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Improving Ridership Projections of Proposed Bus and Rail Transit Projects to Evaluate Congestion Reduction Effects

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16. Abstract:

Transit ridership data comprise one of the performance metrics examined when allocating funding to transportation projects, especially for those designed to reduce traffic congestion. The better the quality of the data, the more efficient the project prioritization process. The purpose of this study was to obtain better ridership data by answering three questions using Virginia-based data: How is transit ridership affected by changes to infrastructure and transit service such as the addition of real-time information systems, shelters, and lighting or increases in service frequency? What percentage of transit ridership occurs during peak hours of congestion? How does crowdsourced transit activity data compare to ridership data from Virginia transit agencies?

Study methods included conducting extensive literature reviews to determine previous findings related to ridership effects of stop improvements and then conducting a before-after study in Virginia using ridership data from one Virginia transit agency. Ridership data were also collected on an hourly basis for year 2019 from six Virginia transit agencies to determine the percentage of ridership during peak travel hours. Generally, ridership data are challenging to obtain directly from transit agencies because there is not a standardized process for data collection, storage, and sharing. Crowdsourced big data platforms such as StreetLight promise easily accessible ridership-related data in standard formats. To explore the value of such data, this study also examined the accuracy of StreetLight transit activity data by comparing them with ridership data from Virginia transit agencies and then calculating the root mean square error.

The results for one Virginia transit agency documented in this study showed statistically significant increases (177%) in ridership where bus stop infrastructure was improved compared to statistically insignificant increases of 27% where bus stops were unchanged, but it is likely that improvements in bus frequency at some treated stops contributed to some portion of this increase. Literature searches found stop-level bus ridership increases ranging from 1.5% to 140% and route-level ridership increases of 2% when basic stop infrastructure was improved or added. The hourly ridership data from transit agencies showed that the peak hourly percentage of daily transit ridership for fixed-route services varied from 10% to 11% of daily ridership for buses and 14% to 26% for heavy rail transit. For commuter rail services, this percentage was much higher, ranging from 37% to 56%. Directly using transit activity data from StreetLight's current algorithm was deemed to be inappropriate without verifying them with agency data, especially for agencies in small- to medium-sized cities such as those in most of Virginia.

The study's first two recommendations are for the Virginia Department of Rail and Public Transportation to consider the findings of this study if updating (1) the peak-hour ridership percentage used when scoring proposed fixed-route bus projects or (2) the percentage of ridership increase used when scoring proposed bus stop improvements in the form of shelters and benches. Implementing both of these recommendations by adjusting parameters used in project scoring should result in improved project prioritization. The third recommendation is for the Virginia Department of Rail and Public Transportation to consider the use of StreetLight transit activity data using the detailed instructions provided in this report. This would ensure efficiency in the use of this data source and knowledge of the expected level of accuracy in its results.

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FINAL REPORT

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ABSTRACT

Transit ridership data comprise one of the performance metrics examined when allocating funding to transportation projects, especially for those designed to reduce traffic congestion. The better the quality of the data, the more efficient the project prioritization process. The purpose of this study was to obtain better ridership data by answering three questions using Virginia-based data: How is transit ridership affected by changes to infrastructure and transit service such as the addition of real-time information systems, shelters, and lighting or increases in service frequency? What percentage of transit ridership occurs during peak hours of congestion? How does crowdsourced transit activity data compare to ridership data from Virginia transit agencies?

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INTRODUCTION

Virginia's project prioritization process (SMART SCALE) evaluates projects for all modes for potential funding. Virginia's Office of Intermodal Planning and Investment (OIPI) oversees SMART SCALE, which includes factor areas such as accessibility, environmental quality, safety, and congestion. The Virginia Department of Rail and Public Transportation (DRPT) participates in scoring the congestion factor area for relevant projects.

The focus of this study was the congestion factor area scoring process for bus and rail transit projects, referred to as "transit projects" throughout this report. This process considers the effects of the proposed projects on person-throughput, person-hours of delay, and peak-hour congestion. Ridership estimates, in particular, are integral to improvements of basic transit infrastructure and most rail projects and are based on existing system ridership and industry research, if available. Basic transit stop infrastructure has sometimes been termed "stop amenities" or "passenger amenities" and refers to items including shelters, seating, and lighting at stops, which have been found to be placed inconsistently in Virginia (DRPT, 2022a). Examples of stop improvements included the addition of shelters, benches, trash cans, lighting, bike racks, sidewalk connections, landing pads, real-time arrival information, etc. Station improvements included those items along with an expansion of the square footage of the station building, a new rail platform, or platform expansion. New or expanded fixed-guideway transit services and implementation of transit signal priority were other examples of transit improvement projects where the effects on ridership were of interest. In addition, congestion relief calculations for transit rely on estimates of new peak-hour transit riders. For the purposes of SMART SCALE scoring, assumptions were that 20% of total ridership occurred during the peak hour for typical fixed-route service and that 40% of total ridership occurred during the peak hour for commuter service (i.e., service that operates only during morning and afternoon commute hours). Although ridership estimates might not comprise the best performance indicator for all transit projects—as not all transit projects are intended to boost ridership—DRPT determined it to be the most appropriate measure for evaluating proposed projects through SMART SCALE, which funds only capital expenses of transit, not operations (Jenkins, 2022).

Ridership estimates are often found in transit studies. One study conducted for transit across the American Legion Bridge (Maryland Transit Administration and DRPT, 2021) included a sensitivity analysis of one of its investment packages to examine the effects of more frequent and faster transit service using the regional travel demand model. The model results indicated a 5% increase in transit demand for a 10% increase in service frequency and a 13% increase in transit demand for a 10% reduction in travel times. Not all transit proposals in SMART SCALE undergo such detailed modeling, however. Projections of transit ridership can also be based on before-after data from implemented transit projects. A recent national study examined planning-level ridership predictions versus actual outcomes 2 years after a project's opening for major projects such as new bus rapid transit (BRT) or light rail lines (Federal Transit Administration [FTA], 2021). OIPI analyzes predicted versus actual outcomes for Virginia projects and although most projects included in that effort are highway-focused, at least one has been related to the comparison of average weekday ridership counts before and after the purchase of expansion buses (Jenkins, 2022; Virginia Smart Portal, 2018). Any analysis of recently completed projects would have been complicated by the ridership effects of the COVID-19 pandemic. Transit ridership had drastically declined to 10% to 40% of pre-pandemic levels in many cities across the United States since mid-March of 2020 (American Public Transportation Association [APTA], 2022). Hence, all studies examined and data collected for this study were from the pre-pandemic years.

Aside from being used in SMART SCALE, ridership estimates are frequently used in state and federal transit funding formulas (DRPT, 2022b; FTA, n.d.b). Transit ridership data comprise one of the key pieces of information needed not only in allocating funding but also in conducting planning and operations research (Yang et al., 2022). For these reasons, the accuracy of ridership forecasts is important, as is the accuracy of ridership datasets used in forecasting. Yang et al. (2022) examined the different ridership data collection methods used by Virginia transit agencies by conducting surveys. Results showed that less than one-third and one-fourth of Virginia transit agencies used automatic passenger counters and fareboxes, respectively, whereas 41% still used simpler tools (e.g., pen and paper, trip sheets, and clickers). Methods of storing the collected data also differed among agencies; survey respondents used formats ranging from spreadsheets and specialized software to handwritten ledgers. These variations in data collection and storage methods among agencies lead to both differing levels of accuracy and complications in obtaining data in standardized formats.

Given the challenges associated with obtaining ridership data in standardized and comparable formats from transit agencies, an emerging source of transit activity data, StreetLight, was examined in this study. Crowdsourced big data platforms such as StreetLight can provide easily accessible, uniformly structured ridership-related data across multiple transit service providers, thereby providing a more convenient data resource for researchers and planners. Specifically, the StreetLight platform collects location-based crowdsourced data and trains its algorithm, using ridership data from select transit agencies, survey responses, and map layers to differentiate among trips of various modes. The company described its primary sources of data as location-based services (LBS) data and "well-validated bus and rail ridership counts" (StreetLight Data, 2021). The resulting StreetLight data product is not a direct estimation of ridership but rather a relative index representing transit rider activity levels (StreetLight Data, 2021). To date, no independent third parties have evaluated the accuracy of bus and rail ridership data from StreetLight. This study explored a subset of StreetLight transit activity data in Virginia in small and medium-sized cities (populations below 250,000) and compared them with data collected from transit agencies serving those cities.

PURPOSE AND SCOPE

The purpose of this study was to identify potential enhancements to DRPT's portion of the SMART SCALE congestion factor scoring methodology. There were three objectives:

1. Determine the ridership effects of transit improvement projects based on the literature and a Virginia-specific case study.

2. Estimate the percentage of transit ridership that occurs during the peak hour for transit service based on data from six Virginia transit agencies.

3. Compare transit activity data from StreetLight with ridership data collected by Virginia transit agencies.

The scope of the study was limited to fixed-route transit services: bus, heavy rail, and commuter rail as defined by the APTA (2023). The scope excluded demand-response transit services, as they tend to have less noticeable effects in reducing congestion. The study focused on improving data for the existing congestion factor; changes to how this factor is defined were outside the scope of this study. This research topic was ranked as a high priority at the spring 2021 meeting of the Virginia Transportation Research Council (VTRC) Transportation Planning Research Advisory Committee (VTRC, 2021).

METHODS

Three main tasks were performed to fulfill the study objectives:

1. Conduct a literature review.
2. Validate the findings from the literature.
3. Assess the accuracy of StreetLight transit activity data.

Conducting the Literature Review

The research team carried out an extensive search for published work through the following sources: (1) Google Scholar; (2) Google search engine; and (3) Transport Research International Documentation (TRID). This helped the research team gain a clear understanding of existing research pertinent to the topic. The primary search terms included combinations of "transit ridership," "transit signal priority," "passenger amenities," "station expansion," "platform expansion," "shelters," and "real time information system." Using subscription databases and freely accessible search tools, the VDOT Research Library also conducted a focused search for published literature that studied and quantified the effects of transit improvement projects on ridership and mode shifts (Winter and O'Leary, 2021).

Validating Findings From the Literature

Ridership data were requested and obtained from selected Virginia transit agencies. The data were used in three ways: (1) to examine the effects of stop improvement projects on bus ridership; (2) to determine the proportion of daily transit riders during peak travel hours; and (3) to assess the accuracy of StreetLight transit activity data.

Examining the Effects of Stop Improvement Projects on Bus Ridership

In order to select transit agencies from which to request ridership data, DRPT provided a list of agencies that had implemented bus stop improvements in recent years. Six transit agencies were contacted via email; Arlington Transit was the only agency contacted that had ridership counts at the stop level.

A study in Utah compared bus ridership before and after improvements were made at a group of bus stops and also at a group of unimproved stops (Kim et al., 2020). Similarly, ridership data from Arlington Transit were requested and obtained for two groups of stops: (1) stops that were improved (treatment stops), and (2) stops that did not undergo any form of improvement during the same time period (control stops). For both groups of stops, stop-level ridership data prior to the improvements and ridership data after the improvements were requested and obtained from Arlington Transit. The improvements consisted of making the stops compliant with the Americans with Disabilities Act (ADA) by installing landing pads for bus accessibility equipment such as lifts or ramps, which often involved relocating the stop. Other improvements included replacing shelters with solar-powered shelters and adding benches or lean bars. Benches and lean bars were provided at stops where the number of daily bus boardings exceeded 10 and 5, respectively (Arlington Transit, 2020).

The stop improvements were made between spring and fall 2018. Therefore, stop-level ridership data were requested from Arlington Transit for 2017 and 2019 for both treatment stops and control stops. In order to ensure that the pre-improvement ridership counts of the two groups were similar in magnitude and thus comparable, data cleaning removed stops identified to be outliers from both groups based on the interquartile range method (Statology, 2021). Thus, all stops with daily boardings above or below the calculated range were removed, as were stops with missing data. The final sample sizes of the stops for the two groups were both below 30; hence, the variety of statistical tests that could be done was limited. F-tests (Statistics Solutions, n.d.) and T-tests (Glen, n.d.) were conducted to determine whether ridership increases over time in each of the two groups of stops (treatment and control) were statistically significant, and then the percentage changes in ridership after the improvements were calculated. Similarly, F-tests and

T-tests were conducted to determine whether the ridership increases in the treatment group were statistically significantly higher than the ridership increases in the control group over the 2-year period. For both cases, the F-test helped determine whether the variances were equal between the groups under consideration; that, in turn, affected the type of T-test to be used.

Both treated stops and control stops were served by Arlington Transit buses and Washington Metropolitan Area Transit Authority (WMATA) Metrobuses, and the data provided by Arlington Transit included ridership for both agencies. During the final stages of this study after all analyses were complete, the research team learned that WMATA had increased the service frequency of its 3Y route, which served multiple treated stops, around the time of the stop improvements (Holloman, 2023).

Blacksburg Transit (BT) provided data to examine the effects of improving bus stop amenities in a qualitative manner using four case studies of stop improvements.

Determining the Proportion of Daily Transit Riders During Peak Travel Hours

Bus

DRPT provided a list of Virginia transit agencies that collect bus ridership data hourly. Hourly ridership data from fixed-route services were requested and obtained from four of these bus transit agencies (see Table 1) via email. Each agency provided hourly ridership data for April and May in 2019 except for Bay Transit, which provided data for September and October of the same year, as the agency did not have the requested data for April and May. Blacksburg Transit provided data for its full service dates, corresponding to the Virginia Tech academic year, which ended in mid-May. The 2019 data were chosen to avoid any ridership-related variations during the COVID-19 pandemic.

Table 1 describes the service characteristics of the chosen transit agencies, obtained from the FTA's National Transit Database (NTD). This study used the average unlinked passenger trips reported by transit agencies as a measure to identify the ridership magnitude of each transit agency. Because transit agencies vary widely in terms of service area populations, service area geographic sizes, and number of buses operated, summaries of studies that looked at specific agencies include these statistics from the NTD. Data from 2019 were used in all cases, although study dates varied.

Data cleaning ensured data were in comparable formats. Analysis was limited to weekdays, defined as Monday through Thursday, as trip patterns on Fridays tend to be different from those on other weekdays. For each agency's fixed routes, the hourly percentages of daily ridership were calculated and then plotted in graphs to analyze hourly variations in ridership. Each agency's peak hour for ridership was identified from the graphs and the corresponding hourly ratios.

Alexandria Transit Company (DASH) serves Alexandria, a city with a larger population than Montgomery County, which is served by BT. However, both the values of service consumed from Table 1 and the ridership count from Figure 1 show that BT had greater ridership than DASH. Of these four chosen agencies, Bay Transit had the smallest 2-month ridership for fixed-route services.

Table 1. Transit Agency Service Characteristics in 2019

Transit Agency	Service Area[a]		Service Supplied[a]	Service Consumed[a]	No. of Fixed Routes Operated
	Population	Area (mi^2)	Average Vehicle Revenue Miles[b]	Average Unlinked Passenger Trips	
Alexandria Transit Company (DASH)	139,966	16	2,365,470	3,996,676	12
Blacksburg Transit	73,554	34	1,147,826	4,659,053	17
Radford Transit	18,368	10	342,655	268,727	6
Bay Transit	Rural[c]	Rural[c]	1,435,007	143,104	4

[a] Source: Federal Transit Administration (n.d.a).
[b] Average vehicle revenue miles refers to the average number of miles that a vehicle travels while generating revenue, i.e., while in passenger service (U.S. Department of Transportation, 2012).
[c] National Transit Database profiles for agencies classified as rural transit providers do not include service area population or size of area served.

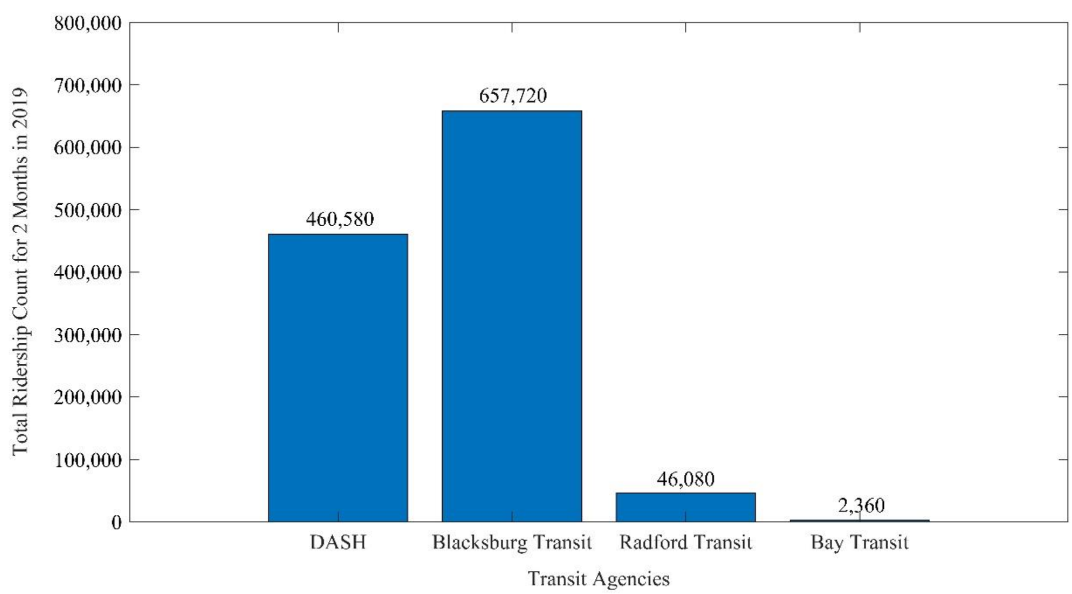

Figure 1. Total Fixed-Route Ridership Across the Four Transit Agencies for 2 Months in 2019 (About 1.5 Months for Blacksburg Transit). Data provided by each agency.

Rail

The data collection for heavy rail (i.e., subways) used data from the WMATA Metrorail via WMATA's website (WMATA, 2022a). For commuter rail, data were also requested and collected from Virginia Railway Express (VRE), which connects the suburbs in Northern Virginia to Alexandria, Crystal City, and downtown Washington, D.C. As with bus transit data, rail ridership data were collected for 2019, but for 4 months (April, May, September, and October) as opposed to the 2 months for bus activity. The hourly percentages of the total daily ridership were calculated, and graphs showing the hourly variation of ridership were plotted for each station. Unlike WMATA, which operated heavy rail throughout the day, VRE operated its commuter rail services only during peak travel hours, so the number of hours of data collected was different for the two rail agencies.

Six of Metrorail's 23 Virginia stations were chosen for this study (see Table 2), and their average hourly number of entries, i.e., train boardings only, were analyzed (WMATA, 2022b). In a similar manner, 6 of VRE's 19 stations were chosen for analysis. Three were chosen from each of its two lines, Fredericksburg and Manassas. The Metrorail stations were chosen across all four of its lines in Virginia. None of the stations chosen were located at the start or end of a line, because end-of-line stations were expected to have mostly entries in the mornings and mostly exits in the afternoons/evenings due to regional commuting patterns. Each station served only Metrorail lines or only VRE lines. Among the chosen VRE stations, each served only one VRE line. Both of these considerations ensured that any analysis in StreetLight would not be affected by the other agency's or other lines' transit activity.

Although Metrorail recorded both station entries and exits using data from the station faregates and made the data available on WMATA's website at an hourly level, VRE's publicly available data were at the train level. The station-level ridership data requested and obtained from VRE were VRE's estimates—used for internal planning and analysis purposes—of the number of riders getting on or off each train at each station, as VRE did not have a way to count actual station-level boardings or alightings (Hoeffner, 2022). The data provided by VRE included estimated boardings by train number for each station. The 2019 train schedules at each station were obtained from VRE (Ruiz, 2022) and examined. It was assumed that all trains were on time. The estimated boardings by train number were matched to the scheduled departure times in order to generate hourly station-level boarding estimates. Issues such as riders evading payment of fares at Metrorail faregates meant that ridership data obtained from WMATA might not always represent 100% of actual ridership.

Table 2. Characteristics of Selected Rail Stations

Metrorail[a]			
Station Name	**Location**	**Line(s) Served**	**Total Entries in Station During April, May, September, and October 2019**
Court House	Arlington	Orange, Silver	488,050
King St–Old Town	Alexandria	Blue, Yellow	406,030
Tysons	McLean	Silver	256,790
McLean	McLean	Silver	178,650
Greensboro	Vienna	Silver	117,330
Spring Hill	Vienna	Silver	89,010
Virginia Railway Express[b]			
Station Name	**Location**	**Line Served**	**Total Estimated Entries in Station During April, May, September, and October 2019**
Leeland Road	Falmouth	Fredericksburg	74,050
Rippon	Woodbridge		50,020
Lorton	Lorton		65,230
Manassas Park	Manassas Park	Manassas	43,760
Backlick Road	Springfield		24,100
Rolling Road	Burke		38,680

[a] Source: Washington Metropolitan Area Transit Authority (2022a).
[b] Source: Virginia Railway Express (Hoeffner, 2022; Ruiz, 2022).

