Improving Ridership Projections of Proposed Bus and Rail Transit Projects

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ADDENDUM TO THESIS

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This addendum consists of newly discovered and disclosed information relating to the first purpose of this thesis, “Examining the Effects of Stop Improvement Projects on Bus Ridership”, in the Methods, Results and Conclusions sections.

As noted in the thesis, it was found that there was a 177% increase in ridership after Arlington Transit improved the stop infrastructure of several bus stops. However, new data received from Arlington Transit indicates that there were increases in service frequency of one of the bus routes that served a majority of the treated bus stops. The bus stops in the study were served by both Arlington Transit and Washington Metropolitan Area Transit Authority (WMATA). One of WMATA’s routes serving the bus stops increased service frequency during the same time period the bus stop infrastructure was being improved. Hence, it becomes difficult to conclude whether the ridership increases were brought about by the stop improvement project, or the change in service frequency. This adds to the conclusion that ridership increases need to be viewed with caution. Further research is needed to determine whether the change in service frequency and the stop improvement projects were influenced by changes in land use.

ABSTRACT

Transit ridership data is 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. This study aimed to seek better ridership data by answering the following three questions, using Virginia-based data: (1) 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 to service frequency? (2) What percentage of transit ridership occurs during peak hours? (3) How does crowdsourced transit activity data compare to ridership data from Virginia transit agencies?

Study methods included extensive literature reviews to understand previous findings related to ridership effects of stop improvements and a before-after study using ridership data from one Virginia transit agency. Ridership data was also collected on an hourly basis for the year 2019 from six Virginia transit agencies to determine the percentage of ridership during peak travel hours. Generally, ridership data is challenging to obtain directly from transit agencies due to non-standardization of data collection processes among the agencies. 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 it against ridership data from Virginia transit agencies.

The results showed statistically significant increases (177%) in ridership when bus stop infrastructure was improved, compared to statistically insignificant increases of 27% where bus stops remained unchanged. The hourly ridership data from transit agencies showed that the 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 value was much higher, ranging from 37% to 56%. Directly using transit activity data from StreetLight's current algorithm was deemed not to be appropriate without verifying against agency data, especially for agencies in small- to medium-sized cities.

Better transit ridership estimates can contribute towards better decision-making and more efficient funding allocation by state agencies. This study has also demonstrated the level of accuracy that can be expected from crowdsourced transit activity data sources when analyzing ridership data in small to medium sized cities.

INTRODUCTION

Transit ridership data are used in different sectors of research and planning practice. Transit agencies everywhere hope to boost ridership, which in turn can lead to less congestion, increased travel time savings, and reduced greenhouse gas emissions. When bus and rail transit projects are proposed for potential funding to state agencies, they are evaluated across multiple criteria such as congestion reduction, accessibility, environmental quality, and safety.

For transit investments to reduce congestion and emissions, there needs to be an increase in transit ridership or person throughput, attributable to travelers changing their mode from autos to transit. This is particularly important during the typical peak hours of congestion for the morning and evening hours. Therefore, there is a critical need for accurate ridership estimates during peak hours of travel. Furthermore, for transit improvement projects, which include improvements to transit stop and station facilities or amenities, ridership estimates are integral. Examples of stop improvements include the addition of shelters, benches, trash cans, lighting, bike racks, sidewalk connections, landing pads, real-time information technology, etc. Station improvements include those items along with an expansion of station building square-footage, a new rail platform, or platform expansion. New or expanded fixed-guideway transit services and implementation of transit signal prioritization are other examples of transit improvement projects where ridership effects are of interest.

Ridership estimates are often found in transit studies. One conducted for transit service across the American Legion Bridge (Maryland Transit Administration and DRPT, 2021) included a sensitivity analysis on 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 for a 10% reduction in travel times. Projections of transit ridership could also be based on before-and-after data from transit projects that were implemented. A recent national study examined planning-level ridership predictions versus actual outcomes two years after a project's opening for major projects such as new bus rapid transit (BRT) or light rail lines (Federal Transit Administration, 2021). 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 percent of pre-pandemic levels in many cities across the United States beginning in mid-March of 2020 (APTA, 2022). Hence, all studies examined and data collected for this project were from the pre-pandemic years.

Aside from being used in project prioritization processes, ridership estimates are frequently used in state and federal transit funding formulas (Virginia Department of Rail and Public Transit, 2022; FTA, 2022). Transit ridership data is one of the key pieces of information needed not only when allocating funding, but also in 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 carrying out surveys. Results showed that less than 33% and 25% of Virginia transit agencies, respectively, used automatic passenger counters and fareboxes, while a 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 across transit agencies, an emerging source of transit activity data, StreetLight, is 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 between 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 it with data collected from transit agencies serving those cities.

This study attempts to improve the ridership estimates of bus and rail transit projects by examining how much ridership changes when transit improvement projects are implemented, by determining the proportion of daily ridership carried by buses and rail during peak travel hours, and by exploring and assessing the accuracy of crowdsourced transit activity data – using Virginia transit agency ridership data.

PURPOSE AND SCOPE

There are three components of this research. First, there is a need to identify case studies of the ridership effects of transit improvement projects. Although it is difficult to quantitatively attribute ridership effects to specific transit improvement projects, examining ridership effects both qualitatively and quantitatively can provide a better understanding of how impactful specific transit improvement projects could be.

Second, to improve peak hour transit planning, there is a need to estimate the percent of transit ridership occurring during the peak hour for bus and rail service. Ridership data is collected from six Virginia transit agencies for analysis.

Third, the validity of transit activity data from StreetLight is assessed through comparisons with ridership data collected from Virginia transit agencies. If StreetLight data shows sufficient accuracy, this easily accessible crowdsourced data could be used where ridership estimates are required but otherwise difficult to obtain. This would especially be beneficial for small-to-medium-sized transit agencies where ridership data collection and storage formats deviate from standard practices.

The scope of the study is limited to fixed-route transit services, as demand-response transit services tend to have less noticeable effects in reducing congestion. Only fixed-route bus, heavy rail, and commuter rail are studied as part of this study's efforts.

LITERATURE REVIEW

(1) Ridership Effects of Transit and Rail Improvement Projects

First, studies are described that investigated changes in ridership in response to transit improvements, including service improvements as well as stop amenities. Then, effects on ridership and mode-shift due to introduction of new transit facilities are briefly described.

Effects of Stop or Station Improvement Projects and Transit Signal Priority on Ridership

Xiong and Li (2021) collected survey data on passengers at bus stops to determine the relationship between the waiting environment at stops and passengers' willingness to choose bus as their travel mode, using the ordered logit model. The survey results found that if passengers deemed the bus waiting environment to be comfortable, they would use the bus more, but the exact amount was not clearly quantified in the study.

Kim et al. (2020) carried out a before-and-after study of bus stop improvements (providing shelters, sidewalk connections, and concrete pads) in Salt Lake County, Utah, to measure 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 service. Utah Transit Authority serves a population of 1.9 million in an area of almost 740 square miles with over 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 amenity improvements were made; these unimproved stops were carefully matched with the improved ones using the technique of Propensity Score Matching. 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 taking place. 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 amenities 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 serves 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 stop amenities were improved for two bus lines after they were converted to BRT; the study acknowledged that these lines had already experienced a growth in ridership after their conversion to BRT and focused on any further increases related to the improvements in the stop amenities. The study also examined the ridership effects of having different combinations of amenities. 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 difference among them were in the varieties of amenities added. The amenities examined include real-time information systems (RTIS), shelters, pedestrian lighting, benches, trash receptacles, and bicycle parking. These amenities were added in sets: benches were added to all stops that had shelters, while 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 amenities: boardings increased by 139.9% after the amenities were added. The amenities that seemed to play the greatest role in influencing ridership were bike parking, RTIS, and shelters. Considering the fact that amenities were installed in sets, the results demonstrated that relative to boardings at stops that saw the fewest improvements in amenities, 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 amenities from three transit agencies to examine whether the level of amenities influenced ridership. Greensboro Transit Authority (Greensboro, North Carolina), King County Metro Transit (Seattle region) and Kansas City Area Transportation Authority (Kansas City region) serves populations of about 300,000, 2 million, and 800,000, respectively, in areas of approximately 100, 2,000, and 450 square miles, with over 40, 1,000 and 150 buses operating in maximum service condition (NTD, 2019). Statistically significant correlations were found between the presence of amenities (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 amenities examined in two of the three cities (Greensboro: 0.251, Seattle: 0.373, Kansas City: 0.345). The overall level of amenities present at the stops 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 prioritization, and a new connection between two transfer facilities via an express bus corridor. Bus service improvements include reductions in peak period headways (Metro Silver Line and Gardena Municipal Bus Lines), addition of new express bus to 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 account for an increase.

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. A bus stop index relating all the features, including the amenities of the bus stops, was calculated. The value of this index was found to be highly statistically significant, with an increase of 1 unit leading to a 31% increase in ridership. Increased ridership was found to have a correlation with bus stops having signs, shelters, schedules, lighting, and paved landing areas, but no values were provided. However, the study acknowledged that it was unable to establish a causal relationship between the bus stops and amenities. It recommended that this could be improved upon by using longitudinal data.

Watkins (2015) examined the impacts 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 three 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 done to evaluate behavior changes. In Atlanta, smart-card fare collection data along with web-based surveys measured changes in transit travel using a before-after design. Tampa and Atlanta did not show any increases in ridership due to the implementation of real-time information, but the authors theorized this might have been because the methodologies used for those cities did not take into account transit riders who were absolutely new to the system. Only New York City showed a ridership increase due to implementation of real-time information, 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 U.S and Canada. The upgrades examined in the study include the 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 lane usage. 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 chosen was ridership productivity (the number of weekday boardings per revenue hour). The results of this second model found that transit signal priority had a statistically significant relationship with ridership productivity, with the number of 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 utilization of the most high-tech buses on select routes (Koonce et al., 2006) was reviewed by the National Academies of Sciences, Engineering, and Medicine (NASEM) (2016). Although there was no substantial transit travel time savings from this scheme, it did correlate with an increase in ridership, which generated increases in fare revenue of about $1.7 million.

The studies highlighted in this section 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 stop amenities, ridership growths of approximately 140 % were found in two different studies (Kim et al., 2020; Shi et al., 2021). Another study 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 (Schroeder et al., 2015). A unit increase in the number of intersections with transit signal priority yielded 41 additional weekday boardings per revenue hour (Stewart et al., 2015).

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 the frequency of the service. Multiple researchers have studied the effects of increases in service frequency on transit ridership.

