GTFS for Estimating Transit Ridership and Supporting Multimodal Performance Measures

December 15, 2017

DOT-VNTSC- OSTR-17-03

Prepared for:

Office of the Under Secretary for Policy

U.S. Department of Transportation

U.S. Department of Transportation
John A. Volpe National Transportation Systems Center

REPORT DOCUMENTATION PAGE

Form Approved
OMB No. 0704-0188

1. REPORT DATE *(DD-MM-YYYY)*
15-12-2017

2. REPORT TYPE
Final

3. DATES COVERED *(From - To)*
2016 - 2017

4. TITLE AND SUBTITLE
GTFS for Estimating Transit Ridership and Supporting Multimodal Performance Measures

5a. CONTRACT NUMBER
OS43A1

5b. GRANT NUMBER

5c. PROGRAM ELEMENT NUMBER

6. AUTHOR(S)
Frances Fisher; Logan Nash; Gary Baker; Paul Teicher; Stephen Zitzow-Childs; Alex Oberg; Emma Vinella-Brusher; Eric Burkman

5d. PROJECT NUMBER
OS43A1

5e. TASK NUMBER
QC228

5f. WORK UNIT NUMBER

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)
U.S. Department of Transportation Volpe Center
55 Broadway
Cambridge, MA 02142

8. PERFORMING ORGANIZATION REPORT NUMBER
DOT-VNTSC-OSTR-17-03

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)
Office of the Under Secretary for Policy
U.S. Department of Transportation
1200 New Jersey Ave, SE
Washington, DC 20590

10. SPONSOR/MONITOR'S ACRONYM(S)
OST-P

11. SPONSORING/MONITORING AGENCY REPORT NUMBER

12. DISTRIBUTION AVAILABILITY STATEMENT
Public

13. SUPPLEMENTARY NOTES

14. ABSTRACT
This project demonstrates a potential avenue to use new data sources to support State and local agencies in measuring the use and effectiveness of their public transportation systems. General Transit Feed Specification (GTFS) data provided by transit agencies only contain schedule data and are primarily intended for use in rider planning apps like Google Maps or the Transit App. But DOT's recent creation of the National Transit Map to aggregate these feeds at a national scale provides opportunities to integrate GTFS data with AADT and demographic predictors of ridership. This project explores how this existing national transit dataset can be used to help State and local agencies estimate segment-level ridership and generate performance data useful for multimodal planning. The tools developed in this project are able to compare vehicle traffic to estimated or measured transit ridership along the same road. All of the multimodal measures developed in this project can be calculated using measured ridership data for agencies that have it, or modeled ridership for agencies that do not.

15. SUBJECT TERMS
gtfs, performance measures, arnold, transit, road snapping, national transit map

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
					Paul Teicher
a. REPORT	b. ABSTRACT	c. THIS PAGE			19b. TELEPONE NUMBER (*Include area code*)
None	None	None			202-366-4114

Executive Summary

This project demonstrates a potential avenue to use new data sources to support State and local agencies in measuring the use and effectiveness of their public transportation systems. It explores opportunities for linking General Transit Feed Specification (GTFS) digital transit schedule data, recently aggregated in the U.S. Department of Transportation's (DOT) National Transit Map, with existing datasets in order to support multimodal performance management. This joint effort is led by the DOT Office of the Under Secretary for Policy (OST-P) with technical assistance from DOT's Volpe National Transportation Systems Center. The tools developed in this project are able to compare vehicle traffic to estimated or measured transit ridership along the same road. The potential of this project is shown in Figure 1, which compares travel by private motor vehicles and public transit along roads in Minneapolis-St. Paul, Minnesota.

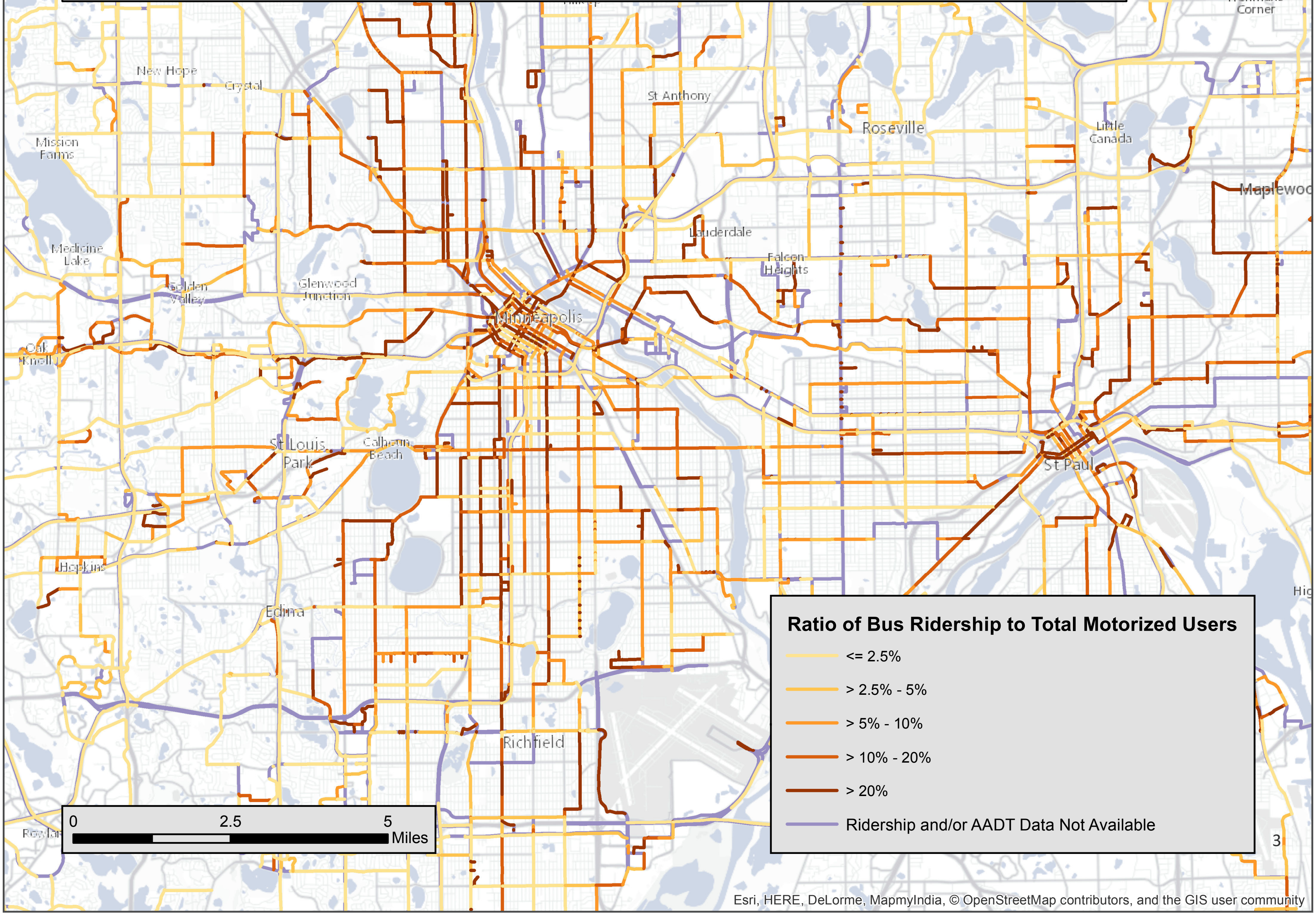
Background: Data for Multimodal Performance Measures

Creating and monitoring performance measures for the transportation system helps agencies track how the system is serving the public and make strategic decisions about where to invest limited resources. Congress established a system of national performance measures under the 2012 transportation authorization, and many State and local agencies around the country have also established performance-based planning systems to better meet transportation needs.[1]

Performance measures that capture all travel on a corridor (including cars and trucks as well as transit riders, pedestrians, and others) present the most accurate picture of access, reliability, roadway capacity, and congestion. However, measuring multi-modal travel can be challenging due to the difficulty of obtaining and reconciling data that are not from personal motor vehicle travel. For transit in particular, there is no nation-wide data on segment-level transit ridership that corresponds to vehicular Average Annual Daily Traffic (AADT), which the Federal Highway Administration (FHWA) makes available for individual road segments across the country. Transit usage data is nationally available only at the regional scale. While some agencies do collect ridership data along routes through automatic passenger counters, fare systems, or other means, it can be an expensive process, especially for smaller transit agencies. Even where transit agencies collect this data, data analysis can be an issue, and matching ridership information to the road network and AADT for multimodal comparison and performance measures is not a simple undertaking. The lack of segment-level data means that the new national performance measures based on person trips and average vehicle occupancy do not account for major differences in transit usage between different roads and corridors.