Assessing the Accuracy of StreetLight Transit Activity Data

The transit agency ridership dataset described in the previous section was also used for determining the accuracy of data from the crowdsourced data platform StreetLight. StreetLight had transit activity data only for the months of April, May, September, and October of 2019 at the time of this analysis, and only full months could be selected. As of February 2023, available data months were expanded to January 2019 through April 2022.

The first step in analyzing StreetLight data is to create "zones" or study areas. The way they are created and analyzed in StreetLight differs for buses and rail. Zones for bus analyses in this study were of the "user-generated" type, which means that the geographical boundaries were set by the analyst. Zones created were "non–pass through," meaning that any trip activity analyzed would be only for trips beginning or terminating, or both, in the selected zone. StreetLight is currently unable to distinguish transit activity data from different transit agencies with overlapping routes. It was also difficult to find bus routes that did not partially overlap another route of the same agency, so StreetLight was not immediately able to estimate route-level ridership data. Hence, the research team chose to focus on analyses involving all bus stops of a transit agency, rather than route-level analyses. Rail analyses were run using rail zones defined by StreetLight based on OpenStreetMap (OSM), which consisted of rail stations and line segments. A set of instructions was also developed as part of this task for others wanting to examine bus transit activity data in StreetLight (see the Appendix). All StreetLight analyses for this study were run during the months of May, June, and July of 2022.

Bus

There are 95 counties and 38 independent cities in Virginia (University of Virginia Weldon Cooper Center, 2020). For many reasons, the use of transit varies across these counties and cities, as seen in Table 1 (e.g., BT had a substantially higher unlinked passenger trip value than Radford Transit). Exploratory analyses of StreetLight transit activity in Virginia revealed multiple localities where at least some level of transit service existed that did not yield any transit data. Thus, it was hypothesized that StreetLight's algorithm may not produce meaningful bus activity data in a region where data values in the platform are lower than a specific threshold value. To determine what this threshold value was in Virginia, a non–pass through zone set was first created in StreetLight that included only counties and cities in Virginia, i.e., each jurisdiction was a zone, and Virginia was the zone set. Choosing "bus" as the mode of travel and selecting all weekdays (Monday-Thursday) of the 4 available months of 2019 as the time period, this zone set was analyzed using the zone activity method for all hours of the day. The analysis for each of the zones within the zone set of Virginia is hereinafter denoted SL1.

This method yielded data on the quantity of bus passenger trips starting or ending in the selected zones, i.e., the geographic limits of each locality. The results showed the percentage of StreetLight bus activity data each locality contributed in 2019 relative to the total StreetLight bus activity in Virginia. By selecting each locality individually, the locality's relative hourly bus activity distribution was examined and plotted, as with the graphs generated for transit agency data. The percentage of total StreetLight bus activity data in Virginia above which localities were generating reasonable data (i.e., StreetLight had data for all hours of the day during which transit typically operated) was deemed to be the threshold. Based on these results, only two of the four initially selected transit agencies (BT and DASH) could be used for further analysis.

Although using locality-level zones is faster, for bus analyses StreetLight recommended using zones consisting of buffered bus stop locations. This should limit trips to those that started (or ended) at bus stops; StreetLight recommended a 50-meter buffer because of the variability in the geographic precision of LBS data. Moreover, for localities with multiple bus operators, using the bus stops from the transit agency of interest should partially mitigate the issue of obtaining unwanted data on bus trips from another agency. General Transit Feed Specification files for BT and DASH (Open Mobility Data, 2019) containing all bus stops as of 2019 were imported into ArcGIS Pro, where the stops were buffered by 50 meters and dissolved (see Figure 2). The shapefiles were then exported into StreetLight as zones. Buffers of 50-meter radii were found to be discrete zones (Figure 2) except where two stops were across the street from each other and on corridors with stops closer together than every other block, confirming that a 50-meter buffer appeared reasonable.

Using these zones, StreetLight zone activity analyses were conducted twice for each transit agency, once using 2 months of data (April and May, analysis SL2) and then using all 4 months of data that were available in StreetLight (analysis SL3), to compare any differences due to the quantity of data analyzed.

To summarize, three graphs were obtained from three StreetLight analyses for comparison with the ground truth for each transit agency:

1. SL1: zone with the county/city boundary limits (4 months of data)
2. SL2: zone with buffered bus stops (2 months of data)
3. SL3: zone with buffered bus stops (4 months of data).

A quantitative analysis using the root mean square error (RMSE) was performed to compare the relative accuracy of StreetLight transit activity data with respect to agency-provided ridership data. The RMSE accounts for the deviation of the StreetLight data from the agency-provided data at each hour, and the final RMSE value obtained is the square root of the mean squared error between the two compared datasets. In this study, the RMSE was calculated using an Excel function. Relative to other commonly used measures such as the mean absolute percent error (MAPE), the RMSE penalizes outliers to a greater extent, as it takes the square of the errors; it is also able to produce results even where actual or ground truth values are zero. These two characteristics of RMSE were ideal for this study, because the objective was to examine the accuracy of StreetLight data and because multiple ground truth values were zero. The unit of RMSE is the percentage of hourly ridership levels relative to daily ridership. A smaller RMSE value indicates less error and higher accuracy.

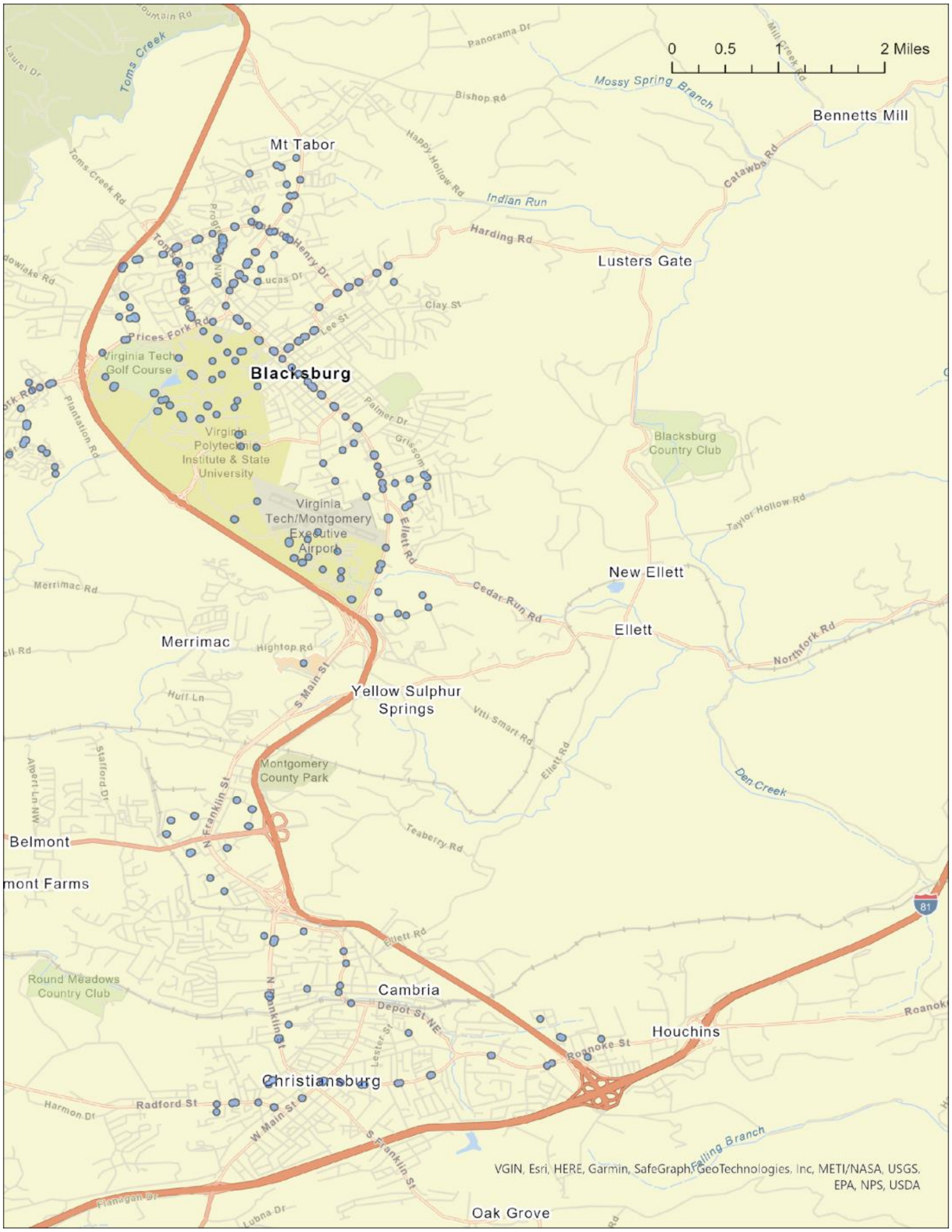

Figure 2. Blacksburg Transit's Buffered Bus Stops in ArcGIS Pro

Rail

Because StreetLight featured preset zones for rail stations, no separate zones had to be created to analyze rail activity data or rail ridership. Zone activity analyses were carried out for the chosen Metrorail and VRE stations by selecting "Rail" as the mode of travel and choosing all weekdays (Monday through Thursday) in the 4 available months of 2019. Remaining steps comprised three selections: (1) "Rail" as the type of zone, (2) the station of interest as the zone, and (3) a checkbox for WMATA or VRE as the agency. Only the ridership for trips that started in the station zones was analyzed, to obtain a measure of the boardings on the trains throughout the day. This process was repeated for all selected stations, and the resulting hourly percentage of daily heavy rail and commuter rail activity was plotted to compare it with data obtained from WMATA and VRE.

RESULTS AND DISCUSSION

Literature Review

Studies highlighting factors that affect transit ridership are summarized first. Next, studies are described that investigated changes in ridership in response to transit improvements including service improvements and basic stop infrastructure. Then, effects on ridership and mode-shift due to introduction of new transit facilities are briefly described.

Factors Affecting Transit Ridership

Table 3 summarizes findings from studies that explored factors affecting transit ridership, presented in alphabetical order by citation. Most studies directly examined ridership effects; two of these studies examined an underlying determinant of ridership instead, indirectly implying effects on ridership. Some factors are external to transit agencies (population characteristics, economy, land use, etc.), and some are internal (stop infrastructure, reliability, vehicle comfort, etc.).

Among the factors internal to transit agencies, the most common elements affecting ridership were on-time performance, fares, and frequency of service. Some studies suggested that increasing comfort at stops and inside the vehicle could indirectly increase ridership. Although in-vehicle travel time of the transit mode is difficult for transit agencies to control, it had an elasticity of −0.4 with transit ridership.

Ridership Effects of Transit and Rail Improvement Projects, Transit Signal Priority, and Stop Infrastructure

Kim et al. (2020) conducted a before-after study of bus stop improvements (providing shelters, sidewalk connections, and concrete pads) in Salt Lake County, Utah, to measure the effects on bus ridership and demand for paratransit service. Paratransit service is provided in part to serve passengers who might not be able to access fixed-route stops, so the hypothesis was that improving bus stops could allow more passengers to use fixed-route service rather than the less cost-effective paratransit). The Utah Transit Authority served a population of 1.9 million in an area of almost 740 square miles with more than 400 buses operating in maximum service (NTD, 2019). The improvements were made between 2014 and 2016, and the data for bus ridership were collected in 2013 and again in 2016. The study used a control group of bus stops where no infrastructure improvements were made; these unimproved stops were carefully matched with the improved stops using propensity score matching.

Table 3. Summary of Findings From Studies of Factors Affecting Transit Ridership

Citation: Title	Methods Used	Transit Ridership Effects
Chakrabarti (2017): How Can Public Transit Get People Out of Their Cars? An Analysis of Transit Mode Choice for Commute Trips in Los Angeles	Based on data from a statewide travel survey in Los Angeles County, circumstances that prompted people coming from car-owning households to use transit services were examined. Multinomial logistic regression models were used to estimate how changes in transit performance relative to auto would influence mode choice among car-owning travelers.	Indirect Effect: Transit travel speed, compared to auto speeds, is crucial in determining transit mode choice. Designing a network that has shorter wait times at transfer points, exclusive rights of way, direct connections, and a greater average speed may support mode shift toward transit.
Chakrabarti (2015): The Demand for Reliable Transit Service: New Evidence Using Stop Level Data From the Los Angeles Metro Bus System	Regression analysis on stop-level service supply, demand, and performance data from the Los Angeles Metro bus system.	Direct Effect: Higher on-time performance and schedule reliability were associated with higher ridership in peak periods. With everything else constant, there were estimated increases in the natural logarithm of the number of boardings for the AM and PM peak periods of 0.08 and 0.03, respectively, with every 10% increase in on-time performance (measured as the percentage of on-time departures). There was no observable effect on ridership from improvements to on-time performance in off-peak periods. Similarly, there were estimated decreases in the natural logarithm of the number of boardings for the AM and PM peak periods of 0.01 and 0.005, respectively, with every 10% increase in the standard deviation of schedule deviation (measured in minutes). There was no observable effect on ridership from improvements to schedule deviations in the early AM off-peak period.
Chakraborty and Mishra (2013): Land Use and Transit Ridership Connections: Implications for State-Level Planning Agencies	Ordinary least squares and spatial error modeling was used to analyze the relationship between transit ridership and land use and socioeconomic variables using data from Maryland. Future ridership was predicted under two scenarios using sets of econometric, land use, and other models.	Direct Effect: Land use, transit accessibility, income, and density were highly related to transit ridership (statistically significant) in the statewide models for Maryland.
Chiang et al. (2011): Forecasting Ridership for a Metropolitan Transit Authority	Transit ridership was forecast using regression analysis, neural networks, and time series models, particularly ARIMA models. A scenario analysis was also done to understand the effects of transit policy on long-term ridership. Monthly ridership data of the Metropolitan Tulsa Transit Authority were used.	Direct Effect: Operating funds had the most significant effect on ridership, and bus fares and the number of people receiving food stamps had an expected negative relationship with transit ridership. (The study's authors suggested that if people receiving food stamps are unemployed and have less need to travel, the negative relationship is expected.) Seasonal factors, such as the occurrence of major events in some months, were related to high ridership levels. Gasoline prices were statistically insignificant. Using an equally distributed weighting of all three forecasting models resulted in higher forecast accuracy than using each model alone.

		That approach can be used to assist in evaluating policy changes in bus fares and changes in levels of funding.
Taylor et al. (2009): Nature and/or Nurture? Analyzing the Determinants of Transit Ridership Across U.S. Urbanized Areas	Data were obtained from the National Transit Database for total urbanized area transit ridership and per-capita urbanized area transit ridership. Linear regression modeling, in the form of ordinary least squares regression, was carried out on the data.	Direct Effect: The study found that external factors such as regional geography, metropolitan economy, population characteristics, and auto/highway characteristics could account for variations in transit use in urbanized areas. Results from regression models suggested that transit policies involving higher service frequency and lower fares could cause ridership to double in an urbanized area.
Transportation Research Board (2016): A Guidebook on Transit-Supportive Roadway Strategies	Review of multiple examples of transit-supportive techniques that promote the reliability and speed of transit, particularly buses, on urban and suburban streets.	Direct Effect: The study identified six main components of transit service quality with an effect on ridership: level of accessibility to the stops, reliability of the service, level of comfort inside the transit vehicle, frequency of service, travel time associated with the service, and travel costs incurred.
Transportation Research Board (2007): Elements Needed to Create High-Ridership Transit Systems	An extensive assessment of existing studies related to creating and maintaining substantial transit ridership levels.	Direct Effect: The study found that the external factors affecting transit ridership were status of local and regional economies, levels of federal transit operating aid, and incorporation of public transportation into public policies and program areas (e.g., social service delivery). The report mentioned several older studies that found that service adjustments, particularly reorganization of routes and services, significantly affected ridership. Other agency actions such as fare policies, planning methods, and service coordination and collaborations (mostly with universities) also affected transit ridership. With regard to mode choice decisions, the study found that five factors commonly affected transit ridership: variations in travel-inducing activities, attributes of the transit-served population, availability of alternative modes of transportation, and transit fares and service levels. The study also found that obtaining a substantial mode shift by improving transit alone was not practical: feasible improvements to transit services could not fully offset the high value people placed on private vehicle travel.
Transportation Research Board (2013): Transit Capacity and Quality of Service Manual, Third Edition	Research compiled to provide guidance on ways to enhance transit service quality including transit capacity, speed, and reliability.	Direct Effect: Transit ridership had an elasticity of −0.4 with travel time. This implies that with an increase of travel time by 1%, transit ridership would decrease by 0.4%.
Xiong and Li (2011): Influence of Bus Stop Waiting Environment on Competitiveness of Transit: What Factors Determine Traveler Choice?	Data were collected via a survey of passengers at bus stops to determine the relationship between waiting environment at stops and passengers' willingness to choose bus as their travel mode. The data were modeled using an ordered logit model.	Indirect Effect: At a 95% confidence level, increasing the amount of comfort at stops was statistically significant. The survey results showed that if passengers deemed the bus waiting environment to be comfortable, they would use the bus more, but the precise amount was not clearly quantified in the study.

This method assigned a score to each of the stops, both improved and unimproved, based on their pre-treatment characteristics. The score helped match stops in the improved group to stops in unimproved groups and ensured they were statistically similar prior to the improvements being made. From observations at 24 treatment stops and 24 control stops, the study found that the growth of bus ridership was 141% higher at bus stops with improvements than at stops without improvements. The growth in paratransit demand was 108% lower in the areas around the stops with improvements than around those without.

Shi et al. (2021) looked at the effects of the presence of stop-level infrastructure elements on BRT ridership in King County, Washington, by measuring the number of boardings before and after the improvements at the stops. The regional transit authority, King County Metro, upgraded some of its traditional bus services to BRT services in October 2010. King County Metro served a population of 2 million in an area of approximately 2,100 square miles with more than 1,000 buses operating in maximum service (NTD, 2019). The bus stops were improved for two bus lines after they were converted to BRT; the study stated that these lines had already had a growth in ridership after their conversion to BRT and focused on any further increases related to the stop improvements. The study also examined the ridership effects of having different combinations of stop infrastructure elements. The study controlled for factors such as frequency and quality of service by ensuring that all stops analyzed underwent the same upgrades in BRT service and the only differences among them were in the varieties of stop infrastructure elements added. The elements examined included real-time information systems (RTIS), shelters, pedestrian lighting, benches, trash receptacles, and bicycle parking. They were added in sets: benches were added to all stops that either already had shelters or were getting new shelters installed, and shelters and bike parking hoops were added to all stops where RTIS was being provided. Results revealed a positive relationship between the number of boardings and the presence of stop infrastructure: boardings increased by 139.9% after the infrastructure elements were added. The elements that seemed to influence ridership the most were bike parking, RTIS, and shelters. Considering the fact that elements were installed in sets, the results demonstrated that relative to boardings at stops with the fewest improvements (including provision of RTIS, litter receptacles, and lighting), boardings at stops with new bike hoops were 203.5% greater, boardings at stops with new RTIS were 199.1% greater, and boardings at stops with new or improved shelters were 81.4% greater.

Talbott (2011) collected data on ridership and bus stop infrastructure from three transit agencies to determine whether the level of infrastructure elements influenced ridership. The Greensboro Transit Authority (Greensboro, North Carolina), King County Metro Transit (Seattle, Washington, region), and Kansas City Area Transportation Authority (Kansas City region) served populations of about 300,000, 2 million, and 800,000, respectively, in areas of approximately 100, 2,000, and 450 square miles, respectively, with more than 40, 1,000, and 150 buses, respectively, operating in maximum service condition (NTD, 2019). Statistically significant correlations were found between the presence of basic transit infrastructure (a binary variable) and ridership in all three regions: 0.121, 0.266, and 0.406 for Greensboro, Seattle, and Kansas City, respectively. The presence of a shelter, in particular, had a higher correlation with ridership than the other types of infrastructure elements examined (benches, signage, trash cans, lighting, adequate sidewalks, and ramps) in two of the three cities (Greensboro: 0.251, Seattle:

0.373, Kansas City: 0.345). The overall level of basic transit stop infrastructure was also found to influence ridership in Seattle and Kansas City.

Schroeder et al. (2015) focused on Los Angeles congestion reduction demonstration projects that used combinations of tolling, transit, telecommuting / travel demand management, and technology and examined their effects on transit ridership. Transit projects included improved security at transit stations, expansions to existing transit stations, bus service increases, transit signal priority, and a new connection between two transfer facilities via an express bus corridor. Bus service improvements included reductions in peak period headways (Metro Silver Line and Gardena Municipal Bus Lines), addition of a new express bus to an existing line (Torrance Transit), and addition of trips in morning and afternoon peak periods to a BRT route and an express service (Foothill Transit). These service increases were facilitated by the purchase of 59 new buses. The Metro Silver Line saw ridership increases of 52% and 41% in the morning and afternoon peak periods, respectively, after the first phase of service increase (change in peak period headway from 30 minutes to 15 minutes). Although increases in ridership were seen after service increases in the other transit agencies, it was difficult to conclude whether they were due to service increases, as there were other changes implemented at the same time, or it was too soon after the implementation to detect any sustainable increases in ridership.