Taylor et al. (2009) used linear regression modeling on data obtained from the National Transit Database (NTD) for total urbanized area transit ridership and per-capita urbanized area transit ridership. Results from regression models suggested that transit policies involving higher service frequency and lower fares could cause ridership to double in an urbanized area.

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

- TriMet in Portland, Oregon
- Miami-Dade Transit in Miami, Florida
- Metro Transit in Minneapolis/St-Paul, Minnesota
- Metropolitan Atlanta Rapid Transit Authority in Atlanta, Georgia

The main findings from 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 counts. 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 the elasticity of ridership varied with daily time periods (NASEM, 2022). For the transit agencies studied, ridership was found to be more responsive to changes in frequency at night relative to day (elasticity values closer to 1), with the exception of TriMet, where ridership was found to be relatively less elastic both day and night. The study noted that although the number of passengers per trip at night were unlikely to be as high as during the day, these findings could hold value to 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, experienced ridership increases (NASEM, 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 third edition of the Transit Capacity and Quality of Service Manual (NASEM, 2013) identified the following transit quality of service factors to be the most important to existing and potential transit users: (i) travel time, which included in-vehicle time along with access, transfer, and wait time; (ii) level of crowding on board transit; (iii) the reliability of transit; (iv) amenities available at bus stops; (v) the availability of real-time arrival information; and (vi) other service aspects such as the clearness of stop announcements and the behavior of the transit driver. It was found that when a bus stop had a shelter with roof and end panel present, 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 in Portland, Oregon at the corridor level using (i) before and after comparisons and (ii) 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. The results showed that at the corridor level, the LRT lines caused both short- and long-run increases in transit ridership, with the Orange Line and Green Line causing increases of 6,404 and 7,225 riders, respectively, in average weekday boardings after the first year, with the ridership increase being substantial particularly for the first three years. For the Orange Line, ridership became stable after the first year, while for the Green Line, it increased by another 500 riders and then became stable.

Traffic congestion decreased only in the short run; the author theorized that induced traffic demand may have affected the results in the long run. At the regional level, most urbanized areas saw an increase in transit ridership, but only some urbanized areas experienced 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 area and found that automobile owners preferred continuing to use their vehicles regardless of how competitive public transit became in terms of service. Initial results from a stated preference (SP) survey showed that car drivers opted to remain with the auto mode in 72% of all scenarios and only switched to transit for about 25% of the scenarios. The authors suggested that based on their results from this SP survey, people's aversion to shifting modes from auto to transit could be related to their habits and mindsets. With data from SP 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 towards public transit or other options were chiefly how occupied the vehicles were with passengers (model parameter = -0.4265) and 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 findings show that travelers are more inclined to shift to rapid and semi-rapid transit alternatives rather than regular bus services.

(2) Determining the Proportion of Daily Transit Riders During Peak Travel Hours

Extensive searches for relevant literature on this subject found no studies that have specifically examined the transit ridership occurring during peak travel hours.

(3) Assessing the Accuracy of StreetLight Transit Activity Data

Crowdsourced data is increasingly being used for many research objectives in the transportation sector. For example, multiple studies have examined the performance of crowdsourced bicycle ridership data (Jestico et al., 2016; Roy et al., Lin and Fan, 2020), but there is limited literature available on the use of crowdsourced data in estimating transit ridership. For this study's purposes, two main bodies of literature were identified. First, literature pertaining to the uses of crowdsourced data for transit from sources other than StreetLight is reviewed, and the associated limitations of the data are identified. The accuracy and uses of StreetLight data for the modes of bicycles and autos are then examined.

Uses of Alternative Sources of Crowdsourced Data for Transit

Misra et al.(2014) reviewed case studies where crowdsourced data from a broad variety of stakeholders had been used in projects in the transportation sector. They determined that assessing the quality of transit and real-time information systems was one of the main purposes of using crowdsourced data in this sector. Tiramisu Transit was an example of a transit information system reviewed. It was an application for smartphones that asked passengers to report on the real time arrivals of buses and how occupied they were at any given time, along with other feedback and suggestions for improvements. By the use of other similar examples, the usefulness of crowdsourced data was highlighted and how it could potentially be used to substitute or improve upon conventional survey methods demonstrated. The study acknowledged that crowdsourced data collected using smartphones might have biases, as certain populations may not have the same level of access to smartphones as others. The authors concluded that this issue could be remedied by using conventional methods of data collection (i.e., not involving smartphones) where necessary.

To predict the occupancy level on buses (i.e., the passenger load) at any given time, Chaudhary et al. (2016) looked at using crowdsourced mobile-based data to generate databases of occupancy data. The results showed that the predictions had an accuracy of 90.81% compared with the ground truth of manual passenger counts at the stop level.

Rodrigues et al. (2017) analyzed the effects of the quality of crowdsourced data on travel pattern approximation. Relying solely on location-based data from crowdsourcing was found to cause substantial errors in the travel speed of various modes. Errors present in the tracking of locations might affect the identification of the travel mode. Trip modes are quintessentially distinguished from one another in crowdsourced data by tracking the device's location and observing attributes such as speed and distance (Biljecki et al., 2013; Stenneth et al., 2011).

Geospatial layers of identified public transit routes may also be used for this purpose to increase accuracy, but this form of data is harder to obtain. The variation in the types of devices and operating systems from crowdsourced data has also been found to affect the quality of data collected (Rodrigues et al., 2017).

Uses of StreetLight Data for Auto and Bicycle Activities

A review of recent data sources including StreetLight for observing bicycle and pedestrian activities discussed the sampling concerns of mobile-based data (Lee and Sener., 2020). Parts of the target population do not have access to smartphones. As a result of this limitation, the study advised to use such data with caution. It further advised that if mobile-based data were combined with data from other sources, e.g., surveys or video readers, this limitation could be mitigated to some degree. The study described StreetLight to be relatively better than other location-based data sources reviewed, such as cell tower mobile phone positioning or data collected over Bluetooth/Wi-fi, as StreetLight utilizes additional data sources (e.g. travel surveys) to validate the location-based data in its algorithm. A limitation of StreetLight that remains is its inability to provide data at the single traveler trip level (Lee and Sener., 2020).

Tsapakis et al. (2020) used probe-based annual average daily traffic (AADT) estimates provided by StreetLight and determined their accuracy by comparing them with multiple state and local agencies' traffic volume data for two areas in Texas. The authors compared the observed AADT data from the agencies and the estimated data from StreetLight. Statistical analysis of the data showed that the MAPE was 50%, which was 15% lower than the same measure determined previously for the transportation network in Minnesota using StreetLight data (Turner and Koeneman, 2017). In general, StreetLight's AADT estimates were more accurate for higher-volume roads and urban roads compared to lower-volume roads and rural roads.

Kothuri et al. (2022) compared the quality of bicycle activity data from crowdsourcing data companies with that of data from traditional sources from local agencies. They also looked at the differences in quality that arose when combining data from multiple sources such as StreetLight, Strava Metro—which provides bicyclist and pedestrian-related data—and bike sharing data. Results showed smaller MAPE values for locations with higher volumes of bicycles. StreetLight was found to produce better results when combined with Strava Metro data, with the study noting StreetLight's requirement to input the mode of travel first, which might require more variables to be added in the model to improve accuracy. Certain situations were identified where StreetLight was mistaking auto and transit trips for bicycle trips or wrongly assigning bike trips to transit routes parallel to bike lanes. The limited sample size and complexity of the machine learning models were acknowledged. Further research is required to comprehend better the data size required to improve the estimation accuracy of the models (Kothuri et al., 2022).

A report generated by StreetLight described its data sources and validation methods for bus and rail (StreetLight Data, 2021). For both bus and rail, the validation processes first consisted of comparing the aggregated trip characteristics from StreetLight (e.g., trip distance) to those of data from the National Household Travel Survey and the National Transit Database. The next step was to compare StreetLight's trips at the bus-stop or rail-station level with monthly ridership numbers provided by a select few transit agencies across the United States. For bus activity, StreetLight used stop-level ridership data from Los Angeles and the greater Columbus, Ohio area; for rail, StreetLight used station-level ridership data from the San Francisco Bay area, Chicago, and the greater Boston area. In this manner, StreetLight performed monthly validations and found that results from StreetLight captured trends fairly accurately compared with transit agency data on the national, system-wide, and stop or station levels. Other sources of data used to enhance the algorithm included OpenStreetMap (OSM) layers, GPS data from transit agencies and travel diaries (some proprietary), and conventional travel surveys on bus and rail trips, such as the National Household Travel Survey and local surveys. Although none of these sources provided ridership data, they provided insight with regard to locations of bus routes, rail stations, and lines; ground truth data to train the algorithm to distinguish bus trips from other modes; and the likely movement patterns of transit trips, all of which StreetLight used to improve the algorithm's abilities to identify bus and rail trips. The report acknowledged that due to the complexities associated with collecting monthly ridership data at the stop or station level directly from all existing transit agencies, limitations in the validation process remained.

Literature Review Summary

To answer the first research question on how transit improvement projects affect bus and rail ridership, all of the studies that were reviewed demonstrated a positive relationship between ridership and improvement of stop amenities. Magnitudes of increases in ridership varied (increases of approximately 140% observed when stop amenities were improved and an increase of 41%-52% during peak hours when bus services were increased), among the different studies, as did the type of areas studied (e.g., urban vs. rural). Some studies were also able to determine which stop amenities, in particular, had the most influence on transit ridership. Overall, the types of transit improvement projects ranged from relatively simple items, such as adding trash receptacles and lighting at stops, to more complex scenarios, such as the addition of new LRT lines or installing transit signal priority. However, it is to be noted that the quantity of literature quantifying ridership changes due to stop improvement projects is limited. Thus, this study attempts to expand upon the literature on this topic by examining ridership changes due to a stop improvement project in a Virginia transit agency.

No relevant studies were found that could help answer the second question involving estimates of the percentage of ridership occurring during peak hours for typical fixed-route bus and rail services. This study attempts to fill this gap by using hourly ridership data from six Virginia transit agencies, both bus and rail.

The literature on crowdsourced data in transportation has reviewed their usefulness and accuracy for multiple purposes. For transit, crowdsourced data have been used to predict the real-time locations and occupancy levels of transit vehicles. Two common limitations associated with all types of crowdsourced data in transportation are (1) equitable access to smartphones by all travelers and (2) data quality concerns related to different mobile operating systems and the variety of devices. StreetLight overcomes some of the limitations of other crowdsourced data platforms by using multiple additional data sources including geospatial layers of identified public transit routes, carrying out mode imputation, and automatically collecting data from all smartphone users without relying on travelers manually providing data nor requiring them to install specific mobile apps. Nevertheless, the literature on StreetLight generally notes lower accuracy in areas with lower volumes of vehicles. StreetLight has acknowledged the difficulties in obtaining ridership data from transit agencies and has also recognized the resulting limitations in its validation of bus and rail metrics (1). A thorough search of all relevant literature found no research conducted by third parties to validate StreetLight’s bus and rail ridership data. In light of this research gap, this study attempted to explore the accuracy of StreetLight transit ridership data through comparisons with ridership data from multiple transit agencies in Virginia.