[1] For more information, see the FHWA website on Transportation Performance Management: https://www.fhwa.dot.gov/tpm/

Figure 1. Bus Riders as a Percentage of Overall Motorized Road Users in Minneapolis/St. Paul.



Project: GTFS for Estimating Ridership and Performance

While no national transit ridership dataset exists, transit schedule data is available through the General Transit Feed Specification, which has become a near-universal de-facto standard for detailed schedule information among U.S. transit agencies. GTFS feeds provided by transit agencies only contain schedule data and are primarily intended for use in rider planning apps like Google Maps or the Transit App. But DOT's recent creation of the National Transit Map to aggregate these feeds at a national scale provides opportunities to integrate GTFS data with AADT and demographic predictors of ridership. This project explores how this existing national transit dataset can be used to help State and local agencies estimate segment-level ridership and generate performance data useful for multimodal planning. All of the multimodal measures developed in this project can be calculated using measured ridership data for agencies that have it, or modeled ridership for agencies that do not.

American transit agencies operate a wide range of modes, but this project focuses on bus transit and, to a lesser degree, rail transit. This is because smaller transit agencies, which may be less able to collect segment-level ridership, usually only operate buses and because buses typically travel on public roads where transit ridership can be directly compared to overall AADT.

Results and Opportunities

This proof-of-concept analysis confirmed that ridership at the road segment level can be estimated using GTFS data combined with other national data sources. The methods and results of this project can be broken down into three main components. While the third component builds on the others and is the most directly applicable to multimodal performance management, each step produced potentially relevant deliverables for use of GTFS in multimodal planning.

Snapping GTFS to the road network and calculating road segment-level transit service: Most transit agencies include route shapes in their GTFS feed. But this data is often inconsistent and independent of accepted road network data. Creating and maintaining route shapes may be a challenge for agencies with limited geographic information systems (GIS) resources, and even the route shapes of larger agencies may become inconsistent as routes are updated over time.

This initial component of this project matched these often-inconsistent GTFS route shapes with FHWA's authoritative All Road Network of Linear Referenced Data (ARNOLD), which is linked to AADT and other road characteristic data. Snapping GTFS to the road network also produced a map of transit service frequency along individual roads, agglomerating multiple routes and even service providers. This conflation generally works well but often required some minor region-specific tweaking in order to address discrepancies between ARNOLD and GTFS spatial shapes. Combining the data sets also depended on the quality of both the GTFS route shapes and the ARNOLD roads data in that service area.

This project demonstrated the potential to adapt this project's ARNOLD snapping code (possibly altered to use Open Street Map) into a tool for transit agencies that currently lack high-quality route shapes in their GTFS. It could help them turn basic or outdated route shapes into accurate routes snapped to an authoritative road network. This tool could be a GIS asset for agencies that already have geospatial resources, but a web-based interface could enable a larger number of agencies to benefit, especially those that lack the expertise or resources for GIS software.

Segment-level ridership modeling: As stated previously, ridership information is not nationally available at the road segment level. This component estimated ridership at the road segment level using GTFS service characteristics (from the prior step) and other nationally-available data like U.S. Census demographics. These estimates were calibrated using data from a handful of case study transit agencies with measured segment-level ridership. The predictive power of the resulting model for transit ridership was similar, in some cases, to that of a typical highway travel demand model. However, the accuracy varied widely depending on the agency where the model was estimating ridership, and additional refinement to the ridership modeling would improve its accuracy.

Such models could possibly be used for planning purposes when rerouting, adding, or removing service to estimate the ridership impact along key corridors. Additionally, if predictions for changes in development, land use, employment, and demographics are available, future year conditions could be modeled to predict ridership changes over time.

Performance measures for multimodal corridor usage: Using ADDT and either the estimated segment-level ridership from the prior component or actual, measured ridership from an agency, this project's tools can calculate proof-of-concept multimodal transportation measures. In particular, the project team estimated total motorized users (private vehicles and transit) on all road segments in certain cities, and then determined the percentage of those users who are transit riders.

Two FHWA-required performance measures for States and metropolitan planning organizations consider levels of transit travel: (1) Annual Hours of Peak-Hour Excessive Delay Per Capita (the PHED measure) and (2) Percent of Non-Single-Occupancy Vehicle (SOV) Travel. FHWA developed a region-wide methodology for calculating these measures, but gave flexibility to use other, more accurate data and methodologies. At the national level, FHWA could consider refining this ridership model and allowing local agencies to use its outputs as an alternative way of calculating the PHED and non-SOV travel measures. Model improvements to support this use could include use of more calibration data from agencies with segment-level ridership counts.

In addition, measures like "transit riders as a percentage of total motorized road users" could be useful at a local level in multimodal planning that identifies corridors where on-road transit improvements (e.g. bus lanes, pullovers) would be most effective.

Potential Next Steps for Researchers and Agencies

This proof-of-concept effort confirmed that GTFS can be a viable foundation for estimating segment-level ridership and matching measured ridership to AADT. While more work is needed to fully take advantage of this data, the project team identified a number of ways that the results above could be useful for performance management and multimodal planning. To encourage others to take advantage of these opportunities, the project team has released the source code for its analysis tools. There are three main potential next steps that would further this research and the development of national multimodal performance measures:

1. **Refine the estimations for multimodal congestion and delay.** While the FHWA transportation performance management (TPM) rulemakings use region-wide transit ridership data for measuring congestion and delay, flexibilities were incorporated into those rquirements so that States and MPOs could use more detailed methods instead. This presents an opportunity for public transit agencies and their State and MPO partners to develop more detailed measures. As a potential next step from this project, FHWA, FTA, or other stakeholders could refine this project's outputs so that there is a clear method for using GTFS-linked estimated or measured ridership data as inputs for existing, defined national TPM measures.

2. **Enhance and validate the ridership model.** The ridership model developed in this report is intended as a proof-of-concept for the use of GTFS to inform segment-level ridership in support of multi-modal performance measures. This work demonstrated the usefulness of variables derived from GTFS data in estimating segment-level ridership. Building on the foundational work described in this report, future work should focus on incorporating GTFS-derived variables into more robust statistical frameworks that maximize internal and external validity so that estimated ridership could be effectively incorporated into a robust multi-modal performance measurement framework.

3. **Apply the tools for other transit agency planning activities.** Local and State agencies may also find these tools useful in their own planning activities. For example, this project's road snapping algorithm could be useful for agencies that currently lack high-quality route shapes in their GTFS. In addition, measures like "transit riders as a percentage of total motorized road users" could be useful in multimodal planning that identifies corridors where on-road transit improvements (e.g. bus lanes, pullovers) would be most effective. This project's data integration and code could be used as a stepping stone for further planning activities not directly related to TPM measures.

