle occupancy (VO) groups where no crashes result. In Table 1, for instance, there are no five-occupant vehicles involved in a crash such that VO=5 shows a value of zero. Type 1 bias correction estimates the potential number of vehicles in those zero-VO groups where no vehicles were involved in the crash.

Table 1. Example of "Zero" Vehicle Occupancy Groups

Locality	PM Peak Vehicle Sample							
	VO=1	VO=2	VO=3	VO=4	VO=5	VO=6	VO=7	VO=8
All Richmond District	7,522	863	249	98	39	9	3	4
Prince George County (raw data)	97	19	4	3	Zero	Zero	Zero	Zero
Prince George County (corrected values)	97	19	4	3	0.503	0.116	0.039	0.052

VO = vehicle occupancy. For example, in Prince George County, there were 3 vehicles that had 4 occupants, but 0 vehicles with 5 or more occupants. In Type 1 bias correction, the "zero" for 5 occupants is replaced with (39/7522)*97=0.503 vehicles. The "zero" for six occupants is replaced with (9/7522)*97=0.116 vehicles.

Quantify the Impact of Type 2 Bias Correction

Type 2 bias correction is considerably more involved than Type 1 and has three substeps: (1) determine the variation in ground truth occupancy data, (2) collect occupancy data for calibration, and (3) develop a bias correction model.

Determine the Variation in Ground Truth Occupancy Data

Two credible methods for obtaining detailed occupancy data without relying on crashes are the windshield method (where stationary observers examine vehicles passing by a point on the roadway) and the carousel method (where an observer rides in a van in the right lane traveling at 10 to 15 mph below the speed of traffic and for a particular segment examines vehicles passing by the van). A small experiment was conducted to determine if these gave the same value for the same site and the same time period.

The northbound route of the red line in Figure 1 represents the data collection route for the carousel method performed by the research group during the same time period and same day as the windshield data collection (the location of the windshield data collection is shown by the blue pin in Figure 1). The carousel method in this study involved two probe vehicles. The two probe vehicles counted different vehicles with starting times approximately 2 minutes apart (the total time for driving the probe vehicles from the start point to the end point on the segment was 2 minutes). Ideally, if one probe vehicle passed the end point, the other probe vehicle would pass the start point and begin counting.

Since there were no entrance or exit ramps on this segment, potentially, the same group of vehicles were observed with the windshield and carousel methods. That said, it is still possible for the vehicles collected by these two methods to differ slightly: for a three-lane corridor, the windshield method collected occupancy data for vehicles on all three lanes whereas the carousel method could collect occupancy data only for vehicles on lanes 2 and 3 (lane 3 being the far-left lane). This experiment allowed one to detect any error attributed solely to what one considered to be ground truth data.

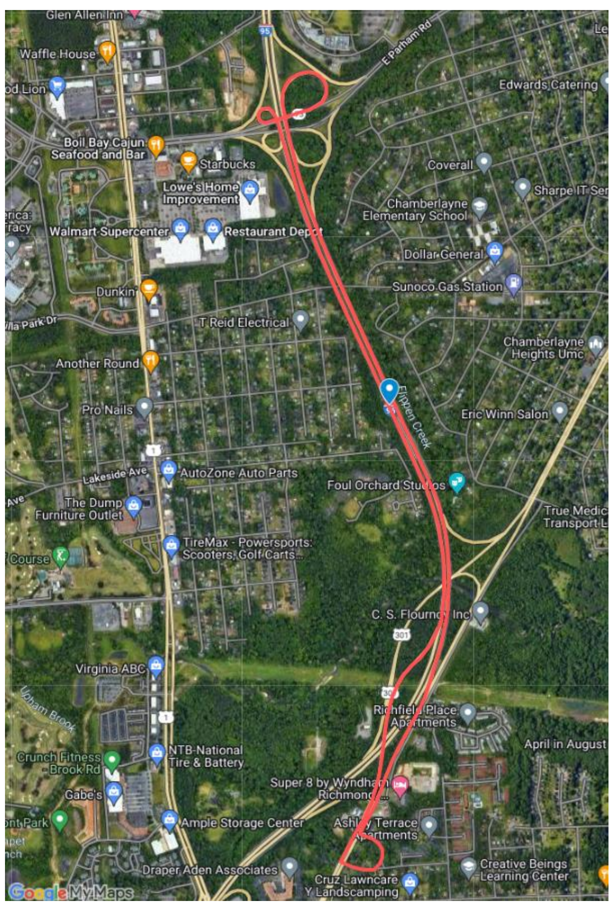

Figure 1. Carousel Data Collection Route on I-95 Between Parham Road and Route 301. Imagery © 2022 Commonwealth of Virginia, Maxar Technologies, U.S. Geological Survey, USDA/FPAC/GEO. The blue marker in the middle of the red section of I-95 is the location of windshield data collectors.

Collect Occupancy Data for Calibration

Windshield occupancies were obtained by The Traffic Group at five interstate sites in the Richmond District:

1. I-64 Eastbound between Parham Road and Glenside Drive (AM period)
2. I-95 Northbound between US 301 Chamberlayne Avenue and SR 73 Parham Road (PM period)
3. I-95 Southbound between US 301 Chamberlayne Avenue and SR 73 Parham Road (AM period)
4. I-295 Northbound between US 33 Staples Mill Road & Nuckols Road (AM period)
5. I-295 Southbound between US 33 Staples Mill Road & Nuckols Road (PM period).

Develop a Bias Correction Model

The windshield occupancies from the five sites—that is, the ground truth—comprised the dependent variable. The AVO from 3 years of crash data comprised the independent variable: all crashes, all property damage only (PDO) crashes, all injured crashes, all male crashes, all female crashes, and all rear end crashes. These variables were chosen through the Apriori test, which examines whether certain variables, such as driver gender, could be associated with specific occupancy levels (e.g., an occupancy of 2, an occupancy of 3, and so forth).

Stepwise linear regression was used to develop the Type 2 bias correction model, which involves excluding those independent variables that are not statistically significant. The R-squared value, testing error (e.g., difference between observed occupancy and estimated occupancy for a site not used to the build the model), and average error for all sites were used to evaluate the models.

Establish Guidance for Bias Correction

The results of the association tests and the impacts of the bias correction were used to establish guidance for performing Type 1 and Type 2 bias correction. This guidance reflects recommended sample sizes for when bias correction might be needed, solutions for special cases that arose in this study, and how to select calibration sites for situations when field data are needed.

Examine the Relationship Between Land Development and Occupancy

The research team also asked the TRP for rough ideas where more detailed occupancies developed during this project could be useful for land development decisions. The TRP responded with three possibilities: (1) the impact of occupancy on a performance measure related to travel time reliability (TTR), (2) ways in which occupancy might be of interest to low-population areas that are seeking SMART SCALE investments, and (3) ways in which occupancy might support land use decisions. The research team explored these three possibilities, with additional emphasis on the third possibility—how land use relates to occupancy.

Acquire Land Use Data

Data were sought for roughly one-half of Virginia's 1,907 census tracts: the 821 tracts that had at least 100 vehicles yielding an occupancy rate for year 2019. A subset of these data is shown in Table 2, and the rightmost column shows example values for one census tract chosen at random: tract 3201 located in Hanover County, Richmond District, that had an occupancy of 1.33. Data in addition to that shown in Table 2 were collected, such as the location of park and ride facilities (VDOT, 2022), other income details, the mean travel time to work, and employment density. However, those variables were ultimately found not to be useful in modeling efforts. Data sources included the U.S. Census Bureau (Undated [a-d]; 2020); most of these were 5-year datasets ending in 2019; employment data were obtained from the OnTheMap application.

The entropy index (Bordoloi et al., 2013; Song and Knaap, 2004; Turner et al., 2001), hereinafter referred to as "entropy," represents the diversity of the land use types in a target area with a value between 0 (completely homogenous) and 1 (completely mixed). For instance, an area with 20% agriculture and 80% industry (or 80% agriculture and 20% industry) yields a value of 0.72 whereas an area with 50% agriculture and 50% industry yields a value of 1.0 (see Eq. 1). In both cases, the denominator k shown in Eq. 1 is two since there are two land uses in the tract. A total of eight land uses were considered (Residential, Commercial, Industrial, Mixed Use, Institutional and Military, Agriculture, Vacant, and Open Spaces Including Parks and Greenways), such that a tract with only a single land use had k = 1 and a tract with 7 of the 8 land uses had k = 7. However, the entropy index was available for only 398 of the 821 tracts having occupancy data in Virginia. Land use mix data in support of the entropy index were extracted from localities (City of Richmond, 2021; County of Henrico, 2022; Hampton Roads Planning District Commission, 2019; Fairfax County, 2023).

$$Entropy = -\frac{\sum_{j=1}^{k} P^j \ln P^j}{\ln k} \qquad \text{(Eq. 1)}$$

where P^j = the percentage of the area that is land use type j
k = total number of land uses in the tract

Table 2. Candidate Variables

Variable	Example for Tract 3201
Percent of households with income less than $15,000	6.5%
Percent of housing units with no vehicles available	2.5%
Mean travel time to work (minutes)	37.2 minutes
Number of persons per acre	0.08 persons per acre
Entropy index (an indicator of land use mix)	Not available

Determine Spatial Disparity

The variables shown in Table 2, which were selected because stepwise regression showed them to be significant, were then used for geographically weighted regression (GWR), a spatial regression technique that evaluates the dependent variable based on the variables falling within the "neighborhood" of each target feature (ESRI, undated [a]). The "neighborhood" reflects those census tracts that are sufficiently close to each tract of interest such that they can be used in evaluating the dependent variable for the tract of interest. For instance, in Figure 2, for the green tract of interest shown near the bottom of the figure, there are 79 tracts with an orange border and 1 tract with a blue border that comprise the neighborhood.

This use of a neighborhood is an attractive option for analysis because of the possibility that a vehicle occupancy from tract x may reflect a driver who lives in tract y. If tracts x and y are relatively close such that tract y is within the neighborhood of tract x, then the analytic error resulting from this mismatch between x and y is reduced (although not eliminated, since closer tracts to x carry greater weight).

For each tract, the number of neighbors was set to be at least 50 but not more than 100; generally, at least 20 neighbors are required and 30 neighbors are suggested for GWR (ESRI, undated [b]). This range was chosen to cover areas such as cities or counties (e.g., Henrico County in the Richmond District, which consists of 47 tracts) and not surpass the total number of tracts in a VDOT construction district (e.g., the Staunton District has a minimum number of 105 tracts). To determine the number of tracts that comprised this neighborhood, the Golden Search tool was used such that the number of neighbors that yielded the lowest Akaike Information Criterion value was chosen. Given that Virginia has 821 tracts in this analysis, GWR presents 821 sets of results, where each result has an intercept, model coefficients and standard error, local R^2, and model significance level. For example, Figure 2 shows that for aforementioned tract 3201, there were 80 tracts that were used to explain the occupancy of tract 3201.

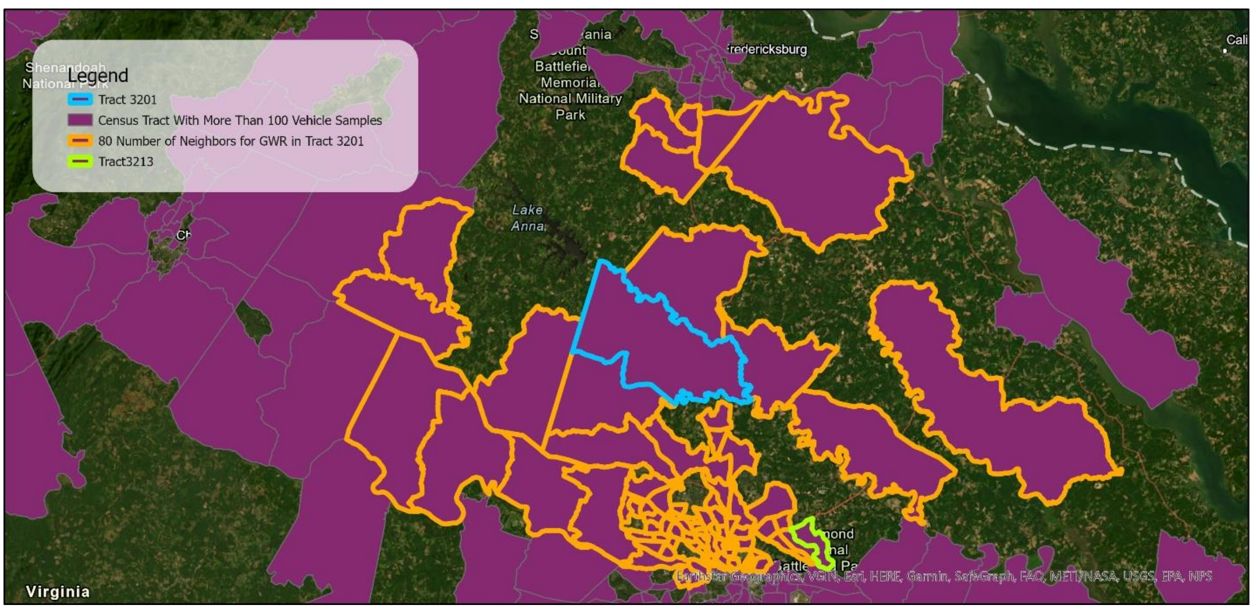

Figure 2. Tracts in the Neighborhood of Tract 3201. Imagery © Esri, NASA, NGA USGS, VGIN, HERE, Garmin, FAO, NOAA, USGS, EPA, NPS.

Because one variable from Table 2—entropy—is available in only 398 of the 821 tracts that were otherwise suitable for analysis, GWR was performed twice: once with all suitable tracts, and once with only those tracts where entropy was included, which were the higher population density areas. As an example, for the Salem District, only 5 of 73 tracts have data for the entropy variable (City of Salem, 2022); thus, GWR with entropy was performed only for higher population density areas (e.g., the Northern Virginia, Richmond, and Hampton Roads districts).

Create Land Development Scenarios

Local land use decisions have the potential to affect the variables shown in Table 2, such as population density, vehicle ownership, travel time to work, and land use mix. Euclidean zoning, for instance, will tend to decrease the entropy index. Policies that support jobs-housing balance, such as the co-location of employment and residential sectors, may impact land use mix. Infill development versus exurban development could reduce travel time to work, depending on the alignment of housing prices and employment salaries and the use of telecommuting. Three scenarios based on the results of GWR were created.