METHODS

Ridership data is requested and obtained from selected Virginia transit agencies. The data is 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

Six transit agencies are contacted via email with requests for ridership data; Arlington Transit is the only agency contacted that had ridership counts at the stop level for the requested data period.

As mentioned in the literature review section, 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 is 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 as well as ridership data after the improvements are requested and obtained from Arlington Transit. The stop improvements were made between spring and fall 2018 as part of a corridor-level program of stop improvements along Washington Boulevard and Langston Boulevard in Arlington County. 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 the replacement of shelters with solar-powered shelters and addition of 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). Therefore, stop-level ridership data from Arlington Transit is requested from 2017 and 2019 for both treatment stops and control stops. In order to ensure the pre-improvement ridership counts of the two groups were similar in magnitude and thus comparable with one another, data cleaning is done to remove outliers from both groups using the Interquartile Range method (Statology, 2021).

The sample sizes of the stops for the two groups were both below 30, hence the variety of statistical tests that could be done were limited. F-tests and T-tests (Statistics Solutions, n.d. and Glen, n.d.) are done to determine whether ridership increases over time in each of the two groups of stops (treatment and control) are statistically significant, and the percentage changes in ridership after the improvements are calculated. Similarly, F-tests and T-tests are done to compare whether the ridership increases in the treatment group were statistically significantly higher than the ridership increases in the control group over the two-year period. For both cases, the F-test helps determine whether the variances are equal between the groups under consideration; that, in turn, affects the type of T-test to be used.

Determining the Proportion of Daily Transit Riders during Peak Travel Hours

Bus

The Virginia Department of Rail and Public Transit provided a list of Virginia transit agencies that collects bus ridership data at an hourly level. Hourly ridership data from fixed route services are 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. The 2019 data is 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 uses the Average Unlinked Passenger Trips reported by transit agencies as a measure to understand 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 are used in all cases, although study dates varied.

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 (FTA, n.d.).

[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. DOT, 2012).

[c] National Transit Database profiles for agencies classified as rural transit providers do not include service area population or size of area served.

Data cleaning ensured data were in comparable formats. Analysis is 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 are calculated and then plotted in graphs to analyze hourly variations in ridership. Each agency's peak hour for ridership is identified from the graphs and the corresponding hourly ratios.

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 agencies, Bay Transit had the smallest two-month ridership for fixed route services.

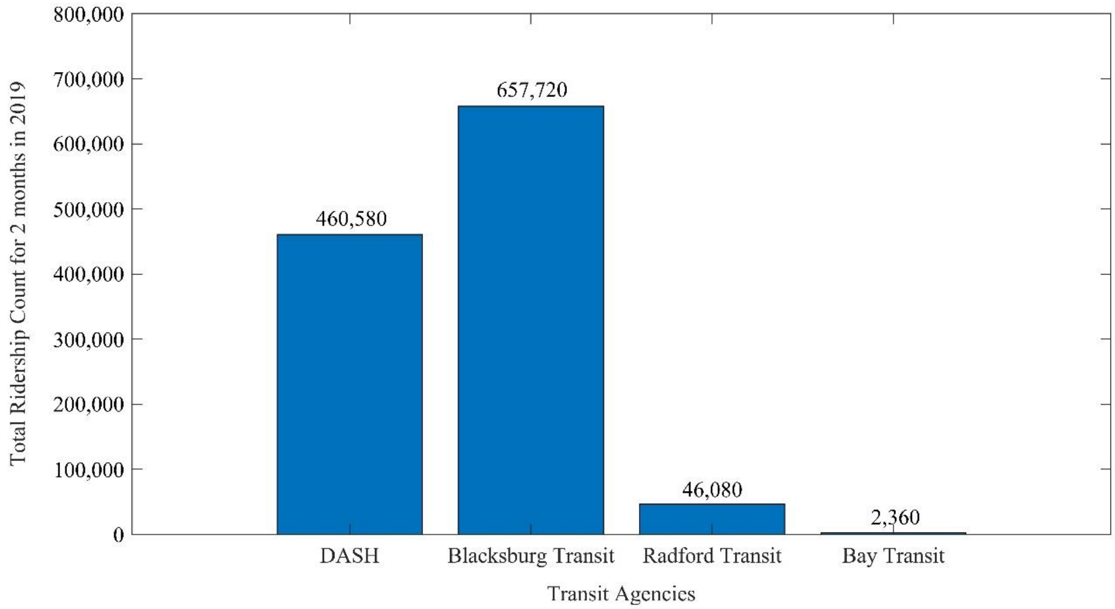

Figure 1. Total Fixed-Route Ridership Across The Four Transit Agencies For 2 Months In 2019 (Data Provided By Each Agency).

Rail

The data collection for heavy rail (i.e., subways) uses data from the Washington Metropolitan Area Transit Authority (WMATA) Metrorail via WMATA's website (WMATA, 2022a). For commuter rail, data is 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 are 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 are calculated, and graphs showing the hourly variation of ridership are plotted for each station. Unlike WMATA, which operates heavy rail throughout the day, VRE only operates its commuter rail services during peak travel hours, so the number of hours of data collected are different for the two rail agencies.

Six of Metrorail's 23 Virginia stations are chosen for this study (see Table 2), and their average hourly number of entries, i.e., train boardings only, are analyzed (WMATA 2022b). In a similar manner, six of VRE's 19 stations are 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 are expected to have mostly entries in the mornings and mostly exits in the afternoons/evenings due to regional commuting patterns. Each station serves either only Metrorail lines or only VRE lines. Among the chosen VRE stations, each serves only one VRE line. Both of these considerations ensured any analysis in StreetLight would not be affected by the other agency's or other lines' transit activity.

Although Metrorail records both station entries and exits using data from the station faregates and makes the data available on the WMATA website at an hourly level, the ridership data requested and obtained from VRE are the agency'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 does not have a way to count actual station-level boardings or alightings (C. Hoeffner [personal communication, September 16, 2022]). Issues such as riders evading payment of fares at Metrorail faregates also mean that ridership data obtained from WMATA might not always represent 100% of actual ridership. The 2019 VRE schedule is requested from the agency, and the estimated number of riders getting on each train at each station is matched to the scheduled departure times to estimate the cumulative value of hourly ridership for each station (N. Ruiz [personal communication, September 22, 2022]).

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 (WMATA, 2022a)

[b] Source: Virginia Railway Express (C. Hoeffner [personal communication, September 16, 2022]; N. Ruiz [personal communication, September 22, 2022])

Assessing the Accuracy of StreetLight Transit Activity Data

The transit agency ridership data set from the previous section is also used for determining the accuracy of data from the crowdsourced data platform StreetLight. StreetLight only had transit activity data for the months of April, May, September, and October of 2019 at the time of this study; as of February 2023, data months have been 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 are of the "user-generated" type, which means that the geographical boundaries are set by the analyst. Zones created are "non-pass through," meaning 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 is also difficult to find bus routes that do not partially overlap another route of the same agency, so StreetLight is not immediately able to estimate route-level ridership data. Hence, this study chooses to focus on analyses involving all bus stops of a transit agency, rather than route-level analyses. Rail analyses are run using StreetLight-defined rail zones based on OpenStreetMap (OSM), which consists of rail stations and line segments. 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., Blacksburg Transit had a substantially higher Unlinked Passenger Trip value than Radford Transit). Exploratory analyses of StreetLight transit activity in Virginia reveals multiple localities where at least some level of transit service existed that did not yield any transit data. Thus, it is 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 as SL1.

This method yields 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 show 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 is 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 are generating reasonable data (i.e., StreetLight had data for all hours of the day during which transit typically operated) is 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 as described above is faster, for bus analyses StreetLight recommends using zones consisting of buffered bus stop locations. This should limit trips to those that started (or ended) at bus stops; StreetLight recommends 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 (GTFS) files for BT and DASH (Open Mobility Data, 2019) containing all bus stops as of 2019 are imported into ArcGIS Pro, where the stops are buffered by 50 meters and dissolved (see Figure 2). The shapefiles are then exported into StreetLight as zones. Buffers of 50 meter radii are 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 appears to be reasonable.