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Introduction

The Moving Ahead for Progress in the 21st Century Act (MAP-21) and subsequent transportation legislation requires that the U.S. Department of Transportation (DOT) propose performance measures for use by agencies including State Departments of Transportation (State DOTs) and metropolitan planning organizations (MPOs). However, while highway usage data is nationally available for individual roads, transit ridership data is nationally available only at the region-by-region level. This disconnect limits multimodal analysis in performance measures that are based on person trips and average vehicle occupancy.

Transit Data Challenges for Measuring Multimodal System Performance

Baseline measures for highway usage like average annual daily traffic (AADT) are nationally available through the Federal Highway Administration's (FHWA) Highway Performance Monitoring System (HPMS). States submit AADT to HPMS on the road segment level, and data from some States even shows road usage changes down to a block-by-block scale. However, information on vehicle type and occupancy is typically not available at this level of detail.

While the Federal Transit Administration's (FTA) National Transit Database (NTD) records unlinked passenger boardings, transit agencies only report this usage data by mode (e.g. for all bus service operated by one agency). While some agencies do collect ridership data at the segment level through automatic passenger counters, fare systems, or other means, it can be an expensive process, especially for smaller transit agencies. Additionally, even high-resolution ridership data is rarely tied to corresponding data about the underlying road network.

National Performance Management

The third rule FHWA promulgated under the National Highway Performance Management Program required under MAP-21 includes two traffic congestion measures that consider levels of transit travel: (1) Annual Hours of Peak-Hour Excessive Delay Per Capita (the PHED measure) and (2) Percent of Non-Single-Occupancy Vehicle (SOV) Travel. [2] Because of current national data availability, the baseline approach for these measures uses one region-wide number for bus occupancy based on the regional number of riders by transit agency and the regional number of vehicles in service. This may limit the effectiveness of performance measures for certain uses, especially comparing different corridors. For example, using region-wide transit usage numbers will overestimate the person-hours of delay on some

[2] https://www.federalregister.gov/documents/2017/05/19/2017-10092/national-performance-management-measures-assessing-performance-of-the-national-highway-system These measures apply to urbanized areas that contain National Highway System mileage and have a population over 200,000 and are in a nonattainment or maintenance area for ozone, carbon monoxide or particulate matter.

corridors where transit may not run or may have limited ridership. It will also underestimate person-hours of delay on high-transit usage corridors, where full buses are delayed alongside passenger cars.

But under national performance management rules, State DOTs and Metropolitan Planning Organizations (MPOs) have flexibility to use more accurate local data if such data are available. The imperfect national picture of public transit passenger ridership at the segment level provides an opportunity to develop more granular estimations using emerging data sources. These could be tested locally and potentially be the basis for future national refinements. Transit agencies can also set locally-specific goals and measures for their own purposes This project explores how the near-universal availability of digital transit schedule data in particular could help rectify transit data challenges for multimodal planning.

General Transit Feed Specification Data Opportunities

The most fine-grained, nationally-consistent data about transit systems is schedule data, which most agencies share using the General Transit Feed Specification (GTFS) format, developed in 2005. Third-party developers such as Google Maps, Apple Maps, or Transit App use this data to provide transit directions and scheduling to their users.[3] In 2016, DOT created the National Transit Map, a voluntary system for agencies to submit data, including GTFS feeds, to a publicly-available national database. Some other websites aggregate links to agency GTFS feeds, but the National Transit Map, for the first time, applies a common usage license and access method across all participating agencies.

While GTFS is largely a format for transit schedules and does not itself contain any ridership data, it contains spatial data about transit stops (and sometimes also routes) and very detailed information about the level of transit service offered along those routes at different times of the day, week, or year. This complements the NTD, which contains a wider range of data, including ridership, but only at the broadest scale (i.e. agency-wide and by mode across the whole year). Combined with other data like NTD, GTFS could be the basis for estimating ridership at this same detailed level or otherwise matching transit data to existing granular highway data sources.

Project Purpose

The goal of this project is to determine if transit ridership at the road segment level can be estimated using GTFS data combined with other data sources, and to see what other roles GTFS could play in multimodal performance measures. This joint effort is led by the DOT Office of the Secretary of Transportation for Policy (OST-P) with technical assistance from DOT’s Volpe National Transportation

[3] GTFS is the standard format for *scheduled* transit data. Data formats for sharing information about *real*-time transit vehicle arrivals (including a GTFS-Realtime specification) are necessarily more complex and a de-facto standard has not yet emerged. However, almost all of them depend on existing scheduled GTFS data to function. This project does not use any realtime data.

Systems Center.

Project Scope

This is an exploratory, proof-of-concept research project that assesses the feasibility of using GTFS to help measure multimodal system performance by linking it to the road network and testing some real-world approaches using transit agency case studies. There are three general steps to the project. These steps build on each other but also produce intermediate deliverables that may have overall value.

1. **Snapping GTFS to the road network and calculating road segment-level transit service**. This puts transit information from GTFS in the same data structure as AADT and other highway data.
2. **Segment-level ridership modeling** that estimates ridership using GTFS service characteristics and other nationally-available data. Measured segment-level ridership data from case study agencies enabled calibration of the model estimates.
3. Developing a **performance measure for multimodal corridor usage** using segment-level transit ridership (either estimated or actual) as well as available road usage data.[4]

The project team assessed the results and usefulness for each of these steps using objective measures (e.g. comparing estimated ridership to actual ridership) as well as through discussions with DOT stakeholders.

[4] This project focuses on multimodal motorized surface users, i.e. transit and private vehicles. It would be useful to be able to integrate nonmotorized users like cyclists and pedestrians, but these modes pose their own distinct challenges for consistent data collection and analysis.

Methodology and Data

GTFS is a user-focused data source designed to share schedule information with the public rather than a management dataset. The largely consistent format across agencies is an advantage for national analysis, but GTFS also poses some challenges when used for performance management rather than traveler information, including:

- GTFS does not contain information about ridership. It is primarily a service schedule with some other basic information also available (e.g. agency website, fares, stop accessibility).
- GTFS has no requirement to include route shapes. Although each stop in GTFS must have a latitude and longitude, the specification does not require agencies to include detailed route shapes between stops.
- Route shapes, when provided, are associated with individual route deviations, and there is no guarantee that these shapes are consistent even within the same route.
- Basic service characteristics such as route frequency are only indirectly available. For example, someone must calculate frequency based on the scheduled arrivals and departures listed in the GTFS feed.

To explore GTFS's potential use for multimodal performance measures, the project team needed to incorporate complementary data sources and develop automated processes that transform and summarize the raw GTFS data. Most of this combination and analysis fell into the three broad steps outlined in the previous section. The list below describes the data sources used in each step. These are discussed in greater detail in the following sections.

- **Snapping GTFS to the road network and calculating road segment-level transit service**
    - Agency-level GTFS schedule from the National Transit Map
    - All Road Network of Linear Referenced Data (ARNOLD) and Highway Performance Monitoring System (HPMS) data from FHWA (2015 data used)
- **Segment-level ridership modeling**
    - GTFS service characteristics from prior step
    - Spatial demographic data from U.S. Census American Community Survey
    - Spatial employment data from U.S. Census Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics (LODES)
    - Agency and mode-level unlinked passenger trips from NTD
    - Measured segment-level transit ridership from individual transit case study agencies
- **Multimodal performance measures**
    - Estimated and actual segment-level ridership from prior step
    - AADT data from HPMS, which uses the ARNOLD network

GTFS network snapping and service characteristics

For the project team to estimate segment-level transit ridership and hence corridor multimodal usage at the same scale, it first had to identify the corridors where transit service exists, calculate the attributes (in particular, the frequency) of that service, and identify the best way to match this data with the corresponding road network.