Brown et al. (2006) collected data from the Triangle area of North Carolina (Raleigh, Durham, and Chapel Hill region) regarding the built environment of 148 bus stops. Regression analysis examined the relationship between Triangle Transit Authority boardings and alightings and the environment around bus stops. Both “urban” and “non-urban” bus stops were examined. The study formulated a bus stop index that related all features, including bus stop infrastructure, based on data from audits and multiple other sources. The audits consisted of questions relating to the environment of bus stops. The value of this index was highly statistically significant, with an increase of 1 unit leading to a 31% increase in ridership. Increased ridership was correlated with bus stops having signs, shelters, schedules, lighting, and paved landing areas, but no values were provided. However, the authors stated that the study was unable to establish a causal relationship between the bus stops and their infrastructure elements. The authors stated that this could be improved upon by using longitudinal data.

Watkins (2015) examined the effects of RTIS on passenger behavior in New York City, Tampa, and Atlanta using multiple methods. For New York City, panel regression techniques were used to analyze route-level bus ridership over a period of 3 years while taking into account any changes made in transit service, socioeconomic status of the region, fares, weather, etc. In Tampa, a before-after control group design was implemented, and then a web-based survey was conducted to evaluate behavior changes. In Atlanta, smart-card fare collection data and web-based surveys measured changes in transit travel with the use of a before-after design. Tampa and Atlanta did not have any increases in ridership due to the implementation of RTIS, but the author theorized that this might have been because the methodologies used for those cities did not take into account transit riders who were new to the system. Only New York City had a ridership increase (340 riders each weekday on the greatest quartile of routes) due to RTIS implementation, and the effects were more pronounced on routes with higher levels of pre-existing transit service. Brakewood et al. (2015) reported on the same New York City study, noting that weekday bus ridership increases of around 2% per route were attributable to the provision of RTIS.

Stewart et al. (2015) studied the ridership effects of implementing BRT upgrades in steps, rather than all at once, in cities in the United States and Canada. The upgrades examined in the study included degree of priority lane usage (percentage of the length of the corridor with a priority lane), transit signal priority, boarding through all doors, spacing between stops, service hours (percentage change in vehicle service hours), and travel time. Both longitudinal and cross-sectional models were used. The results of the longitudinal model revealed that ridership was most influenced by changes in service hours (i.e., the amount of transit service provided, which could include frequency and/or span of service, and an increase in the degree of priority lanes. Specifically, a longitudinal model incorporating lane priority, service hours, stop spacing, and travel time indicated that ridership increased by 0.734% and 0.629% for every 1% change in vehicle service hours and length of corridor with a priority lane, respectively. For the cross-sectional model, the authors wanted the dependent variable to account for the level of service, so the dependent variable was ridership productivity (the number of weekday boardings per revenue hour). The results of this second model indicated that transit signal priority had a statistically significant relationship with ridership productivity, with weekday boardings per revenue hour increasing by approximately 41% for every 1% increase in the number of intersections with signal priority.

A study from Portland, Oregon, of TriMet's plan of bus stop consolidation, provision of transit signal priority, installation of curb extensions, and use of the most high-tech buses on select routes (Koonce et al., 2006) was reviewed in TCRP Report 183 (Transportation Research Board [TRB], 2016). Although there was no substantial savings in transit travel time from this scheme, it did correlate with an increase in ridership, which generated increases in fare revenue of about $1.7 million.

These highlighted studies either quantified increases in ridership when improvements were made or determined the statistical significance of the relationships between ridership changes and improvement projects. In sum, with the addition of basic transit stop infrastructure, ridership growths of approximately 140% were found in two studies (Kim et al., 2020; Shi et al., 2021). These and other studies reporting ridership changes after stop improvements are summarized in Table 4. Schroeder et al. (2015) found that ridership increased by 52% and 41% during morning and afternoon peak hours, respectively, when bus services were increased by reducing peak hour headways from 30 minutes to 15 minutes through the addition of new buses. A unit increase in the number of intersections with transit signal priority yielded 41 additional weekday boardings per revenue hour (Stewart et al., 2015).

Table 4. Summary of Reported Ridership Changes From Studies That Included Stop Improvements

Citation: Title	Description of Improvements	Ridership Change as Reported by Author(s)
Kim et al. (2020): Another One Rides the Bus? The Connections Between Bus Stop Amenities, Bus Ridership, and ADA Paratransit Demand	Addition of shelters, sidewalk connections, and concrete pads to bus stops.	Growth of bus ridership was 141% higher at bus stops with improvements than at stops without improvements.
Shi et al. (2021): Does Improving Stop Amenities Help Increase Bus Rapid Transit Ridership? Findings Based on a Quasi-Experiment	Upgrade from traditional bus service to BRT and subsequent addition of RTIS, shelters, pedestrian lighting, benches, trash receptacles, and bicycle parking.	Stop boardings increased by 139.9% after the stop infrastructure elements were added.
Talbott (2011): Bus Stop Amenities and Their Relationship With Ridership: A Transportation Equity Approach	Addition of stop infrastructure elements ranging from shelters, benches, signs, lighting, trash cans, and ADA compliance elements (wheelchair ramps and sidewalks with elevated bumps).	Stop boardings increased from 1.5% to 16.5% in the three cities studied.
Brown et al. (2006): Understanding How the Built Environment Around TTA Stops Affects Ridership: A Study for Triangle Transit Authority	Addition of signs, schedules, seating, lighting, sidewalks and paved landing areas.	A unit increase in the Bus Stop Index (calculated based on presence of stop infrastructure) was linked to a 31% increase in ridership.
Brakewood et al. (2015): The Impact of Real-Time Information on Bus Ridership in New York City	Provision of RTIS.	Ridership increased 2% on each route.

ADA = Americans with Disabilities Act; BRT = Bus Rapid Transit; RTIS = Real-Time Information Systems.

Effect of Service Levels on Ridership

Changes in the service levels of a transit agency can refer to changes in its operating hours, number of routes operated, or frequency of the service. Multiple researchers have studied the effects of increases in service frequency on transit ridership.

Berrebi et al. (2021) examined the relationship between transit ridership and service frequency in terms of elasticity across multiple studies. Four transit agencies were studied:

1. TriMet in Portland, Oregon
2. Miami-Dade Transit in Miami, Florida
3. Metro Transit in Minneapolis–St. Paul, Minnesota
4. Metropolitan Atlanta Rapid Transit Authority in Atlanta, Georgia.

The main findings of this study showed that ridership was inelastic to the frequency of service offered. This meant that introducing more frequent services would not generate equivalent increases in ridership. For all four agencies, increasing the frequency of services by 1% resulted in ridership increases ranging from 0.66% to 0.78%. With the exception of Metro Transit, the routes with the most frequent service had the least ridership response to increases in frequency.

Further analysis of the same agencies showed that the elasticity of ridership varied with daily time periods (TRB, 2022). Ridership was more responsive to changes in frequency at night relative to day (elasticity values closer to 1), with the exception of TriMet, where ridership was relatively less elastic both day and night. The study noted that although the number of passengers per trip at night was unlikely to be as high as during the day, these findings could hold value for transit agencies planning on expanding their services. The authors also noted that because transit planners typically intend to increase service on routes where they believe there is increasing demand for transit, the relationship between increases in frequency and increases in ridership is unlikely to be completely causal.

The same study also found that transit agencies that had redesigned bus networks with the objective of increasing services along certain corridors, rather than prioritizing how much of the geographic area was covered by transit service, had ridership increases (TRB, 2022). This was seen in multiple cities in the United States, with more transit agencies planning to do the same as of 2020. The study did not quantify the ridership increases in response to network restructuring but noted there were equity concerns, as these changes generally increased access to transit for high-income communities while lowering access for low-income neighborhoods.

The *Transit Capacity and Quality of Service Manual* (TRB, 2013) identified six transit quality of service factors to be the most important to existing and potential transit users: (1) travel time, which included in-vehicle time along with access, transfer, and wait time; (2) level of crowding on board transit; (3) the reliability of transit; (4) infrastructure available at bus stops; (5) the availability of real-time arrival information; and (6) other service aspects such as the clearness of stop announcements and the behavior of the transit driver. When a bus stop had a shelter with a roof and end panel, the passengers' perceived in-vehicle travel time equivalent decreased by 1.3 minutes. On the contrary, where the bus stop was unclean, the perceived in-vehicle travel time equivalent increased by 2.8 minutes.

Effect of New Transit or Rail Facility or Transfer Facility on Ridership

Yang (2021) studied two new light rail transit (LRT) lines (Orange Line and Green Line) in Portland, Oregon, at the corridor level using (1) before-after comparisons, and (2) difference-in-difference regression models in both the short term and long term. On a regional level, a synthetic control method was used in several urbanized areas to understand any effects of the absence of LRT. At the corridor level, the LRT lines caused both short- and long-term increases in transit ridership. The Orange Line and Green Line caused increases of 6,404 and 7,225 riders, respectively, in average weekday boardings of all bus and rail stops in road segments parallel to each of the two lines, after the first year, with the ridership increase being substantial particularly for the first 3 years. For the Orange Line, ridership became stable after the first year; for the Green Line, it increased by another 500 riders and then became stable. Traffic congestion decreased only in the short term; the author theorized that induced traffic demand may have affected the results in the long term. At the regional level, most urbanized areas saw an increase in transit ridership, but only some urbanized areas saw a fall in traffic demand, and both varied with time.

Effect of New or Expanded Fixed-Guideway Service on Mode-Switch

Idris et al. (2015) used data gathered from the Toronto region in Canada and found that automobile owners preferred continuing to use their vehicles regardless of how competitive public transit became in terms of service. According to the results of a stated preference survey, car drivers opted to remain with the auto mode in 72% of all scenarios and switched to transit for only about 25% of the scenarios. The authors suggested that based on the survey results, peoples' aversion to shifting modes from auto to transit could be related to their habits and mindsets. With data from stated preference and revealed preference surveys and other psychology-related studies, the study formulated mode-shift models specifically targeting auto drivers. The features of public transit that were most likely to move drivers away from their cars and toward public transit or other options were chiefly how packed the vehicles were with passengers (model parameter = −0.4265) and the on-time performance of the competing transit service (model parameter = −0.4135), with the technological factors of transit (model estimate = 0.3168) and how often passengers would need to transfer (model estimate = −0.2716) following in importance. The results showed that travelers were more inclined to shift to rapid and semi-rapid alternatives rather than regular bus services.

Discussion

The literature search found several studies that examined the relationships between ridership and variables external to transit agencies such as regional geography, economy, and population characteristics (e.g., socioeconomic factors). The literature also showed how transit ridership has elastic responses to changes in various factors such as travel time and frequency of service. Certain attributes of the transit service itself have also been shown to influence ridership, such as level of comfort inside the transit vehicle, frequency of service, level of accessibility to the stops, etc. These findings align with the seven demands of transit from riders that Walker (2012) identified through the use of multiple case studies and discussion.

To answer the first study question regarding how transit improvement projects affect bus and rail ridership, all of the studies reviewed found a positive relationship between ridership and improvement of stop infrastructure. The magnitude of increases in ridership varied (with increases of approximately 140% when stop infrastructure elements were improved and an increase of 41% to 52% during peak hours when bus services were increased) among the studies, as did the type of areas studied (e.g., urban vs. rural). Some studies were also able to determine which elements of basic transit stop infrastructure had the most influence on transit ridership. The types of transit improvement projects ranged from simple, such as adding trash receptacles and lighting at stops, to complex, such as adding new LRT lines or installing transit signal priority. Most studies looked at ridership impacts on buses; there were very few on rail.

Although causality is often difficult to prove, if stop improvements such as shelters and benches do contribute to ridership growth as the literature suggests, there is potential to grow transit ridership in Virginia through stop improvements. For example, the Greater Richmond Transit Company's Essential Infrastructure Plan noted that of the region's 1,609 bus stops, only 21% and 5%, respectively, had a bench or a shelter as of 2022 (Greater Richmond Transit Company, 2022). If the agency meets the plan's 5-year goal of 50% to 75% of stops having seating or shelter, the short-term ridership growth from improving hundreds of stops could be substantial.

No relevant studies were found that could help answer the second study question regarding estimates of the percentage of ridership occurring during peak hours for typical fixed-route bus and rail services.

Validation of Findings From the Literature

The effects of stop improvement projects on bus ridership were examined for one Virginia transit agency to validate the finding that ridership tends to increase after stop improvements. For more context, four case studies where bus stops were improved at another Virginia transit agency illustrate a combination of reasons for the improvements beyond ridership growth, such as to improve passenger safety, comfort, and access. To explore the unanswered question of the proportion of daily transit riders during peak hours, transit agency data were examined and then comparisons were made between those data and StreetLight transit activity data.

Effects of Stop Improvement Projects on Bus Ridership

Stop-Level Ridership for Arlington Transit

This section summarizes the effects on ridership of a set of bus stop improvement projects by Arlington Transit. Tables 5 and 6 show the changes in ridership at a stop level for the treatment group (improved stops) and the control group (unimproved stops). Table 5 also shows the 16 stops that were served by Metrobus route 3Y, which had increases in service frequency during the study period. WMATA provided 3Y schedule information for September 2017 and December 2019 (Castrovinci, 2023). Comparing service frequency changes, the number of bus trips increased from 7 to 13 and from 8 to 13 in the morning and afternoon peak periods, respectively. The bus headways in 2017 ranged from 11 minutes to 30 minutes in the morning peak period, which improved to 10 to 15 minutes in 2019. Similarly, the bus headways in 2017 for the afternoon peak period ranged from 20 to 30 minutes and improved to 12 to 24 minutes in 2019. In both tables, the average daily ridership provided by Arlington Transit represents the average daily boardings at the stop over a calendar year rounded to the nearest whole number. The pre-improvement ridership counts for both groups were ensured to be comparable to each other through the removal of outliers. Any stops with missing data were removed. The sample size of unimproved stops was smaller (N = 11) than the sample size of improved stops (N = 30). The percentage change in ridership for both groups was calculated, and the results of the F-tests and T-tests are shown. Table 7 describes the mean ridership change in the treatment and control groups, and Table 8 compares the mean ridership change over time for the two groups. The tables also show whether the results were statistically significant.

Table 5. Differences in Ridership Counts for Each Treated Stop Between 2017 and 2019

Stop No.	Average Daily Ridership (Boardings/Day)		
	2017	**2019**	**Difference After Improvement (δ1)**
1	4	6	(+) 2[a]
2	3	10	(+) 7[a]
3	4	19	(+) 15[a]
4	6	27	(+) 21[a]
5	9	11	(+) 2[a]
6	2	17	(+) 15[a]
7	2	8	(+) 6[a]
8	1	20	(+) 19[a]
9	3	18	(+) 15[a]
10	3	10	(+) 7[a]
11	0	5	(+) 5[a]
12	0	0	(+) 0[a]
13	0	2	(+) 2[a]
14	0	10	(+) 10[a]
15	0	2	(+) 2[a]
16	0	12	(+) 12[a]
17	3	14	(+) 11
18	4	4	0
19	2	7	(+) 5
20	1	13	(+) 12
21	2	1	(-) 1
22	6	9	(+) 3
23	1	1	0
24	8	9	(+) 1
25	3	5	(+) 2
26	6	11	(+) 5
27	7	21	(+) 14
28	13	8	(-) 5
29	9	18	(+) 9
30	11	15	(+) 4

[a] Stop affected by service increases in one route (3Y).

Table 6. Differences in Ridership Counts for Each Control Stop Between 2017 and 2019

Stop No.	Average Daily Ridership (Boardings/Day)		
	2017	**2019**	**Difference After No Improvement (δ2)**
1	1	11	(+) 10
2	18	23	(+) 5
3	8	6	(-) 2
4	12	20	(+) 8
5	2	3	(+) 1
6	10	24	(+) 14
7	1	2	(+) 1
8	7	4	(-) 3
9	2	5	(+) 3
10	6	4	(-) 2
11	15	2	(-) 13

Table 7. Mean Ridership Statistics for Treatment and Control Stops in 2017 and 2019

Statistic	Treatment Stops		Control Stops	
	2017	**2019**	**2017**	**2019**
Mean Ridership	3.77	10.43	7.45	9.45
Variance	12.39	45.84	34.07	75.27
Sample Size (N)	30		11	
T-test Statistic	4.79***		0.63	

*p < 0.1; **p < 0.05; ***p < 0.01.

Table 8. Ridership Change Statistics for Treatment and Control Stops in 2017 and 2019

Statistic	Treatment Stops	Control Stops
Mean Increase in Ridership (2017-2019)	6.67	2.00
Variance	41.75	53.8
Sample Size (N)	30	11
T-test Statistic	1.86**	

*p < 0.1; **p < 0.05; ***p < 0.01.

For both the treatment and control groups, the mean ridership in 2017 and 2019 was calculated using the data provided, i.e., the mean ridership at the stops before and after any improvements were implemented. The F-test and T-test were used to examine statistical significance. The stop-level ridership increased in a statistically significant manner for the treatment group at all tested significance levels using the T-test for unequal variances, but for the control group, the increase in ridership was not statistically significant at any tested significance level using the T-test for equal variances. In addition, the 177% increase in ridership in the treatment group was statistically significantly higher than the increase in the control group (27%) over the same time period at the 90% and 95% confidence intervals using the T-test for unequal variances. Overall, stop-level ridership growth was 233.33% higher at bus stops with improvements than at stops without improvements based on the data provided by Arlington Transit. In both cases, other factors besides stop improvements may have contributed to the increase.

The literature reviewed in the previous section indicated similarly large increases in ridership when improvements were made to bus stops in Salt Lake City, Utah (Kim et al., 2020). Despite the observed growth in ridership, Kim et al. did not definitively conclude that improving stop infrastructure had caused the increases in ridership. They were not able to distinguish between whether the increased ridership was due to new riders using the improved stops, riders switching from unimproved stops to improved stops, or pre-existing riders choosing to ride transit more frequently. Similarly, the present study cannot determine the exact cause of the growth in ridership for the Arlington stops. It is unclear how long it takes for ridership to respond to stop improvements, and this is also likely to depend on internal factors such as the marketing efforts of the transit agency and external factors such as regional geography and preferences of the locality's residents (Jenkins, 2022). Although a set of control stops was used with pre-improvement ridership levels similar to the improved stops, it is possible that the larger growth in ridership at improved stops can be attributed to factors other than the stop improvements alone. It is also possible that the stops were improved because of changes in land use nearby, e.g., the development of new apartment complexes, in which case the growth in ridership would be largely attributable to changes in land use. In addition, census data show that the population in Arlington County increased by 0.9% from 234,647 in 2017 to 236,842 in 2019, which may have led to an increase in bus riders overall (U.S. Census Bureau, 2019).

Further, it was discovered in the final stages of this study that 16 of the 30 treated stops had also had changes in service frequency for one of the routes that served the stops, and the literature shows that ridership is affected by changes in service levels. If one excludes the 16 stops from Table 5 where there was a change in bus service frequency, then the remaining 14 improved stops in Table 5 showed a positive impact on ridership, but the results were less dramatic than those reported in Tables 7 and 8. For instance, whereas mean ridership based on all treated stops grew by a factor of almost 3 (from 3.77 to 10.43 per stop as reported in Table 7), this growth was by a factor of only about 2 (from 5.43 to 9.71 per stop) when only the last 14 improved stops from Table 5, although the difference was statistically significant ($p = 0.02$). As another example, the increase in ridership for the treated group was just 79% (when considering only the last 14 improved stops from Table 5) compared to 177% (when considering all improved stops from Table 5), and the difference in growth rates between control sites and treated sites was not significant ($p = 0.20$). This highlights the fact that real-world conditions are challenging to control. Isolating effects is particularly complex where multiple agencies are involved, as in this case where routes from both Arlington Transit and WMATA served the same bus stops. Both transit agencies had made changes to either stop infrastructure or service frequency that likely contributed to changes in ridership. As a consequence, results involving ridership changes need to be viewed with caution, as it remains unclear how much of the ridership change can be attributed to each of the two types of changes made by the two transit agencies and to other changes exogenous to the agencies.

Blacksburg Transit Bus Stop Improvement Case Studies

A BT transportation planner provided the information in this section (Olsen, 2023). BT identified four bus stops where ridership changes followed stop improvements. However, BT indicated that the ridership changes could not be directly attributed to the bus stop improvements; rather, the ridership changes were generally driven by nearby development. Given BT's context, these ridership changes were due in large part to the expansion and growth of Virginia Tech.

Although these case studies do not quantify the ridership changes, the case study approach can put other data in context by illustrating some of the complexities that arise when implementing bus stop improvements. The cases describe the improvements for each bus stop; the reasons improvements were made, such as to improve safety, provide shelter, and increase stop access for all citizens; and the factors involved in identifying stops for improvements, planning, securing funding, and performing construction.

Bus Stop 2101, Republic and Salem Northbound. Located in the Town of Christiansburg near The Bluffs, an apartment complex served by an hourly bus route, this bus stop was previously in a location with no paved standing area and no sidewalk (Figure 3).

Figure 3. BT Stop 2101: Before (left) and After (right) Installation of Solar Shelter With Bench, Concrete Pad, Sidewalk, and Intersection Curb Ramp. Images by Erik Olsen of BT.