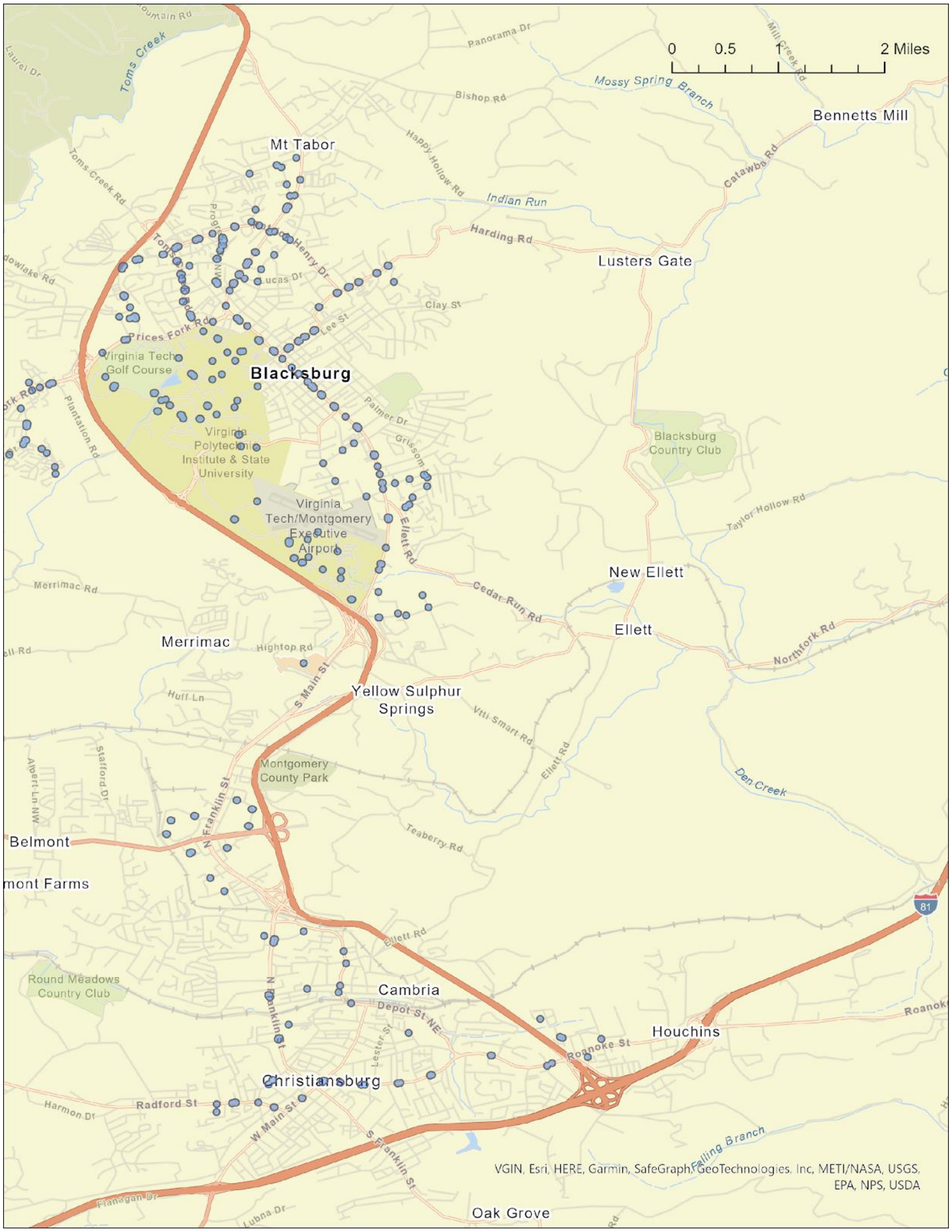

Figure 2. Blacksburg Transit's Buffered Bus Stops in ArcGIS Pro.

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

To summarize, three graphs are obtained from the following 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 Root-Mean-Square-Errors (RMSE) is performed to compare the relative accuracy of StreetLight transit activity data with respect to agency-provided ridership data. The method of 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. A smaller RMSE value indicates less error and higher accuracy.

Rail

Because StreetLight featured preset zones for rail stations, no separate zones have to be created to analyze rail activity data or rail ridership. Zone activity analyses are 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 are three selections: “Rail” as the type of zone, the station of interest as the zone, and a checkbox for WMATA or VRE as the agency. Only the ridership for trips that start in the station zones is analyzed, to obtain a measure of the boardings on the trains throughout the day. This process is repeated for all selected stations, and the resulting hourly percentage of daily heavy rail and commuter rail activity is plotted to compare it with data obtained from WMATA and VRE.

RESULTS AND DISCUSSION

Effects of Stop Improvement Projects on Bus Ridership

This section summarizes the ridership effects of a set of bus stop improvement projects that Arlington Transit carried out. Tables 3 and 4 show the changes in ridership at a stop level for both the treatment group (improved stops) and the control group (unimproved stops). The pre-improvement ridership counts for both groups were ensured to be comparable to one another through the removal of outliers. The sample size of unimproved stops is smaller (N = 11) than the sample size of the improved stops (N = 30). The percentage change in ridership for both groups is calculated, and the results of the F-tests and T-tests are shown. The outcomes of the two aforementioned tests determine the statistical significance of the changes in ridership for both groups of stops.

Table 3. Differences of Ridership Counts at Each of the Treated Stops between 2017 and 2019

Treatment Group			
Stop No.	**Average Daily Ridership (Boardings/Day) at Each Stop**		
	2017	**2019**	**Difference After Improvement (δ1)**
1	4	6	(+) 2
2	3	10	(+) 7
3	4	19	(+) 15
4	6	27	(+) 21
5	9	11	(+) 2
6	2	17	(+) 15
7	2	8	(+) 6

8	1	20	(+) 19
9	3	18	(+) 15
10	3	10	(+) 7
11	0	5	(+) 5
12	0	0	(+) 0
13	0	2	(+) 2
14	0	10	(+) 10
15	0	2	(+) 2
16	0	12	(+) 12
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

Table 4. Differences of Ridership Counts at Each of the Control Stops between 2017 and 2019

Control Group			
Stop No.	**Average Daily Ridership (Boardings/Day) at Each Stop**		
	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 5. Mean Ridership Statistics of the Treatment and Control Stops in 2017 and 2019

	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 6. Ridership Change Statistics of the Treatment and Control Stops in 2017 and 2019

	Treatment Stops	Control Stops
Mean Change in Ridership (2017-2019)	6.67	2.00
Variance	41.75	53.8
Sample Size (N)	30	11
T test Statistic	1.98**	

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

For both the treatment group and the control group of Arlington stops, the mean ridership in 2017 and 2019 is calculated using the data provided, i.e., the mean ridership at the stops before and after any improvements were implemented. As seen in Table 5, the mean ridership at the treated stops before the improvements was lower than the mean ridership of the control stops, indicating that the stops may not have been chosen for improvement based on ridership magnitude. The F-test and T-test are used to examine statistical significance. The stop-level ridership is found to have increased in a statistically significant manner for the treatment group at all tested significance levels, but for the control group, the increase in ridership is not deemed to be statistically significant at any tested significance level (see Table 5). Additionally, the 177%

increase in ridership in the treatment group is found to be statistically significantly higher than the increase in the control group (27%) over the same time period at the 90% and 95% confidence intervals (see Table 6). 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.

The literature reviewed 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 amenities had caused the increases in ridership. The authors of that study 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 (T. Jenkins [personal communication, October 24, 2022]). Although a set of control stops was used with similar pre-improvement ridership levels 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.

Proportion of Daily Transit Riders During Peak Travel Hours

This section summarizes differences among the hourly ridership distributions of the four bus transit agencies.

Bus Transit Agency Data

The hourly ridership variations of the four selected bus transit agencies and their ridership counts are displayed in Figure 3, and their respective locations in Virginia are shown in Figure 4.

Operating hours varied among the four agencies. Bay Transit's fixed routes operated from 9 a.m. through noon (much of its service was demand-response), so fixed-route ridership distribution was concentrated within 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 serve college towns, and their hourly ridership distributions differed from that of DASH. Furthermore, the student population of Virginia Tech in Blacksburg is almost four 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 mid-afternoon, 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%.

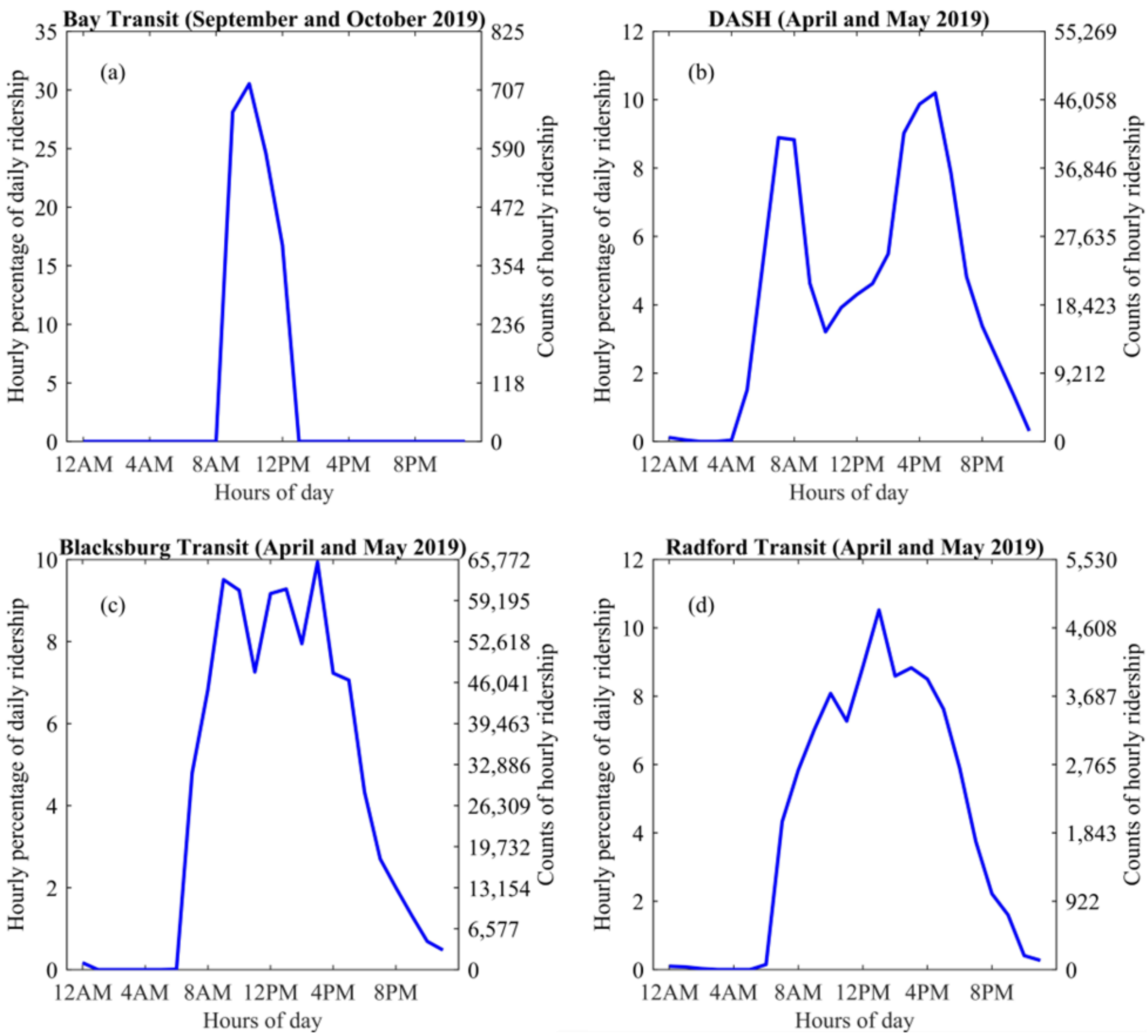

Figure 3. Hourly Variations of Bus Ridership across the Four Agencies over Two Months.