Fortunately, GTFS describes the location and supply of transit service at a very granular level. In particular, it has the location of transit stops and information that can be used to calculate service frequency to those stops. But as outlined above, it is challenging to calculate basic service characteristics from GTFS because the data is structured for providing user schedules rather than for analysis, and data quality can vary widely even within agencies.

This contrast is especially apparent when comparing GTFS to spatial tools designed for management and analysis. Systems like FHWA's HPMS are linear referenced, meaning that there is one set of spatial data (e.g. ARNOLD), and HPMS characteristics such as speed limit, AADT, or lanes are referenced to the network by milepost in a separate table or series of tables that can easily be integrated with the spatial data. Therefore, attributes such as the number of lanes can be easily queried with other attributes such as AADT, and analysts can quickly answer questions like "what are the highest traffic two-lane roads in our system?"

Figure 2 diagrams the challenges of working with GTFS shapes since they do not inherently line up with a consistent road network. In this example, the Red Bus and Green Bus follow the same road for part of their routes. However, because of GTFS's data structure, each of these two bus services has its own unique set of coordinates that make up its route shape. In many cases, these route shapes largely align where they overlap. However, in this example the route shapes are slightly different. While this is not a problem for calculating service frequency along either of the routes in isolation, it presents two problems for analysis at the level of the road segment:

- It makes it difficult to calculate the combined frequency of the routes where they overlap.
- Neither route aligns with the underlying road network, which makes it difficult to programmatically compare road characteristics (e.g. AADT) to transit characteristics (e.g. frequency, ridership).

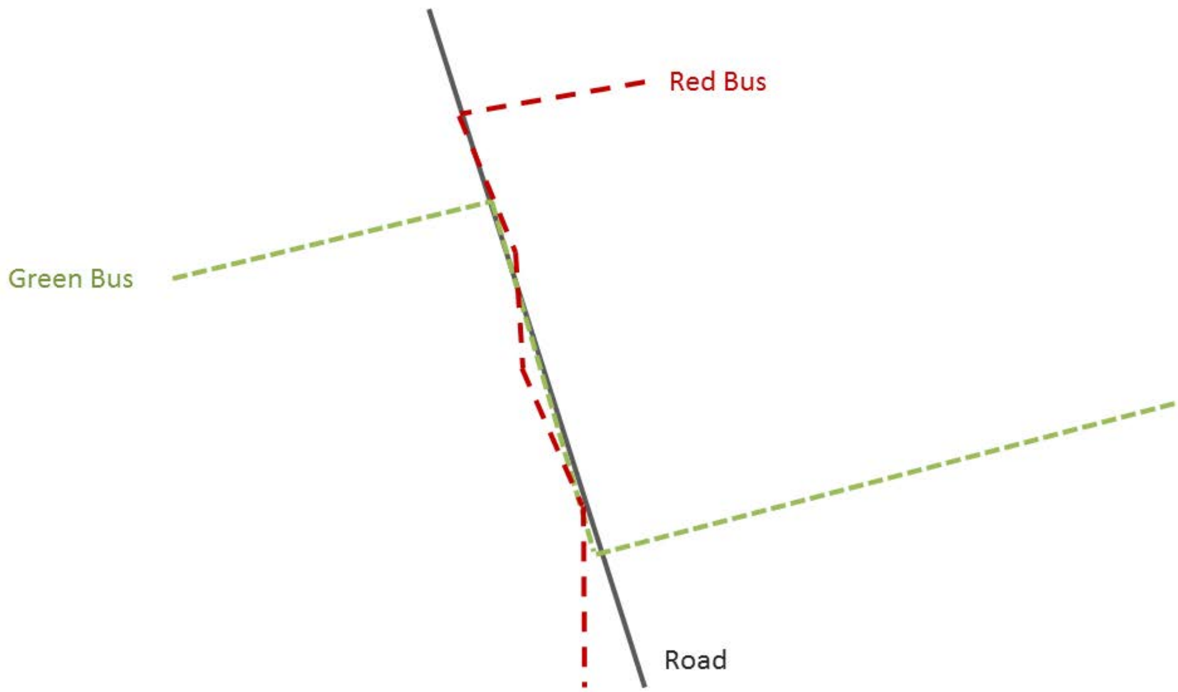

Figure 2: GTFS shapes, where route shapes do not align even when they are traversing the same road.

Snapping to the ARNOLD Network

To help resolve this challenge, the project team developed a Python script that attaches or "snaps" on-road transit routes to a master road network. The team chose to use ARNOLD data as the master road network, since this is the same network used for linear-referencing HPMS and national AADT data. Having transit data referenced to the same network as AADT not only resolves the route shape consistency challenge, but also enables automated analysis and comparisons between road data like AADT and transit data calculated from GTFS or other sources. Segment-specific data used in FHWA's third performance management rulemaking either come from HPMS or will be conflated with HPMS data.

The shapes table in a GTFS feed contains a series of coordinates representing the path of travel for each shape ID—hereafter referred to as a route shape—in a transit network. The ARNOLD snapping process attempts to match each route shape and stop from the GTFS feed to the closest location along the ARNOLD network. The algorithm describes each route shape as a series of ARNOLD road segments broken up at every intersection, transit stop, or change in AADT data. Breaking up the route shape at such a granular level along the road network allows detailed analysis of ridership, AADT, and other measures. Figure 3 shows the native GTFS route shape compared to the same route shape snapped to ARNOLD, with each link shown using brackets.

Figure 3: Image on the left is the native GTFS route shape. Image on the right shows result of ARNOLD snapping, including how links are broken up.

Challenges with Road Snapping

The success of this snapping process depends on the data quality of both the GTFS route shapes and the ARNOLD network. GTFS does not require the shapes table— which details the path of each route shape—in the specification, and some agencies do not have this data in their feeds. In those cases, the GTFS stops table can be used to roughly identify the outline of a route shape (this is common practice for many transit trip planning apps). While these rough lines can be snapped to ARNOLD, the result is often inacurrate, with transit routes resolving to roads where they may not actually travel. The current route snapping script therefore requires the presence of a GTFS shapes table.

For ARNOLD, data quality varies from State to State, at least in the 2015 data used for this project. In some—such as Florida and Pennsylvania— the ARNOLD submission does not include all public roads, and therefore, GTFS route shapes cannot be accurately snapped to the road network. In addition, because ARNOLD is submitted on a State-by-State basis and is not yet designed to operate as a seamless national network, roads do not typically align at State borders and associated attributes (e.g. AADT) may sharply change as routes cross the border. Across each State, there is also an inconsistent approach for handling dual carriageways (i.e. two way roads separated by a median). ARNOLD sometimes includes both dual carriageways—with HPMS data only attached to one of the two carriageways. In other cases—

only one of the dual carriageways is included but the exclusion of the other dual carriageway negatively impacts the street network's connectivity—and as a result, leads to quality issues with the snapping and routing processes.

These challenges mean that good-quality ARNOLD snapping is not as straightforward for some transit agencies, especially those that operate across more than one State or are located in States with incomplete ARNOLD data. Using a different road network such as OpenStreetMap (OSM), which is widely used in consumer-facing navigation tools such as Google Maps, could potentially address ARNOLD data quality issues. However, this would mean that GTFS transit characteristics would not be seamlessly attaching to the same road network used to linear-reference HPMS measures such as AADT. This connection would have to be made using another process that matches OSM roads to ARNOLD counterparts.