RESULTS AND DISCUSSION

A Workflow for Extracting Occupancies From Crash Data

The supplemental material for this report consists of four files. One file shows Python processing steps, one file contains steps for creating the maps, and two text files provide scripts the user can implement. Together, these files show the key steps for extracting crash data. For example, after duplicative vehicle information is deleted, four attributes are added that are essential for derivation of representative occupancies: (1) the identification of holiday crashes; (2) a week attribute that categorizes all crashes into three groups as defined in Xu et al. (2022a) (weekday [Tuesday-Thursday], weekend, and transition days [Monday and Friday]); (3) a period attribute (morning peak, evening peak, off peak, and transition hours); and (4) a "Vehicleocc" attribute that calculates the vehicle occupancy for each vehicle involved in a crash. Figure 3 outlines the steps in the supplemental material used to process these crash data.

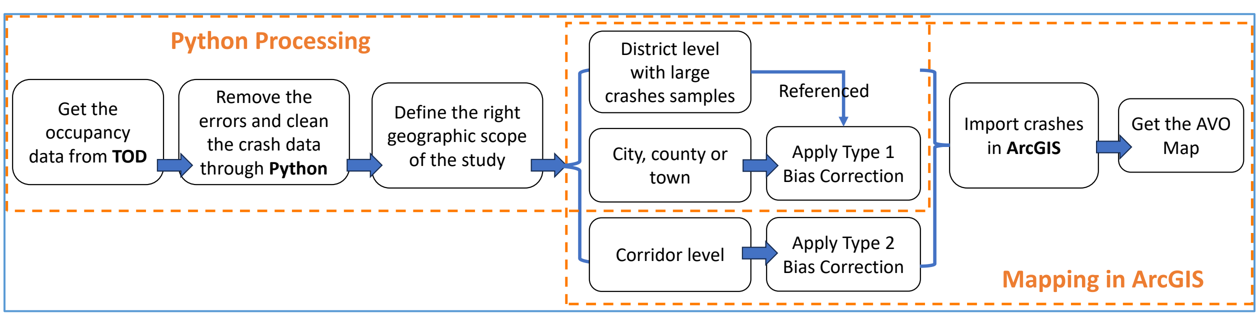

Figure 3. Summary of Steps for Processing Crash Data. TOD = VDOT's Traffic Operations Division; AVO = average vehicle occupancy.

The workflow in Figure 3 was used to develop six maps of interest to the TRP. These maps were made publicly available through a University of Virginia ArcGIS Online account. Then, after consultation with VDOT's Information Technology Division (ITD) staff, these maps were transferred to a VDOT ArcGIS Online account that is available, at present, only to VDOT staff. The research team shared these maps with VDOT's ITD staff, who will review them and then decide whether or not they can be shared outside VDOT. These six maps all report occupancy but are differentiated as follows:

1. bias-corrected by city and county (Figure 4)
2. uncorrected by city and county (Figure 5)
3. bias-corrected by block group (Figure 6)
4. uncorrected by block group (Figure 7)
5. uncorrected by VDOT district (Figure 8)
6. uncorrected by corridor (Figure 9).

The maps shown in Figures 4 through 8 enable the user to have occupancies by year for 2018-2022. For the map shown in Figure 9, which is the corridor-level AVO map, the user has the choice of two AVO values: 2018-2019 (pre-pandemic), and 2020-2022 (after the onset of the pandemic). The version of Figure 9 shown here shows the use of the 2020-2022 period. Generally, there is a smaller set of vehicle occupancies at the corridor level, which is why multiple years of data were necessary for Figure 9.

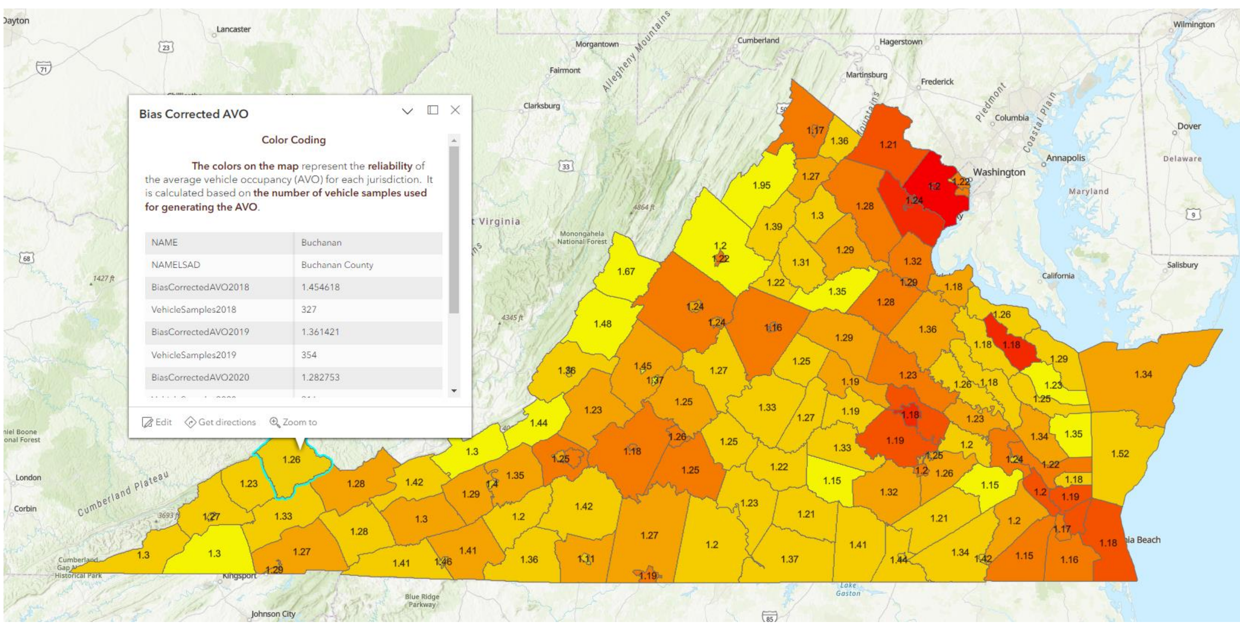

Figure 4. Screenshot of the Jurisdiction 2018-2022 Bias-Corrected Average Vehicle Occupancy Map. Imagery © Esri, NASA, NGA USGS, VGIN, HERE, Garmin, FAO, NOAA, USGS, EPA, NPS.

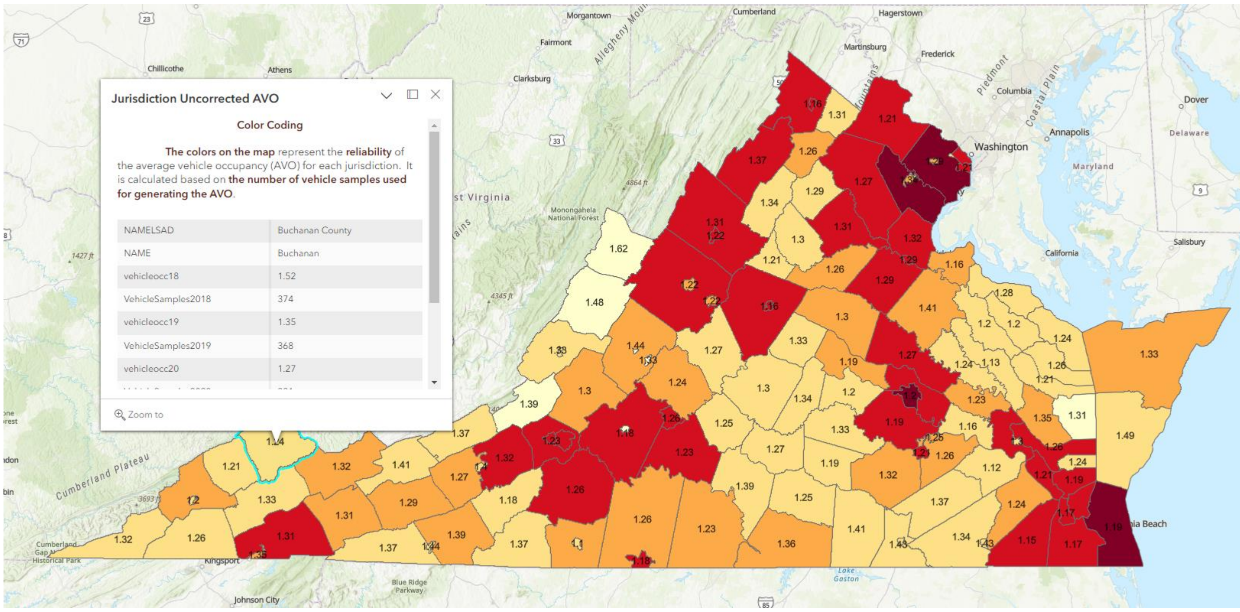

Figure 5. Screenshot of the Jurisdiction 2018-2022 Uncorrected Average Vehicle Occupancy Map. Imagery © Esri, NASA, NGA USGS, VGIN, HERE, Garmin, FAO, NOAA, USGS, EPA, NPS.

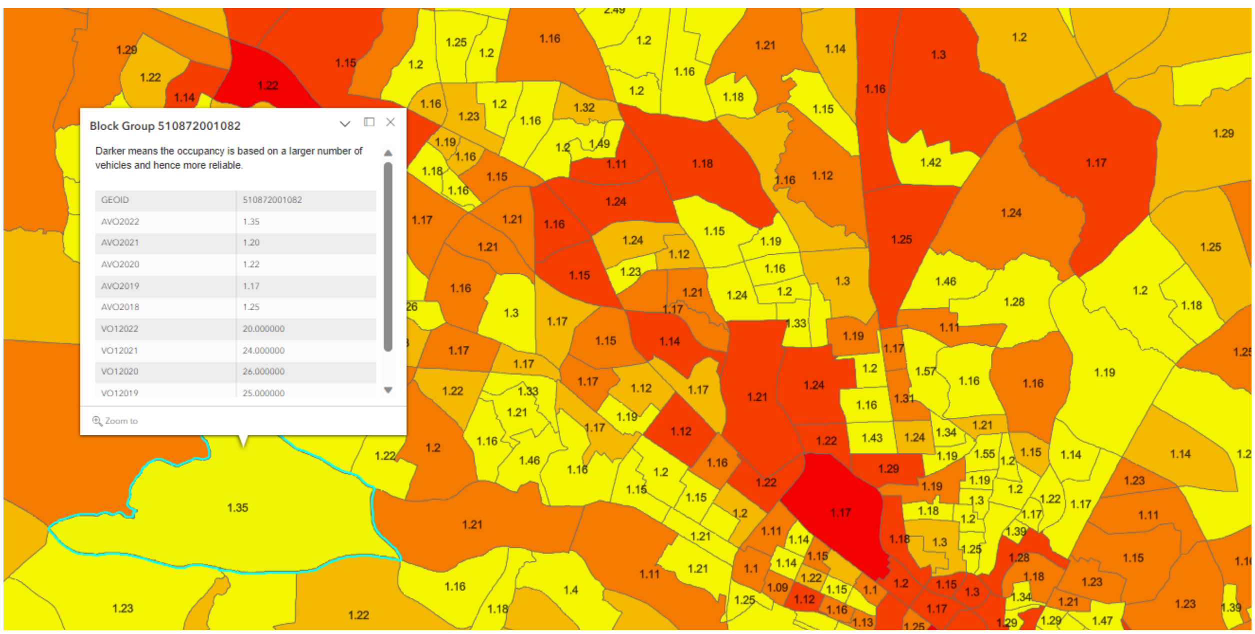

Figure 6. Screenshot of Block Groups 2018-2022 Bias-Corrected Average Vehicle Occupancy Map. The area largely reflects the City of Richmond and Henrico County. Imagery © Esri, NASA, NGA, USGS | County of Henrico, VGIN, Esri, HERE, Garmin, SafeGraph, GeoTechnologies, Inc, METI/NASA, USGS, EPA, NPS, USDA.

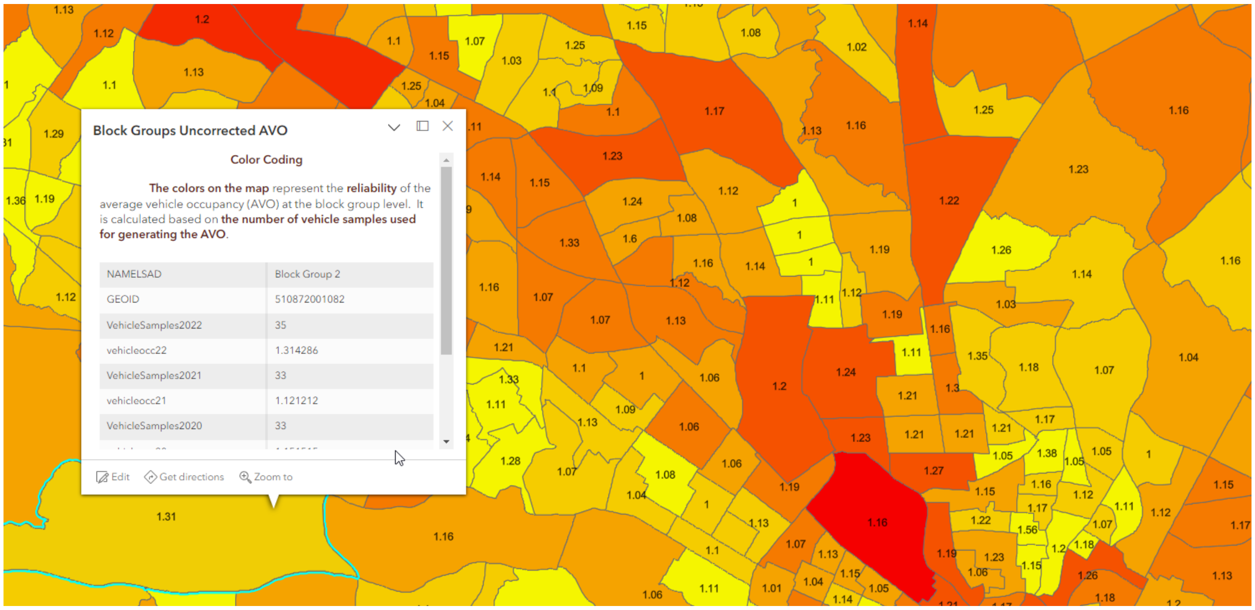

Figure 7. Screenshot of Block Groups 2018-2022 Uncorrected Average Vehicle Occupancy Map. The area largely reflects the City of Richmond and Henrico County. Imagery © Esri, NASA, NGA USGS, VGIN, HERE, Garmin, FAO, NOAA, USGS, EPA, NPS.