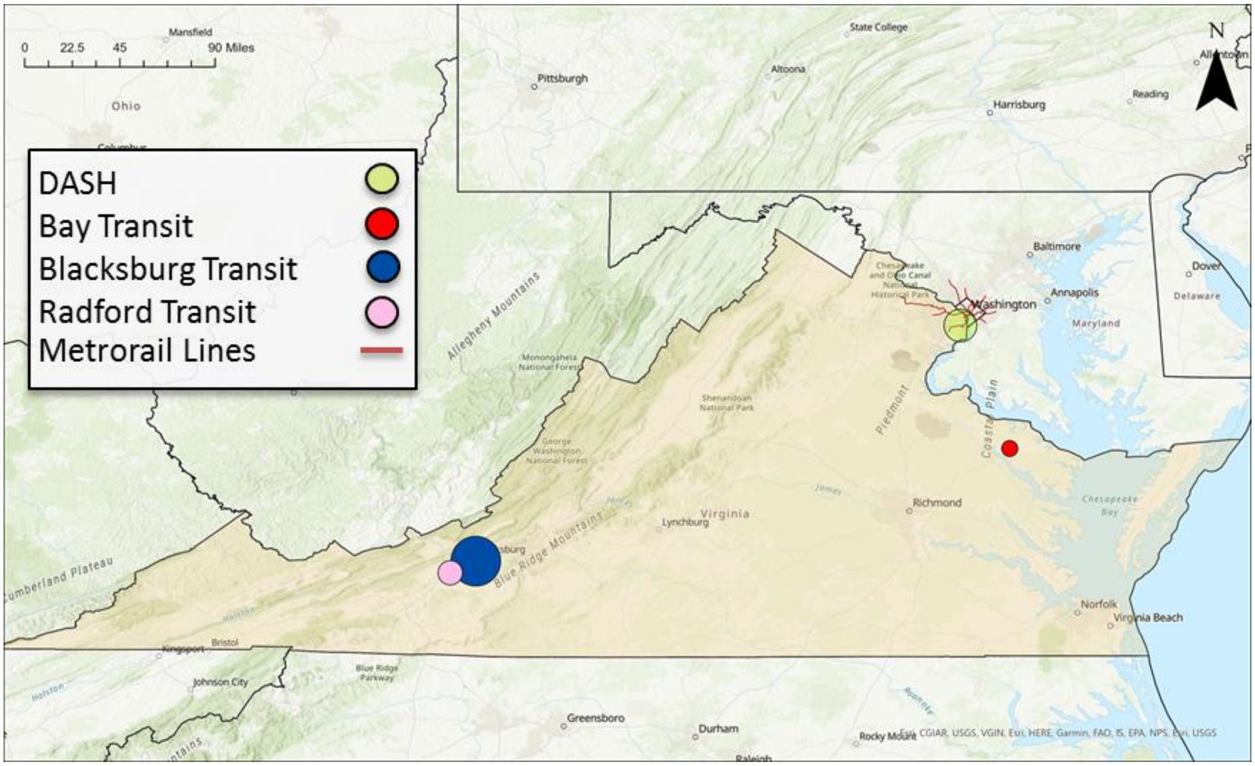

Figure 4. Map Showing Locations And Relative Ridership Levels (Indicated By Dot Size) Of The Four Selected Bus Transit Agencies

Rail Transit Agency Data

According to WMATA data, the six studied Metrorail stations have entry volumes that range 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 5. Of these six stations (locations shown in Figure 6), Court House in Arlington has the highest average entries during the day, and Spring Hill, the westernmost station of four in the Tysons area, has the fewest. Court House and King St-Old Town in Alexandria both have more entries in the mornings compared to evenings, with the opposite pattern at Greensboro, Tysons, and McLean. Spring Hill has a marginally higher number of entries in the morning compared to the evening. In all cases, morning peaks are at 8 a.m. and evening peaks at 5 p.m., aligning with the region's peak hours for traffic congestion, suggesting that heavy rail trips through these stations are highly commuter-oriented. The ridership during the peak travel hour for the six analyzed Metrorail stations range from 14%-26%.

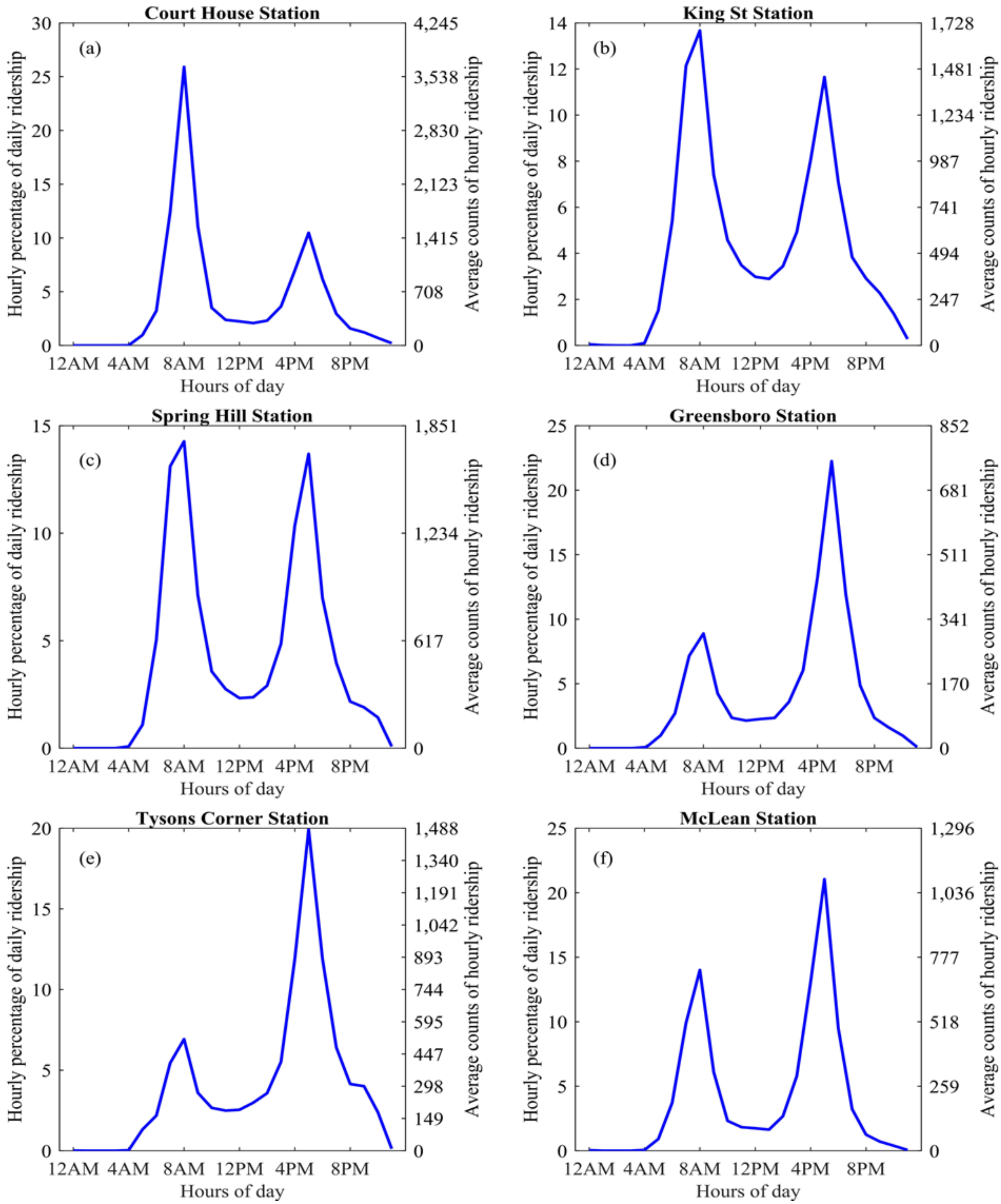

Figure 5. Hourly Variation of Ridership (Station Entries) at Six Metrorail Stations in 2019 (April, May, September, and October).

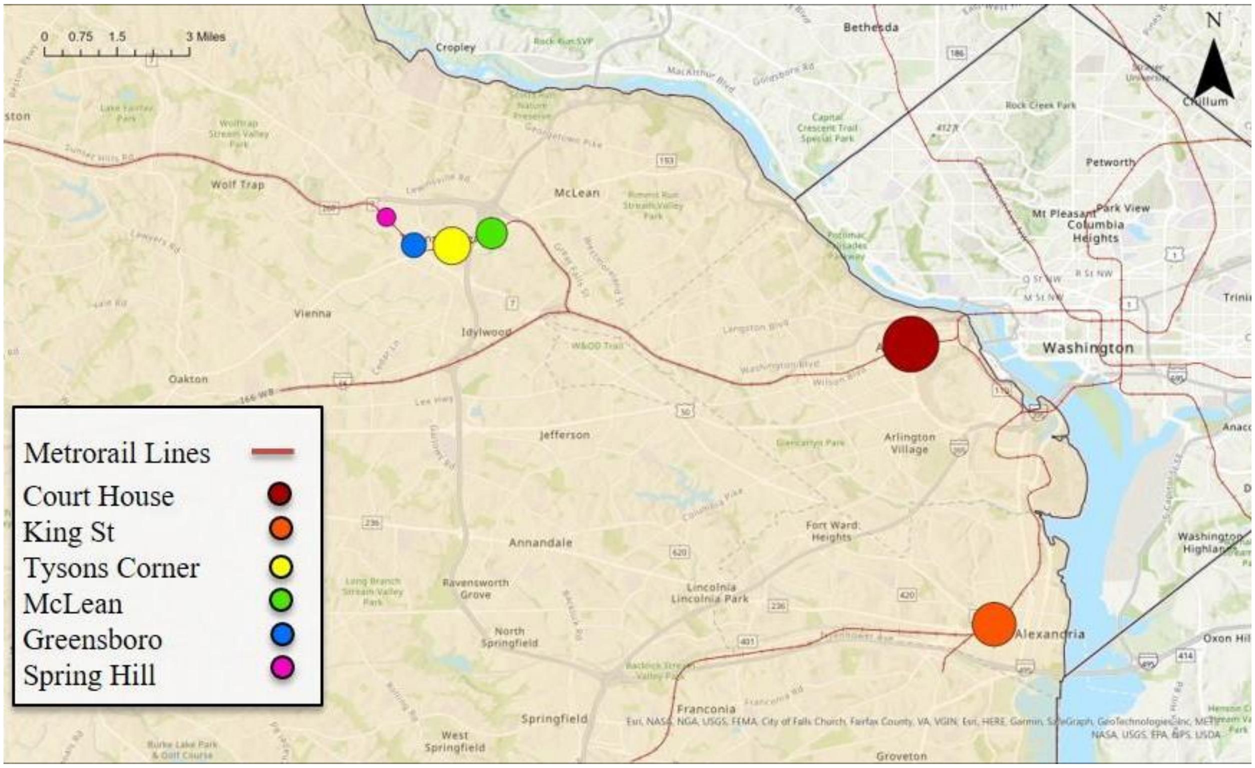

Figure 6. Map Showing Locations and Relative Ridership Levels (Indicated by Dot Size) of the Six Metrorail Stations in Virginia.