Working with Non-Street-Running Transit

Another important caveat for conflating GTFS routes to ARNOLD or any road network is that such networks are of limited use for transit service that does not run primarily on the road system (e.g. rail, some bus rapid transit, ferry). Even bus routes that primarily run on the public road network may have certain sections that operate in dedicated rights-of-way such as bus tunnels or on private rights-of-way such as parking lots. For this project, the project team manually added these rights-of-way to ensure the route is represented accurately. However, these manually-added segments obviously do not have AADT data that is linked to the ARNOLD network.

The project team chose not to snap services that run entirely or primarily apart from public streets. There is not a comparable, nationally available master network similar to ARNOLD for modes like rail, and any master network would not have AADT data. Also, native GTFS shapes for rail and BRT appeared to largely be good quality compared to shapes for other bus services. Comparisons between highway usage and transit usage are still possible, but must be mapped and compared manually instead of the programmatic spatial comparisons possible when the data are attached to the same network.

Ridership modeling

While granular service characteristics such as route location, stop location, and frequency can be calculated directly from GTFS feeds, there is no ridership data in GTFS. As stated previously, the focus of this project is to explore if this information from GTFS feeds could be combined with other datasets to estimate ridership at the road segment level. The main data for this proof-of-concept effort is:

- Service characteristics calculated from GTFS,
- Nationally-available ridership predictors such as U.S. Census demographic data, and
- Actual stop/route-level ridership data from certain case study transit agencies.

The project team developed a linear-combination ridership model that estimates segment-level ridership using the data described above. The model works by estimating ridership for each transit segment (path between two stops) based on potentially predictive features which describe the segment and the area near the origin stop. GTFS service characteristics are the most fundamental piece, since this information determines supply, i.e. there cannot be transit riders on roads where there is no transit service. External inputs such as demographic data estimate the usage of this supply while real ridership data from case study agencies calibrate the relationship between these predictors and transit ridership.

It is important to note that this ridership model was developed as a proof-of-concept for demonstrating the possibility of using GTFS to estimate segment-level ridership in support of multi-modal performance measures. This work demonstrated the usefulness of variables derived from GTFS data in estimating segment-level ridership. Building on the foundational work described in this report, future work should focus on incorporating GTFS-derived variables into more robust statistical frameworks that maximize internal and external validity so that estimated ridership could be effectively incorporated into a robust multi-modal performance measurement framework. Additionally, the model was developed using day-total measures based on a typical 2016 day (total ridership, total service, etc.) to keep in line with AADT measures. However, alternative timeframes could be used, such as morning or evening peak periods, in order to examine the behavior of transit users who are commuting to and from work rather than those using transit for shopping or entertainment purposes.

Nationally-available ridership predictors

Because this project focuses on addressing gaps in nationally-available performance data, the project team chose to use predictors of transit ridership that are available across the entire country and can be used to estimate ridership on any system in the National Transit Map. Volpe consulted with staff at FTA and OST on the selection and availability of different national-level measures. The list of data inputs was fairly extensive, but the significance of each variable was assessed during calibration to exclude non-relevant inputs.

The sections below describe the data sources, specific variables used, and how the model makes use of the data. In nearly all cases, demographic-type data were aggregated within a ¼-mile radius of each transit stop. This was done regardless of the transit mode serving each stop, although rail ridership catchments may be larger than those for bus service.

U.S. Census American Community Survey (ACS)

The demographic information from the Census Bureau's American Community Survey is a standard nationwide tool for transportation planners. It describes socio-demographic characteristics of residential populations across the country. While ACS includes a number of data products, detailed data at the block group scale is only available using the ACS 5-year estimates. This project uses the 2011-2015 estimates.

ACS variables were aggregated using a ¼-mile buffer around each stop in the transit system, and either summed or averaged based on U.S. Census block group-level information. Because census block group geographies do not line up with the ¼-mile buffers around each transit stop, the ACS data is proportionally aggregated based on the percentage of each relevant block group that lies within the buffered area. Key variables focused on:

- Population
- Age
- Race
- Education
- Housing
- Workers/Commute
- Income

U.S. Census Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics (LODES)

The Census LODES dataset includes a variety of spatial data about employment. Particularly relevant for this project, it summarizes the number of jobs by employment sector and earnings at various Census geographies. This is a useful complement to residentially-focused ACS data since many transit trips are commute-to-work trips.

The model ingests block-level LODES data summarized at ¼ mile buffers around each transit stop. As was also the case for the ACS block group-level data, census blocks do not always align with the ¼-mile buffers around each transit stop. To address this, the algorithm proportionally aggregates LODES data based on the percentage of each relevant block that lies within the buffered area. Jobs data were broken out according to average monthly earnings and North American Industry Classification System (NAICS) sectors.

FTA National Transit Database

Although NTD only collects ridership data at the mode level for each agency, it is valuable as an official nationwide source for ridership. The high-level data in NTD provides a mechanism for the model to adjust granular ridership within each system based on overall "size" of the agency's service. While the project team discussed using NTD boardings (unlinked trips) as an absolute system-wide ceiling on the ridership estimates generated for individual segments, boardings and passenger load are not directly comparable figures. While it would be possible to instead compare estimated passenger miles traveled (PMT) to PMT as reported in NTD, the project team found that even PMT calculated from measured segment-level ridership did not always match with NTD, so using this approach could introduce more uncertainty into the model (see Results section).

FHWA ARNOLD

The project team primarily used ARNOLD for the road snapping process described above and AADT data for comparison to transit usage. However, the project team also used intersection density in ARNOLD as a proxy for physical walkability, which is not well captured in demographic data.[5]

The model uses the total number of intersections within a ¼-mile radius around the origin stop of each two-stop transit segment.

Measured ridership data from case study transit agencies

In addition to the inputs above, which are used as potential predictors of segment-level ridership, the project team calibrated the model using measured segment-level ridership from several case study transit agencies. This was critical for calculating coefficients for national demographic data and GTFS inputs and also to identify those inputs that do not appear to be significantly correlated with ridership.

The OST-P and Volpe project team worked with FTA to identify a subset of transit agencies willing to participate in the calibration process. Although the size, context, modes operated, and available data varied among each of these agencies, all had at least some stop or segment-level ridership data.

The following transit agencies provided ridership data to help calibrate the estimation model:

- Bay Area Rapid Transit – San Francisco, CA
- Long Island Railroad – New York, NY
- Massachusetts Bay Transportation Authority – Boston, MA
- Metro Transit – Minneapolis and St. Paul, MN
- North Arizona Intergovernmental Public Transportation Authority – Flagstaff, AZ
- San Joaquin Regional Transit District – Stockton, CA
- Valley Metro – Phoenix, AZ

Weekend and off-season ridership data

While some of these agencies also collect ridership data for weekends and off-season, the baseline information across all agencies is for a typical or aggregate weekday. Since GTFS contains weekday as well as weekend service schedules, and often includes ridership in different seasons, the model could theoretically be used to calculate ridership for a variety of conditions.[6] However, the project team chose to focus on weekday ridership since this was the common level of data availability across the case study transit agencies and is consistent with the single-baseline approach of an AADT value.

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[5] For more on the connection between walkability, intersection density, and transit see Environmental Protection Agency, "EnviroAtlas Fact Sheet: Estimated Density of Walkable Roads," August 2015. https://enviroatlas.epa.gov/enviroatlas/DataFactSheets/pdf/Supplemental/Estimatedintersectiondensityofwalkableroads.pdf

[6] Currently, the National Transit Map aggregates the GTFS data available from each agency on one consistent day (i.e. all GTFS feeds are downloaded from agencies at around the same time). However, in the future it may be possible to agglomerate feed versions so that year-round service data is available even when agencies only post one season at a time.