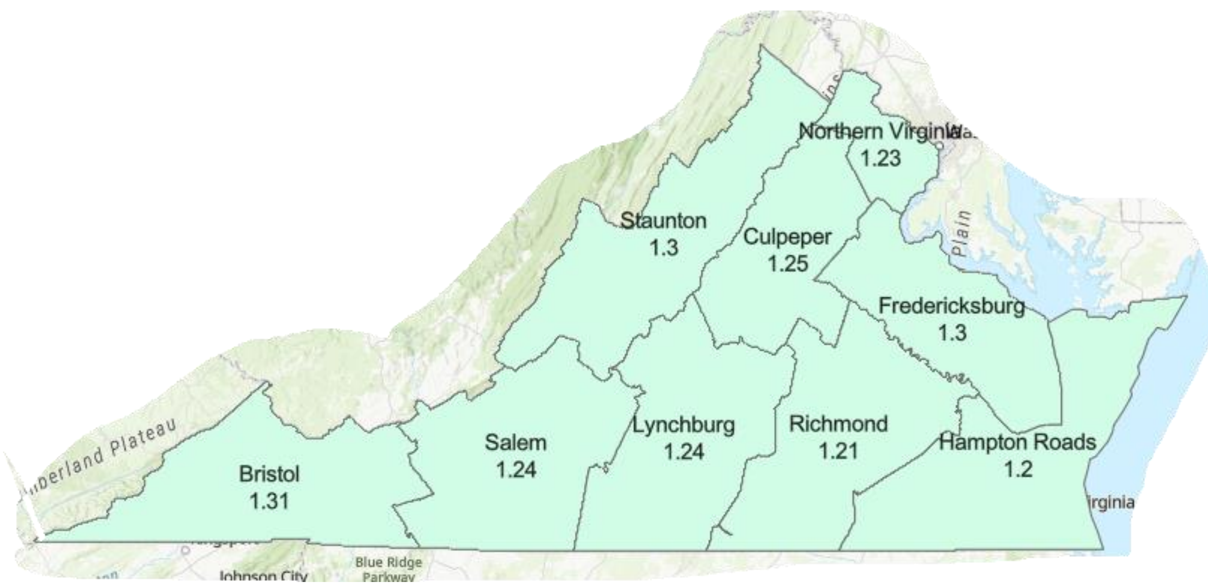

Figure 8. Screenshot of the District-Level 2018-2022 Uncorrected Average Vehicle Occupancy Map. Imagery © Esri, USGS | VGIN, Esri, HERE, Garmin, FAO, NOAA, USGS, EPA, NPS.

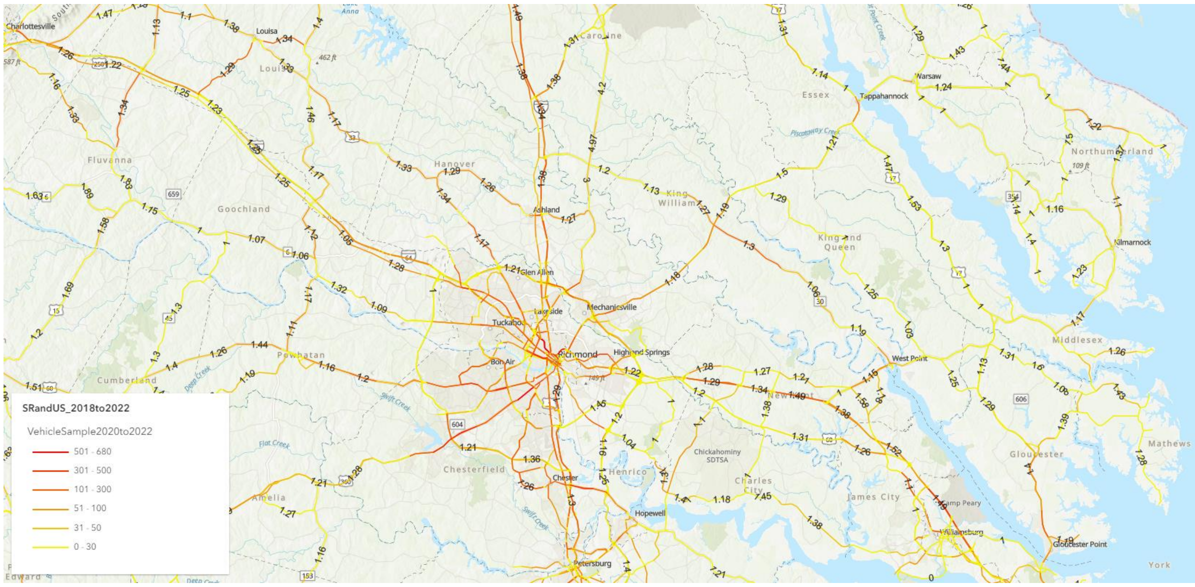

Figure 9. Screenshot of the Corridor-Level 2018-2022 Uncorrected Average Vehicle Occupancy Map. The area includes Richmond and surrounding locations such as Goochland, Hanover, Henrico, and Petersburg. Imagery © Esri, NASA, NGA USGS, VGIN, HERE, Garmin, FAO, NOAA, USGS, EPA, NPS.

Benefits and Processing Costs of Removing Potential Crash Bias

After crash-based occupancies were obtained and bias correction was performed, four key sets of results were obtained:

1. sample sizes requiring bias correction
2. impact of Type 1 bias correction
3. impact of Type 2 bias correction
4. guidance for bias correction.

Sample Sizes Requiring Bias Correction

Tests of Association

Eta-squared values, which measure the association between occupancy and five variables (crash severity, driver age group, driver gender, vehicle year, and collision type), were calculated based on 2019 Richmond District crashes. Table 3 presents the results in descending order of sample size for all jurisdictions in the Richmond District, using 24-hour occupancy data. For the Richmond District as a whole, as well as for Henrico County, Chesterfield County, and the City of Petersburg, none of the variables showed significant associations with occupancy, indicating that no bias correction was needed. However, for the remaining jurisdictions with fewer vehicle samples, associations were found (based on Eta-squared exceeding 0.01), suggesting some bias correction was needed.

Table 3. Eta-Squared Results for Localities in the Richmond District

Vehicle Sample Group	Locality	Vehicle Sample	Crash Severity	Driver Age Group	Vehicle Year Group	Driver Gender	Collision Type
Sample > 1,000	All Richmond District	43492	-	-	-	-	-
	City of Richmond	11627	+	-	-	-	-
	Henrico County	10849	-	-	-	-	-
	Chesterfield County	9984	-	-	-	-	-
	Hanover County	2658	-	+	-	-	-
	City of Petersburg	1373	-	-	-	-	-
100 < Sample < 1,000	Goochland County	922	+	-	-	-	+
	New Kent County	921	-	+	+	-	+
	City of Hopewell	685	-	+	-	-	+
	Prince George County	685	-	-	-	-	++
	City of Colonial Heights	650	-	+	+	-	+
	Dinwiddie County	634	-	-	-	-	+
	Powhatan County	524	-	+	-	-	+
	Mecklenburg County	364	+	-	-	+	+
	Brunswick County	292	-	-	+	-	++
	Town of Ashland	275	+	+	-	-	+
	Amelia County	274	-	+	+	+	+
	Nottoway County	219	-	+	+	-	++
	Town of South Hill	144	-	+	-	-	++
	Lunenburg County	132	+	+	+	++	++
	Charles City County	129	++	+	-	-	++
Sample < 100	Town of Crewe	35	-	++	+++	++	+
	Town of Blackstone	33	-	++	+++	++	++
	Town of Clarksville	19	+	+++	++	-	+++
	Town of Chase City	16	+++	++	+++	+++	+++
	Town of Boydton	10	++	+++	+++	+	+++
	Town of McKenney	10	++	+++	+++	++	+++
	Town of Alberta	9	N/A				
	Town of Brodnax	5					
	Town of Burkeville	5	+++	+++	+++	+++	-
	Town of Lawrenceville	4	-	+++	+++	++	+++
	Town of Victoria	3	-	+++	-	+++	+++
	Town of La Crosse	2	N/A				

Eta-squared < 0.01, the association is negligible shown as “-”; eta-squared < 0.06, the association is small shown as “+”; eta-squared < 0.14, the association is medium shown as “++”; eta-squared >= 0.14, the association is large shown as “+++”; N/A = testing sample does not have a valid eta-squared value.

Relationship Between Tests of Association and Sample Size

Figure 10 shows the results of the association test. The x-axis represents the number of vehicle samples in the crashes, and the y-axis represents the number of variables associated with occupancy. The exponential regression line indicates the need for bias correction. As the number of vehicle samples increases, the number of variables associated with occupancy decreases. For instance, the Town of Crewe, with only 35 vehicle samples in the crashes, shows associations with four variables (driver age, vehicle year, driver gender, and collision type) whereas the City of Petersburg, with more than 1,000 vehicle samples, shows no variables associated with occupancy.

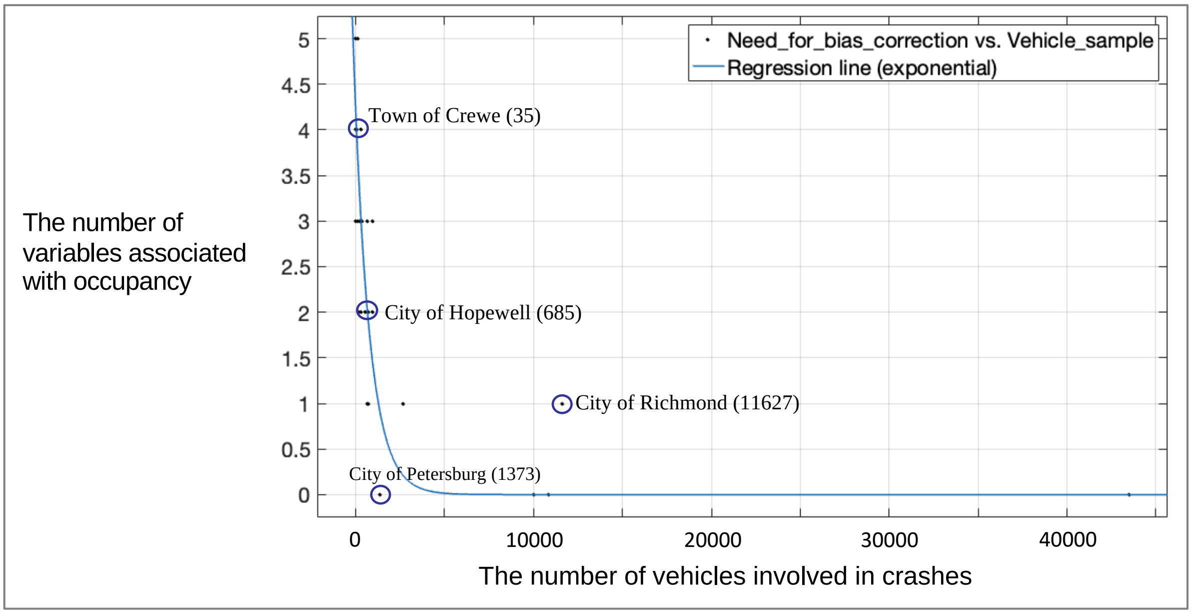

Figure 10. Relationship Between Variables Associated With Occupancy and Vehicle Sample Size. Each point represents a city, county, or town, but not all points are labeled with the name of their corresponding city, county, or town.

Figure 10 suggests that if a locality or corridor has fewer than 100 vehicle samples, bias correction is likely needed, as most variables are associated with occupancy. If a locality or corridor has 100 to 1,000 vehicles, bias correction may be needed. If a locality or corridor has more than 1,000 vehicles, bias correction is probably not necessary, as most of the association results are negligible. Although Figure 10 focuses on jurisdiction-level occupancies, this guidance can theoretically be applicable for other situations such as block groups and corridors, although such situations tend to have a smaller number of vehicles such that bias correction is always required.

To be clear, the only way one can definitively determine if bias correction is needed is to compare crash-reported occupancies with ground truth data such as field observations. If that comparison is not made, the next best way to make this determination is to conduct an association test. If an association test is not conducted, the next best way is to use guidance inferred from an association test—in this case, bias correction is generally not needed with more than 1,000 vehicles. However, Figure 10 shows there can be exceptions: for instance, even though it showed 11,627 vehicles, the City of Richmond also had an association between occupancy and crash severity. For that reason, the thresholds of 100 and 1,000 are guidelines—not hard rules.

Impact of Type 1 Bias Correction

Type 1 bias correction yielded general jurisdiction-level occupancies for the 24-hour, AM peak, PM peak, and off-peak periods. Detailed results of the Type 1 correction are provided in Appendix A. Table 4 provides a summary of the mean absolute difference between the corrected AVO and the original AVO for each period. In this case, Type 1 bias correction results in AVO changes ranging from 0.04 to 0.08.

Table 4. Mean |Difference| Between the Raw and Corrected Average Vehicle Occupancy

Period	24-Hour	AM Peak	PM Peak	Off-Peak
Mean Corrected AVO - AVO|	0.04	0.05	0.04	0.08

AVO = average vehicle occupancy.

Although a difference of 0.04 may seem small, significant benefits were observed for smaller jurisdictions (e.g., a correction of 0.10 in the Town of Crewe and 0.22 in the Town of Chase City).

Figure 11 diagrams this process of bias correction for both Type 1 (described here) and Type 2 (described in the next section).

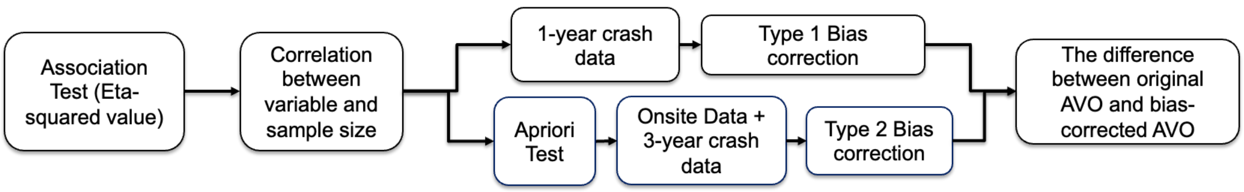

Figure 11. Process for Obtaining the Impact of Bias Correction. AVO = average vehicle occupancy.

Impact of Type 2 Bias Correction

The Variation of Ground Truth Occupancy Data

Table 5 compares the differences between the results of the windshield method and the carousel method at the same site and the same time. Table 5 shows a difference of 0.07 in the two methods: the result for the carousel method (1.22) is statistically higher than that for the windshield method (1.15) (p = 0.05). Two possible reasons for the difference are (1) some vehicles were missed by the carousel method, and (2) it may be challenging for the windshield method to capture backseat passengers in high-speed traffic conditions (Blair, 2023). A third possible reason is variation among carousel data collectors where the occupancy differs by 0.02, although this difference in Table 6 (p = 0.30) is not statistically significant.