Planning for improvements began in 2012 when a resident requested a hard-surfaced standing area. A lighting analysis and input from a transit working group led to site visits and further discussion to consider improvements including a concrete pad with a shelter, a sidewalk, and an intersection curb ramp. To take advantage of good sun exposure, a shelter with a solar light was considered and ultimately installed (Figure 4). Funding for the project was obtained through a capital grant along with matching funds provided by the town. A schedule was set for improvements, and a construction easement was recorded; the shelter installation occurred in early 2019.


Figure 4. BT Stop 2101 During (left) and Shortly After (right) Construction. Images by Erik Olsen of BT.

Bus Stop 1414, Pheasant Run. This popular late-night stop is located in Blacksburg near several apartment buildings at the end of a street without overhead streetlights (Figure 5, left). It was BT's most vandalized stop at one time; its glass panels had been broken several times, and trash and graffiti were problems.

Figure 5. BT Stop 1414 Before Improvements at Night (left) and in the Daytime During Improvements (Electrical Connection Prepared) (right). Images by Erik Olsen of BT.

BT had previously worked with the property owner to provide an electrical connection (Figure 5, right) for a shelter light and assistance with maintenance before discussion of additional street lighting began in 2011. BT staff recommended that the Town of Blacksburg's traffic committee conduct a review of this location. To facilitate this review, BT arranged for a generator-powered auxiliary light to be placed near the stop on a busy night to demonstrate how additional lighting would improve the safety of the area. After review by the traffic committee, the project was recommended for improvements including the installation of four new streetlights, one near the stop. BT agreed to contribute to the project's expenses related to the light nearest to the bus stop and recommended additional improvements: replacing the existing shelter, extending the concrete pad, and reorienting the shelter to face the street. After the streetlights were installed in 2015, the shelter replacement work was completed by January 2017 (Figure 6).

Figure 6. BT Stop 1414 During Installation of Reoriented Replacement Shelter With Bench (left) and After Construction Including New Street Lighting (right). Images by Erik Olsen of BT.

Bus Stop 1200, Prices Fork/Old Glade Westbound. Located on the outbound side of the heavily traveled Prices Fork Road in Blacksburg, the original bus stop was along the sidewalk with a trash can and there were safety concerns related to the heavy traffic in the area and the stop's proximity to a busy intersection (Figure 7). In 2010, a resident comment was received suggesting that a shelter be installed after a woman with a baby was observed waiting in the rain. Additional input was received from residents about the addition of a shelter; problems with the trash can not being emptied; and conversely, traffic concerns caused by the trash truck stopping nearby to empty the trash can.

After review, BT staff recommended that the stop be moved away from the busy intersection and that a shelter be installed. Following this recommendation, discussions began with the adjacent property owner, Virginia Tech. An agreement was signed between Virginia Tech and the Town of Blacksburg regarding the relocation, construction, and ongoing maintenance of the bus stop/shelter. Improvements to the bus stop were completed in late 2015 and included a new shelter with bench, trash can, bike rack, and lighting, all at a new location (Figure 8).

Figure 7. BT Stop 1200 Before Improvements. Images by Erik Olsen of BT.

Figure 8. BT Stop 1200 During Improvements (left) (image by Erik Olsen of BT) and After Improvements (right) (image capture: June 2019 © 2023 Google).

Bus Stop 1328, Progress/Broce Southbound. This stop is located in Blacksburg along a road that has seen various improvements over the years resulting from coordination with the property owners and the town. The original condition of the stop featured a small pad, bench, and sign with no connecting sidewalk but well-worn dirt paths (Figure 9).

The original request to install a shelter at this stop was received from a nearby property owner who planned to build a new apartment at the corner of Broce Drive and Progress Street. The development ultimately did not occur, but improvements to the area did happen over time in support of providing better access to the heavily used bus stop. A regional study assessing bus stop safety and accessibility ranked the stop in the top 10 of stops for improvement (New River Valley Metropolitan Planning Organization, Blacksburg Transit, and Kimley-Horn, 2015). The study analyzed various characteristics of bus stops such as existing infrastructure, safety concerns, ridership, visibility, etc., to rank locations for improvement. After the study, additional improvements occurred along this corridor to include additional sidewalks, bike lanes, a new pad for a shelter, and shelter installation. These improvements were completed in coordination with the Town of Blacksburg and the adjacent property owner by November 2022 (Figure 10).

Figure 9. BT Stop 1328 Before (left) and After (right) Installation of Sidewalk. Images by Erik Olsen of BT.

Figure 10. BT Stop 1328 During (left) and After (right) Installation of Shelter With Bench. Images by Erik Olsen of BT.

Summary of BT Case Studies. Common themes in the case studies of BT stop improvements included the following:

- The improvements included citizen input, whether as part of the initiation of the request for improvements, through a review committee, or through a planning process.
- The improvements included the addition of, or in one case the replacement of, a shelter.
- Lighting was a consideration related to safety and comfort and could include solar-powered shelter lighting, standard shelter lighting, and streetlights.
- Examples of coordination with adjoining property owners included recording a construction easement, extending electrical service, and developing written agreements or memoranda.
- Coordination was required between the transit agency and the town's public works department and utility providers.
- Stop improvements occurred in coordination with other efforts such as sidewalk installation and road improvements.
- Stops required maintenance, even after improvements (e.g., trash pick-up and shelter maintenance).

Proportion of Daily Transit Riders During Peak Travel Hours

This section summarizes differences among the hourly ridership distributions of the four bus transit agencies and discusses the hourly ridership distributions for two rail agencies.

Bus Transit Agency Data

The hourly ridership variations of the four selected bus transit agencies and their ridership counts are displayed in Figure 11, and their respective locations in Virginia are shown in Figure 12.

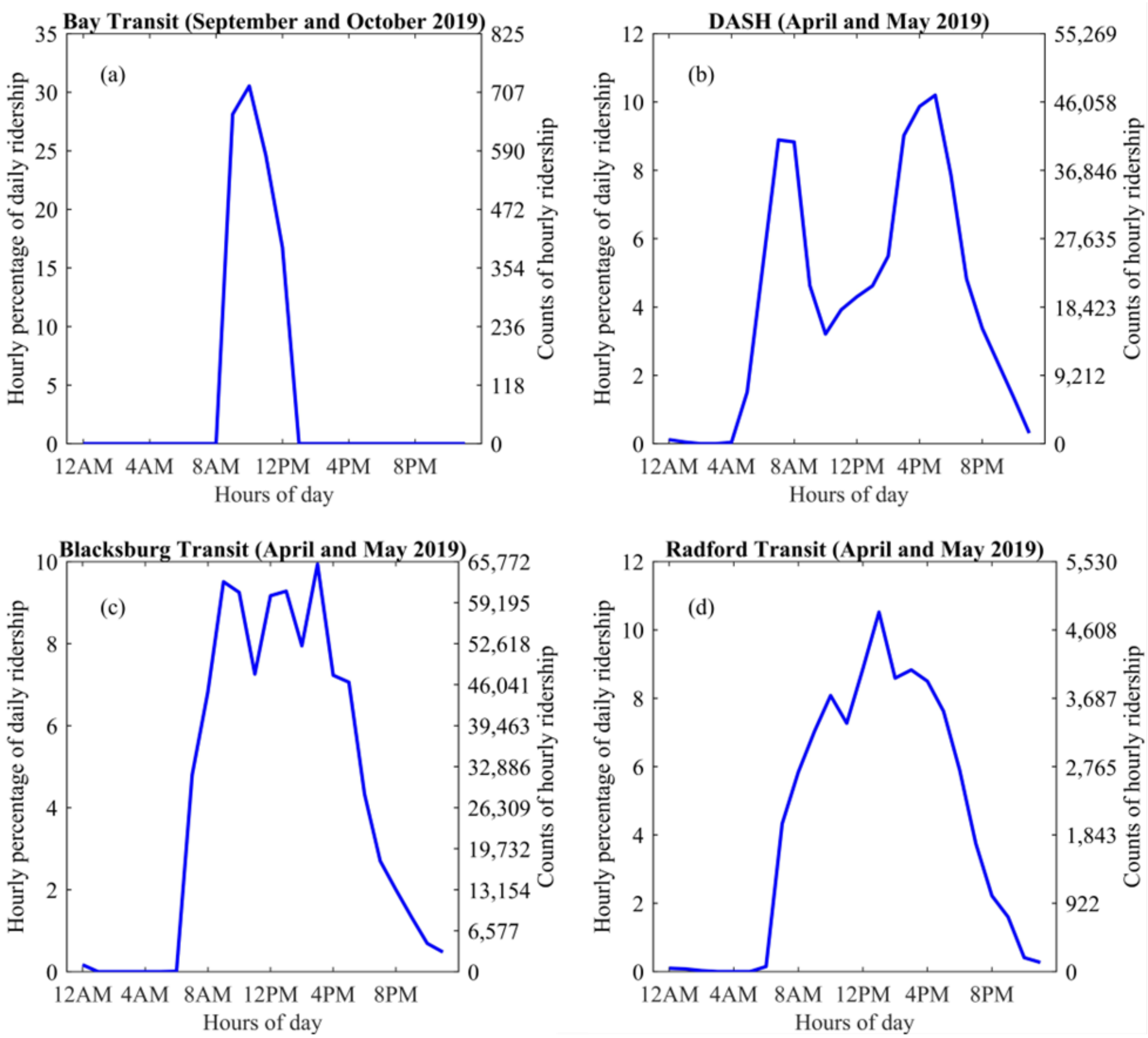

Figure 11. Hourly Variations of Bus Ridership Across the Four Bus Agencies in 2019: (a) Bay Transit (September and October); (b) DASH (April and May); (c) Blacksburg Transit (April and part of May); (d) Radford Transit (April and May).

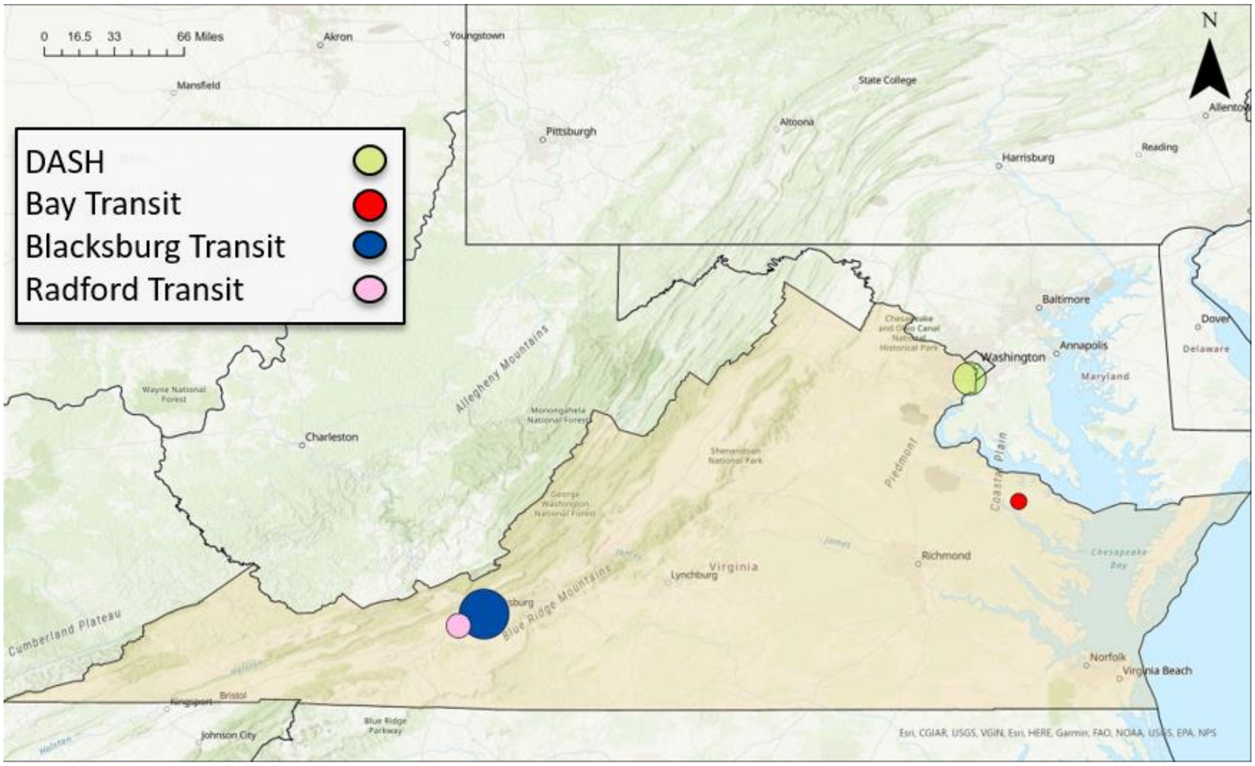

Figure 12. Map Showing Locations and Relative Ridership Levels (Indicated by Dot Size) of the Four Selected Bus Transit Agencies

Operating hours varied among the four agencies. Bay Transit's fixed routes operated from 9 AM through noon (much of its service was demand-response), so fixed-route ridership distribution was concentrated in the 3 operating hours with high hourly percentages, exceeding 30% at its peak hour. DASH had the longest span of service, at 22 hours, and its ridership peaked at typical morning and afternoon commute hours of peak traffic congestion. BT and Radford Transit both served college towns, and their hourly ridership distributions differed from those of DASH. Further, the student population of Virginia Tech in Blacksburg was almost 4 times larger than that of Radford University as of 2020 (Data USA, n.d.). BT and Radford Transit both displayed fairly consistent ridership throughout the day rather than discernible morning and afternoon peaks. Moreover, BT had a triple-peak pattern of morning, midday, and midafternoon, and Radford Transit had one peak during the lunch hour. These peaking patterns likely reflect the high levels of on-campus activity during the day, along with (possibly) lunchtime trips made by university personnel. With the exception of Bay Transit, the percentage of daily ridership during the peak travel hour at the three other transit agencies ranged from 10% to 11%. This was lower than DRPT's current assumption of 20% for all fixed-route services.

Rail Transit Agency Data

According to WMATA data, the six studied Metrorail stations had entry volumes that ranged from approximately 90,000 to 500,000 for the 4-month period of April, May, September, and October 2019. The average hourly entries at each station are shown in Figure 13.

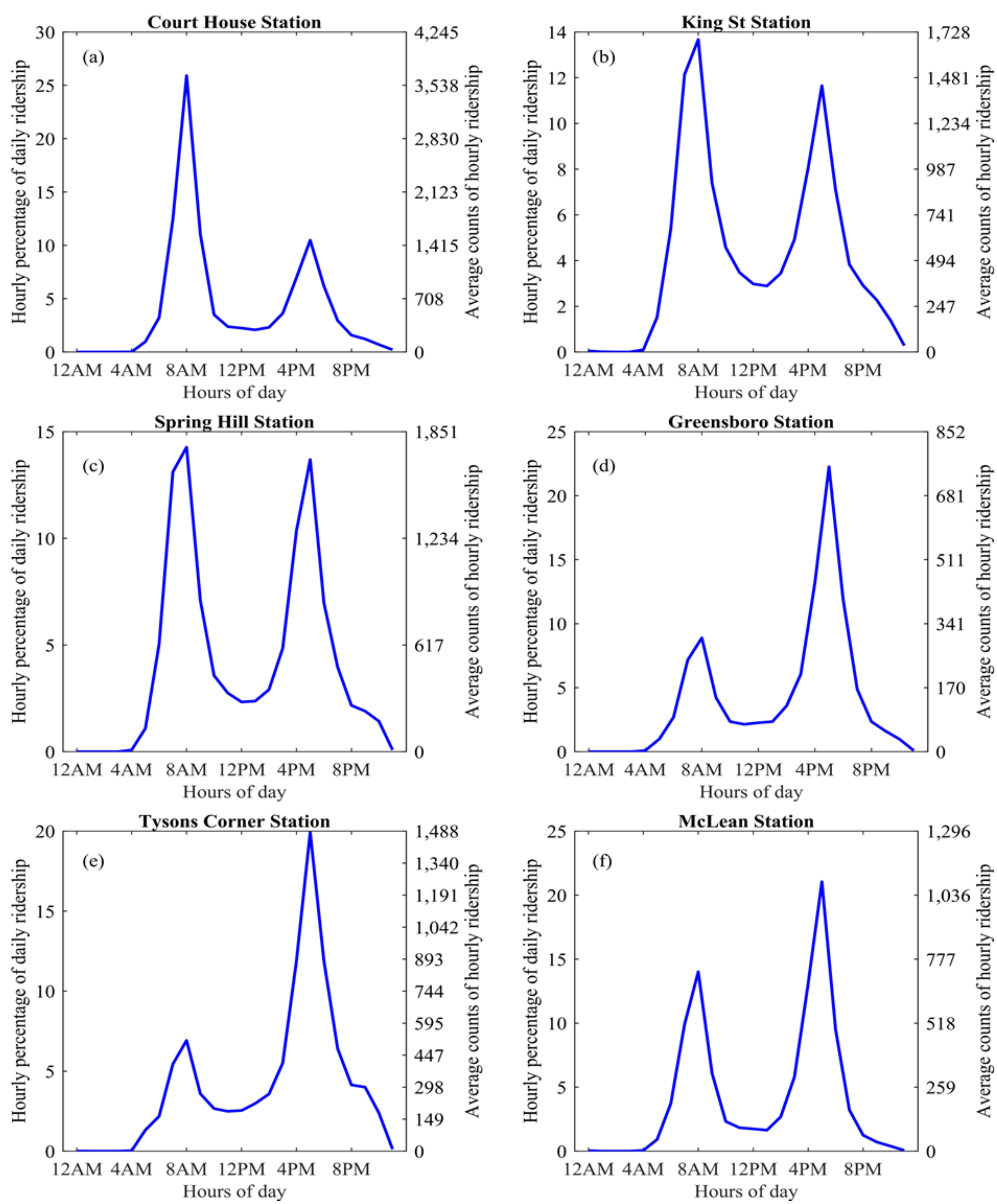

Figure 13. Hourly Variation of Ridership (Station Entries) at Six Metrorail Stations in 2019 (April, May, September, and October): (a) Court House; (b) King St; (c) Spring Hill; (d) Greensboro; (e) Tysons Corner; (f) McLean.

Of these six stations (locations shown in Figure 14), Court House station in Arlington had the highest average entries during the day, and Spring Hill station, the westernmost station of four in the Tysons area, had the fewest. Court House and King St–Old Town stations in Alexandria both had more entries in mornings compared to evenings, with the opposite pattern at the Greensboro, Tysons, and McLean stations. Spring Hill station had a marginally higher number of entries in the morning compared to the evening. In all cases, morning peaks were at 8 AM and evening peaks were at 5 PM, aligning with the region's peak hours for traffic congestion, suggesting that heavy rail trips through these stations were highly commuter oriented. The ridership during the peak travel hour for the six analyzed Metrorail stations ranged from 14% to 26%, in line with DRPT's current assumption of 20%.

The entry volumes derived from VRE data for the six studied VRE stations ranged from approximately 24,000 to 74,000 for the same time period. Figure 15 displays the hourly variations of each station's entries during the day, and Figure 16 shows their respective locations in Northern Virginia. Leeland Road station had the highest average daily entries, and Backlick Road station had the lowest. The hourly percentage of daily ridership during the peak travel hour for the six analyzed VRE stations varied from 37% to 56%, roughly in line with DRPT's current assumption of 40% for commuter route services.