Running the estimation model

The ridership estimation model is written in the Python programming language and designed modularly so that it can easily be adapted or updated based on different inputs or techniques. In general the use of the model can be broken down into the following steps, each of which includes at least one Python module that can be modified with minimal impact on the other modules:

1. Import GTFS feed and assess service parameters
2. Format measured ridership inputs
3. Import additional socio-demographic and other information
4. Fit a ridership model
5. Estimate ridership with fitted model

Step 2 is only required when incorporating measured ridership data from transit agencies for the purpose of calibrating or validating a ridership model, and both steps 2 and 4 can be omitted if existing calibration coefficients are being used to produce ridership estimations in step 5. If a set of accurate calibration coefficients is established, a transit agency or other user would only need to set a few parameters based on their GTFS feed to estimate ridership.

1. Import and assess GTFS service parameters

This module contains functions that read the entire GTFS feed for a given agency and construct a relational database which defines all routes, trips, stop times, and service calendars. The module then produces segment-based service characteristics for all routes/trips. As discussed above, the project team focused on estimation of ridership on a typical weekday, primarily using service schedules from fall (October) of 2016.

2. Format measured ridership inputs

Each transit agency provided ridership data in slightly varying formats, a challenge and opportunity that is discussed later in this document. Most agencies provided either daily passenger loads for segments between stops for each route or stop-level boardings and alightings. But some agencies instead provided origin-destination pairs, which required route assignments, or trip-by-trip loads that had to be aggregated into a full day of data.

This module includes steps that reformat the boarding, alighting, and passenger loading measurements into the same segment-by-segment format used in the prior step. In particular, it aggregates data provided on particular route segments into ridership along each road segment across all routes, which is consistent with the data structure used by the model and enables mapping of agency data onto the ARNOLD network.

The Python modules in this step are customized to match the ridership format used by each agency providing calibration data. This presents a notable but surmountable challenge for this project since only seven case study agencies provided data. However, since each individual agency requires at least one customized function, this can quickly become unmanageable as the number of agencies increases. A common format for ridership data, possibly directly tied to the GTFS standard, would streamline this entire process, and will be discussed at greater length later in the document.

3. Import socio-demographic/other data

The final input component to the ridership model includes a series of additional functions to handle socio-demographic data from various sources. These data, calculated for every stop within each case study agency, are imported and related to the segment-based service and ridership data based on the origin stop of each transit segment. For example, a segment from stop 1000 to stop 1001 would incorporate socio-demographic or other data from stop 1000.

4. Fit a ridership model

To weight the various GTFS and demographic inputs, this step calculates model coefficients based on actual ridership measurements. It begins with segment-level ridership (from the calibrating transit agencies) and compares it to the input GTFS service characteristics and demographic data to find a set of best-fit model parameters. The resulting calibrated coefficients are the key input into the next step of the model. Figure 4 diagrams the fitting process starting with input features and ending with these calibration parameters. This step also calculates an assessment of the effectiveness and significance of the model coefficients using an adjusted R-squared to describe how closely the estimation process matches the observed (measured) data.

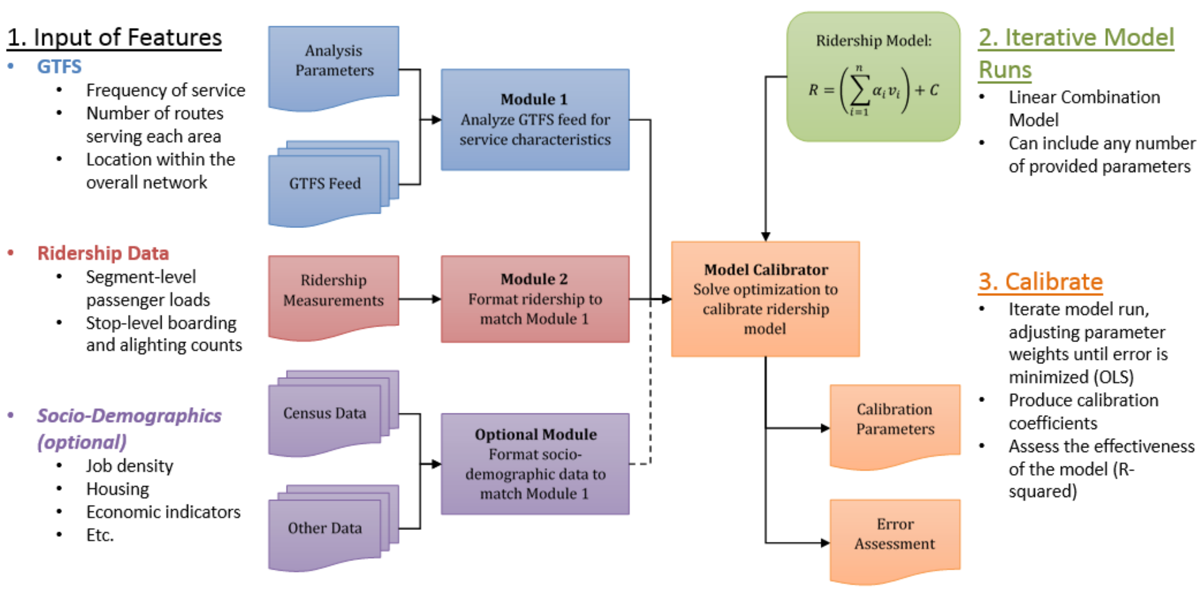


Figure 4: Diagram showing the fitting process (step 3) for the ridership model

The model itself is a linear combination model, which takes the form:

$$R = \gamma_0 + \sum_{i=1}^{n} \gamma_i x_i$$

where:

R	is predicted ridership
$\gamma_0, \gamma_1, \ldots, \gamma_n$	are calibrated coefficients assigned to each input parameter (γ_0 is the intercept)
$x_1, \ldots, x_n$	are input parameters from GTFS or other national data sets
n	is the total number of input parameters

Essentially, the model includes a coefficient on each input parameter as well as an overall intercept value (γ_0) which are summed to estimate ridership for any given transit segment. An ordinary least squares (OLS) optimization within the *statsmodels* Python package is used.

This model form was selected for two reasons: it is flexible in dealing with multiple input parameters, and it is straightforward to interpret and understand. The project team could calibrate the model using a "menu" of input parameters that could be tailored for different model iterations. Data fields from any of the data sources could be added or dropped from any given analysis without issue. Optimization routines, which are included in scientific Python packages, were also easy to incorporate to produce best-fit coefficients. Different models and approaches for further research beyond the scope of this project are discussed later in the opportunities and insights section.

For interpretation, the model generates a coefficient for each input parameter that indicates the predictive direction and strength of that parameter. The coefficients help describe the parameters that affect ridership most and whether the relationship between each input and ridership is positive or negative. This will be discussed in more detail in the results section.

The coefficients that the model uses to predict ridership in the next step (and for each iterative model run) depends on which of the set(s) of ridership data from the case study transit agencies are used for calibration. The project team tested a variety of fitting approaches using the various transit agency calibration data available. Results are included in a later section, but the calibration approaches included using:

- All case study agencies, regardless of mode
- All case study agencies, segregated by mode (i.e. different calibration parameters for bus and rail)
- All case study agencies except for a test agency

5. Estimate ridership with fitted model

In this final step the previously defined and calibrated ridership model, as well as the service and demographic characteristics, are used to produce an estimate of ridership at the segment level. Figure 5 diagrams this process ending with the output of estimated ridership for a given agency.