Table 5. Comparison Between Carousel Method and Windshield Method

Method	Mean	Standard Deviation	Sample Size	95% Confidence Interval		Variance	T-test
Carousel All	1.22	0.502	816	1.18	1.25	0.252	$p < 0.05$
Windshield All	1.15	0.379	6168	1.14	1.16	0.144	

Table 6. Comparison Between Two Data Collectors for Carousel Method

Method	Mean	Standard Deviation	Sample Size	95% Confidence Interval		Variance	T-test
Carousel Person1	1.21	0.466	391	1.16	1.26	0.217	0.30
Carousel Person2	1.23	0.534	425	1.18	1.28	0.285	

Development of a Bias Correction Model

The occupancy data collected by the windshield method for five sites were used to develop a Type 2 bias correction model for the interstates in the Richmond District using 3 years of crash data (2018, 2019, and 2022). The reason for selecting these 3 years was to acquire a large enough dataset for calibration and to have a set of data that the research team believed would avoid some of the effects of the COVID-19 Pandemic. Columns 5 through 10 in Table 7 display occupancies based on the crash data, which are used as independent variables for model development.

Although the eta-squared test had shown that none of the five variables (crash severity, driver age, vehicle year, driver gender, or collision type) were associated with occupancy at the Richmond District level, the Apriori test, which looks at how these variables could be associated with specific occupancy levels, had found that two of these variables were associated with an occupancy of two: driver gender and crash severity, as shown in Table 8.

Based on columns 6 and 7 in Table 7, Site 4 was excluded from the model-building process. This decision was made because, in general, the AVO for all injured crashes was higher than the AVO for PDO crashes. This observation holds true for 17 of 22 jurisdictions in the Richmond District, which accounts for 39,946 vehicles. The remaining 5 jurisdictions have only 2,368 vehicles. Table 9 further confirms this trend by showing that, based on the T-test results, occupancies for injured crashes are statistically higher than those for PDO crashes when all of the crashes in the Richmond District are considered. Consequently, Site 4, which does not align with this trend (e.g., the AVO for PDO crashes is 1.17, higher than the 1.06 for injured crashes), was excluded from the modeling process.

Table 7. Sites Used for Type 2 Bias Correction Model

Data Collected From Field Observations				AVO Extracted From Crash Data					
Site No. (1)	**Road Name (2)**	**Time (3)**	**Windshield (4)**	**All Crashes (5)**	**All PDO (6)**	**All Injury (7)**	**Male (8)**	**Female (9)**	**Rear End (10)**
1	I-64 EB	AM Peak	1.04	1.08	1.04	1.19	1.12	1.04	1.09
2	I-95 NB	PM Peak	1.15	1.09	1.00	1.33	1.00	1.25	1.22
3	I-95 SB	AM Peak	1.13	1.13	1.12	1.14	1.15	1.11	1.1
4	I-295 NB	AM Peak	1.03	1.14	1.17	1.06	1.15	1.13	1.16
5	I-295 SB	PM Peak	1.03	1.09	1.03	1.30	1.11	1.06	1.1

WB = westbound; EB = eastbound; AVO = average vehicle occupancy; PDO = property damage only.

Table 8. Apriori Test Results for 2019 Richmond District Crashes (24-Hour)

Rule No.	Antecedent	Consequent	Support	Confidence[a]	Lift	Leverage	Conviction
1	Occupancy = 2	Driver Gender (Male)	0.057	0.518	0.996	0.000	0.996
2		Driver Gender (Female)	0.052	0.475	1.004	0.000	1.004
3		Crash Severity (PDO)	0.077	0.702	0.898	-0.009	0.733

[a] Only rules with a confidence of 0.30 or greater are shown. PDO = property damage only.

Table 9. Average Vehicle Occupancy by Crash Severity

Crash Severity	Average Vehicle Occupancy	Standard Deviation	95% Confidence Interval	T-test
PDO	1.20	0.594	1.19-1.21	$p < 0.01$
Injured	1.33	0.735	1.31-1.35	

PDO = property damage only.

The remaining four sites were used to build the model. Three were used for training in the stepwise regression model, and one was used as the testing site. The stepwise linear regression analysis revealed that only the AVO_{PDO} (average vehicle occupancy for PDO crashes) was a statistically significant variable. Of all models developed, only one model performed well; the others showed poor performance with negative R-squared values:

$$AVO_{estimated} = -0.120 + 1.116 * AVO_{PDO} \quad \text{(Eq. 3)}$$

However, the testing error for site 2 was large: 0.15, as shown in Table 10. That is, even though the average error for the three training sites was less than 0.01, the testing error was unacceptable. One explanation may be that the crash occupancy at site 2 was very low (1.00). In retrospect, it would have been better to have collected data at sites where crash occupancies were not that low.

In sum, when developing the Type 2 bias correction model, two types of sites should be avoided for data collection:

1. sites where the AVO_{PDO} is equal to 1
2. sites where the AVO_{PDO} is higher than AVO_{injury}.

Table 10. Summary of Type 2 Bias Correction Model for Interstates in the Richmond District

Training Sites	Model	Testing Site	Testing Error	Training Error	Average Error	R^2	*p*-Value for Model
1, 3, 5	$-0.120 + 1.116\ AVO_{PDO}$	2	0.15	0.01	0.04	1	0.01

AVO_{PDO} = average vehicle occupancy for property damage only crashes.

Establish Guidance for Bias Correction

With infinite resources, one would always perform bias correction: but when is bias correction essential and when is it nice but not required?

Benefits and Costs of Performing Bias Correction

Table 11 summarizes the benefits and costs associated with performing Type 1 and Type 2 bias correction in the Richmond District and, for comparison, the Hampton Roads District.

For Type 1 bias correction, it took approximately 2 hours to correct the bias for PM peak occupancies in each jurisdiction. To the extent the bias correction method shown in Table 11 is preferable to uncorrected occupancies, this process resulted in an improvement of approximately 0.04 per site in the Richmond District and 0.03 per site in the Hampton Roads District. Although the improvement of 0.04 per site may seem small, it can have a larger impact for less populated jurisdictions where the number of crashes is smaller than for larger jurisdictions. For instance, for the PM peak, with no bias correction the occupancy for Crewe was 1.17; with bias correction, the occupancy was 1.27.

On the other hand, Type 2 bias correction requires more time due to the inclusion of field data collection. The process involves collecting field occupancy data for at least three sites and developing and verifying the models. Type 2 bias correction does not guarantee a benefit in improved corridor occupancies. For instance, in the case of interstates in the Hampton Roads District, spending 45 hours on Type 2 bias correction led to an accuracy improvement of approximately 0.04 per site. However, in the Richmond District, spending 22 hours on Type 2 bias correction did not result in any observed benefit.

Table 11. Benefits and Costs of Performing Bias Correction

Bias Correction Type	Richmond District		Hampton Roads District	
	Cost	**Average Accuracy Improved**	**Cost**	**Average Accuracy Improved**
Type 1	2 hours	0.04 per site (PM-peak occupancy)	2 hours	0.03 per site (PM-peak occupancy)
Type 2	22 hours (5 sites)	No benefit per site	45 hours (10 sites)	0.04 per site (PM-peak occupancy)

Guidelines for When Bias Correction Should Be Performed

Table 12 suggests guidance for determining when Type 1 and Type 2 bias correction are needed. Generally, Type 1 bias correction entails the use of all crash data whereas Type 2 bias correction entails field collection at multiple sites and the use of PDO crashes as opposed to all crashes.

Table 12. Approximate Guidance for Performing Bias Correction[a]

<table>
<tr><th colspan="2">Decision</th><th>Type 1 Bias Correction</th><th>Type 2 Bias Correction</th></tr>
<tr><td colspan="2">Which crash data are needed?</td><td>1 year of all crash data</td><td>3 years PDO crash data</td></tr>
<tr><td colspan="2">Which field data are needed?</td><td>None</td><td>At least for 3 sites, more preferred</td></tr>
<tr><td rowspan="3">Does the sample size indicate bias correction is needed?</td><td>Bias correction strongly suggested</td><td>Jurisdictions have < 100 vehicle samples (e.g., Town of Crewe)</td><td>Corridors have < 100 vehicle samples (e.g., short roadway segment in Richmond district)</td></tr>
<tr><td>Bias correction should be considered</td><td>Jurisdictions have 100-1,000 vehicle samples (e.g., Hanover County)</td><td>Corridors have 100-1,000 vehicle samples (e.g., longer corridors such as the whole I-64 in Richmond district)</td></tr>
<tr><td>Bias correction not needed</td><td>Jurisdiction has > 1,000 vehicle samples (e.g., Henrico County)</td><td>Corridors have > 1,000 vehicle samples</td></tr>
<tr><td colspan="2">Are there any special situations that should influence the process?</td><td>If a jurisdiction has no single-occupant vehicles involved in a crash, consider:
• Using 2 or 3 years of crash data
• Using the technique shown in Appendix B</td><td>Avoid choosing sites that meet either criterion:
• $AVO_{PDO} = 1.00$
• $AVO_{PDO} > AVO_{injury}$</td></tr>
</table>

[a] Guidance is approximate. For instance, with limited resources, a user might elect not to do bias correction for a jurisdiction with 90 vehicles. PDO = property damage only; AVO_{PDO} = average vehicle occupancy for vehicles in property damage only crashes; AVO_{injury} = average vehicle occupancy for vehicles in injury crashes.

The guidelines in Table 12 are approximate rather than hard rules. For instance, with additional resources, one could perform Type 2 bias correction for long corridors; the key is having enough sites where field data can be obtained.

Land Use Impact on Local Occupancy Rates

GWR was used to identify land use variables influencing vehicle occupancy (AVO) at the census tract level.

Explanatory Power of Land Use Variables on Occupancy

Whereas stepwise linear regression had explained roughly 14% of the variation in occupancy, GWR increased local R^2 to an average value of 0.40, with larger increases in areas of larger census tracts, such as the Richmond District (local R^2 greater than 0.50 in Figure 12). One possible explanation is that with larger tracts, the probability that occupancies reflect vehicles with an origin or destination in the tract increases.

The improved R^2 suggests spatial differences in the relationship between local land use and occupancy, with mean travel time, population density, income, and vehicle ownership being explanatory factors, although the impact of each factor varied by location. This locational variation is best shown with two variables: mean travel time to work, and percent of households with incomes less than $15,000.

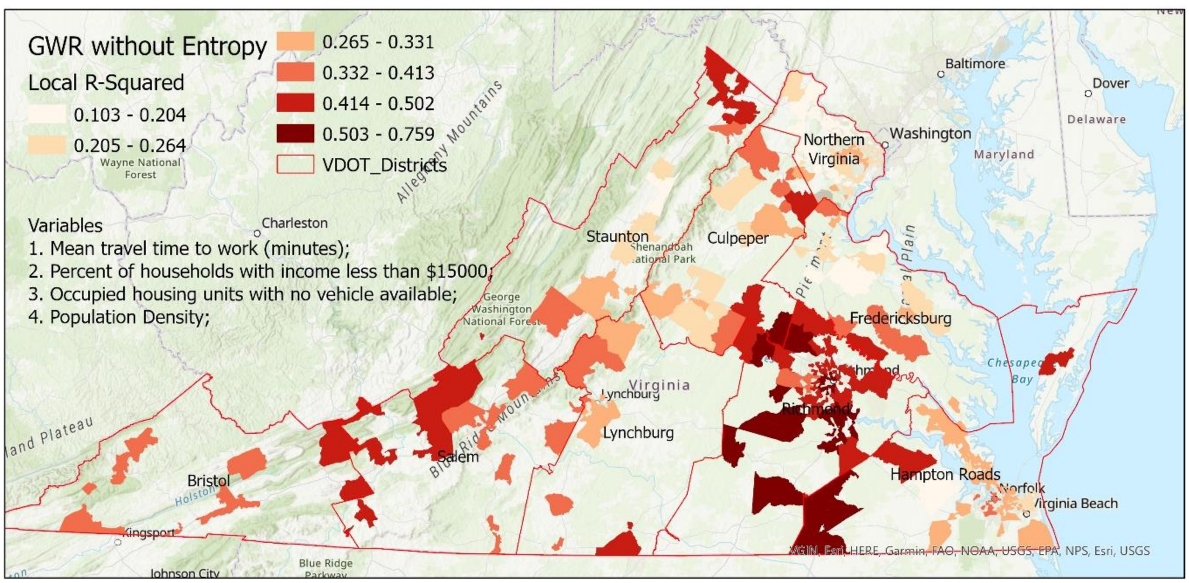

Figure 12. Local R^2 From the Geographically Weighted Regression Without Entropy. Imagery © Esri, NASA, NGA USGS, VGIN, HERE, Garmin, FAO, NOAA, USGS, EPA, NPS.

Mean Travel Time to Work

Figure 13 shows that travel time to work was always positively associated with AVO in the more rural Bristol, Salem, and Staunton areas. In urban areas, travel time to work was sometimes, but not always, negatively associated with AVO.

The literature explains some but not all of these findings. Xu et al. (2022b) found that the demand for park and ride use is correlated with the number of people who travel longer distances to work in Bristol, Salem, and Staunton but not elsewhere. Further, Kim et al. (2017) noted that when waiting time increases, the probability of carpooling decreases, such that in these rural areas, commuters may be more likely to share vehicles for longer-distance travel if the change in the waiting time, compared to total travel time, is relatively small.

However, it is not clear why travel time to work has both positive and negative coefficients in more urban districts. For instance, in Northern Virginia, travel time to work is associated with higher occupancy in the close-in suburbs of Washington, D.C., such as Arlington and Alexandria but associated with lower occupancy in the exurban locations of western Loudoun or southern Prince William County. That said, for certain inner areas such as the City of Richmond, one possible explanation is that commuters have more choices for travel such that carpooling demand is replaced by other modes.