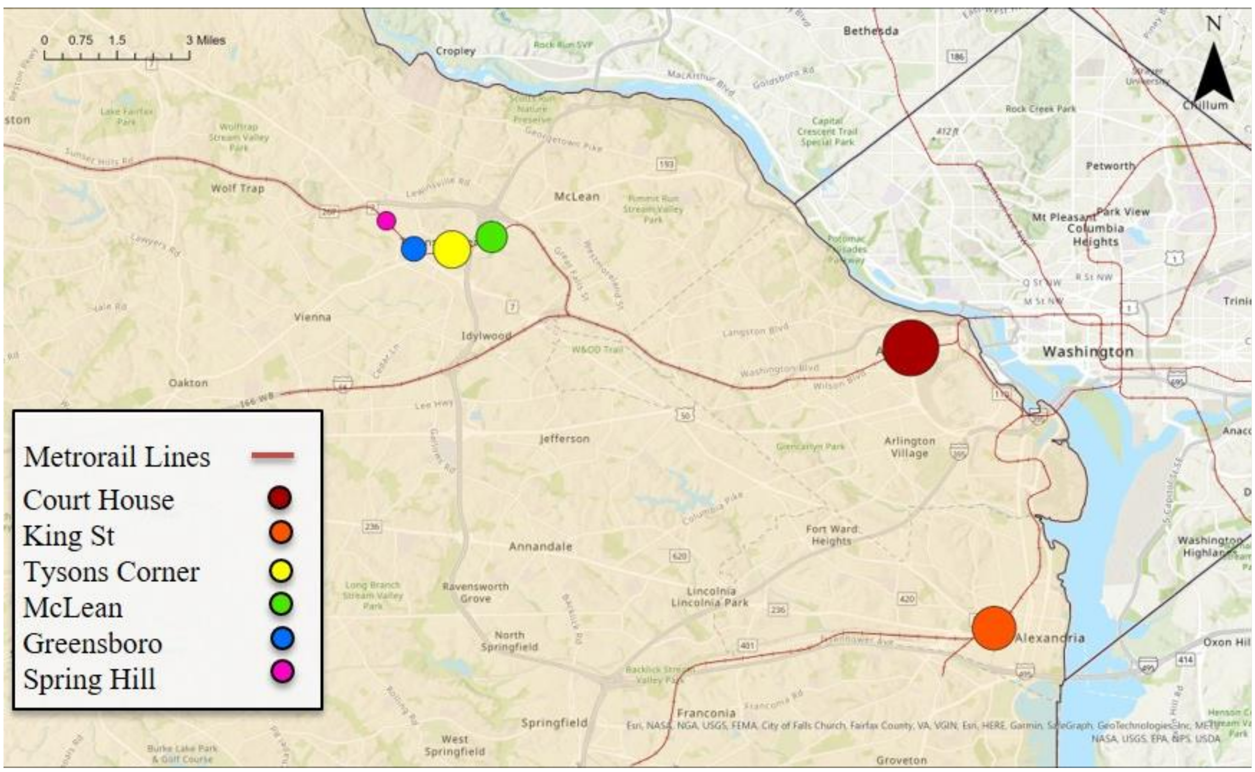

Figure 14. Map Showing Locations and Relative Ridership Levels (Indicated by Dot Size) of the Six Selected Metrorail Stations in Virginia

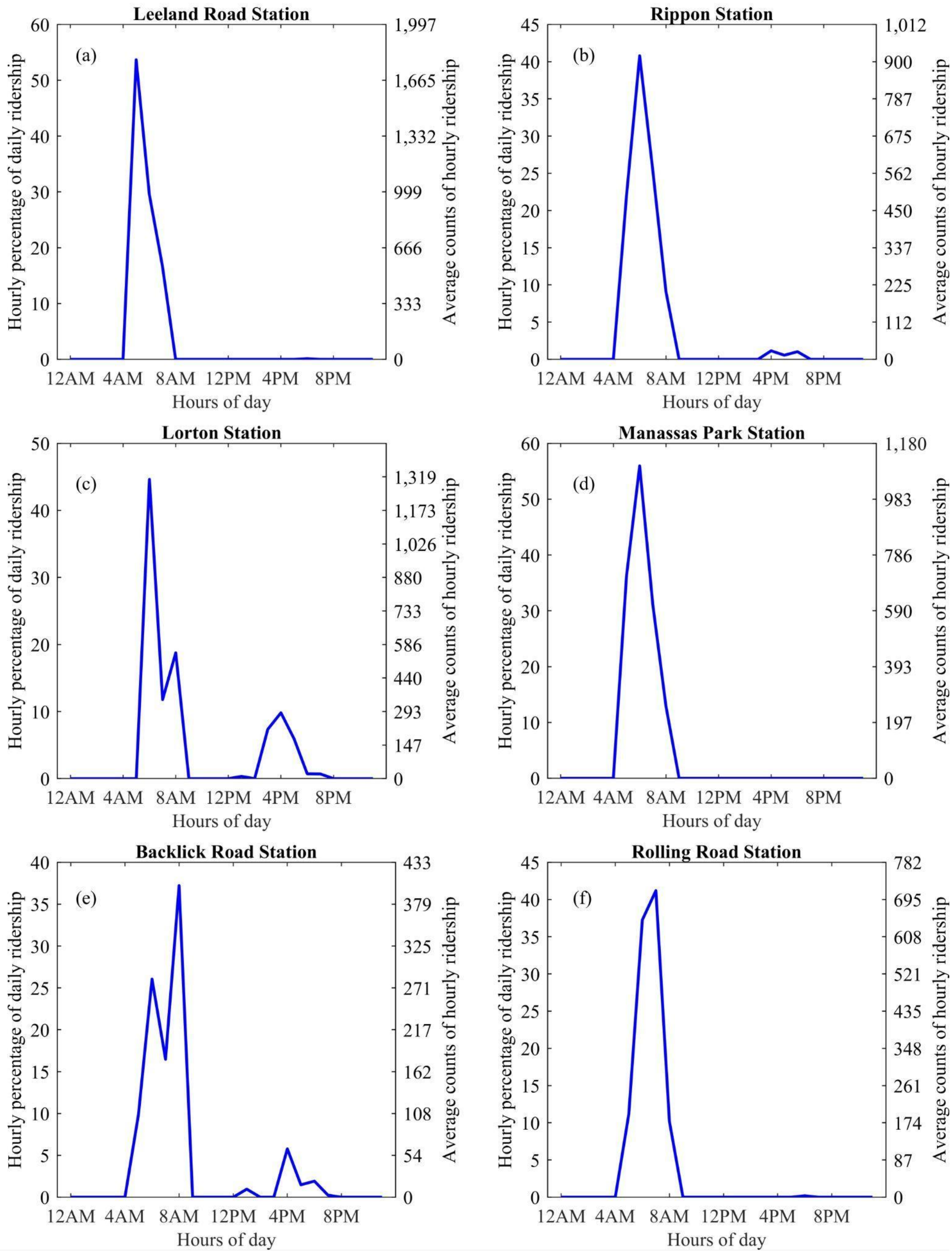

Figure 15. Hourly Variation of Ridership (Station Entries) at Six Virginia Railway Express Commuter Rail Stations in 2019 (April, May, September, and October): (a) Leeland Road; (b) Rippon; (c) Lorton; (d) Manassas Park; (e) Backlick Road; (f) Rolling Road.

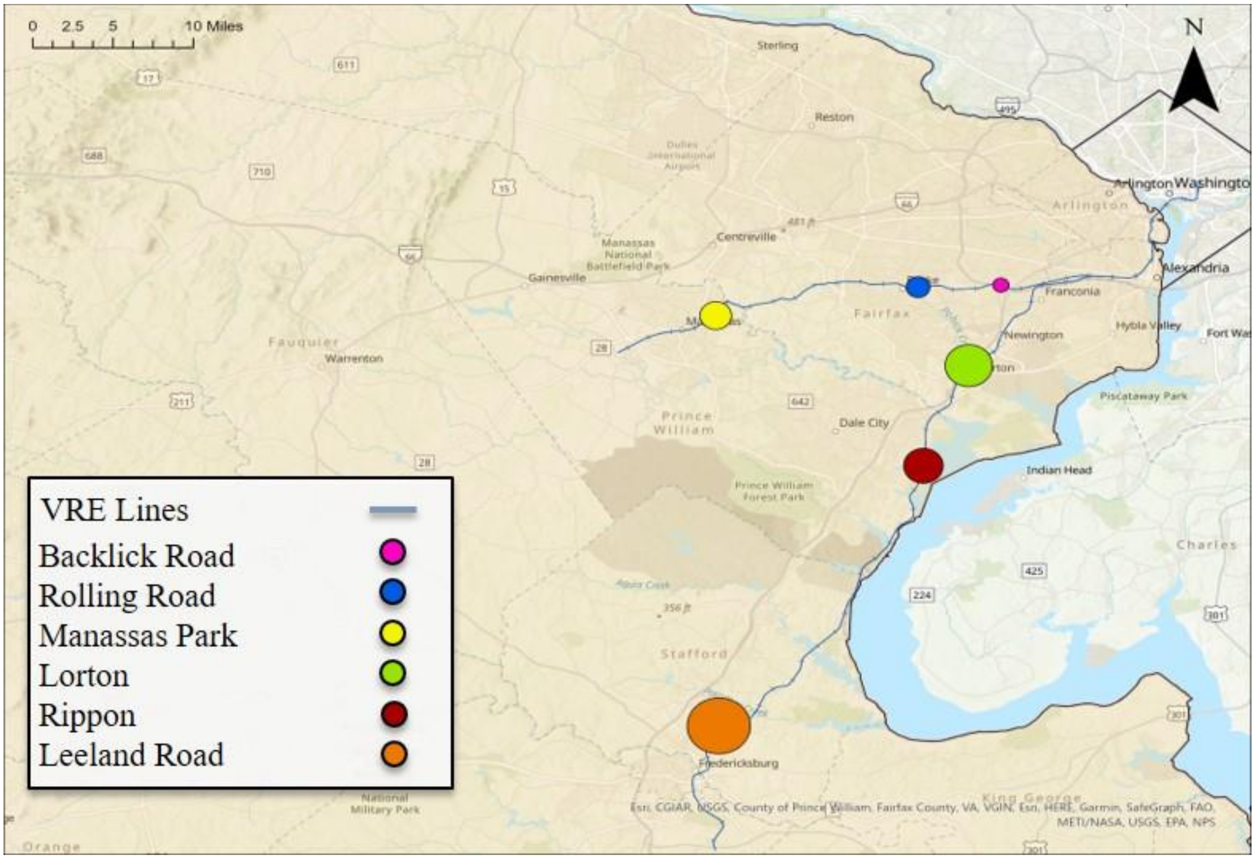

Figure 16. Map Showing Locations and Relative Ridership Levels (Indicated by Dot Size) of the Six Selected Virginia Railway Express Commuter Rail Stations in Virginia

Unlike Metrorail, which operates throughout the day, the VRE commuter rail service operates only during the mornings and afternoons/evenings. This, along with the fact that the six studied stations were outside the region's urban core, resulted in very high hourly percentages of daily boardings during the morning (between 4 AM and 9 AM) compared to the rest of the day. That is, the commuting pattern in Northern Virginia is that people board the train in the morning outside the urban core to travel to work in the urban core. Among the six VRE stations studied, four had almost no entries in the evening period, as seen in Figure 15(a), (b), (d), and (f); this was to be expected for a commuter-type service as the outlying stations have mostly commuters exiting in the evening when returning from work. Lorton station in Figure 15(c) on the Fredericksburg line had a small peak of approximately 10% during the 4 PM hour, and Backlick Road station in Figure 15(e) on the Manassas line had 6% of its daily boardings during the 4 PM hour. For all six stations, there were no train boardings between 9 AM and 1 PM because no VRE trains served these stations during these hours.

Assessment of Accuracy of StreetLight Transit Activity Data

This section presents the outcomes of the StreetLight analyses for the selected transit agencies and compares them with the transit agency ridership data from the previous section. Research on crowdsourced transportation data has evaluated the accuracy of StreetLight data using the MAPE (Tsapakis et al., 2020; Turner and Koeneman, 2017), Akaike information criterion (Kothuri et al., 2022), and RMSE (Kothuri et al., 2022). For the selected rail stations, this study used RMSE to make quantitative comparisons between StreetLight data and the boarding data obtained from WMATA and VRE.

StreetLight Analysis of Bus Activity Levels

An analysis of bus ridership for each locality in Virginia in StreetLight (analysis SL1) showed 80 cities and counties with no data, with the remaining 53 localities showing shares of ridership ranging from 0.00% to nearly 30% of the total bus ridership in Virginia. A possible explanation for why some regions with fixed-route bus services showed 0.00% shares of bus activity, even if they would be expected to show larger shares based on their known ridership statistics, is that StreetLight linked its modal imputations and bus activity data to bus routes included in OSM as of 2019; however, some agencies' routes had not been added to OSM at that time. Analysis of the hourly ridership distribution of the 53 localities showed that a region needed to have at least 0.1% of StreetLight's total bus activity values in Virginia in order to register StreetLight bus activity data throughout typical transit operating hours. Localities with shares below 0.1% consistently had data missing for a substantial number of hours. The results of only two of the localities containing agencies shown in Table 1 were above the 0.1% threshold: Alexandria (9.52%), and Montgomery County (0.60%). Both had unlinked passenger trip values of the same order of magnitude (7-digit numbers) according to the transit agency profile data from NTD (2019). Radford Transit and Bay Transit both had unlinked passenger trip values smaller than those of DASH and BT but of the same order of magnitude. Hence, DASH in Alexandria and BT in Montgomery County were analyzed further in StreetLight.

Although other agencies (including WMATA) operate fixed-route buses in Alexandria, DASH is the city's major bus transit provider (City of Alexandria, 2022). Figure 17 shows that StreetLight data correctly captured the bimodal distribution of DASH ridership and identified the 5 PM peak, with an hourly ridership ratio close to DASH's ground truth value.

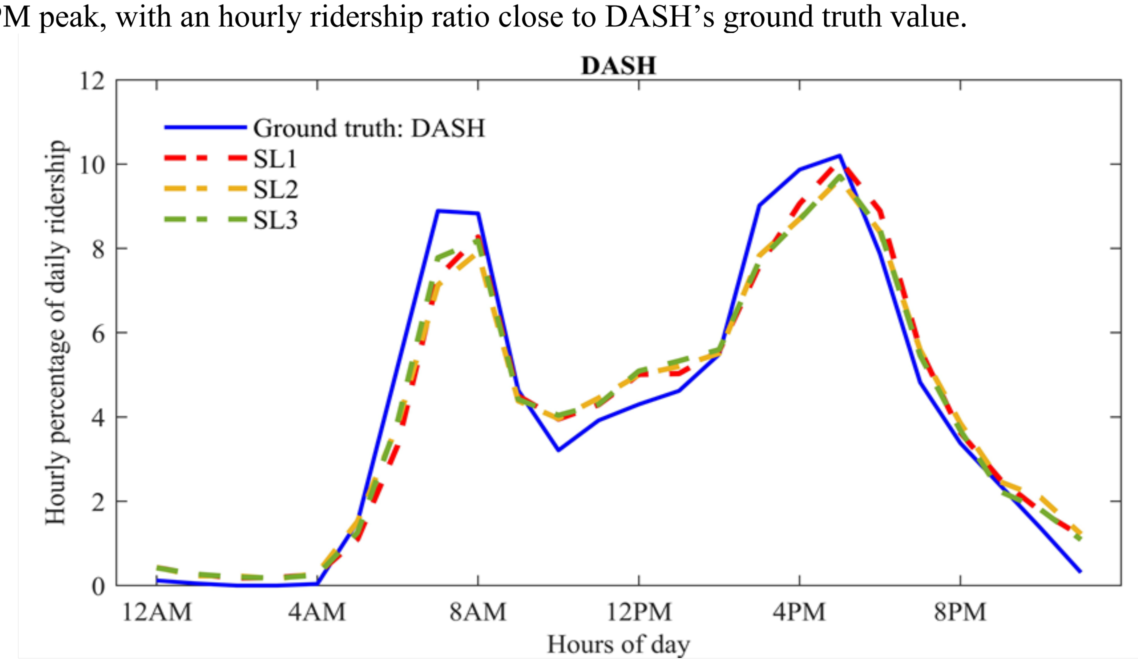

Figure 17. Comparison of StreetLight Analyses of DASH With Ground Truth Data. Metrics from StreetLight InSight®.

The three StreetLight analyses also mirrored the morning peak but with slightly less precision. Analysis SL3 followed the shape of the ground truth curve in the morning peak somewhat more closely than analysis SL2.

SL1 is the aggregate of all StreetLight-derived bus boardings within the entirety of a locality's geographic limits. SL2 and SL3 are the aggregate of StreetLight-derived bus boardings near the transit agencies' bus stops.

Figure 18 shows ground truth ridership data from BT and StreetLight analyses. Although routes from Radford Transit and Valley Metro enter Montgomery County, BT is the county's major transit provider, so analysis SL1 at the county level would be expected to reflect BT's bus ridership patterns. All three StreetLight analyses misrepresented the temporal distribution of the ground truth ridership data: hourly ridership as reported by StreetLight peaked sharply at noon with a smaller peak at 5 PM; the ground truth data displayed neither of these peaks. It is possible that students—BT's primary rider demographic—use applications that generate LBS data (e.g., applications for navigation or food delivery) more when traveling later in the day than when traveling in the morning.

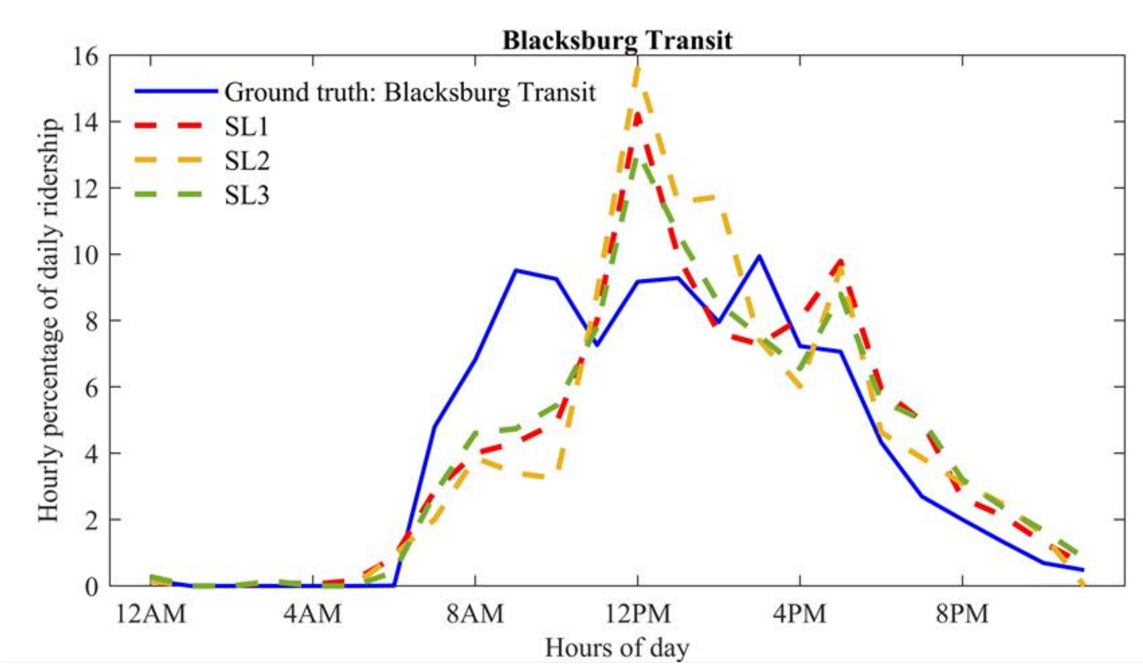

Figure 18. Comparison of StreetLight Analyses of Blacksburg Transit With Ground Truth Data. Metrics from StreetLight InSight®.

RMSE values were calculated for all three analyses, as seen in Table 9. For DASH, analyses SL1 and SL2 had the same RMSE value, and analysis SL3 was marginally more accurate. Although, as with analysis SL3, analysis SL1 used 4 months of data, it was less accurate than analysis SL3. This might have been because StreetLight was picking up activity data from privately owned buses, WMATA Metrobuses, or other agencies' buses, an issue that would be expected to be worse under the jurisdiction-wide analysis of SL1 than in the analyses using only DASH bus stops. These non-DASH bus trips might have a peaking pattern different from that of DASH trips. All three StreetLight analyses were subject to data imperfections due to possible errors in modal imputation (e.g., if auto or bike trips along a bus route were mistaken as bus trips). This might explain why StreetLight indicated nonzero bus-activity levels between 1 AM and 4 AM, which were outside DASH's operating hours. No clear explanation presents itself for the higher off-peak period percentages from 9 AM to 2 PM shown in Figure 17 and the corresponding lower peaks, but three possibilities are as follows:

1. Some form of systematic bias may also exist in the data, as more trips might be mistakenly imputed as being via bus during off-peak hours than during peak hours, possibly because of lower levels of traffic congestion during off-peak hours.

2. Relative to trips during peak hours, higher proportions of off-peak trips might generate LBS data, such as would occur if a higher proportion of off-peak than on-peak passengers used LBS-enabled smartphones.

3. Overcounting in the ground truth data may occur during peaks (or undercounting may occur during off-peaks).

Similar to the DASH analysis results, analysis SL3 for BT yielded the smallest RMSE (Table 9). Although analysis SL1 for BT had a higher RMSE value than analysis SL1 for DASH, analysis SL1 for BT outperformed analysis SL2 for BT. One explanation for the particularly high RSME of BT analysis SL2 could be that the 2 months of SL data included the full month of May 2019 whereas the comparison data provided by BT excluded the portion of May with reduced service levels, which might have different hourly ridership patterns versus full service. Analyses using 4 months of SL data where the additional months reflect full service levels might compensate for this somewhat. Analysis SL1 could have been picking up bus trips not operated by BT, such as Valley Metro's SmartWay commuter buses between Blacksburg and Roanoke. The data imperfections discussed for DASH could also be present here. Depending on the goal of the user, using analysis SL1 might be considered adequate due to the simplicity of the process. Where greater accuracy is required, the more time-consuming technique of buffering bus stops from General Transit Feed Specification files could be used, as done in analyses SL2 and SL3.