The entry volumes derived from VRE data for the six studied VRE stations range from approximately 24,000 to 74,000 for the same time period. Figure 7 displays the hourly variations of each station's entries during the day, and Figure 8 shows their respective locations in Northern Virginia. Leeland Road station has the highest average daily entries, and Backlick Road station has the lowest. The hourly percentage of daily ridership during the peak travel hour for the six analyzed VRE stations vary from 37% to 56%. Unlike Metrorail, which operates throughout the day, the VRE commuter rail service only operates during the mornings and afternoons/evenings. This, along with the fact that the six studied stations are outside the region's urban core, result in very high hourly percentages of daily boardings during the mornings (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 stations have almost no entries in the evening period, as people mostly exit the stations in the evening when returning from work. Lorton station on the Fredericksburg line has a small peak of approximately 10% during the 4 PM hour, and Backlick

Road station on the Manassas line has 6% of its daily boardings during the 4 PM hour. For all six stations, there are no train boardings between 9 AM and 1 PM, because no VRE trains serve these stations during these hours.

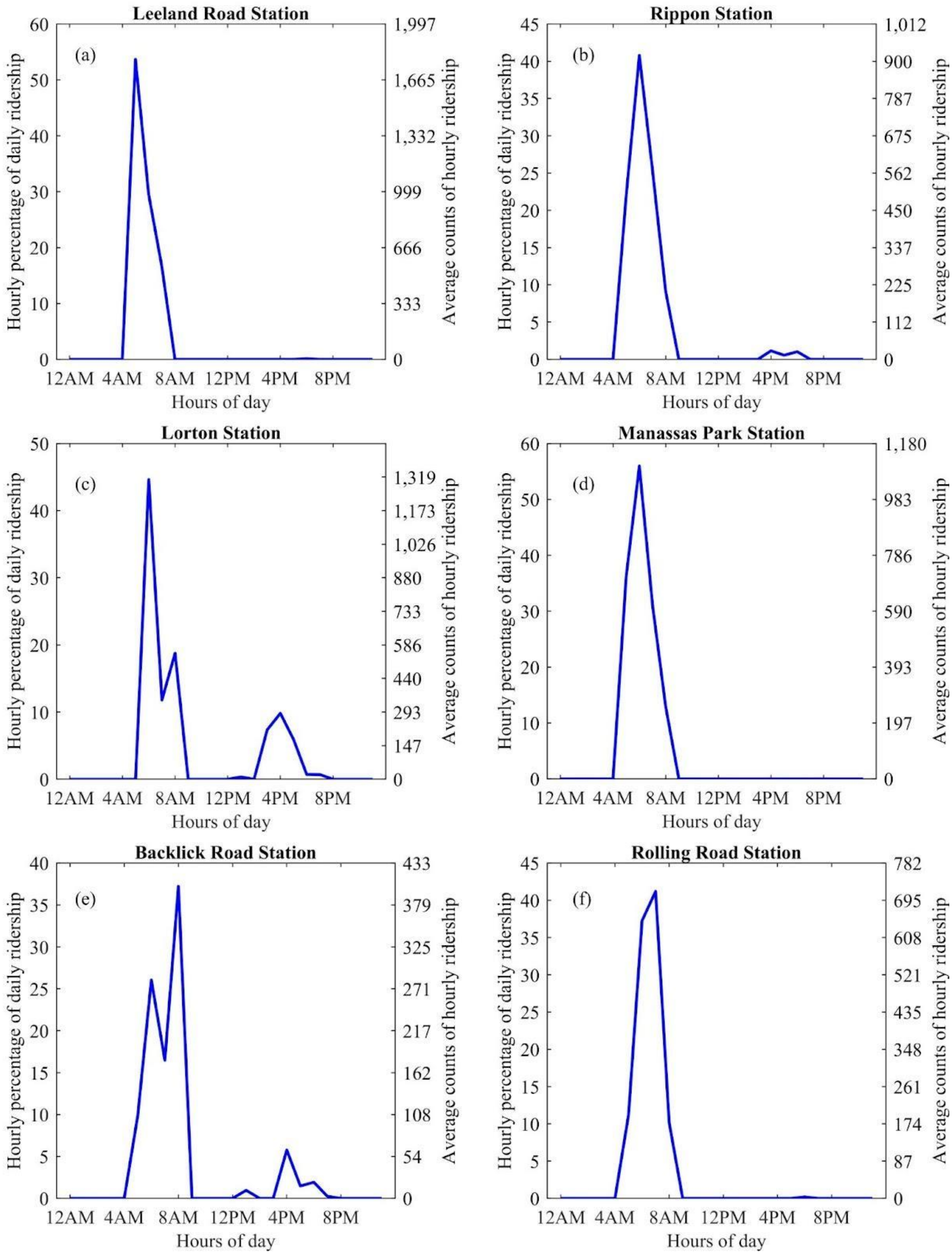

Figure 7. Hourly Variation of Ridership (Station Entries) at Six Virginia Railway Express Commuter Rail Stations in 2019 (April, May, September, and October).

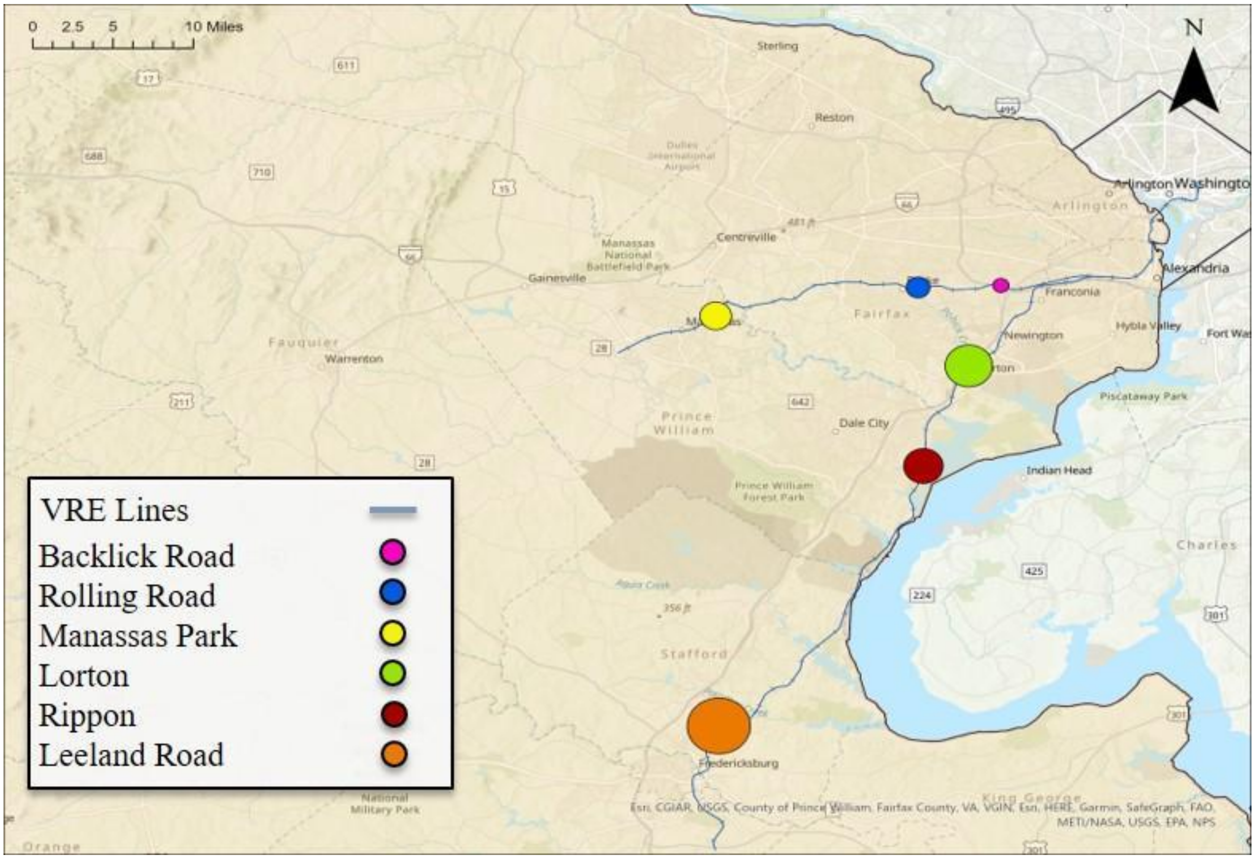

Figure 8. Map Showing Locations and Relative Ridership Levels (Indicated by Dot Size) of the Six Virginia Railway Express Commuter Rail Stations in Virginia

The proportion of daily riders using fixed-route buses during peak travel hours is found to be 10-11% based on hourly ridership data from DASH, Blacksburg Transit and Radford Transit. Although ridership in DASH peaks at typical morning and evening commute hours of traffic, Blacksburg Transit and Radford Transit both serve college towns and do not show peaks in the same hours. For fixed-route rail, the six analyzed Metrorail stations show a peak hour ridership percent ranging from 14%-26%, during morning peak hours at 8 AM and evening peak hours at 5 PM. As commuter rail like VRE operate for fewer hours, this percent is higher and ranges from 37-56%. VRE ridership is also found to peak earlier in the mornings, than Metrorail ridership as passengers might be traveling larger distances to work using VRE.

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 mean absolute percent error (MAPE) (Tsapakis et al., 2020, and Turner and Koeneman, 2017), Akaike information criterion (Kothuri et al., 2022), and RMSE (Kothuri et al., 2022). For example, for auto and bicycle modes, some regions with higher vehicle volumes have been identified to provide more accurate results than those with lower volumes (Tsapakis et al., 2020, and Kothuri et al., 2022). For the selected rail stations, this study uses RMSE to make quantitative comparisons between StreetLight data and the boarding data obtained from WMATA and VRE.

StreetLight Analysis of Bus Activity Levels

Analyzing bus ridership for each locality in Virginia in StreetLight (analysis SL1) shows 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 links its modal imputations and bus activity data to bus routes included in OSM as of 2019; however, some agencies' routes have not been added to OSM at that time. Analysis of the hourly ridership distribution of the 53 localities found that a region needs 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 have data missing for a substantial number of hours. Based on these results, the results of only two of the localities containing agencies shown in Table 1 are above the 0.1% threshold: Alexandria (9.52%) and Montgomery County (0.60%), both of which have Unlinked Passenger Trip values of the same order of magnitude (7-digit numbers) according to the transit agency profile data from the NTD (2019). Radford Transit and Bay Transit both have Unlinked Passenger Trip values smaller than DASH and BT but of the same order of magnitude. Hence, DASH in Alexandria and BT in Montgomery County are 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 9 shows that StreetLight data correctly captures the bimodal distribution of DASH ridership and identifies the 5 p.m. peak, with an hourly ridership ratio close to DASH's ground-truth value. The three StreetLight analyses also mirrors the morning peak but with slightly less precision. Analysis SL3 follows the shape of the ground truth curve in the morning peak somewhat more closely than analysis SL2.