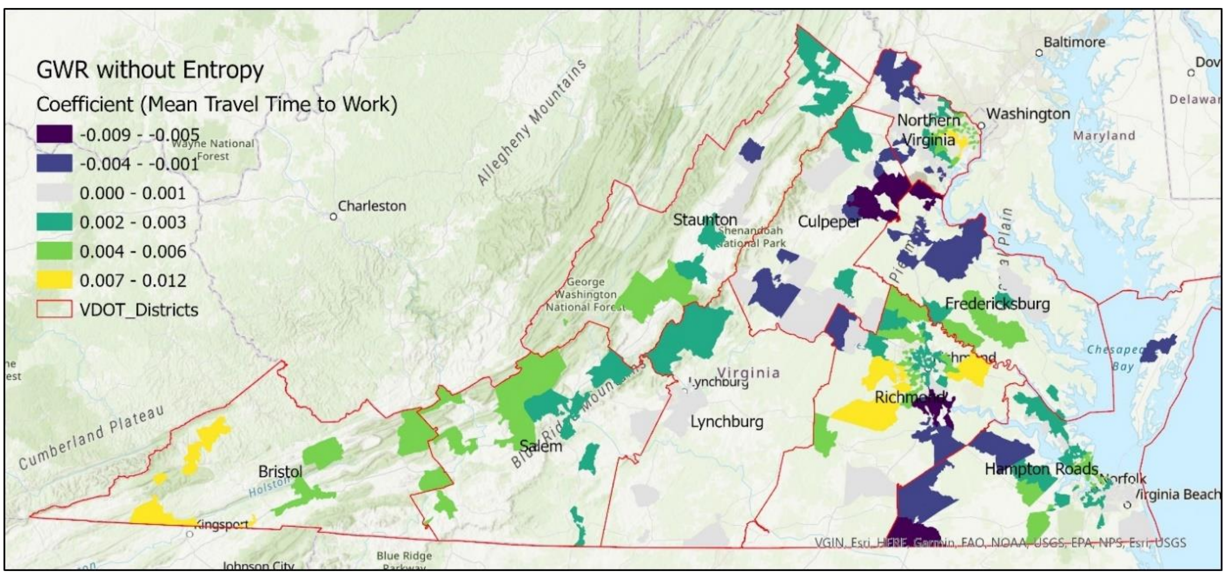

Figure 13. Coefficient of Mean Travel Time to Work. Imagery © Esri, NASA, NGA USGS, VGIN, HERE, Garmin, FAO, NOAA, USGS, EPA, NPS.

Percent of Households With Incomes Less Than $15,000

Figure 14 shows that the association between the percent of households with income less than $15,000 and AVO varies by region of the state. In five VDOT districts (Staunton, Richmond, Hampton Roads, the eastern portion of Northern Virginia, and Fredericksburg), income is positively correlated with AVO. This positive correlation means that in those locations, AVO tends to be higher when there are more low-income households.

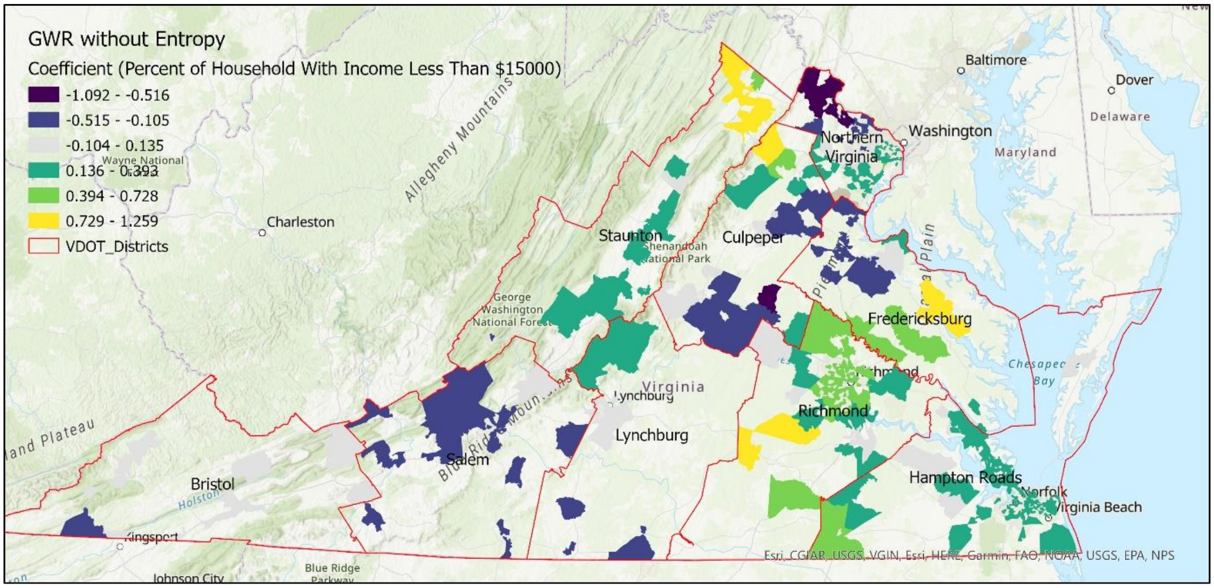

Figure 14. Coefficient of Percent of Households With Income Less Than $15,000. Imagery © Esri, NASA, NGA USGS, VGIN, HERE, Garmin, FAO, NOAA, USGS, EPA, NPS.

By contrast, Bristol, Salem, and the southern part of the Culpeper districts show a negative association with AVO. This suggests that in those locations, AVO tends to be lower when there are more low-income households.

An Evaluation of Model Impacts on Land Development Decisions

One type of local land use decision that can be supported by these models regards how a locality should consider proposed new construction. Table 13 shows three scenarios for examining how these model results can be used to inform land development decisions. Each scenario presumes a new development is proposed in a given location: the urban City of Richmond, the rural Bristol District, or the suburban area of the Thomas Jefferson Planning District. The intercept captures the local AVO values; for instance, the City of Richmond has the lowest AVO compared to the other two areas. Further, the variable coefficients vary for each region.

Table 13. Models for Three Scenarios

Scenario	Community Type	Locality	Model Coefficients: INT	No Vehicle Available[a]	Income Less Than $15,000[b]	Mean Travel Time to Work	Population Density
1	Urban	City of Richmond	1.13	-0.0002	0.582	0.002	-0.003
2	Rural	Bristol District	1.23	-0.0002	-0.08	0.007	-0.017
3	Suburban	TJPD	1.29	-0.0003	-0.118	-0.001	-0.005

INT = intercept; TJPD = Thomas Jefferson Planning District.
[a] Occupied housing units with no vehicle available.
[b] Percent of households with income less than $15,000.

Travel Time to Work

Mean travel time to work was not associated with a substantial influence on occupancy except in the Bristol District. The mean travel time to work for tracts therein ranged from 12.5 to 39.4 minutes. If such trends hold in the future, then one would expect a development that is placed in a location where travel time to work is 39.4 minutes to have an occupancy that is about to be about 0.19 higher than the occupancy where the travel time to work is 12.5 minutes.

Does such variation matter? The answer is modestly, depending on the land development review process. Suppose a residential development of detached dwelling units is under consideration and that local conditions indicate that the transportation network can accommodate up to 200 additional vehicle trips during the peak hour. Based on a relatively low density of 2 households per acre, no zero-vehicle households, and no households with income below $15,000, the occupancy is 1.28 in tracts with the shortest travel times to work and 1.47 in tracts with the longest travel time to work. A development in the former area could thus generate up to 256 person-trips, compared to up to 294 person-trips in the latter area. The researchers are not aware of a source that estimates person-trips per detached dwelling unit in a rural area, but the Institute of Transportation Engineers (2021) suggested a rate of 0.94 vehicle-trips per unit (PM peak hour of adjacent street traffic). If for a rural area this is presumed to be 0.94 person-trips per unit, then a development in the former area could accommodate 272 homes and a development in the latter area could accommodate 313 homes.

In this way, occupancy, because it influences the capacity of the network to move people, can be incorporated into land development decisions. Occupancy's impact should not be overstated: clearly, the driver of demand in this example is the vehicle trip generation component. Further, because GWR shows that occupancy varies by location, different thresholds may be used for different regions. That said, this example suggests that incorporation of occupancy can cause about a 15% difference (e.g., 313/272 – 1) in how one evaluates the impact of land development on the transportation network.

Income

The coefficient of household income (below $15,000 per year) did not have a substantial influence on occupancy in scenarios 2 and 3. If the percentage of households were to increase by 10%, then AVO would be reduced by 0.01 for both the Bristol District and the Thomas Jefferson Planning District. However, a 10% increase in households with income under $15,000 annually suggests that AVO would increase by 0.06 in the Richmond area. Note that without other variables (only income was considered in GWR), the size of the coefficient will be decreased to 0.274 in the Richmond areas but remain the same (-0.08) in the Bristol district. This means that if the percentage of those households were to increase by 10%, the AVO would increase by 0.03 in the Richmond area and still decrease by 0.01 in the Bristol District. As was the case with travel time, these findings suggest that the impact of poverty level on occupancy can vary depending on the specific community context.

Summary of Potential Impacts on Land Use Decisions

The land use results showed that occupancy can potentially inform certain planning decisions but the impacts are neither necessarily always large nor always expected. Exploration of two other areas suggested that there will be other situations where occupancy may not have a consistent impact on planning level decisions: the influence of land use mix on occupancy, and the influence of occupancy on TTR.

Regarding the former, Cervero (1989) suggested that a higher land use mix, which is reflected by a positive value of the entropy variable, has a positive relationship with shared trips in high-density areas. To the extent that occupancy is associated with vehicle sharing, the research team had initially expected entropy to be associated with occupancy. Figure 15 shows the coefficient of the entropy index for 398 of Virginia's census tracts. Most of these tracts (396) are in three metropolitan areas: Fairfax County (in the Northern Virginia District); the City of Richmond and Henrico County (in the Richmond District); and all localities in the Hampton Roads District. When only entropy was considered, there was a positive correlation between occupancy and the level of land use mix in some of these areas (e.g., the City of Richmond, Norfolk, Virginia Beach, and the southern part of Fairfax County)—but not in all areas, such as portions of Arlington and the northern portion of Fairfax County.

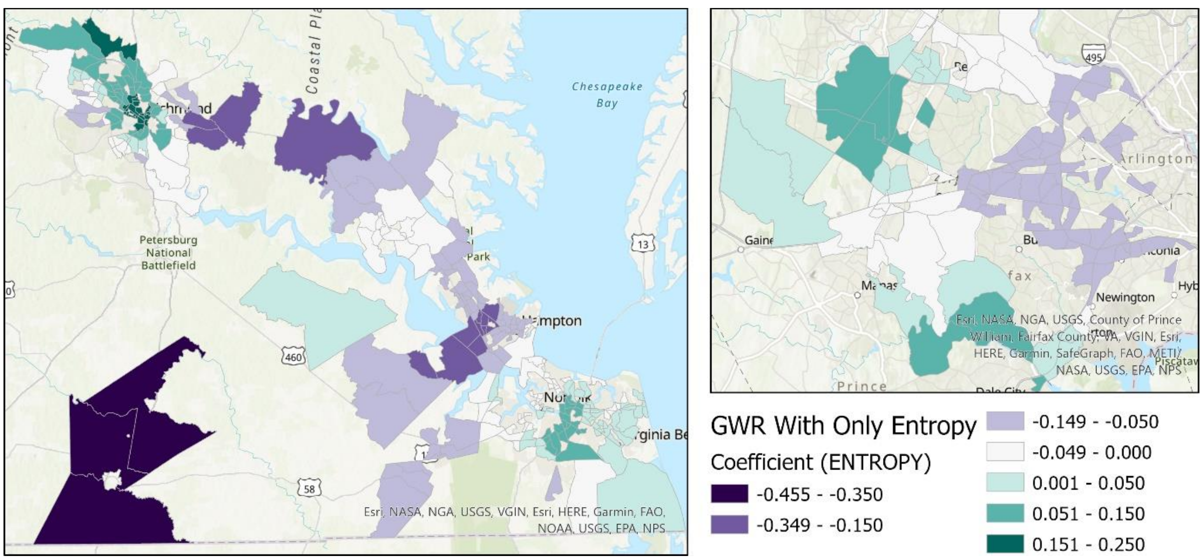

Figure 15. Coefficient of the Entropy Index for the 3 Urban Areas Where Entropy Data Are Widely Available: Fairfax County, Metropolitan Richmond (City of Richmond and Henrico), and the Hampton Roads Construction District. Imagery © Esri, NASA, NGA USGS, VGIN, HERE, Garmin, FAO, NOAA, USGS, EPA, NPS.

The latter example arose from TRP members: how might occupancies affect an evaluation of the TTR index? Appendix C shows that the overall index for TTR changed by only approximately 2.6% (a very small value) when the occupancy changed by as much as 0.60. That is, the use of location-specific values for occupancy rather than a default value does not affect the computation of the performance measure. This TTR analysis provided a different result from a previous sensitivity analysis in Xu et al. (2022a) where a modest change in occupancy of just 0.10—if VDOT's project prioritization process were adjusted to use locality-specific occupancies—shifted the rankings for 11% to 32% of all projects. Thus, the lesson is that occupancy's importance varies by application.

CONCLUSIONS

- *A systematic process for extracting passenger occupancies from vehicles involved in crashes, regardless of whether an injury occurred or not, was developed, and it requires the use of Python and GIS tools for mapping.* The process is not fully automated, but it has been tested by persons not on the research team.

- *Crash data may require some type of bias correction depending on the number of vehicles in the sample used to derive occupancy.* The relationship between tests of association and sample size indicated that bias correction is likely needed for jurisdictions or corridors with fewer than 100 vehicle samples and that bias correction may be needed for those with 100 to 1,000 vehicles. Jurisdictions or corridors with more than 1,000 vehicles typically do not require bias correction.

- *Type 1 bias correction usually takes approximately 2 hours to correct the bias that varies by location.* Type 1 bias correction is generally required for all crash data from 1 year. Use of the Type 1 bias correction method for PM-peak occupancies resulted in a mean improvement of approximately 0.04 per jurisdiction in the Richmond District. Although this improvement is relatively small, these corrections had a greater impact for less populous jurisdictions; examples are a correction of 0.10 for Crewe and 0.22 for Chase City.

- *Type 2 bias correction, which incorporates field data collection and model development, proved to be more time-consuming than Type 1 bias correction.* Type 2 bias correction involves the collection of field data for at least three sites. Specific considerations include avoiding sites where AVO_{PDO} is equal to 1.00 or is higher than AVO_{injury}. This method required 45 hours of effort in the Hampton Roads District, resulting in an accuracy improvement of approximately 0.04 per site. However, in the Richmond District, despite the 22 hours invested in Type 2 bias correction, no observable benefit in improved corridor occupancies was observed.

- *There is some, albeit limited, potential to incorporate occupancy into land development decisions.* In some locations, an increase in occupancy is associated with an increase in travel time to work. Traditionally, land development reviews have focused on the number of vehicle trips generated and the resultant impact on highway level of service; if one considers passenger network capacity rather than vehicular capacity, then in some situations an increase in occupancy can mitigate these impacts. This report provided a case study where the increase in occupancy would offset up to 15% of the increase demand from a proposed development depending on where that development was placed. That said, the impacts of land development on occupancy depend on the region as shown by the disparity in coefficients in the regional models.