The result of DASH's StreetLight analysis was closer to ground truth than BT's. It is interesting to note that the initial analysis of all cities and counties in Virginia using StreetLight showed Alexandria City's bus transit activity to be more than 15 times that of Montgomery County. This stands in stark contrast to ridership numbers obtained directly from the transit agencies, where BT reported about 200,000 more riders than DASH during the same period. More DASH routes may have been present in the OSM of 2019 compared to BT routes, resulting in this difference. There might have been more smartphone users in Alexandria relative to Montgomery County. In addition, Alexandria has bus routes from high-ridership transit agencies such as WMATA, whereas Montgomery County's major bus transit agency is BT. Moreover, the higher RMSE values of BT relative to DASH might reflect the possibility that the StreetLight algorithm could have been trained using datasets more similar to Alexandria than to Blacksburg. In the StreetLight analysis for both agencies, temporal distributions were better captured with longer analysis periods (more months of data), and morning peaks were not captured by StreetLight's algorithm as accurately as evening peaks.

In sum, as shown in Figures 17 and 18 and Table 9, StreetLight results for relative hourly bus activity levels throughout the day were reasonably close to ground truth for DASH and less close for BT, despite the two agencies having unlinked passenger trip numbers with the same order of magnitude (Table 1). Bus transit agencies in Virginia with 2019 unlinked passenger trip numbers less than 10 million from the NTD were found to be unlikely to have 2019 transit activity data in StreetLight.

Table 9. Root Mean Square Errors of StreetLight Analyses of Blacksburg Transit and DASH Relative to Ground Truth

Transit Agency	StreetLight Analysis	Root Mean Square Error
DASH	SL1	0.78
	SL2	0.78
	SL3	0.70
Blacksburg Transit	SL1	2.13
	SL2	2.68
	SL3	1.87

StreetLight Analysis of Rail Activity Levels

In the StreetLight analysis of the six heavy rail (Metrorail) stations, Court House had the most error relative to ground truth. Figure 19(a) shows that StreetLight underestimated the relative level of station entries in the mornings and overestimated the activity level in the evenings. Although exits from the other stations were not analyzed in this study, a brief StreetLight examination of exits for the Court House station found that they better resembled the shape and peak of the ground truth entry data. It is possible that the relatively large RMSE value (see Table 9) resulted from a systematic error that led StreetLight to mislabel the entries and exits for this station.

For all six stations (see Figure 19), StreetLight's peak ridership (entry) percentages were higher in the evenings than in the mornings. Although this matched the hourly patterns of the WMATA data for some stations, it conflicted with patterns at stations with higher morning peaks or roughly equal morning and afternoon peaks—i.e., Court House, King St–Old Town, and Spring Hill, as seen in Figure 19(a), (b), and (c), respectively. The StreetLight analyses of the King St–Old Town and Court House stations did not detect the peak ridership hours per the ground truth data. The StreetLight-predicted morning and afternoon peak ridership hours at the Court House station were both 1 hour earlier than the ground truth. Further, there were substantial differences in temporal distribution between the StreetLight analysis of the Court House station and the ground truth data. As the Court House station is below street level, it is possible that StreetLight might be unable to detect mobile phone pings properly.

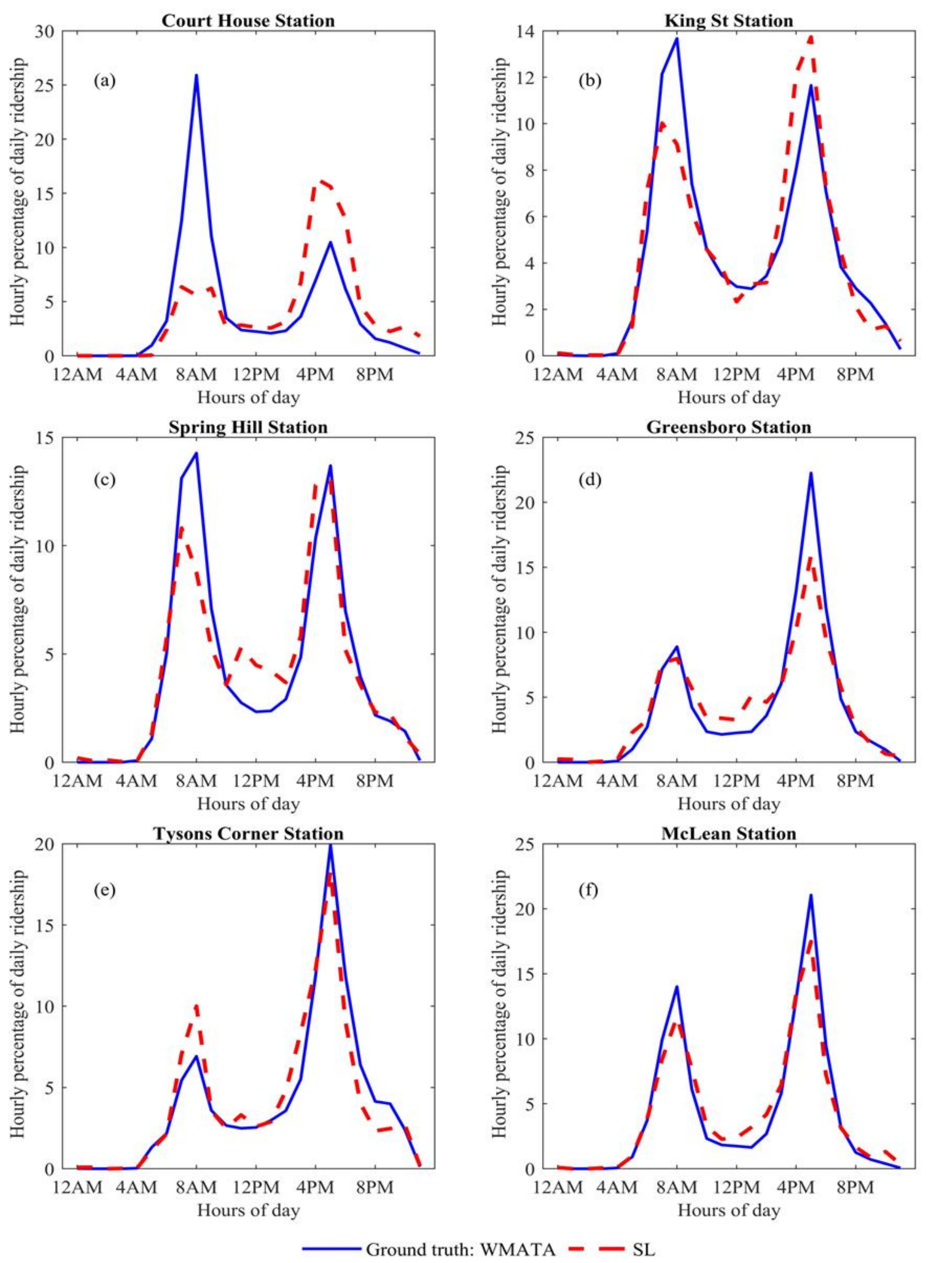

Figure 19. Comparison of StreetLight Analyses of Hourly Heavy Rail Ridership Activity Levels (labeled "SL") at Six Metrorail Stations With Ground Truth Data (labeled "WMATA"): (a) Court House; (b) King St; (c) Spring Hill; (d) Greensboro; (e) Tysons Corner; (f) McLean. Metrics from StreetLight InSight®.

StreetLight's analysis of the King St–Old Town station missed the actual morning peak by 1 hour, but the temporal distribution was more accurate, with a difference of 4% from the ground truth during the morning peak and a smaller difference of 2% during the evening peak. The McLean station had the lowest RMSE and, as shown in Figure 19(f), a relatively good fit. At four of the six stations, the values from StreetLight analyses underestimated the magnitude of the morning peak hour ratio. This might be because, as previously suggested, people might be using applications that generate LBS data on their phones less in the mornings and more later in the day.

Figure 20 shows how the StreetLight analyses for the six VRE commuter rail stations compared to the ridership data requested from VRE, and Table 10 provides RMSE values by station. As shown in Figure 20(e) and Table 10, the StreetLight analysis of the Backlick Road station, with the lowest number of passenger entries among all six stations, had the most error relative to VRE-provided ridership data. However, the Leeland Road station, as seen in Figure 20(a), with the most entries, did not have the lowest RMSE value. The afternoon StreetLight activity data for the Manassas Park and Backlick Road stations, as seen in Figure 20(d) and (e), respectively, were either equal to or higher than the activity in the mornings. As suggested earlier, StreetLight might have mislabeled exits from stations as entries, resulting in the high peak values in the afternoon. With the exception of the Backlick Road and Rolling Road stations, as seen in Figure 20(e) and (f), respectively, StreetLight was able to identify the morning peak hour correctly.

Overall, the RMSE values for the VRE commuter rail stations were higher than those for the Metrorail stations. There are a few possible explanations for this:

- VRE ridership counts are only estimates by the agency, which could contribute to some degree of inaccuracy, whereas WMATA routinely records its ridership counts.

- VRE ridership estimates at each station were lower than WMATA station-level ridership counts. Lower volumes of big-data pings detected at VRE stations could affect accuracy.

- VRE riders and WMATA rail riders could have different smartphone use characteristics, leading to differing ping detection rates by StreetLight.

- In certain hours of the day, VRE trains might stop at stations for long enough that the StreetLight algorithm might "break" the trip (i.e., end the current trip and start another rail trip at that station), which would result in an inaccurately high amount of relative station boarding activity data during that period.

In some cases, StreetLight showed data during hours that Metrorail and VRE were not operating, suggesting it picked up noise, possibly by mislabeling bike, bus, or auto trips as rail trips.

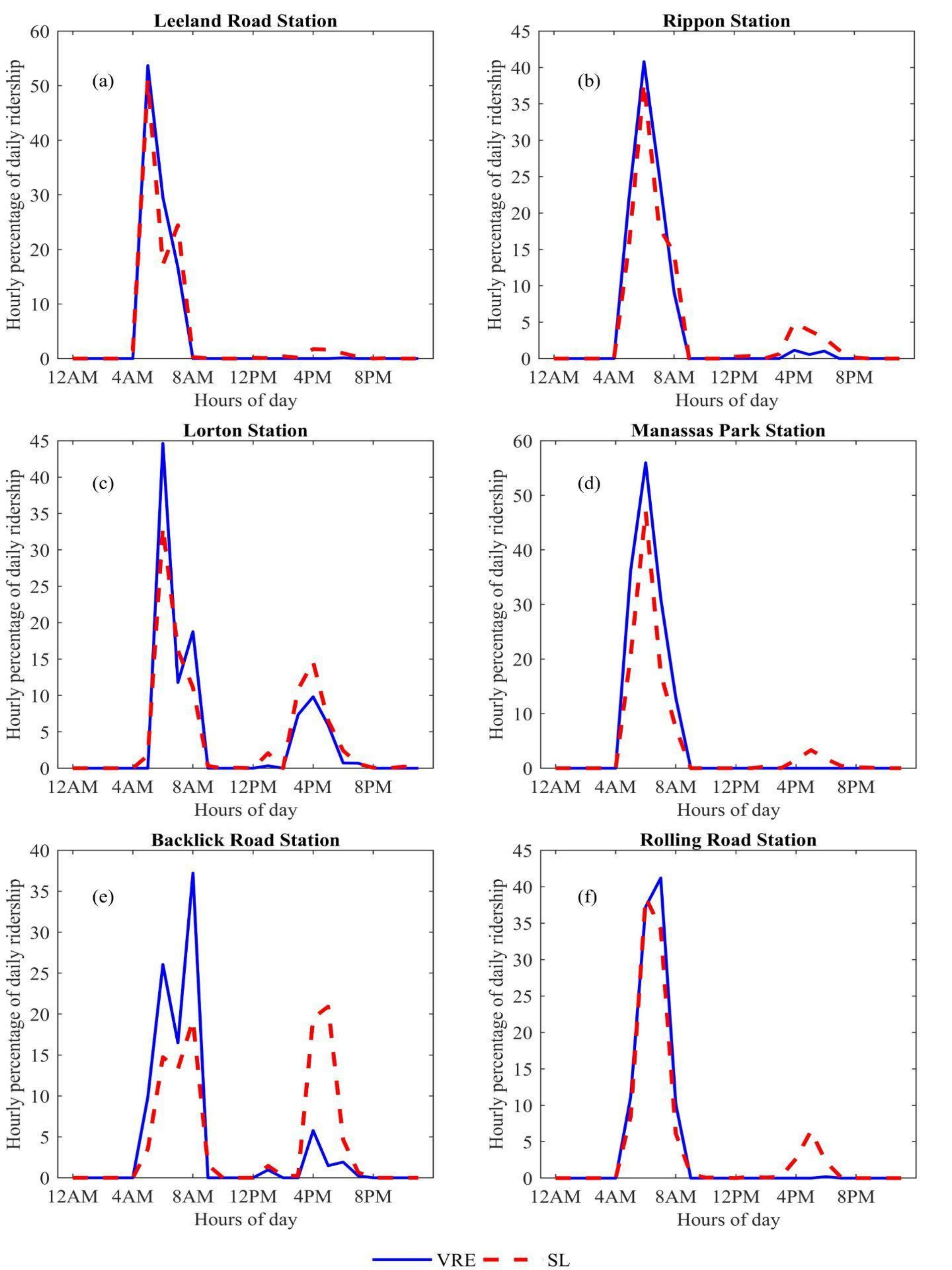

Figure 20. Comparison of StreetLight Analyses of Hourly Commuter Rail Ridership Activity Levels (labeled "SL") at Six Virginia Railway Express Stations With Agency-Provided Data (labeled "VRE"): (a) Leeland Road; (b) Rippon; (c) Lorton; (d) Manassas Park; (e) Backlick Road; (f) Rolling Road. Metrics From StreetLight InSight®.

Table 10. Root Mean Square Error (RMSE) Values for StreetLight Analyses by Rail Station

Transit Agency	Station Name	RMSE
WMATA	Court House	5.22
	King St–Old Town	1.53
	Spring Hill	1.65
	Greensboro	1.74
	Tysons	1.36
	McLean	1.22
VRE	Leeland Road	3.09
	Rippon	2.60
	Lorton	3.26
	Manassas Park	4.83
	Backlick Road	6.71
	Rolling Road	2.31

CONCLUSIONS

- *All of the studies that were reviewed demonstrated a positive relationship between ridership and improvement of transit stop infrastructure, and this study found similar bus ridership increases using data from one Virginia transit agency that had improved a set of its bus stops.* Before-after studies on stop improvements in states other than Virginia had demonstrated bus ridership increases when shelters, concrete pads, sidewalk connections, real-time information systems, pedestrian lighting, benches, trash receptacles, and bicycle parking were added. These increases ranged from 1.5% to 140% at a stop level and up to 2% at a route level. This study found statistically significant stop-level bus ridership increases of a similar order of magnitude (177%) using data from one Virginia transit agency (Arlington County) that had added ADA-compliant landing pads, a few benches, and lean bars and had replaced a few shelters with solar-powered shelters at its bus stops, but it is likely that improvements in bus frequency at some treated stops contributed to some portion of the ridership increase. If the stops where service frequency increased are removed from the analysis, the remaining Arlington stops showed a 79% increase in ridership.

- *Multiple factors have relationships of varying elasticities with transit ridership.* Some of these factors are external to the transit agency, e.g., the built environment of stops/stations and the demographics of the population. Others are internal: service hours, frequency of service, and stop or station infrastructure. Studies have shown that these internal factors generally have positive relationships with ridership; e.g., an increase in service frequency would also lead to an increase in ridership for the transit service. Although the literature is relatively consistent on the directions of these relationships, numerical values vary and likely depend on local context.

- *Although ridership increases were quantitatively examined for the improvements to bus stops, it is important to view these results with caution as ridership changes can also occur due to other factors.* As noted in the literature review, ridership changes could be caused by riders switching from unimproved stops to improved stops. Ridership changes could also be attributed to changes in land use near the stops, such as the construction of a new apartment complex, or to variations in the marketing strategies of the transit agencies. In sum, it is difficult to attribute changes in ridership to one factor alone. It is also important to note that the full effect of bus stop improvements on ridership may take an indefinite amount of time to occur.

- *There may be a need to adjust one of three DRPT assumptions regarding the percentage of daily ridership during the peak travel hour.* The percentage of daily ridership occurring during the peak hour for fixed-route bus boardings was approximately one-half of the previously assumed 20%. Although this study did not examine commuter bus routes, future research could do so if agencies have hourly boarding data. For heavy rail, the percentage of daily ridership during the peak hour was more variable but in line with the assumption of 20%, and for commuter rail, the percentage was roughly in agreement with the current assumption of 40%.

- *For 2019 data, the results from StreetLight analyses showed that it was possible to use a bus transit agency's unlinked passenger trip number or ridership to determine whether using StreetLight to examine relative hourly transit ridership activity levels would be minimally feasible (i.e., whether StreetLight would have relatively complete transit activity data for the agency at the hourly level).* However, no correlation was found between the magnitude of the agency's ridership and the accuracy of StreetLight's results when compared to agency data. For 2019 data, if a transit agency had an unlinked passenger trip number less than 10 million from the NTD, it was unlikely to find relatively complete hourly transit activity data from StreetLight. Similarly, for the months of April-May and September-October of 2019, a locality needed to have at least 0.1% of Virginia's statewide bus activity levels on StreetLight in order to generate results.

- *StreetLight's rail activity data were more likely to be complete, and its analysis process was simpler, for station-level analyses of Virginia agencies than StreetLight bus activity data for Virginia's bus transit agencies.* The accuracy of one mode was not better than the other, but results showed more complete activity data for rail relative to bus.

RECOMMENDATIONS

1. *DRPT should consider the findings of this study if updating the percentage of daily ridership during the peak hour it currently uses for fixed-route bus services.* The findings for rail did not differ from factors DRPT was using, but for three fixed-route bus agencies examined in this study, substantially less of the daily ridership was occurring in the peak hour than DRPT's factors would predict.

2. *DRPT should consider the findings of this study if updating the percentage of ridership increase it currently uses for evaluating bus stop improvements in the form of shelters and benches.* Although this study did not isolate a specific percentage increase for adding these types of stop facilities individually, the literature and data from Virginia suggest that they can contribute to substantial ridership increases.

3. *DRPT should consider using transit activity data from StreetLight for analysis of both heavy rail and commuter rail services.* Although the accuracy of rail activity data in StreetLight was not found to be higher than that of bus activity, StreetLight was found to be more likely to have complete rail activity data than bus activity data. If DRPT chooses to use this data source, instructions in the Appendix provide a starting point for both rail and bus activity data.

IMPLEMENTATION AND BENEFITS

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

Implementation

Recommendations 1 and 2 will be implemented by DRPT's Transit Planning Team. This will be done after completion of an ongoing SMART SCALE program review, the timeline of which is uncertain, but the recommendation is expected to be implemented by August 2024, when benefit calculations begin for Round 6 of SMART SCALE.

Related to Recommendation 2, DRPT has other recent and ongoing initiatives regarding improvements to transit stops such as accessibility upgrades. In fall 2022, the agency updated its policy for its MERIT (Making Efficient and Responsible Investments in Transit) capital grants program to incentivize transit infrastructure accessibility improvements (DRPT, 2022a). Following the recommendations of a study that sampled 700 of the 15,000 bus stops in Virginia, DRPT also plans to develop bus stop infrastructure standards that DRPT and Virginia's transit agencies can use in managing bus stop assets (DRPT, 2022a).

Recommendation 3 will be implemented by DRPT's Rail Planning Team by August 2024, after completion of an ongoing OIPI before-after analysis of funded projects. It is possible that by that time, StreetLight will have updated its datasets and/or algorithms, which might have implications on the accuracy of results. (For example, during the drafting of this report, StreetLight announced improvements to its algorithm to identify bus and rail trips better.)

Benefits

The primary benefits of implementing Recommendations 1 and 2 are improvements in the current project prioritization process with more appropriate valuations of peak-hour transit ridership percentages and ridership changes when basic transit infrastructure such as shelters and benches are added. Based on the first five rounds of SMART SCALE, the funding amount requested for bus transit projects has ranged widely from approximately $152,000 to $102 million per project (Commonwealth of Virginia, 2022). Among these, the funding awarded through SMART SCALE ranged from approximately $219,000 to $57 million per project, with an average cost of $17.7 million per project (Commonwealth of Virginia, 2022) for all five rounds of SMART SCALE. Assuming that a change in project ranking due to the implementation of these recommendations will affect only two projects, one of which would be funded and the other would not, then around $35 million in expenditures could be affected. In sum, there may be a benefit in terms of project prioritization by using more accurate ridership percentages.

Implementing Recommendation 1 would mean applying a smaller percentage of daily fixed-route bus ridership estimates than is done at present during the scoring process for the congestion factor area of SMART SCALE. This could conceivably reduce the scores of some transit projects because their projected congestion-reduction effects would be smaller than under current assumptions. However, an overall benefit might be that this updated scoring process better reflects reality: the peaking patterns seen in 2019 transit ridership data have likely become even less focused on traditional commuting hours in the post-COVID era. Although analysis of post-2019 data was outside the scope of this study, surveys carried out by the APTA showed that more than one-half of all surveyed transit agencies expected peak period travel to be decreasing, which aligns with workplace changes in the post-pandemic era, with more people working remotely and at more flexible hours (APTA, 2021). Put another way, a greater share of transit trips might now take place during off-peak hours and within local communities. In order to reflect the benefits of transit options that serve such trip patterns, DRPT may wish to recommend adjustments to other factor areas of SMART SCALE to account for both the change to the congestion factor area and larger changes in transit ridership patterns.