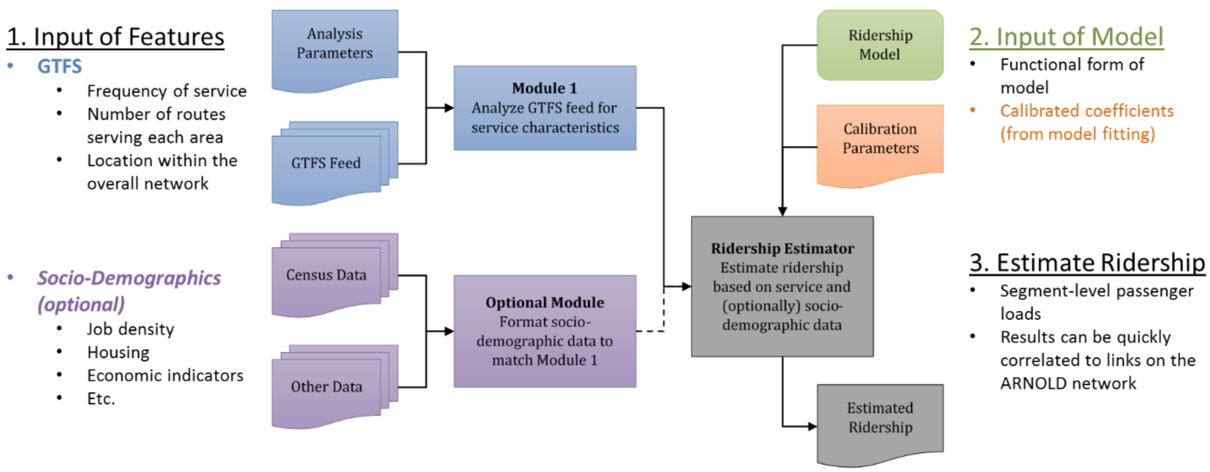


Figure 5: Diagram showing the ridership estimation process (step 4) for the ridership model

The estimated segment-level ridership from this step can be attached to the ARNOLD network for visualization/mapping and comparison with other data such as AADT.

Multimodal performance measures

The ultimate end product for this project is a prototype, corridor-level multimodal performance measure that builds on the availability of AADT road usage data and GTFS schedules. The two proposed performance measures discussed here take advantage of having AADT and bus ridership in the same data format. The measures are:

- **Total daily motorized road users**: Obtained by multiplying AADT on a road segment by an average vehicle occupancy. The project team used 1.6, the average vehicle load factor from the 2009 National Household Travel Survey, although it would be simple to substitute a different or regionally-specific number.[7]
- **Percentage of motorized road users on transit**: Obtained by dividing the number of transit riders on a road segment by the total motorized road users.

Importantly, the measures above can be calculated using either the estimated segment-level ridership

[7] FHWA, “Summary of Travel Trends: 2009 National Household Travel Survey,” 2011. http://nhts.ornl.gov/2009/pub/stt.pdf

from this project's model or measured ridership if a transit agency has that data available. This project's code enables the use of measured ridership data since they convert various agency-specific formats for sharing ridership data into one format that can be matched with GTFS and ARNOLD.

As a caveat for the above measures, this project's case study transit agencies primarily submitted weekday ridership data, while AADT is an average annual measure that includes weekends as well. While acceptable for the demonstration purposes of this project, future adaptations of this work could use weekday AADT data, which is often available at the State/local level, weekend transit usage.

In addition, the project team also calculated Revenue Vehicle Miles Travelled and Passenger Miles Travelled for two systems based on ARNOLD snapping and agency-provided ridership. While these performance indicators are already reported in NTD, comparing the calculated and NTD-reported values could highlight useful differences. In addition, this project's approach could be the basis for a streamlined way for agencies to calculate and report these numbers.

Results

This exploratory project found that it is possible to, with some degree of accuracy, estimate segment-level transit ridership using GTFS and other nationally-available data for agencies where granular ridership data is not available. Because this modeling effort is working with human-driven behaviors, perfect estimation is impossible, but an overall model predictive power (r-squared statistic) greater than 0.7 generally indicates a strong model which captures relevant features. Predictive power less than 0.5 indicates that notable underlying factors which affect ridership are not being captured in the model and further development should be pursued. This project's overall r-squared for estimating bus ridership of all case study agencies, as discussed in more length below, is 0.695.

The ridership estimation algorithm was one component of this project, but transportation organizations and researchers may also find value in the two other main components: snapping transit service characteristics derived from GTFS to the road network, and calculating multimodal road usage by combining AADT and segment-level ridership (either estimated or measured).

GTFS network snapping and service characteristics

As noted in the methodology section, the success of ARNOLD road snapping is highly dependent on both the quality of the shapes in each GTFS feed and the ARNOLD data available for each State. However, where this data is good and with some small manual adjustment or road additions, this project's algorithm can successfully attach transit service data to an authoritative road network with few errors.

Attaching GTFS shapes to the road network allowed the project team to successfully calculate service frequency from the GTFS schedule and display it not just route-by-route, but in aggregate frequency across all routes that traverse a road. Figure 6 shows the resulting map for the Boston area, where the convergence and divergence of routes, and related changes in frequency of service on the roadway, are easy to discern. This also sets GTFS schedules into the same data structure as AADT, so that any data that is calculated from GTFS (like modeled ridership) or described in terms of GTFS data structures (like actual ridership from many agencies) can be combined and described with HPMS AADT or other road data.