RECOMMENDATION

1. *VDOT's TMPD should work with VTRC to make the maps of vehicle occupancy publicly available*. These maps are those at the jurisdiction and block group levels and reflect occupancy for each year from 2018-2022 and at the corridor level with an average occupancy for years 2020-2022. In future years as needed, the process outlined in this report (and the two sets of instructions in the supplemental material) could be used to update these occupancy maps.

IMPLEMENTATION AND BENEFITS

Researchers and the TRP (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. The implementation plan and the accompanying benefits are provided here.

Implementation

To implement Recommendation 1, two key steps will be undertaken: (1) make the maps available, and (2) provide guidance on how they should be interpreted. These steps will be completed within 1 year of the publication of this report.

Making the Maps Available

VTRC staff will work with VDOT's ITD to make the following six sets of occupancy maps publicly available:

1. jurisdiction level occupancy with bias correction
2. jurisdiction level occupancy without bias correction
3. block group level occupancy with bias correction
4. block group level occupancy without bias correction
5. VDOT district level occupancy without bias correction
6. corridor level occupancy without bias correction.

The first five map sets have the capability to give an occupancy for each year from 2018-2022. The sixth map set gives a single occupancy representing the average for the three most recent years of data available, which are 2020-2022. Examples of these maps were shown in Figures 4 through 9.

Providing Guidance on How the Maps Should Be Interpreted

The guidance is provided here. Options for disseminating it to likely users, such as VDOT district planners or planners who work for planning district commissions, include, but are not limited to, mentioning this guidance in the online mapping applications, referring users to the report, and highlighting this information at quarterly planning and programming meetings hosted by the Office of Intermodal Planning and Investment and/or monthly district planning meetings.

The six map sets offer the following strengths and weaknesses, which could influence the situations under which an analyst might use them:

- The district-wide occupancies, map set 5, have the largest sample size and generally should be the most reliable of the six map sets. However, if there is variation in occupancy throughout a VDOT district, these maps will not show this variance.

- The locality occupancy maps, map sets 1 and 2, are better for showing local variation in occupancy than the district maps; however, the sample sizes will be smaller. For very small localities, the bias-corrected locality maps, map set 1, are believed by the research team to be more reliable based on the properties of the Type 1 bias correction method that has been used. However, it is not possible to confirm this belief because there is not a corresponding dataset that shows true occupancies that reflect an entire locality.

- The block group occupancy maps, map sets 3 and 4, have the potential to show highly localized variation in occupancy but have even smaller sample sizes than the locality maps, map sets 1 and 2. The bias-corrected block group maps, map set 3, are believed to be more reliable than the block group maps without bias correction, map set 4. Although all occupancy maps reflect vehicle occupancies from the roadway, which may or may not be indicative of the occupancies of residents within the block group, this explanation is critical for the block group occupancy maps. The reason is that because the block group occupancy maps may appear similar to census maps, a reader could incorrectly believe they are based on residents' vehicle occupancies.

- The corridor occupancies, map set 6, enable one to detect vehicle occupancies from a specific roadway and offer the greatest geographical specificity but with less reliability due to smaller sample sizes and uncorrected data. Because these maps do not show block groups, cities, or other census geography, the maps may also convey more clearly than maps with census geography that occupancies are based on vehicles traversing the roadway rather than residents within a specific area.

Discussions with the TRP after the maps were produced suggested four pieces of guidance that could inform potential uses of the maps:

1. All maps are based on occupancies extracted from the roadway.

2. If it is desired that occupancies reflect vehicles driven by nearby residents with no additional processing performed by the analyst, then the best maps for this purpose are the district-wide occupancies followed by the city and county maps, simply because larger areas are logically more likely to contain vehicles driven by residents than smaller areas.

3. The maps themselves only present data and do not explain why occupancies differ. Thus, some analyst judgment may be required when determining which occupancy should be used for a specific application. For instance:

    - Suppose one needs an occupancy for use in a regional model. Such occupancies would ideally reflect those of residents living within a traffic analysis zone (TAZ). Although block groups may align with TAZs used in the regional model, block group occupancies, such as those shown in Figure 7, are not necessarily based on residents within the zone because the represented area is relatively small. Therefore, it would be more appropriate to use either the district maps (Figure 8) or the bias-corrected jurisdiction maps (Figure 4).

    - Suppose one needs a roadway-specific occupancy where a project spans multiple corridor segments. One approach might be to compute a weighted average where the weights are based on the number of samples or average daily traffic for each segment rather than each segment's length (Figure 9).

4. In situations where it is critical that a reported occupancy be accurate for a specific corridor, analysts may wish to consider Type 2 bias correction, which combines crash-based occupancies with field observations (illustrated in Table 10).

Benefits

There are at least two methods to estimate the benefits of implementing Recommendation 1 assuming vehicle occupancy is ultimately necessary for VDOT's mission. Only Method 1 lends itself to monetary benefits.

Method 1. Reduction in Data Collection Costs for Jurisdiction-Level Occupancies

Suppose one wanted a 24-hour occupancy for each of Virginia's 133 cities and counties. As reported in Xu et al. (2022a), professional data collectors can obtain occupancy for a single lane for 1 hour at a cost of $360 per hour per lane. This cost is all inclusive once a site is identified: preparation, travel to and from the site, collection of occupancies from the windshield method, and processing of data. Suppose further that one decided that two sites per jurisdiction might be representative of all occupancies in that jurisdiction, such that one chose either an interstate or primary site (two lanes per direction) and a secondary road site (one lane per direction), with each site being visited twice for 1 hour (once during a peak period and once during an off-peak period). The hourly costs required would be calculated as 133 jurisdictions X (4 lanes [for a primary or interstate site] + 2 lanes [for a secondary site]) X 2 hours X $360/hour = $574,560.

Suppose Recommendation 1 in this report for obtaining city and county occupancies is instead used. The research team estimates that an 8-hour day would be required to replicate this process. After the February testing by TMPD staff who have Python and GIS skills, the approach was modified and then retested by an individual with no Python experience; the individual required roughly 2 to 4 hours to use the approach but noted that someone with no GIS experience might require more time, such that 1 day was a safe estimate. The processing costs might thus be roughly 8 hours, but one could then spend another 8 hours making the occupancies look aesthetically pleasing on a statewide map. With a loaded cost of $100 per hour, this approach with the recommendation might entail a processing cost of $1,600 for a 2-day period.

However, looking critically at the use of crash data, some localities might later express a concern that field collection is needed because their city or county has fewer than 200 samples. (200 samples was generally a threshold at which bias correction becomes essential.) The data in Table A3 show that of the 18 jurisdictions, 2 had slightly fewer than 200 samples and a third had slightly more than that amount. Thus, a more critical assessment of the costs might be to assume that if this pattern in the Richmond District is repeated statewide, then on average (3/18)(133) = 22 jurisdictions would require field data collection, which would add hourly costs of 22 jurisdictions X (4 lanes [for a primary or interstate site] + 2 lanes [for a secondary site]) X 2 hours X $360/hour = $95,040. In short, implementation of the recommendation would cost $1,600 (for processing) + $95,040 (for some data collection) for a total of $96,640.

Thus, if it is assumed that a 24-hour occupancy is required for each jurisdiction, then the benefit of implementing Recommendation 1 is estimated as $574,560 − $96,640 = $477,920. To avoid conveying a false sense of precision, this estimate is rounded down to roughly $400,000. If occupancies were updated every 3 years, then this amount would be saved over a 3-year period.

Method 2. Enhanced Support for Other Planning Tasks

The research team and the TRP have thus far identified three situations where knowing area-wide occupancies, such as at the jurisdiction level or the census tract level, are useful. One situation was reported in Xu et al. (2022a), which pertained to more precise estimation of congestion reduction benefits for certain transportation projects. A second situation was one where it was found that occupancies were not needed: the TRP communicated to the research team that it was helpful to know that occupancies did not materially affect the TTR index. A third situation, described in this report, was a better understanding of how certain variables related to land development, such as mean travel time to work and the percent of households with income below $15,000, influence occupancy. It is generally not appropriate to try to quantify these benefits further because they do not yet lead to specific actions VDOT should take.

However, as occupancies become more widely available, analysts may start to consider how they can be used further to support planning needs.

ACKNOWLEDGMENTS

The research team thanks the individuals who supported this research through provision of essential insights and data. The TRP guided this project through participation in quarterly review meetings and comments on interim deliverables. The TRP was composed of Jungwook Jun, Planning Data Solutions Manager, VDOT TMPD, and Peng Xiao, Modeling and Accessibility Program Manager, VDOT TMPD (Project Champions); Angela Effah-Amponsah, Assistant Hampton Roads District Planner, VDOT; David Caudill, Director of Tolling Operations, VDOT; Ben Cottrell, Principal Research Scientist, VTRC; Ray Hunt, Hampton Roads Transportation Planner, VDOT; Naquana Jenkins, Hampton Roads Transportation Planning Specialist, VDOT; Liz McAdory, Richmond District Transportation Planner, VDOT; Vahid Moshtagh, Senior Project Manager, NOVA District Megaprojects, VDOT; Eric Stringfield, Hampton Roads Transportation Planning Director, VDOT; and Rahul Trivedi, Assistant Planning Director, VDOT Northern Virginia District. Critical review comments were also provided by T. Donna Chen, Mike Fitch, Mike Fontaine, Andrew Mondschein, Peter Ohlms, Brian Park, Ivan Rucker, and Kevin Wright. Help with obtaining data was provided by Sayed Adel, Patrick Brown, Heze Chen, Allie Cognata, Shan Di, Afrida Raida, Tina Simmons, Nishara Vavitta Parambil, Eric Williams, and Qiaomin Zhang.

REFERENCES

Blair, J. Email to L.E. Dougald, May 5, 2023.

Bordoloi, R., Mote, A., Sarkar, P.P., and Mallikarjuna, C. Quantification of Land Use Diversity in the Context of Mixed Land Use. *Procedia-Social and Behavioral Sciences*, Vol. 104, December 2013, pp. 563-572.

Cervero, R. *Land-Use Mixing and Suburban Mobility.* University of California Transportation Center, UC Berkeley, 1989.

City of Richmond. *Existing Land Use*, May 4, 2021. https://www.arcgis.com/home/item.html?id=562452ec01414ca591ca1748173378a9. Accessed March 21, 2023.

City of Salem. *Existing Land Use*, March 25, 2022. https://data-salemva.opendata.arcgis.com/datasets/102340de21a74a0282e4bf0a0f6cfa0e_0/explore. Accessed May 26, 2023.

Commonwealth Transportation Board. *SMART SCALE Technical Guide*. Richmond, VA, 2021. https://smartscale.org/documents/2020documents/technical-guide-2022.pdf. Accessed October 4, 2021.

County of Henrico. *Existing Land Use*, May 10, 2022. https://data-henrico.opendata.arcgis.com/datasets/existing-land-use/. Accessed September 19, 2022.

ESRI. *Geographically Weighted Regression (GWR) (Spatial Statistics),* Undated (a). https://pro.arcgis.com/en/pro-app/latest/tool-reference/spatial-statistics/geographicallyweightedregression.htm. Accessed June 25, 2023.

ESRI. *How Geographically Weighted Regression (GWR) Works,* Undated (b). https://pro.arcgis.com/en/pro-app/latest/tool-reference/spatial-statistics/how-geographicallyweightedregression-works.htm. Accessed January 26, 2022.

Fairfax County. *Existing Land Use – Generalized*, February 23, 2023. https://data-fairfaxcountygis.opendata.arcgis.com/datasets/existing-land-use-generalized/explore. Accessed May 8, 2023.

Federal Highway Administration. *National Performance Management Measures; Assessing Performance of the National Highway System, Freight Movement on the Interstate System, and Congestion Mitigation and Air Quality Improvement Program*. 82 FR 5970. Federal Highway Administration, Washington, DC, January 18, 2017. https://www.federalregister.gov/documents/2017/01/18/2017-00681/national-performance-management-measures-assessing-performance-of-the-national-highway-system. Accessed May 23, 2022.

Federal Transit Administration. *2010 Census Urbanized Area Population and Population Density Data*. Washington, DC, 2022. https://www.transit.dot.gov/funding/apportionments/census-urbanized-area-population-and-population-density-data-used-section. Accessed May 31, 2022.

Hampton Roads Planning District Commission. *Existing Land Use for Hampton Roads,* August 20, 2019. https://hrgeo-hrpdc-gis.opendata.arcgis.com/datasets/59c824a83b0446b19b09313d76e72e0a_0/explore?location=37.022235%2C-76.535229%2C9.51. Accessed March 5, 2023.

Institute of Transportation Engineers. *Trip Generation Manual, 11th edition*. Washington, DC, 2021.

Jun, J. Email to L.E. Dougald, January 24, 2023.

Kim, J., Rasouli, S., and Timmermans, H.J. The Effects of Activity-Travel Context and Individual Attitudes on Car-Sharing Decisions Under Travel Time Uncertainty: A Hybrid Choice Modeling Approach. *Transportation Research Part D: Transport and Environment,* Vol. 56, October 2017, pp. 189-202.

Simmons, T. Email to J.S. Miller, November 15, 2022.

Song, Y., and Knaap, G.J. Measuring the Effects of Mixed Land Uses on Housing Values. *Regional Science and Urban Economics,* Vol. 34, No. 6, November 2004, pp. 663-680.

Turner, M.G., Gardner, R.H., and O'Neill, R.V. *Landscape Ecology in Theory and Practice*. Springer, New York, 2001.

U.S. Census Bureau. *OnTheMap Data for 2019*, 2020. https://onthemap.ces.census.gov/. Accessed February 21, 2020.

U.S. Census Bureau. *Table DP03. Selected Economic Characteristics, Five-Year Census Estimate (2019*), Undated (a). https://data.census.gov/table?q=DP03. Accessed February 21, 2023.

U.S. Census Bureau. *Table DP04. Selected Housing Characteristics, Five-year Census Estimate (2019)*, Undated (b). https://data.census.gov/table?q=DP04. Accessed February 21, 2023.

U.S. Census Bureau. *Table DP05. ACS Demographic and Housing Estimates, Five-year Census Estimate (2019)*, Undated (c). https://data.census.gov/table?q=DP04. Accessed February 21, 2023.

U.S. Census Bureau. *Table S0801. Commuting Characteristics by Sex, One-Year Census Estimates (2019 and 2021)*, Undated (d). https://data.census.gov/table?q=S0801. Accessed July 2, 2023.

Virginia Department of Transportation. *Virginia Park and Ride Inventory (2021) Public View*, May 10, 2022. https://www.arcgis.com/home/item.html?id=5e1398ec24c74bba8cf131e72d265eab. Accessed May 3, 2023.