The main benefit of implementing Recommendation 3 is the facilitation of proper and time-efficient use of StreetLight's transit activity data in transit projects. This will allow both existing and potential users (e.g., planners and engineers) in DRPT, OIPI, VDOT, and partners (e.g., regional planners, consulting companies, etc.) to have an informative reference with detailed step-by-step instructions to determine whether the transit activity data in StreetLight are appropriate for their projects. Users will be able to learn two different methods of estimating bus activity data in Virginia, each with a different level of accuracy and duration to complete, along with the process of estimating station-level rail activity data in Virginia. They would also be aware of possible reasons for inaccuracies in the data.

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APPENDIX

ANALYZING BUS AND RAIL HOURLY ACTIVITY LEVELS USING STREETLIGHT

Instructions

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Peter Ohlms (peter.ohlms@vdot.virginia.gov)

August 2022
March 2023 (updated)

It should be noted that StreetLight is continually updating its interface along with its datasets and algorithms. The research team initially used the version of StreetLight between May 2022 and July 2022. As of March 2023 when this appendix was updated to add the Rail portion, the StreetLight interface had undergone minor changes that are reflected in the Rail portion. Thus, although the StreetLight InSight® platform is the source for all StreetLight screenshots in these instructions, the screenshots might reflect slightly different versions.

EXECUTIVE SUMMARY

StreetLight is a crowdsourced big-data platform that can generate data on transit activity levels in different localities. Planners could potentially use StreetLight data to observe variations in hourly bus and rail ridership activity in cases where it is difficult to obtain ridership data directly from transit agencies.

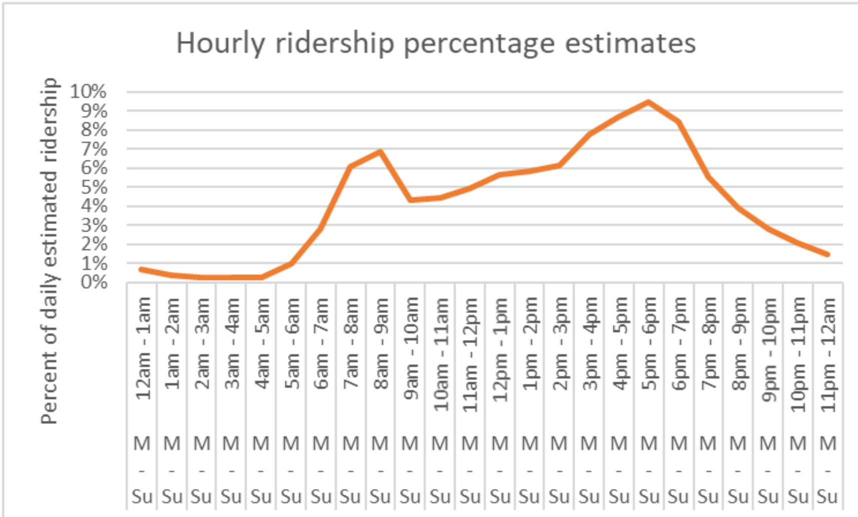
For rail, the process is simple with one method. However, for bus, this could be achieved in two ways:

1. analyzing bus activity levels at a locality (county or city) level or
2. analyzing bus activity levels for all bus stops of the transit agencies serving the locality.

This document describes the steps for analyzing hourly ridership levels for bus and rail (with two ways shown for bus). Note that these analyses produce only estimates of the hourly percentages of daily transit activity levels based on the StreetLight algorithm, which could be considered an approximation of the hourly percentages of bus or rail ridership levels.

For bus activity, Method 1 (locality level) requires less time to carry out relative to Method 2 (bus stops) but could also be less accurate. Inaccuracies in method 1 may arise as StreetLight may pick up trips made on private buses or non–transit agency buses in that locality. The type of method to be used could depend on a number of factors. If the locality of interest has a single transit agency serving it and/or if speed is more important than accuracy, method 1 may be considered adequate. Method 2, while more time-consuming and requiring use of a GIS tool, could yield more accurate results and should be used where more than one bus transit agency is present if there is a need to differentiate between agencies.

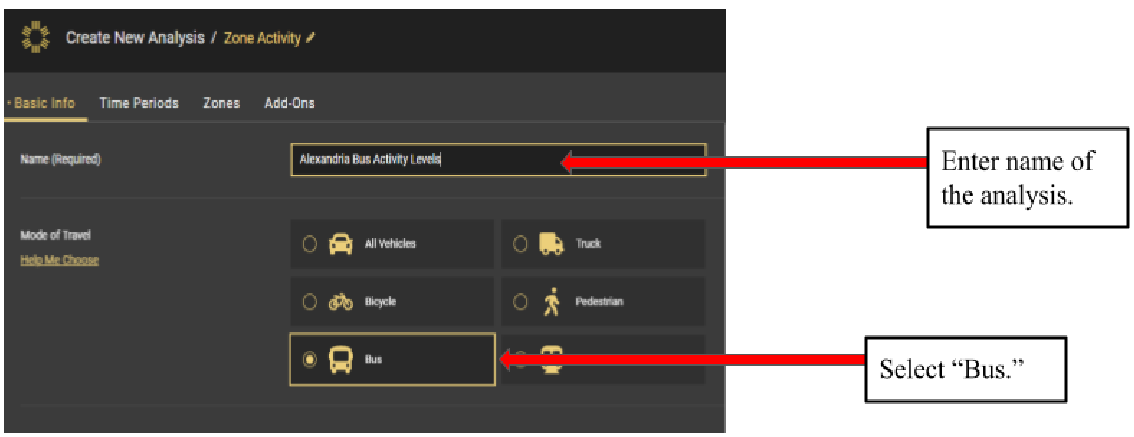
Example Result:



BUS

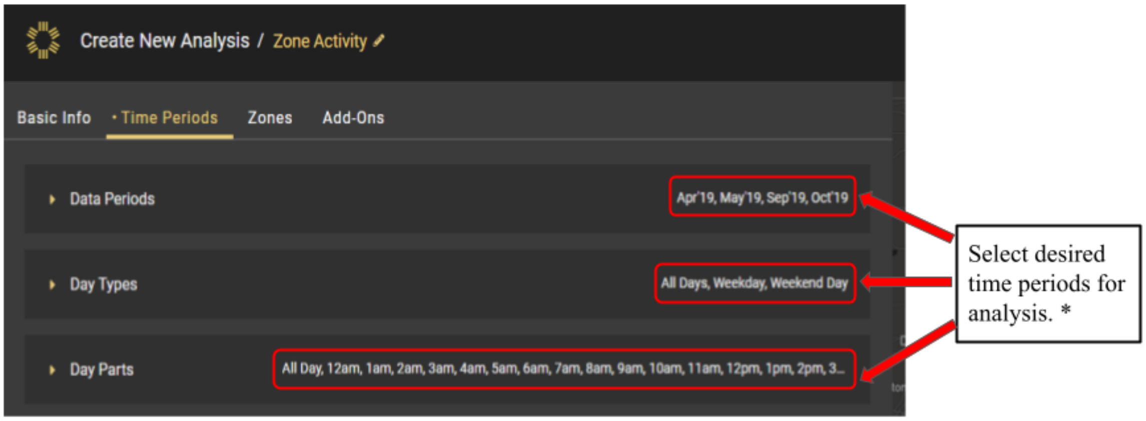
METHOD 1: LOCALITY (COUNTY/CITY) LEVEL (Estimated time to complete: 6 minutes)

1. In StreetLight, select "Create New Analysis" from the Analyses tab;
2. Select "Zone Activity";
3.



METHOD 1: LOCALITY (COUNTY/CITY) LEVEL

4. In the “Time Periods” tab:

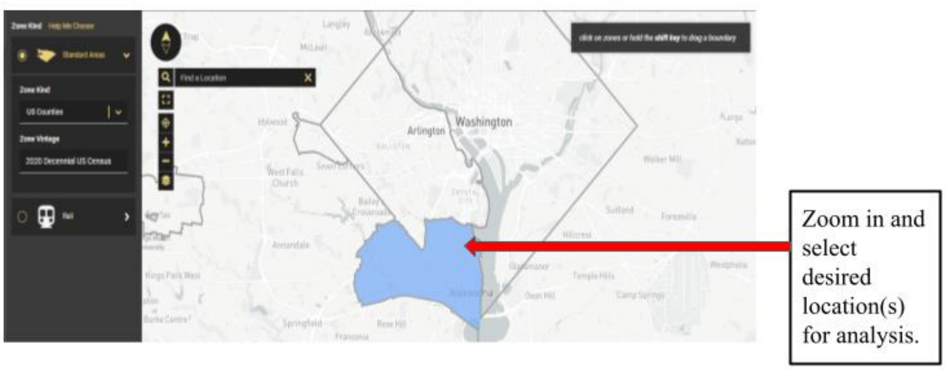


** Analyzing bigger data periods (more months/years) will produce more accurate results. Day Types and Parts may be modified to include or exclude any days or hours, respectively, as required.*

5. In the “Zones” tab, Select “Standard Areas” for the prompt “What Kind of Zone Do You Want to Choose?”

6. Select “US Counties” when prompted to “Choose a type of standard area” (even if your locality of interest is a city).

7.

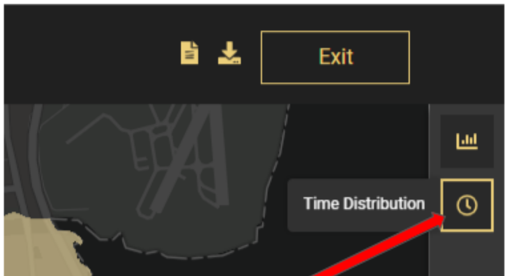


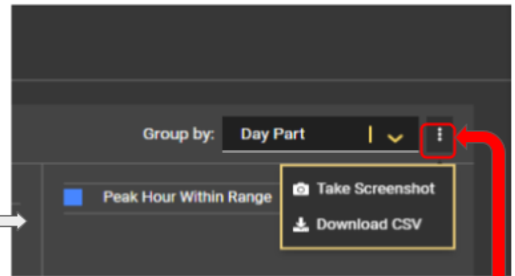
METHOD 1: LOCALITY (COUNTY/CITY) LEVEL

8. Confirm analysis at the bottom right corner of the screen.

9. Once the analysis is complete, select “Open in Viz3D” from the “Actions” drop-down menu.

10.



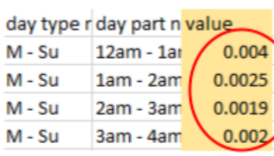


Click the “Time Distribution” icon (upper right of window).

Click here and download CSV. *.

** The day type, day part, and type of trip (starting/ending) of the CSV can be selected from the left side of the screen prior to downloading.*

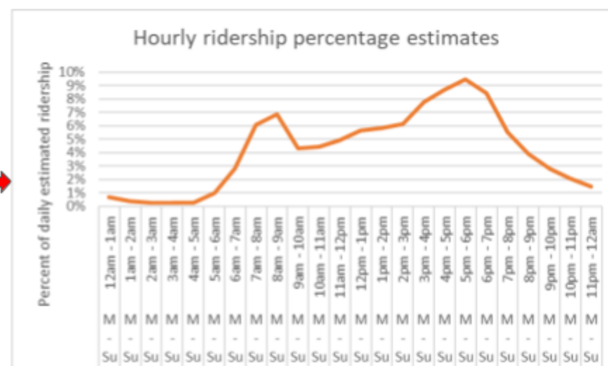
11. Open the CSV file in Excel.



day type r	day part n	value
M - Su	12am - 1ar	0.004
M - Su	1am - 2am	0.0025
M - Su	2am - 3am	0.0019
M - Su	3am - 4am	0.002

Multiply these values by 100 or use Excel’s “Percent Style” number format to get the hourly percentages of bus transit activity levels.

12. Plot a graph of hourly transit activity percentages against hours of the day.



METHOD 2: TRANSIT AGENCY BUS STOPS (Estimated time to complete: 30 minutes)

This method uses ArcGIS Pro. For similar instructions using QGIS, contact StreetLight.

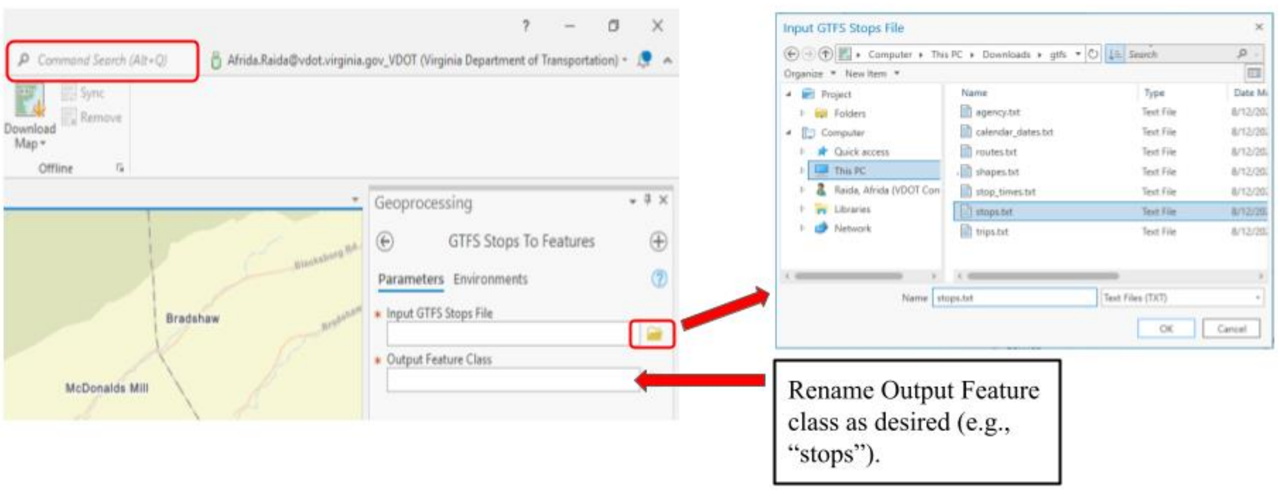
1. Identify the bus transit agency or agencies* serving the locality of interest.

2. Obtain a GTFS file representing the bus stops of the agencies, either directly from the transit agency/agencies or from the website https://virginia-gtfs.com/, for the time period to be analyzed in StreetLight. (For older GTFS files, e.g., for a StreetLight analysis using 2019 data, follow links to other sites such as Transitfeeds.) Unzip the folder if required in order to work with the file "stops.txt."

** For localities with multiple transit agencies:*

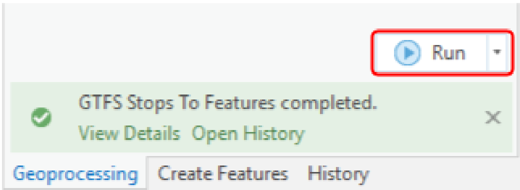
- *To estimate cumulative ridership across multiple agencies, perform steps 2 through 5 for each agency of interest, thus producing multiple feature classes. Before step 6, use the GIS data management tool "merge" to create a single feature class representing all bus stops of agencies of interest.*
- *To estimate ridership of each transit agency, perform all steps in Method 2 for the first agency of interest, then repeat for each additional agency.*

3. Create a new map in ArcGIS Pro and open the geoprocessing tool "GTFS Stops To Features (Public Transit Tools) from the Command Search bar. Import stops into the map.

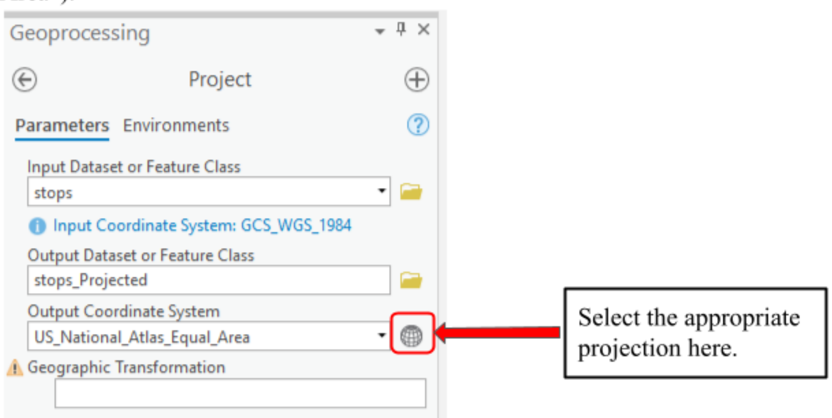


METHOD 2: TRANSIT AGENCY BUS STOPS

4. Click "Run" at the bottom right corner of the screen. A layer with the stops will appear on the map.

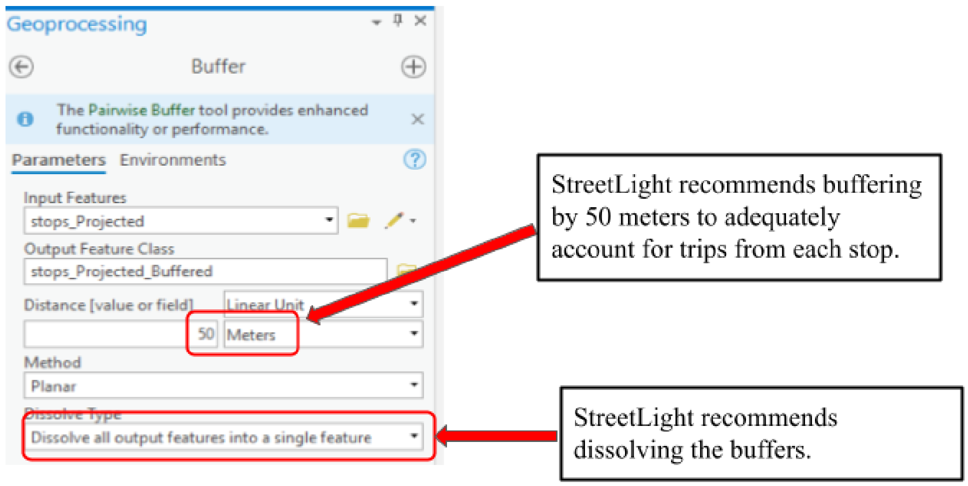


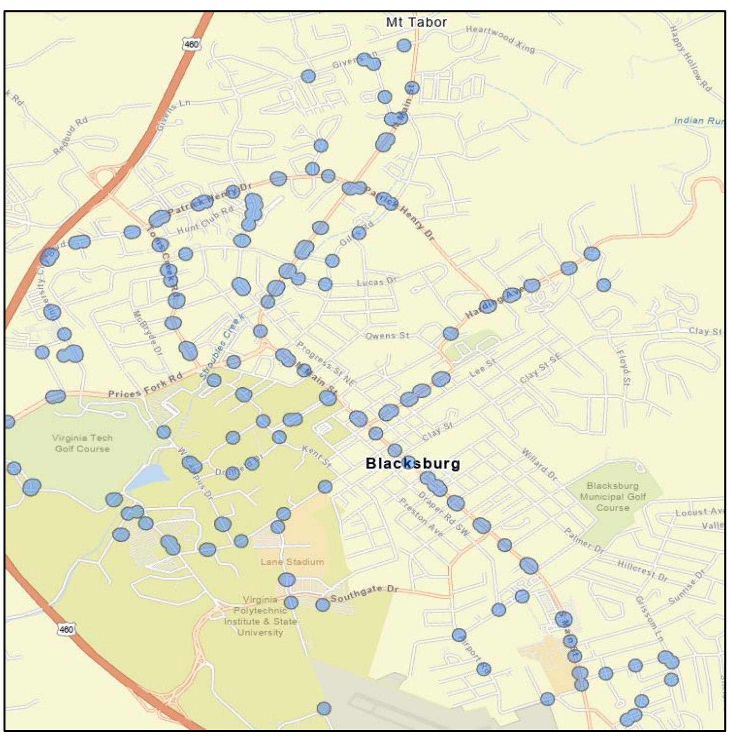
5. Open "Project (Data Management Tools)" from the Command Search bar. Use it to convert the resulting stop layer to the appropriate projection for the locality and click Run (StreetLight recommends using "US National Atlas Equal Area").



METHOD 2: TRANSIT AGENCY BUS STOPS

6. Open “Buffer (Analysis Tools)” from the Command Search bar. Buffer the projected stops layer resulting from the previous step.