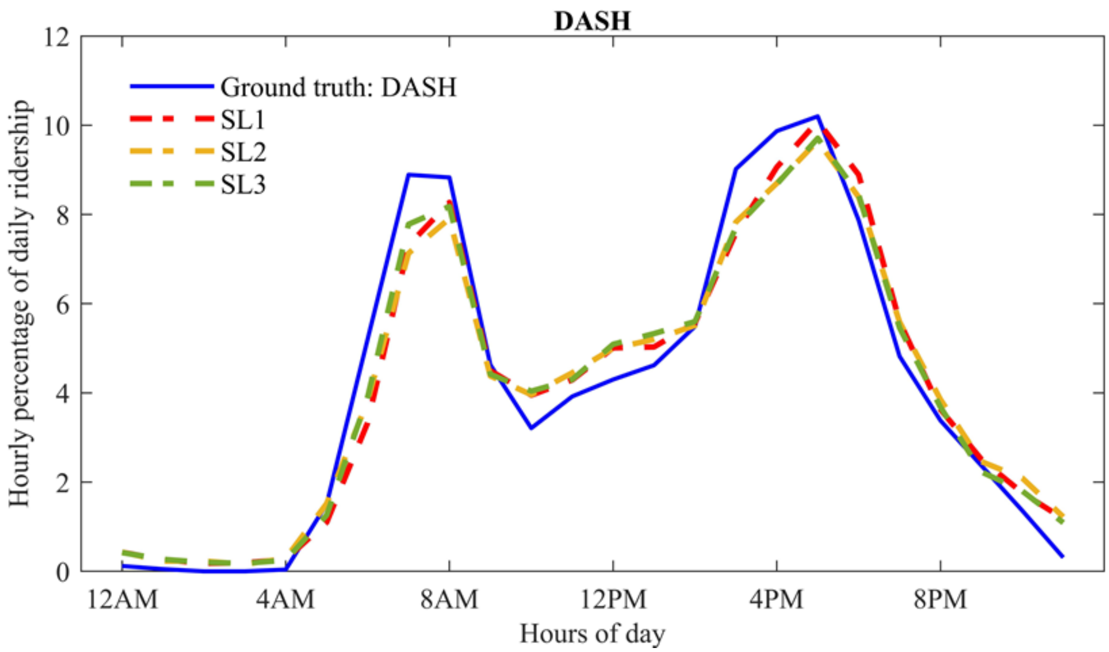

Figure 9. Comparison of StreetLight Analyses of DASH with Ground Truth Data.

Figure 10 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 misrepresent the temporal distribution of the ground-truth ridership data and peak sharply at noon with a smaller peak at 5 p.m., while the ground-truth data display 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 mornings.

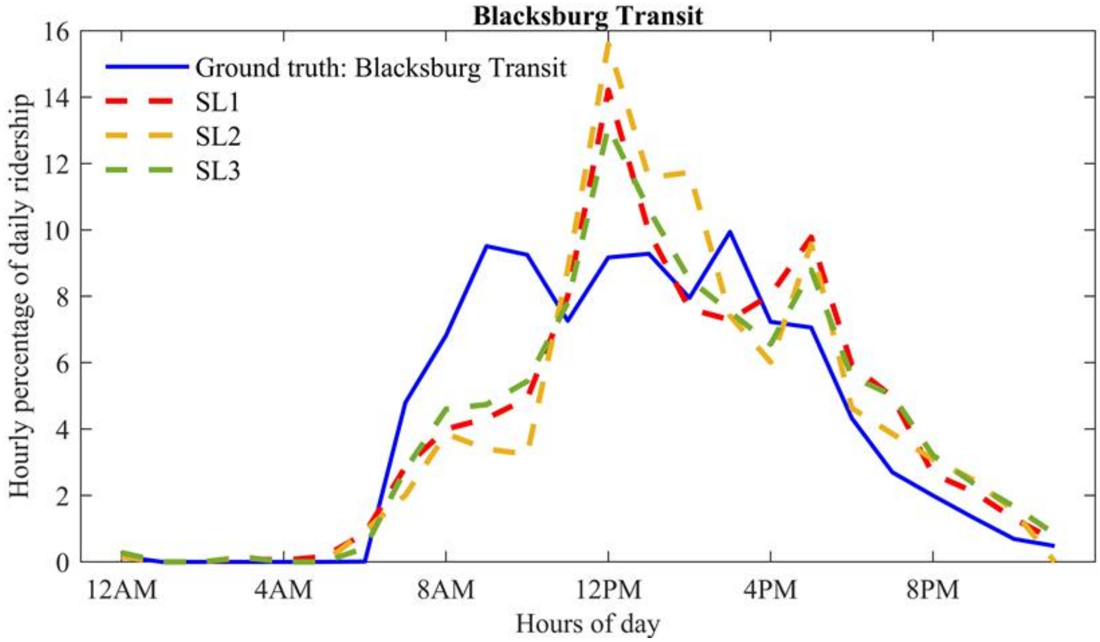

Figure 10. Comparison Of Streetlight Analyses Of Blacksburg Transit With Ground Truth Data.

RMSE values are calculated for all three analyses, as seen in Table 7.

Table 7. 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

For DASH, analyses SL1 and SL2 have the same RMSE value, and analysis SL3 is marginally more accurate. Although, like analysis SL3, analysis SL1 uses 4 months of data, it is less accurate than analysis SL3. This might be because StreetLight picks 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 are subject to imperfections in data due to possible errors in modal imputation (i.e., 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 a.m. and 4 a.m., which are outside DASH's operating hours. No clear explanation presents itself for the higher off-peak period percentages from 9 a.m. to 2 p.m. shown in Figure 9 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. Higher proportions of off-peak trips might generate LBS data than trips during peaks, 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 during peaks (or undercounting off-peak).

Similar to DASH analysis results, analysis SL3 of BT yields the smallest RMSE (Table 7). Although analysis SL1 has a higher RMSE value, it outperforms analysis SL2. Analysis SL1 could be 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 GTFS files could be used as done in analyses SL2 and SL3.

DASH’s StreetLight analysis is 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 shows 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 reports 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 like WMATA, while Montgomery County’s major bus transit agency is BT. In the StreetLight analysis for both agencies, temporal distributions are better captured with longer analysis periods (more months of data), and morning peaks are not captured by StreetLight’s algorithm as accurately as evening peaks.

In sum, as shown in Figures 9 and 10 and Table 7, StreetLight results for relative hourly bus activity levels throughout the day are 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 an unlinked passenger trip number less than 10 million are found to be unlikely to have 2019 transit activity data in StreetLight.

StreetLight Analysis of Rail

In the StreetLight analysis of the six heavy rail (Metrorail) stations, Court House has the most error relative to ground truth. Figure 11(a) shows that StreetLight underestimates the relative level of station entries in the mornings and overestimates the activity level in the evenings. Although exits from the other stations are not analyzed in this study, a brief StreetLight examination of exits for the Court House station found that they better resemble the shape and peak of the ground truth entry data. It is possible that the relatively large RMSE value (see Table 8) results from a systematic error that led StreetLight to mislabel the entries and exits for this station.

For all six stations, StreetLight’s peak ridership (entry) percentages are higher in the evenings than in the mornings. Although this matches the hourly patterns of the WMATA data for some stations, it conflicts 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. The StreetLight analyses of King St-Old Town and Court House do not detect the peak ridership hours per the ground-truth data. The StreetLight-predicted morning and afternoon peak ridership hours at Court House are both one hour earlier than the ground truth. Furthermore, there are substantial differences in temporal distribution between the StreetLight analysis of Court House and the ground-truth data. As Court House station is located below street level, it is possible that StreetLight might be unable to properly detect mobile phone pings. StreetLight's analysis of King St-Old Town misses the actual morning peak by 1 hour, but the temporal distribution is 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. McLean has the lowest RMSE and, as shown in Figure 11(f), has a relatively good fit. At four of the six stations, the values from StreetLight analyses underestimate the magnitude of the morning peak-hour ratio. This might be because, as previously suggested, people might use applications that generate LBS data on their phones less in the mornings and more later in the day.