Xu Y., Dougald, L.E., and Miller, J.S. *Development of Guidance for a Vehicle Occupancy Rate Data Collection Program.* Virginia Transportation Research Council, Charlottesville, 2022a.

Xu Y., Dougald, L.E., and Miller, J.S. Location-Specific Demand Forecasting for Park and Ride Lots: The Use of Models in Practice. *Case Studies on Transport Policy*, Vol. 10, No. 3, September 2022b, pp. 1872-1884.

APPENDIX A. TYPE I BIAS CORRECTION RESULTS

Table A1. AM Peak Average Vehicle Occupancy (AVO) for the Richmond District

Locality	AM Peak Vehicle Sample								Average Vehicle Occupancy		
	VO=1	**VO=2**	**VO=3**	**VO=4**	**VO=5**	**VO=6**	**VO=7**	**VO=8**	**AVO**	**Corrected**	**|Difference|**
All Richmond District	4815	407	121	39	9	1	1	**0**	1.15	1.15	0.00
Amelia County	22	3	2	1	**0.041**	**0.005**	**0.005**	**0**	1.36	1.36	0.01
Brunswick County	31	4	1	1	**0.058**	**0.006**	**0.006**	**0**	1.24	1.25	0.01
Charles City County	8	3	**0.201**	**0.065**	**0.015**	**0.002**	**0.002**	**0**	1.27	1.33	0.05
Chesterfield County	1149	77	28	7	1	**0.239**	**0.239**	**0**	1.13	1.13	0.00
Dinwiddie County	53	5	2	**0.429**	**0.099**	**0.011**	**0.011**	**0**	1.15	1.18	0.03
Goochland County	114	5	**0.990**	*1*	**0.213**	**0.024**	**0.024**	**0**	1.07	1.09	0.02
Hanover County	327	19	9	3	1	**0.068**	**0.068**	**0**	1.14	1.14	0.00
Henrico County	1224	83	21	10	1	**0.254**	1	**0**	1.12	1.12	0.00
Lunenburg County	12	**1.014**	**0.302**	**0.097**	**0.022**	**0.002**	**0.002**	**0**	1.00	1.15	0.15
Mecklenburg County	23	6	3	1	**0.043**	**0.005**	**0.005**	**0**	1.45	1.46	0.01
New Kent County	80	8	4	4	**0.150**	**0.017**	**0.017**	**0**	1.29	1.30	0.01
Nottoway County	32	4	1	**0.259**	1	**0.007**	**0.007**	**0**	1.26	1.28	0.02
Powhatan County	99	6	2	1	**0.185**	**0.021**	**0.021**	**0**	1.12	1.13	0.01
Prince George County	49	5	3	**0.397**	**0.092**	**0.010**	**0.010**	**0**	1.19	1.22	0.03
City of Colonial	38	7	2	**0.308**	**0.071**	**0.008**	**0.008**	**0**	1.23	1.26	0.03
City of Hopewell	40	5	1	**0.324**	**0.075**	**0.008**	**0.008**	**0**	1.15	1.18	0.03
City of Petersburg	95	10	5	**0.769**	**0.178**	**0.020**	**0.020**	**0**	1.18	1.21	0.03
City of Richmond	1376	148	37	10	5	1	**0.286**	**0**	1.18	1.18	0.00
Town of Blackstone	4	**0.338**	**0.101**	**0.032**	**0.007**	**0.001**	**0.001**	**0**	1.00	1.15	0.15
Town of Alberta	-	-	-	-	-	-	-	-	-	-	-
Town of Ashland	13	6	**0.327**	**0.105**	**0.024**	**0.003**	**0.003**	**0**	1.32	1.36	0.05
Town of Boydton	-	-	-	-	-	-	-	-	-	-	-
Town of Brodnax	-	-	-	-	-	-	-	-	-	-	-
Town of Burkeville	-	-	-	-	-	-	-	-	-	-	-
Town of Chase City	2	**0.169**	**0.050**	**0.016**	**0.004**	**0.000**	**0.000**	**0**	1.00	1.15	0.15
Town of Clarksville	1	**0.085**	**0.025**	**0.008**	**0.002**	**0.000**	**0.000**	**0**	1.00	1.15	0.15
Town of Crewe	6	**0.507**	**0.151**	**0.049**	**0.011**	**0.001**	**0.001**	**0**	1.00	1.15	0.15
Town of La Crosse	-	-	-	-	-	-	-	-	-	-	-
Town of	-	-	-	-	-	-	-	-	-	-	-
Town of McKenney	-	-	-	-	-	-	-	-	-	-	-
Town of South Hill	17	3	**0.427**	**0.138**	**0.032**	**0.004**	**0.004**	**0**	1.15	1.22	0.07
Town of Victoria	-	-	-	-	-	-	-	-	-	-	-

VO = vehicle occupancy; bold numbers = bias corrected.

Table A2. PM Peak Average Vehicle Occupancy (AVO) for the Richmond District

	PM Peak Vehicle Sample								Average Vehicle Occupancy		
Locality	VO=1	VO=2	VO=3	VO=4	VO=5	VO=6	VO=7	VO=8	AVO	Corrected AVO	|Difference|
All Richmond District	7522	863	249	98	39	9	3	4	1.22	1.22	0.00
Amelia County	33	5	1	1	1	**0.039**	**0.013**	**0.018**	1.34	1.35	0.01
Brunswick County	30	5	3	**0.391**	**0.156**	**0.036**	**0.012**	**0.016**	1.29	1.34	0.05
Charles City County	16	2	1	**0.208**	**0.083**	**0.019**	**0.006**	**0.009**	1.21	1.27	0.06
Chesterfield County	1923	208	49	23	7	3	1	2	1.20	1.20	0.00
Dinwiddie County	70	14	7	2	1	**0.084**	**0.028**	1	1.47	1.48	0.01
Goochland County	242	12	2	**0.990**	**0.990**	**0.290**	**0.097**	**0.129**	1.06	1.10	0.04
Hanover County	469	63	22	13	4	1	0.187	0.249	1.29	1.30	0.00
Henrico County	2134	201	58	18	8	1	1	**1.135**	1.17	1.17	0.00
Lunenburg County	16	4	1	**0.208**	**0.083**	1	**0.006**	**0.009**	1.50	1.54	0.04
Mecklenburg County	40	8	3	3	**0.207**	**0.048**	**0.016**	**0.021**	1.43	1.45	0.02
New Kent County	108	24	3	3	**0.560**	**0.129**	**0.043**	**0.057**	1.28	1.31	0.02
Nottoway County	22	4	1	**0.287**	**0.114**	**0.026**	**0.009**	**0.012**	1.22	1.28	0.05
Powhatan County	63	12	4	4	**0.327**	**0.075**	**0.025**	**0.034**	1.39	1.41	0.02
Prince George County	97	19	4	3	**0.503**	**0.116**	**0.039**	**0.052**	1.29	1.32	0.02
City of Colonial Heights	112	12	7	4	**0.581**	**0.134**	**0.045**	**0.060**	1.28	1.31	0.03
City of Hopewell	76	21	2	1	1	1	**0.030**	**0.040**	1.36	1.37	0.00
City of Petersburg	172	47	16	2	4	1	**0.069**	**0.091**	1.44	1.44	0.00
City of Richmond	1819	182	60	17	13	1	1	1	1.20	1.20	0.00
Town of Blackstone	8	1	**0.265**	1	**0.041**	**0.010**	**0.003**	**0.004**	1.40	1.46	0.06
Town of Alberta	-	-	-	-	-	-	-	-	-	-	-
Town of Ashland	42	10	2	2	**0.218**	**0.050**	**0.017**	**0.022**	1.36	1.38	0.02
Town of Boydton	-	-	-	-	-	-	-	-	-	-	-
Town of Brodnax	-	-	-	-	-	-	-	-	-	-	-
Town of Burkeville	-	-	-	-	-	-	-	-	-	-	-
Town of Chase City	3	**0.344**	**0.099**	**0.039**	**0.016**	**0.004**	**0.001**	**0.002**	1.00	1.22	0.22
Town of Clarksville	6	**0.688**	**0.199**	**0.078**	**0.031**	**0.007**	**0.002**	**0.003**	1.00	1.22	0.22
Town of Crewe	5	1	**0.166**	**0.065**	**0.026**	**0.006**	**0.002**	**0.003**	1.17	1.27	0.10
Town of La Crosse	-	-	-	-	-	-	-	-	-	-	-
Town of Lawrenceville	-	-	-	-	-	-	-	-	-	-	-
Town of McKenney	1	**0.115**	1	**0.013**	**0.005**	**0.001**	**0.000**	**0.001**	2.00	2.02	-
Town of South Hill	15	8	2	1	**0.078**	**0.018**	**0.006**	**0.008**	1.58	1.59	0.02
Town of Victoria	-	-	-	-	-	-	-	-	-	-	-

VO = vehicle occupancy; bold numbers = bias corrected.

Table A3. 24-Hour Average Vehicle Occupancy (AVO) for the Richmond District

Locality	24-Hour Vehicle Sample								Average Vehicle Occupancy		
	VO=1	VO=2	VO=3	VO=4	VO=5	VO=6	VO=7	VO=8	AVO	Corrected AVO	|Difference|
All Richmond District	36937	4496	1300	521	175	42	10	11	1.22	1.22	0.00
Amelia County	211	35	18	7	3	**0.240**	**0.057**	**0.063**	1.38	1.39	0.01
Brunswick County	237	41	8	5	**0.990**	**0.269**	**0.064**	1	1.27	1.29	0.02
Charles City County	102	21	6	**0.990**	**0.483**	**0.116**	**0.028**	**0.030**	1.26	1.30	0.04
Chesterfield County	8581	968	287	99	32	11	3	3	1.21	1.21	0.00
Dinwiddie County	480	97	36	13	6	**0.546**	**0.130**	2	1.39	1.39	0.01
Goochland County	838	68	9	6	1	**0.953**	**0.227**	**0.250**	1.12	1.13	0.01
Hanover County	2213	286	96	36	21	5	**0.599**	1	1.26	1.27	0.00
Henrico County	9537	914	252	110	27	6	2	1	1.18	1.18	0.00
Lunenburg County	108	14	6	1	2	1	**0.029**	**0.032**	1.32	1.32	0.00
Mecklenburg County	298	41	17	8	**0.990**	**0.339**	**0.081**	**0.089**	1.27	1.29	0.02
New Kent County	704	139	42	25	7	3	1	**0.210**	1.38	1.38	0.00
Nottoway County	168	37	10	2	2	**0.191**	**0.045**	**0.050**	1.32	1.33	0.01
Powhatan County	439	60	15	9	**0.990**	1	**0.119**	**0.131**	1.23	1.24	0.01
Prince George County	543	91	25	17	7	2	**0.147**	**0.162**	1.34	1.34	0.00
City of Colonial Heights	497	98	31	17	6	1	**0.135**	**0.148**	1.37	1.37	0.00
City of Hopewell	552	89	31	8	2	3	**0.149**	**0.164**	1.29	1.29	0.00
City of Petersburg	1037	226	72	24	10	2	2	-	1.37	1.37	0.00
City of Richmond	9960	1176	319	118	43	7	1	3	1.21	1.21	0.00
Town of Blackstone	28	3	**0.985**	2	**0.133**	**0.032**	**0.008**	**0.008**	1.27	1.34	0.07
Town of Alberta	9	**0.990**	**0.317**	**0.127**	**0.043**	**0.010**	**0.002**	**0.003**	1.00	1.22	0.22
Town of Ashland	205	53	8	5	3	**0.233**	1	**0.061**	1.37	1.38	0.01
Town of Boydton	8	**0.974**	1	1	**0.038**	**0.009**	**0.002**	**0.002**	1.50	1.56	0.06
Town of Brodnax	5	**0.609**	**0.176**	**0.071**	**0.024**	**0.006**	**0.001**	**0.001**	1.00	1.22	0.22
Town of Burkeville	4	1	**0.141**	**0.056**	**0.019**	**0.005**	**0.001**	**0.001**	1.20	1.30	0.10
Town of Chase City	14	**0.990**	**0.493**	2	**0.066**	**0.016**	**0.004**	**0.004**	1.38	1.48	0.10
Town of Clarksville	16	2	1	**0.226**	**0.076**	**0.018**	**0.004**	**0.005**	1.21	1.27	0.05
Town of Crewe	26	6	**0.915**	2	1	**0.030**	**0.007**	**0.008**	1.46	1.50	0.05
Town of La Crosse	2	**0.243**	**0.070**	**0.028**	**0.009**	**0.002**	**0.001**	**0.001**	1.00	1.22	0.22
Town of Lawrenceville	3	1	**0.106**	**0.042**	**0.014**	**0.003**	**0.001**	**0.001**	1.25	1.34	0.09
Town of McKenney	6	2	2	**0.085**	**0.028**	**0.007**	**0.002**	**0.002**	1.60	1.63	0.03
Town of South Hill	105	26	7	4	2	**0.119**	**0.028**	**0.031**	1.42	1.42	0.01
Town of Victoria	1	1	1	**0.014**	**0.005**	**0.001**	**0.000**	**0.000**	2.00	2.02	0.02

VO = vehicle occupancy; bold numbers = bias corrected.