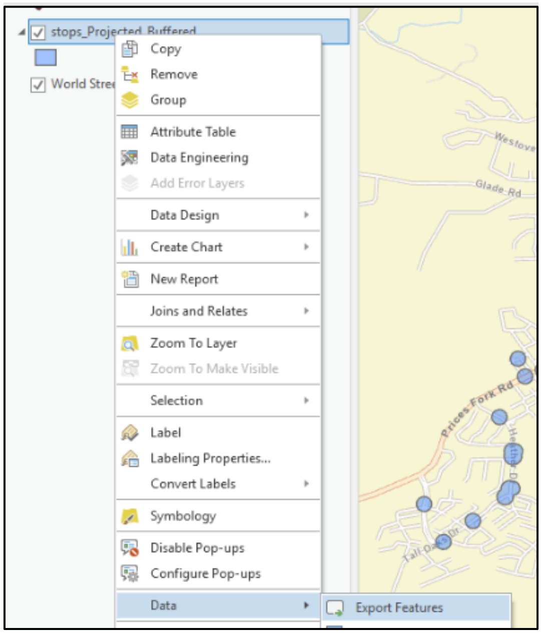


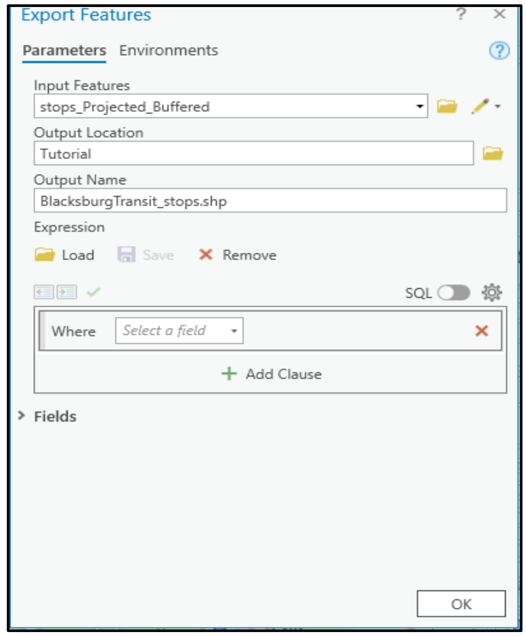


After turning off other stop layers, the resulting stops should appear something like the above map.

METHOD 2: TRANSIT AGENCY BUS STOPS

7. Export the buffered stops feature class for use in StreetLight.



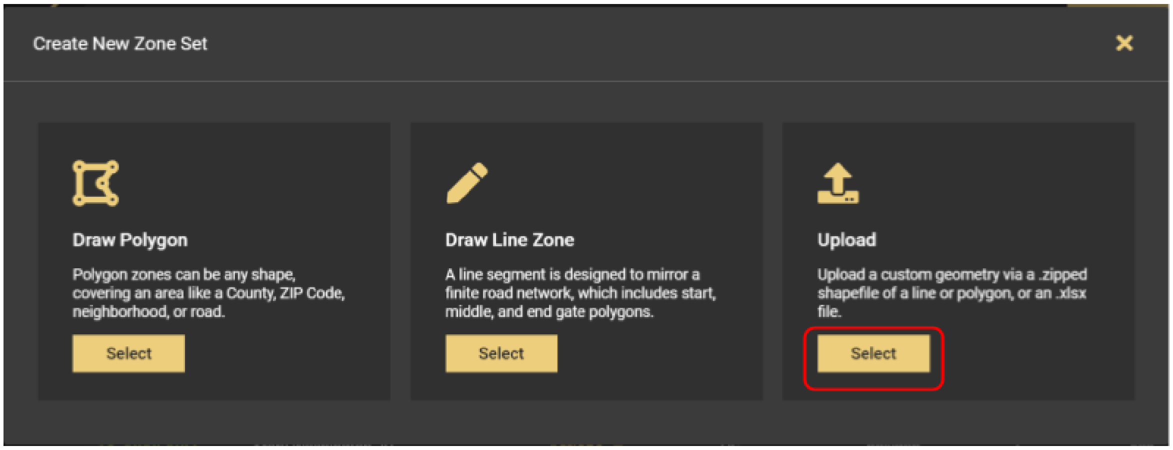


8. Open the folder and compress the following files into a zip folder that StreetLight can accept.

BlacksburgTransit_stops.cpg	8/12/2022 11:55 AM	CPG File	1 KB
BlacksburgTransit_stops.dbf	8/12/2022 11:55 AM	DBF File	1 KB
BlacksburgTransit_stops.prj	8/12/2022 11:55 AM	PRJ File	1 KB
BlacksburgTransit_stops.shp	8/12/2022 11:55 AM	SHP File	169 KB
BlacksburgTransit_stops.shx	8/12/2022 11:55 AM	SHX File	1 KB

METHOD 2: TRANSIT AGENCY BUS STOPS

9. In StreetLight, go to the Zones tab and click "+Create New Zone Set" at the top right corner.



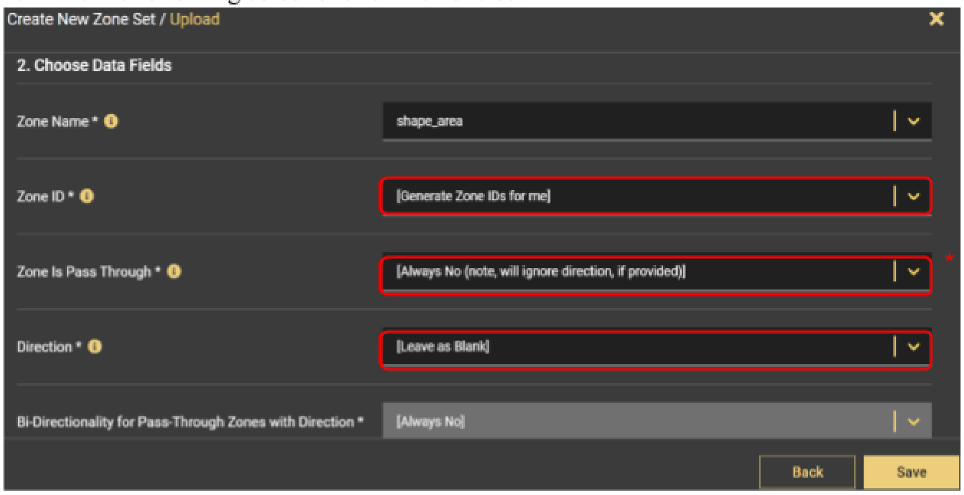
10.

10a. Upload the zip folder.

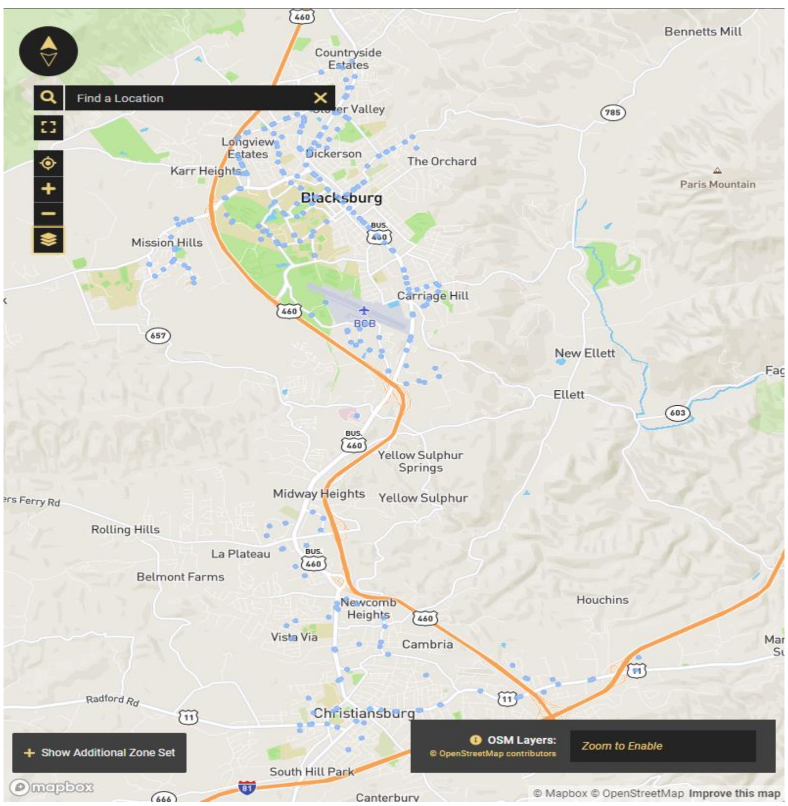
10b. The zip folder will appear here after being uploaded.

METHOD 2: TRANSIT AGENCY BUS STOPS

11. Make the following selections for the zone set.



**Zones should be non-pass-through to prevent overcounting of trips.*



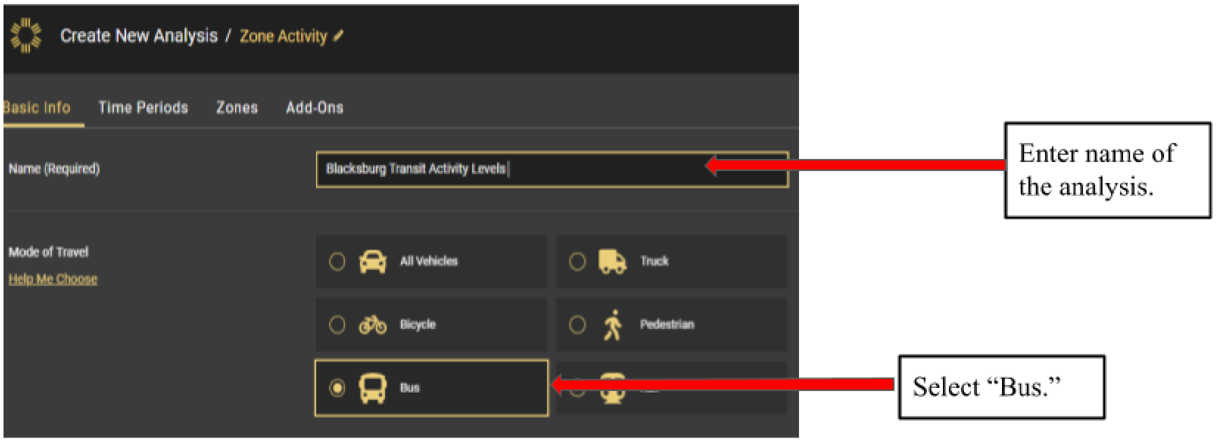
The final zone set should appear something like the above.

METHOD 2: TRANSIT AGENCY BUS STOPS

12. Select "Create New Analysis" from the Analyses tab;

13. Select "Zone Activity";

14.



15. Define the time periods for the analysis.

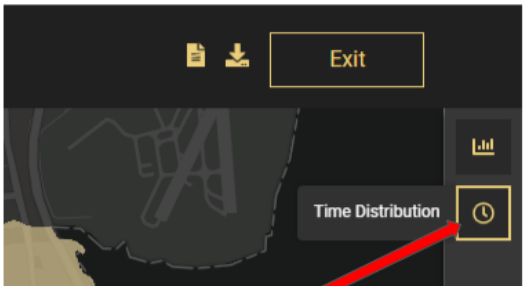
16. Select the zone that was created in step 11.

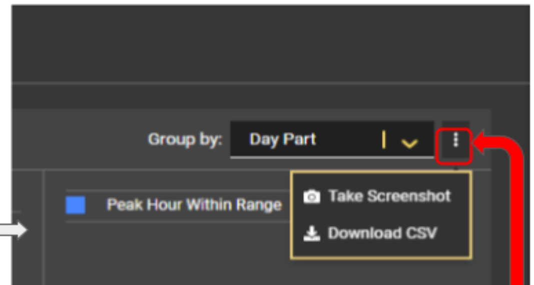
METHOD 2: TRANSIT AGENCY BUS STOPS

17. Confirm analysis at the bottom right corner of the screen.

18. Once the analysis is complete, select "Open in Viz3D" from the "Actions" drop-down menu.

19.





Click the "Time Distribution" icon (upper right of window).

Click here and download CSV. *.

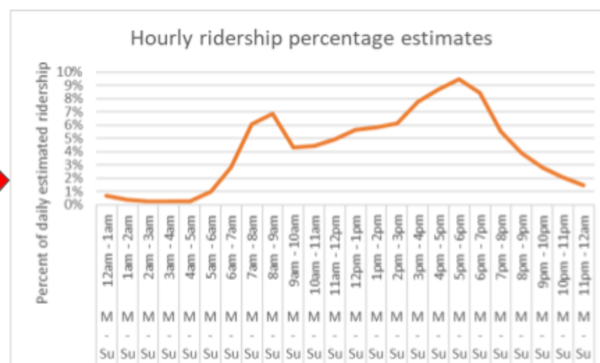
** The day type, day part, and type of trip (starting/ending) of the CSV can be selected from the left side of the screen prior to downloading.*

20. Open the CSV file in Excel.

day type r	day part n	value
M - Su	12am - 1ar	0.004
M - Su	1am - 2am	0.0025
M - Su	2am - 3am	0.0019
M - Su	3am - 4am	0.002

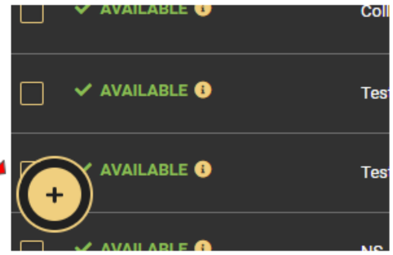
Multiply these values by 100 or use Excel's "Percent Style" number format to get the hourly percentages of bus transit activity levels.

21. Plot a graph of hourly transit activity percentages against hours of the day.

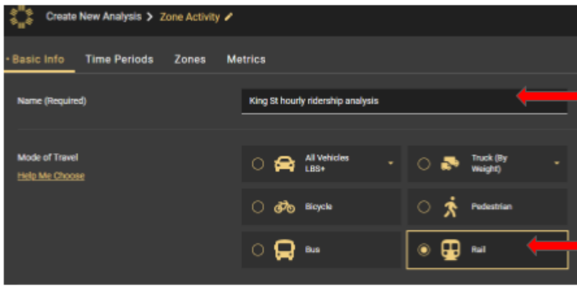


RAIL

1. In StreetLight, click the "+" sign in the bottom left of the screen from the Analyses tab;



2. Select "Zone Activity";



Enter name of the analysis.

Select "Rail".

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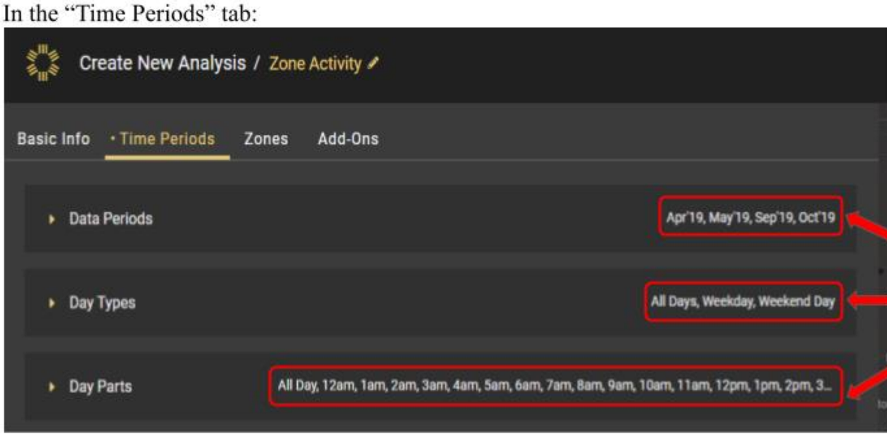
3. In the "Time Periods" tab:



4. Select desired time periods for analysis. *

** Analyzing bigger data periods (more months/years) will produce more accurate results. Day Types and Parts may be modified to include or exclude any days or hours, respectively, as required.*

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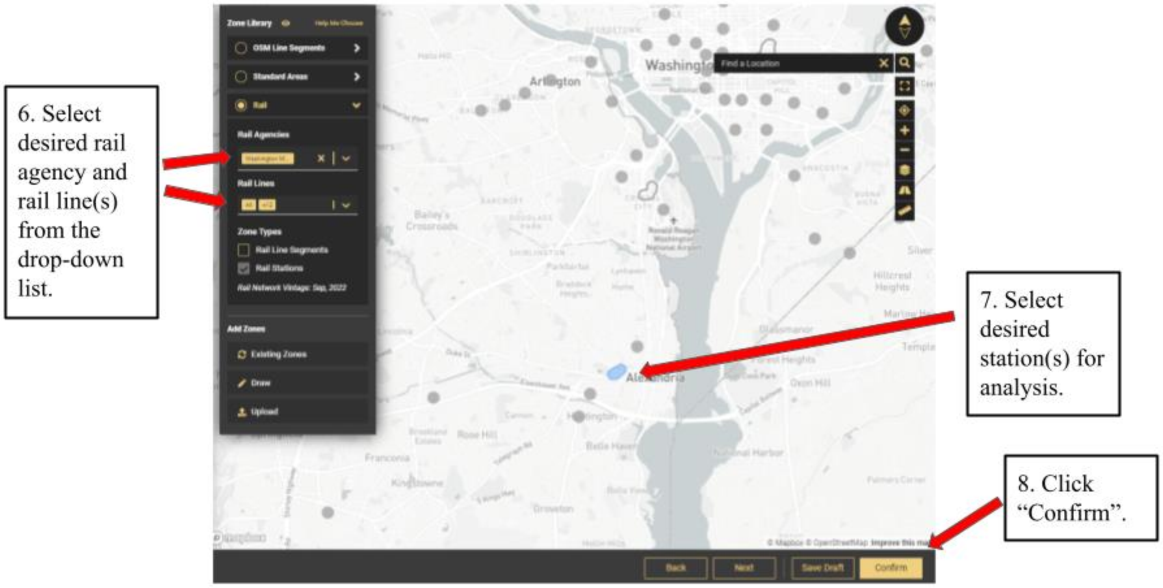
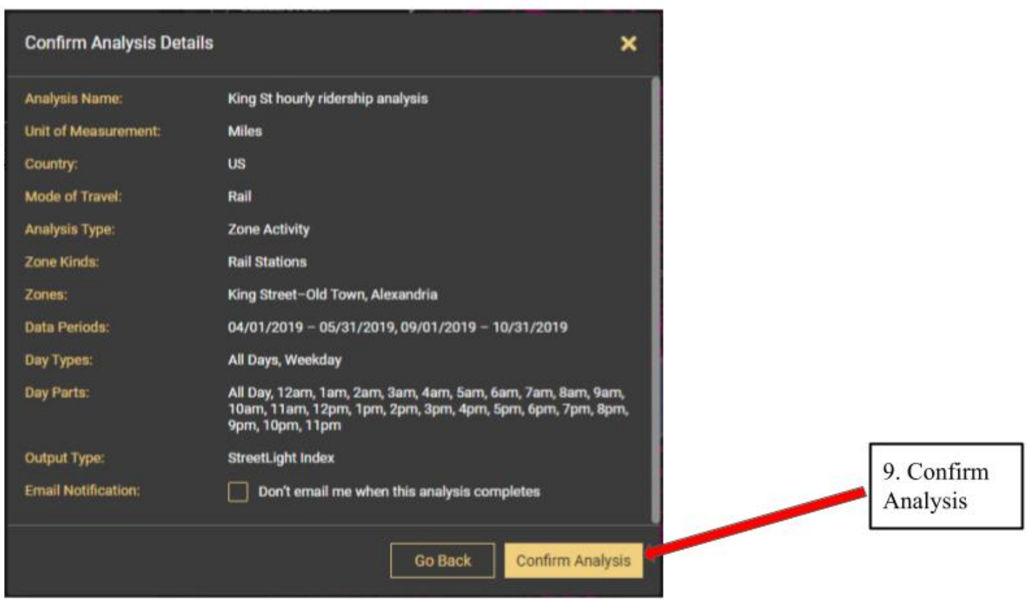
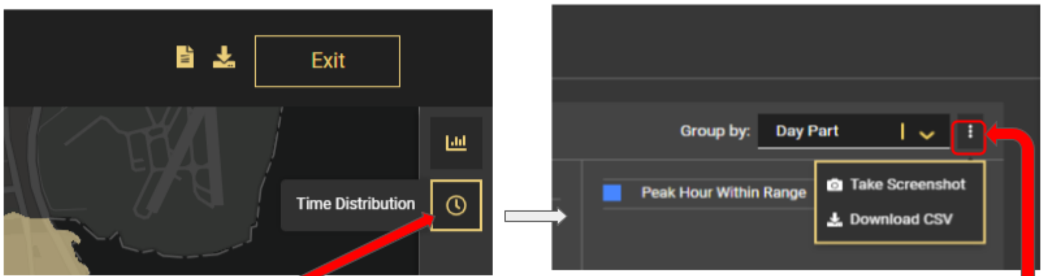
5. In the “Zones” tab, Select “Rail” from the Zone Library, and zoom in to the desired location(s) for analysis.





10. Once the analysis is complete, select "Open in Viz3D" from the "Actions" drop-down menu.

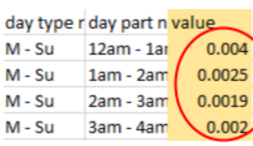


11. Click the "Time Distribution" icon (upper right of window).

12. Click here and download CSV. *.

** The day type, day part, and type of trip (starting/ending) of the CSV can be selected from the left side of the screen prior to downloading.*

13. Open the CSV file in Excel.



day type r	day part n	value
M - Su	12am - 1ar	0.004
M - Su	1am - 2am	0.0025
M - Su	2am - 3am	0.0019
M - Su	3am - 4am	0.002

Multiply these values by 100 or use Excel's "Percent Style" number format to get the hourly percentages of bus transit activity levels.

14. Plot a graph of hourly transit activity percentages against hours of the day.