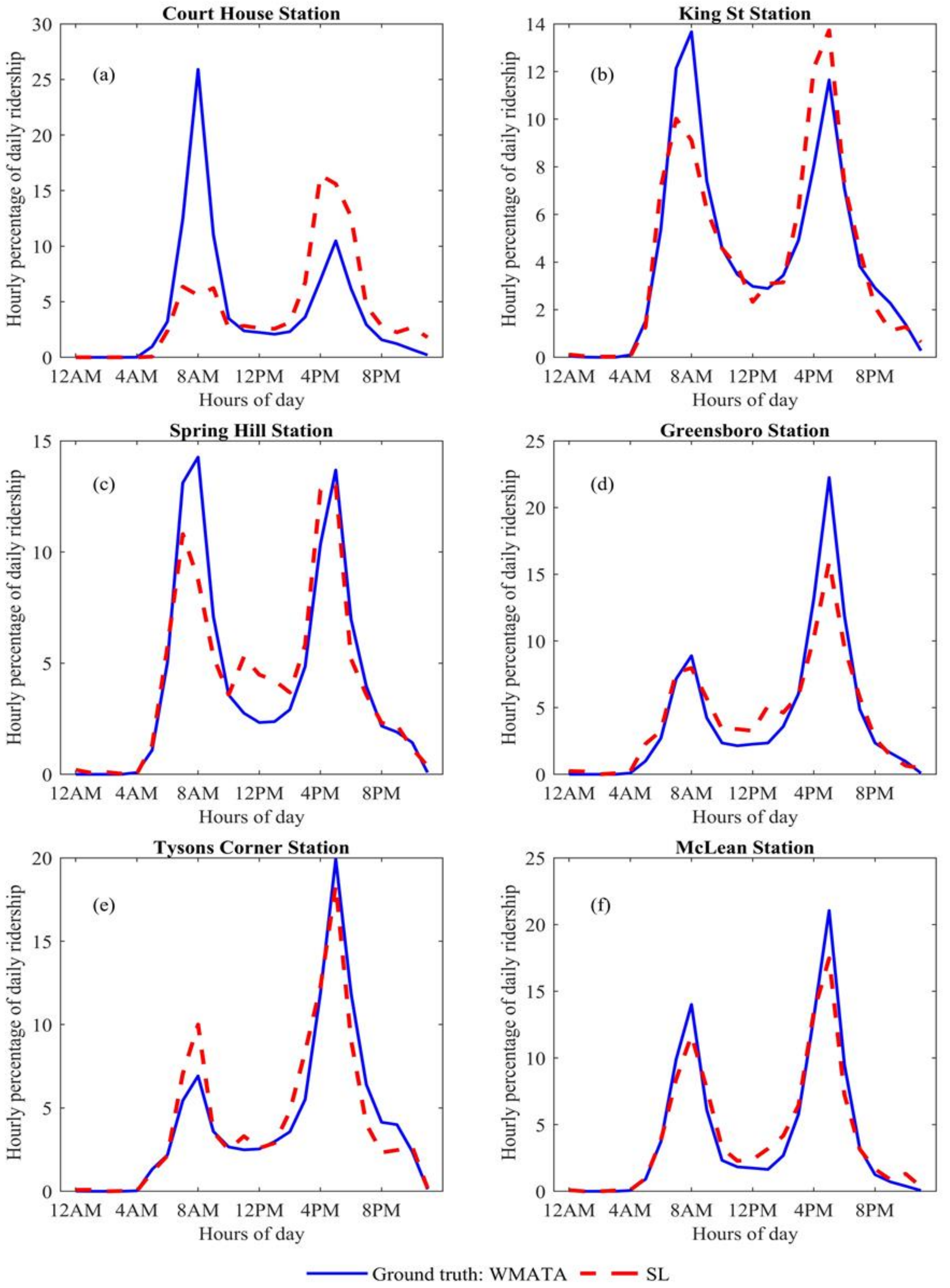

Figure 11. Comparison of StreetLight Analyses of Hourly Heavy Rail Ridership Activity Levels (labeled "SL") at Six Metrorail Stations with Ground Truth Data (labeled "WMATA").

Figure 12 shows how the StreetLight analyses for the six VRE commuter rail stations compares to the ridership data requested from VRE, and Table 8 provides RMSE values by station. As shown in Figure 12(e) and Table 8, the StreetLight analysis of Backlick Road station, with the lowest number of passenger entries among all six stations, has the most error relative to VRE-provided ridership data. However, Leeland Road station, with the most entries, does not have the lowest RMSE value. The afternoon StreetLight activity data for both the Manassas Park and the Backlick Road stations are 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 Backlick Road station and Rolling Road station, StreetLight is able to correctly identify the morning peak hour.

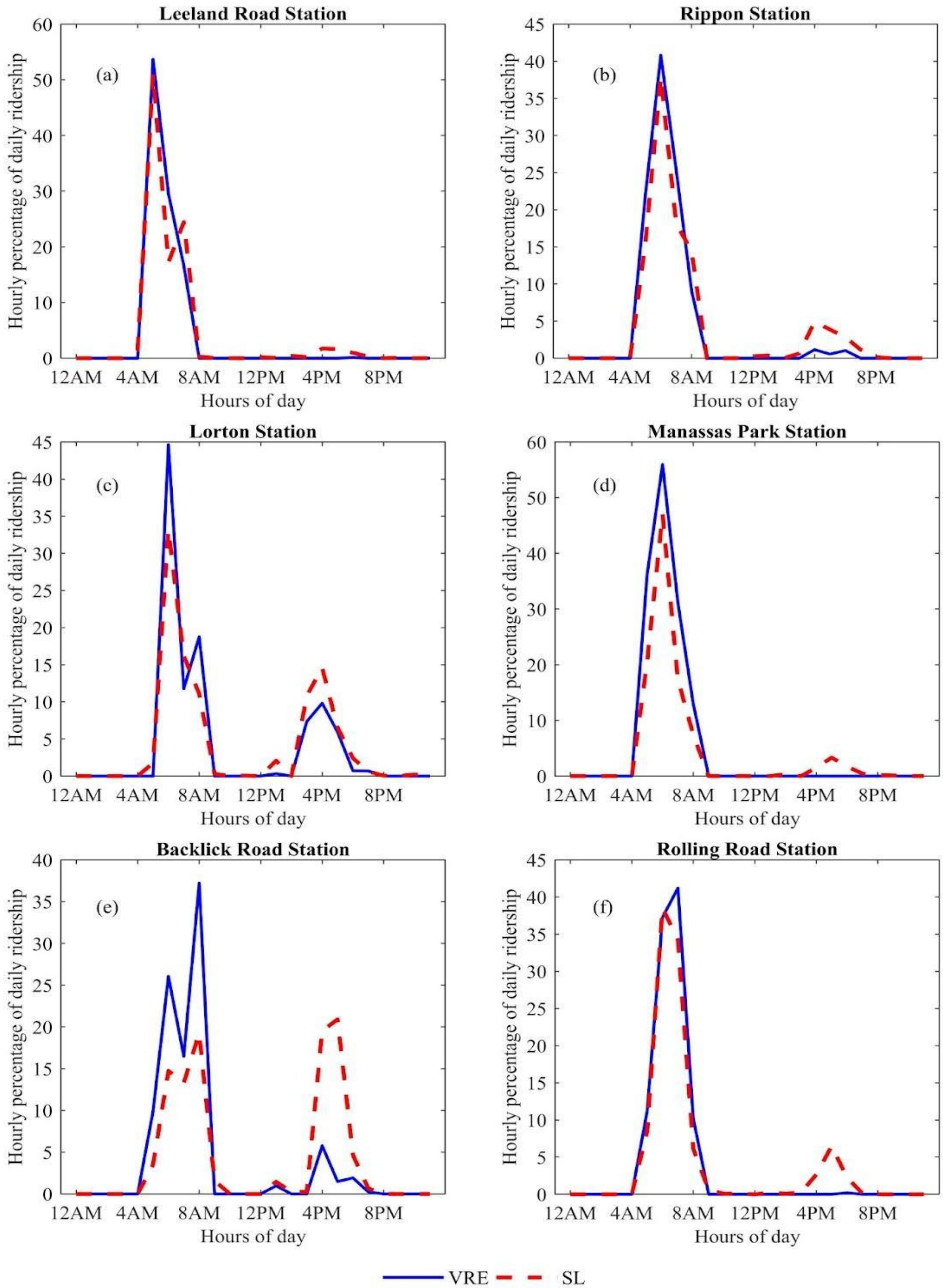

Figure 12. Comparison of StreetLight Analyses of Hourly Virginia Railway Express Commuter Rail Ridership Activity Levels (labeled "SL") with Agency-provided ata (labeled "VRE").

Table 8. Root Mean Square Error Values for StreetLight Analyses by Rail Station

Transit Agency	Station Name	Root Mean Square Error
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

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

1. VRE ridership counts are only estimates by the agency, which could contribute to some degree of inaccuracy, while WMATA routinely records its ridership counts.
2. 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.

3. VRE riders and WMATA rail riders could have different smartphone use characteristics, leading to differing ping detection rates by StreetLight.
4. 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 Metrorail and VRE are not operating, suggesting it picks up noise, possibly by mislabeling bike, bus, or auto trips as rail trips.

CONCLUSIONS

Ridership estimates are a key performance indicator for bus and rail transit projects, and are used by state and federal funding agencies to allocate funding to transit agencies. The better the ridership estimates, the more efficient the project prioritization process for proposed transit projects. Thus, this study sought improved transit ridership estimates by attempting to answer the following three research questions, using Virginia based data: (1) 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 to service frequency? (2) What percentage of transit ridership occurs during peak hours? (3) How does crowdsourced transit activity data compare to ridership data from Virginia transit agencies?

Before-after studies on stop improvements in other US states have demonstrated bus ridership increases when shelters, concrete pads, sidewalk connections, real-time information systems, pedestrian lighting, benches, trash receptacles, and bicycle parking amenities were added. This study also finds statistically significant stop-level bus ridership increases of a similar order of magnitude using data from one Virginia transit agency (Arlington County) that added ADA-compliant landing pads, benches, and lean bars, and replaced a few shelters with solar-powered shelters at its bus stops.

Using hourly ridership data from three Virginia transit agencies (DASH, Blacksburg Transit, Radford Transit), the percentage of daily ridership during the peak hour for fixed-route bus boardings is observed to be approximately 10% of the daily ridership. For heavy rail such as WMATA, it is more variable but generally higher than what it is for fixed-route buses. For commuter rail, this percentage is found to be the highest using hourly ridership estimates from VRE, which is to be expected given its limited operating hours.

The results from StreetLight analyses of DASH and Blacksburg Transit ridership show that, for 2019 data, it is 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. However, no correlation is found between the magnitude of the agency's ridership and the accuracy of StreetLight's results when compared to agency data. StreetLight's rail activity data is more likely to be complete as seen when analyzing WMATA and VRE stations, and its analysis process is simpler, for station-level analyses of Virginia agencies than StreetLight bus activity data for Virginia's bus transit agencies. The accuracy of one mode has not been found to be better than the other, but results show more complete activity data for rail relative to bus. It is important to view ridership responses to stop improvement projects with caution. The ridership increases at the improved bus stops might be caused by passengers switching from nearby unimproved stops, or due to changes in land uses over the studied time period. Thus, it is difficult to attribute changes in ridership to one factor alone. It is also important to note that the full impact of improvements to bus stops on ridership may take an indefinite amount of time to appear. Future research efforts could use more transit agencies, in both urban and rural areas, to further examine the ridership changes when stops are improved. This study did not examine commuter bus routes, future research could do so if transit agencies have stop-level boarding data. Although StreetLight only had four months of data at the time of this study, as of February 2023, more data periods have been added which could be utilized to further study the level of accuracy with respect to transit agency ridership data. Additionally, the accuracy and availability of transit activity data from StreetLight might be better in localities where StreetLight algorithms have already been used to train data.

Through attempts to answer the three research questions, this study has expanded the literature on ridership changes caused by transit improvement projects using a case study in Virginia. Project prioritization processes and decision-making of funding agencies would benefit from knowledge of the range of ridership changes that may occur in response to stop improvements, as shown in this study. This study also filled in certain gaps in literature by determining transit ridership proportions during peak hours for various illustrative types of transit agencies and by assessing the accuracy of crowdsourced transit activity data from StreetLight. Transit agencies serving small- to medium-sized cities like those in Virginia can use results from this study to obtain a better understanding of how ridership may vary throughout the day, which in turn may be used by transit agencies to adjust their service levels accordingly. Furthermore, an understanding of the feasibility and accuracy of using StreetLight transit activity data might help both transit agencies and researchers studying hourly variations in ridership of transit. In sum, this study attempted to yield better ridership estimates for evaluating proposed bus and rail transit projects.

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