Table A4. Off-Peak Average Vehicle Occupancy (AVO) for the Richmond District

Locality	Off-Peak Vehicle Sample								Average Vehicle Occupancy		
	VO=1	VO=2	VO=3	VO=4	VO=5	VO=6	VO=7	VO=8	AVO	Corrected AVO	|Difference|
All Richmond District	15956	2117	607	250	94	22	4	6	1.24	1.24	0.00
Amelia County	89	19	10	2	2	**0.123**	**0.022**	**0.033**	1.43	1.44	0.01
Brunswick County	121	21	3	3	**0.713**	**0.167**	**0.030**	1	1.29	1.31	0.02
Charles City County	56	12	4	**0.877**	**0.330**	**0.077**	**0.014**	**0.021**	1.28	1.34	0.06
Chesterfield County	3449	438	120	48	18	4	2	**0.990**	1.23	1.23	0.00
Dinwiddie County	218	50	23	8	4	**0.301**	**0.055**	1	1.47	1.48	0.01
Goochland County	275	36	4	2	1	**0.379**	**0.069**	**0.103**	1.17	1.18	0.01
Hanover County	936	141	34	13	10	3	**0.235**	1	1.27	1.27	0.00
Henrico County	3933	418	119	54	16	4	**0.986**	1	1.20	1.20	0.00
Lunenburg County	49	6	2	**0.768**	1	**0.068**	**0.012**	**0.018**	1.24	1.29	0.04
Mecklenburg County	146	17	7	3	**0.860**	**0.201**	**0.037**	**0.055**	1.23	1.26	0.03
New Kent County	356	77	24	9	6	3	1	**0.134**	1.41	1.42	0.00
Nottoway County	77	19	4	2	1	**0.106**	**0.019**	**0.029**	1.36	1.37	0.01
Powhatan County	177	21	4	1	**0.990**	**0.244**	**0.044**	**0.067**	1.16	1.19	0.03
Prince George County	274	42	14	10	5	2	**0.069**	**0.103**	1.37	1.38	0.00
City of Colonial Heights	224	49	12	7	3	**0.309**	**0.056**	**0.084**	1.36	1.37	0.01
City of Hopewell	296	37	19	4	**0.990**	1	**0.074**	**0.111**	1.26	1.28	0.02
City of Petersburg	544	117	34	15	4	1	**0.136**	**0.205**	1.35	1.35	0.00
City of Richmond	4511	547	159	60	18	4	**0.990**	2	1.22	1.22	0.00
Town of Blackstone	14	2	**0.533**	1	**0.082**	**0.019**	**0.004**	**0.005**	1.29	1.37	0.08
Town of Alberta	9	**0.990**	**0.342**	**0.141**	**0.053**	**0.012**	**0.002**	**0.003**	1.00	1.24	0.24
Town of Ashland	105	25	5	3	2	**0.145**	1	**0.039**	1.41	1.42	0.01
Town of Boydton [a]	**26.287**	**3.488**	1	1	**0.155**	**0.036**	**0.007**	**0.010**	3.50	1.29	2.21
Town of Brodnax	3	**0.398**	**0.114**	**0.047**	**0.018**	**0.004**	**0.001**	**0.001**	1.00	1.24	0.24
Town of Burkeville	4	1	**0.152**	**0.063**	**0.024**	**0.006**	**0.001**	**0.002**	1.20	1.31	0.11
Town of Chase City	7	**0.929**	**0.266**	1	**0.041**	**0.010**	**0.002**	**0.003**	1.38	1.51	0.13
Town of Clarksville	8	2	1	**0.125**	**0.047**	**0.011**	**0.002**	**0.003**	1.36	1.42	0.05
Town of Crewe	12	5	**0.457**	1	1	**0.017**	**0.003**	**0.005**	1.63	1.67	0.04
Town of La Crosse	-	-	-	-	-	-	-	-	-	-	-
Town of Lawrenceville	3	1	**0.114**	**0.047**	**0.018**	**0.004**	**0.001**	**0.001**	1.25	1.35	0.10
Town of McKenney	3	**0.398**	**0.114**	**0.047**	**0.018**	**0.004**	**0.001**	**0.001**	1.00	1.24	0.24
Town of South Hill	56	13	4	2	2	**0.077**	**0.014**	**0.021**	1.45	1.46	0.01
Town of Victoria	1	1	**0.038**	**0.016**	**0.006**	**0.001**	**0.000**	**0.000**	1.50	1.56	0.06

VO = vehicle occupancy; bold numbers = bias corrected; [a] bias corrected AVO is lower than original AVO.

APPENDIX B. SPECIAL CASE OF NO SINGLE OCCUPANT VEHICLES OBSERVED

A special case arose when applying Type 1 bias correction for off-peak AVO in the Town of Boydton. In the 2019 crash data for the Town of Boydton, only two vehicles were observed, with occupancies of 3 and 4, respectively. Typically, Type 1 bias correction is based on the proportion of VO=1 vehicles in the entire vehicle sample and uses the ratio of other VO groups to the VO=1 group in the standard occupancy distribution (e.g., the occupancy distribution for the Richmond District) to correct the zero VO groups for each jurisdiction. However, in this particular case, since there were no VO=1 vehicles, the research group modified the Type 1 bias correction by using the VO=3 vehicle group as an alternative.

To calculate the number of VO=1 vehicles, the following formula was used:

$$\textit{Estimated number of 1-occupancy vehicles} = \frac{\textit{the number of } 1\textit{-occupancy vehicles in Richmond district}}{\textit{the number of } 3\textit{-occupancy vehicles in Richmond district}} \times \textit{the number of } 3-\textit{occupancy vehicles in Town of Boydton} \quad \text{(Eq. B1)}$$

Applying Equation B1 leads to the corrected AVOs shown in Table B1.

Table B1. Special Case for Bias Correction: Town of Boydton

Off-Peak Vehicle Sample								Average Vehicle Occupancy		
VO=1 (1)	VO=2 (2)	VO=3 (3)	VO=4 (4)	VO=5 (5)	VO=6 (6)	VO=7 (7)	VO=8 (8)	AVO (9)	Corrected AVO (10)	|Difference|* (11)
26.287	**3.488**	1	1	**0.155**	**0.036**	**0.007**	**0.010**	3.50	1.29	2.21

* |Difference| in column 11 is the absolute value of the corrected AVO in column 10 minus the AVO in column 9.
VO = vehicle occupancy; AVO = average vehicle occupancy; bold numbers = bias corrected.

Note that Equation 2 from the VTRC study that initially looked at vehicle occupancy (Xu et al., 2022a) is not applicable for correcting AVO in the Town of Boydton:

$$\mathrm{W}_{5\ \mathrm{corrected}} = \min(\mathrm{W}_1 \frac{\mathrm{H}_5}{\mathrm{H}_1}, 0.99) = 314 \frac{167}{42{,}708} = 0.99 \quad \text{(Eq. B2)}$$

where

$\mathrm{W}_{5\ \mathrm{corrected}}$ = estimated number of five-occupant vehicles in the jurisdiction
W_1 = number of SOVs in the jurisdiction
H_1 and H_5 = the single-occupant and five-occupant vehicles in the Richmond District.

This modification was made because there is one vehicle in the three-occupancy vehicle group in the Town of Boydton and it is reasonable to assume that the numbers for the VO=1 and VO=2 vehicle groups will be higher than for the VO=3 or VO=4 vehicle groups. Therefore, Equation B2 is not applicable in this special case. The values in columns 1 and 2 will thus retain the values calculated by Equation B1.

APPENDIX C. IMPACT OF OCCUPANCY ON TRAVEL TIME RELIABILITY

Toward the end of the May 23, 2023, update, the TRP asked how jurisdictional occupancy factors might affect TTR metrics. TTR is a measure of how consistent the travel time is from one roadway segment to another over different periods within a day and over days within a week. For computing TTR measures, 23 CFR § 490.509(d) requires that the AVO factors needed to calculate the measures come from the most recently available data tables published by FHWA unless other allowed data source(s) are used. Based on the most recent FHWA AVO publication, the AVO factor for all vehicles is 1.7.

To obtain TTR metrics, vehicle probe data from the National Performance Management Research Data Set are used and processed through the analytical software tool known as the Regional Integrated Transportation Information System (RITIS). RITIS provides interstate and non-interstate level of travel time reliability (LOTTR) for all segments in Virginia that are part of the National Highway System. The value of LOTTR is obtained by comparing the "normal" travel time (which is defined as the 50th percentile travel time) on a segment with either the 80th percentile or 95th percentile travel time to determine the overall reliability of that segment. If the difference between the normal travel time and the longer travel time (80th or 95th percentile time) is greater than 50%, then the segment is unreliable. The interstate TTR specified in 23 CFR § 490.507(a)(1) is computed by Equation C1. In essence, based on Equation C1, reliability of interstate segments can be defined as follows: Reliability = ∑(Reliable Person Miles) ÷ ∑(Total Person-Miles).

$$100 \times \frac{\sum_{i=1}^{R} SL_i \times AV_i \times OF_j}{\sum_{i=1}^{T} SL_i \times AV_i \times OF_j} \qquad \text{(Eq. C1)}$$

where

R = total number of interstate system reporting segments that are exhibiting an LOTTR below 1.50 during all of the time periods identified in § 490.511(b)(1)(i) through (iv)

i = interstate system reporting segment "*i*"

SL_i = length, to the nearest thousandth of a mile, of interstate system reporting segment "*i*"

AV_i = total annual traffic volume to the nearest single vehicle of the interstate system reporting segment "*i*"

j = geographic area in which the reporting segment "*i*" is located where a unique occupancy factor has been determined

OF_i = occupancy factor for vehicles on the NHS within a specified geographic area within the state/metropolitan planning area

T = total number of interstate system reporting segments.

District-Level Travel Time Reliability

As noted by the TRP during the May 23 meeting, if the occupancy factor is a constant value, OF_j in the numerator and denominator of Equation 1 will cancel out, leaving segment level TTR = segment length x (365 x segment AADT). This occurs when any default value, such as FHWA's occupancy factor of 1.7, is used. However, if jurisdictions within a district have distinct occupancy factors, an analysis can be performed where OF_j will not cancel out, such that these occupancy factors may affect the final result. Therefore, a district-level TTR analysis was performed for the Hampton Roads, Richmond, and Northern Virginia districts. Table C1 shows the jurisdictions within each district, the vehicle occupancy factor used per jurisdiction based on crash data from 2019 (VOCr), and the number of interstate segments within each jurisdiction. Note that Table C1 is different from Table A3. The occupancies in Table A3 came from the crash data for all roadways and the occupancies in Table C1 came from the crash data for interstates only.

Table C1. Jurisdictions Within Districts and Associated Occupancy Factors

District	Jurisdiction	VOC_r	No. of Interstate Segments
Hampton Roads	City of Chesapeake	1.23	68
	City of Hampton	1.30	58
	James City County	1.30	10
	City of Newport News	1.16	44
	City of Norfolk	1.25	155
	City of Portsmouth	1.28	29
	City of Suffolk	1.22	14
	City of Va Beach	1.22	43
	York County	1.38	14
Richmond	Brunswick County	1.29	20
	Chesterfield County	1.21	22
	City of Colonial Heights	1.37	8
	Dinwiddie County	1.41	24
	Goochland County	1.12	20
	Hanover County	1.28	32
	Henrico County	1.18	121
	City of Hopewell	1.29	4
	Mecklenburg County	1.35	18
	New Kent County	1.39	16
	City of Petersburg	1.37	38
	Prince George County	1.37	30
	City of Richmond	1.22	84
Northern Virginia	City of Alexandria	1.23	27
	Arlington County	1.22	101
	Fairfax County	1.24	216
	Prince William County	1.24	62

VOC_r = vehicle occupancy factor for each jurisdiction based on 2019 crash data.

Table C2 shows the results of the TTR analysis for the three districts based on 2019 RITIS data. Rows 1 and 2 show the total number of interstate segments within each district and the percentage of those segments deemed unreliable (segment LOTTR ≥ 1.5), respectively. Rows 3 and 4 provide details of the unreliable segments in terms of segment length; rows 5 and 6 provide details of reliable segments in terms of segment length; and rows 7 and 8 provide the TTR based on Equation C1 using occupancy factors from jurisdictional crash data (see Table C1) and using a constant default value, respectively.

The purpose of analyzing reliability based on segment length is to show that most of the unreliable segments are shorter and most likely associated with interchanges. This is more evident in the Hampton Roads and Richmond districts where the percentage of unreliable segments that are ¼ mile or less in length were 45% and 57%, respectively. In the Northern Virginia District, the effect of interchanges (short segment lengths up to ¼ mile) had less of an impact (31% unreliable versus 25% reliable).

Jurisdictional occupancy factors found from crash data had a negligible effect on TTR for all three districts. The difference between TTR using jurisdictional occupancy factors and a constant default value was 0.02, 0.16, and 0.01 for the Hampton Roads, Richmond, and Northern Virginia districts, respectively.

Table C2. Travel Time Reliability Metrics

Row No.	Metric	Hampton Roads	Richmond	Northern Virginia
1	Total number of segments	434	437	407
2	% Unreliable segments	16%	8%	39%
3	Avg. length of unreliable segments (miles)	0.42	0.32	0.65
4	% Unreliable (1/4-mile segments)	45%	57%	31%
5	Avg. length of reliable segments (miles)	0.68	1.26	0.65
6	% Reliable (1/4-mile segments)	28%	19%	25%
7	TTR VOC_r (from Table C1)	89.76	95.49	59.06
8	TTR (default)	89.78	95.33	59.05

TTR = travel time reliability; TTR VOC_r = travel time reliability based on a vehicle occupancy factor for each jurisdiction derived from 2019 crash data.

Occupancy Factor Sensitivity Analysis

A sensitivity analysis was performed to examine further the effect of using jurisdictional occupancy factors on a specific interstate corridor in the Northern Virginia District. The Northern Virginia District was chosen because it had the lowest TTR compared to the Hampton Roads and Richmond districts (rows 7 and 8 in Table C2). Based on values of LOTTR ≥ 1.5, it was found that for I-66, 40% of the interstate segments were unreliable; for I-495, 31% were unreliable; for I-395, 42% were unreliable; and for I-95, 41% were unreliable. Each interstate passed through three jurisdictions with the exception of I-495, which passed through only Fairfax County. Based on the percentage of unreliable segments, I-395, which spans the City of Alexandria, Arlington County, and Fairfax County, was chosen for the sensitivity analysis. There are 105 interstate segments on I-395 in the Northern Virginia District, of which 44 have a LOTTR ≥ 1.5.

To perform the sensitivity analysis, occupancy factors of 1.1, 1.4, and 1.7 were used for six scenarios shown as Sc A through Sc F in Table C3. For each scenario, TTR was calculated and compared to a constant occupancy factor. Compared to the TTR using a default occupancy factor (TTR = 53.07), the range in the difference across the six scenarios was -1.27% to +1.30%, or 2.57%.

In sum, when TTR is considered, the effect of using jurisdictional occupancy factors for district-wide analyses is negligible compared to using a default value. This holds true using a wide range of occupancy factors, as shown with the sensitivity analysis.

Table C3. Sensitivity Analysis of I-395 in the Northern Virginia District

Location	Sc A	Sc B	Sc C	Sc D	Sc E	Sc F	CrVO	DefVO
City of Alexandria	1.1	1.1	1.4	1.4	1.7	1.7	1.23	1.7
Arlington County	1.4	1.7	1.7	1.1	1.4	1.1	1.22	1.7
Fairfax County	1.7	1.4	1.1	1.7	1.1	1.4	1.24	1.7
TTR	54.09	52.83	51.80	54.37	52.01	53.33	53.12	53.07
Diff. from default TTR	1.02	-0.24	-1.27	1.30	-1.06	0.26	0.05	-

Sc = Scenario; CrVO = crash-based vehicle occupancy; DefVO = default vehicle occupancy; TTR = travel time reliability; Diff. = difference.