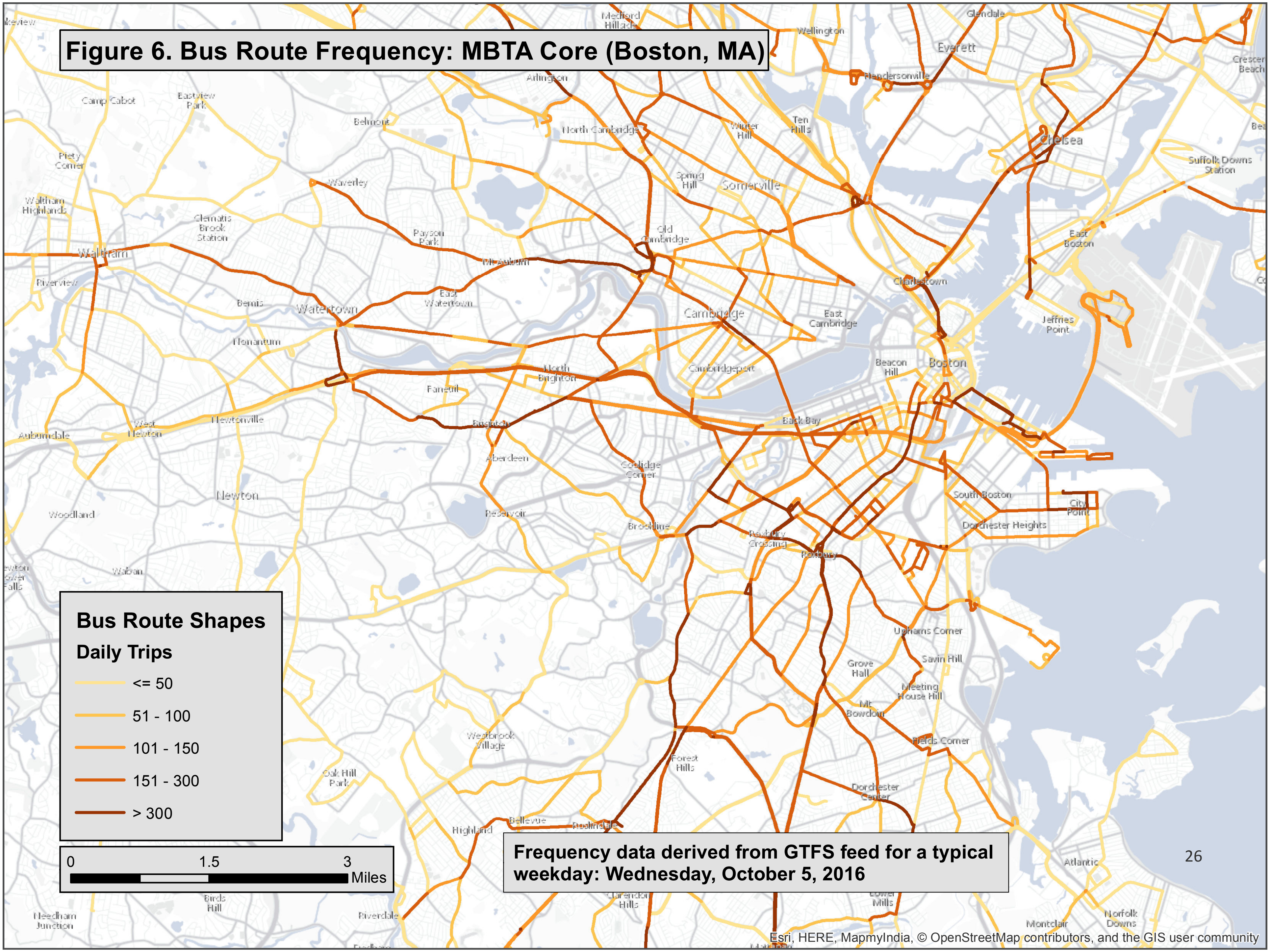
For this proof-of-concept effort, the project team focused on calculating service frequency from GTFS since it is a key input into the ridership estimation model. However, the code underlying this approach could also be adapted to calculate other characteristics such as service hours along a road or average scheduled travel speed. The project team looked into calculating average travel speed as an input into the ridership model but encountered complexities in calculating and reporting it as a model input. In particular, the code's data structure focuses on service characteristics for road segments rather than route segments. An express bus and a local bus sharing the same road would distort the average travel speed.

One key advantage of this code is that it requires very few data inputs (GTFS and ARNOLD) and calculates results based on authoritative schedules rather than estimating with uncertainty, as in the ridership model. However, while this makes it easy to apply these analyses broadly, for example across the entire National Transit Map, uncorrected data quality issues could create road snapping results that do not reflect actual conditions. In addition, the ARNOLD data that was used for this project is more detailed than what is available to the general public.

Non-Street-Running Transit

As discussed in the methodology section, rights-of-way that are not public streets, like rail lines, exclusive BRT routes, and ferries are not included in ARNOLD. The project team developed a method of calculating service frequency from GTFS for these services, but it relies more extensively on the native GTFS shapes and cannot be cleanly integrated with road-associated data like AADT other than through manual comparison. For these reasons, the project team did not extensively pursue calculating service characteristics from rail or other off-road transit.

Figure 6. Bus Route Frequency: MBTA Core (Boston, MA)



Ridership modeling

Unlike the GTFS service characteristics and road snapping procedure, the segment-level ridership model is an estimate rather than a direct calculation and thus includes some inherent uncertainty. Whether this uncertainty is sufficiently small depends on the user's goals for the estimation and the type of transit agency data that is being estimated. To test the accuracy of the model, the project team compared estimated ridership along each stop-to-stop segment to actual ridership provided by several case study transit agencies. If the positive correlation between these two datasets is strong, the r-squared value will be closer to 1, indicating a more accurate prediction.

Calibration data

The ridership data provided by the case study agencies was broken into four sets for calibration analysis. The following table details which agencies and modes were included in each calibration data set.

Table 1: Model iterations run on different modes and calibrated using different case studies and calibration parameters.

Calibration ID	Modes included	Agencies Used to Calibrate	Calibration Parameters
1 (all data)	All	All	All
2a (bus only)	Bus only (3)	All but LIRR, BART	All
2b			Only significant variables from 2a
2c			Only significant variables from 2b
2d			Only significant variables from 2c
3 (rail only)	Rail only (0, 1, 2)	LIRR, BART, MBTA, MetroTransit	All
4a (bus w/o Valley Metro)	Bus only (3)	MBTA, MetroTransit, NAIPTA, SJRTD	All
4b			Only significant variables from 4a
4c			Only significant variables from 4b
4d			Only significant variables from 4c

The first calibration set included all ridership data provided from all case study agencies without regard to mode. All possible calibration features, listed in the data description sections above, were included. Calibrations 2a through 2d focused only on bus trips, thus completely eliminating the ridership data from LIRR and BART, which only offer rail service. Moving from calibration 2a to 2d, each subsequent calibration omitted prediction variables that were not found to be statistically significant. Thus, features which were not statistically significant in 2b were excluded for the next calibration in 2c, although the underlying data did not change.

Calibration set 3 focused on rail ridership, which was only present in LIRR, BART, MBTA, and MetroTransit. Three rail modes as defined by the GTFS standard were included: subway, light rail, and intercity rail. This included all calibration parameters. The final calibration set 4a through 4d mirrors set

2a through 2d, but the underlying ridership data does not include ridership information from Valley Metro in Phoenix, Arizona.

The goal of calibration 4 was to create a set of fitted coefficients using one set of case study agencies in order to validate against a separate dataset not included in calibration. The project team used Valley Metro for this validation since it is a mid-sized agency which provided a reasonable quantity of ridership data. It is important to note that Valley Metro was selected *prior* to any of the analyses being completed. It was not selected because it followed a different pattern than the other case study agencies, although it later emerged that its patterns were different.

Overall model prediction accuracy

Figure 7 shows the results of calibration 2a, with each measured-versus-estimated ridership point colored according to transit agency. Along the x-axis is the measured (real) ridership for each transit segment (that is, every stop-to-stop pair) while the y-axis indicates the estimated ridership based on the calibrated model. The line at 45° indicates a perfect estimate, any points under the line indicate an underestimate by the model, and all points above the line are overestimates.

R-squared and adjusted r-squared

The results described below use the adjusted r-squared measure to describe how closely estimated ridership matches with measurements from the various case study transit agencies. R-squared (not adjusted) compares the measured ridership for each segment versus the average value of ridership for all segments – this represents a 'fit' using no input parameters, just a constant value – against the estimated ridership for each segment. A model calibrated on a given data set will have an r-squared value between 0 and 1, with higher values indicating that the model fits or 'explains the data' more closely.

Adjusted r-squared modifies r-squared by accounting for the number of input parameters and the total number of data points used for calibration. When the number of input parameters approaches the number of data points, the adjusted r-squared drops. This is because including too many parameters with too few data points produces an over-fitted model – all the data can be 'explained' but the model is meaningless.

However, there are certain fringe cases that must be considered. If the number of calibration parameters *exceeds* the number of data points, adjusted r-squared can *exceed 1*. This occurs in only one case in the results below: for rail in Minneapolis because Metro Transit only operates two relatively short light rail lines. Many other cases show the other end of the spectrum, where the adjusted r-squared drops below zero. In those instances, the model estimates are *worse* than a simple mean constant value. This occurs because the model is calibrated using one set of data (e.g. all case study bus systems) and adjusted r-squared values are determined for subsets of that data that do not follow the same trend as the larger body of data (e.g. Valley Metro's bus system, as discussed below).

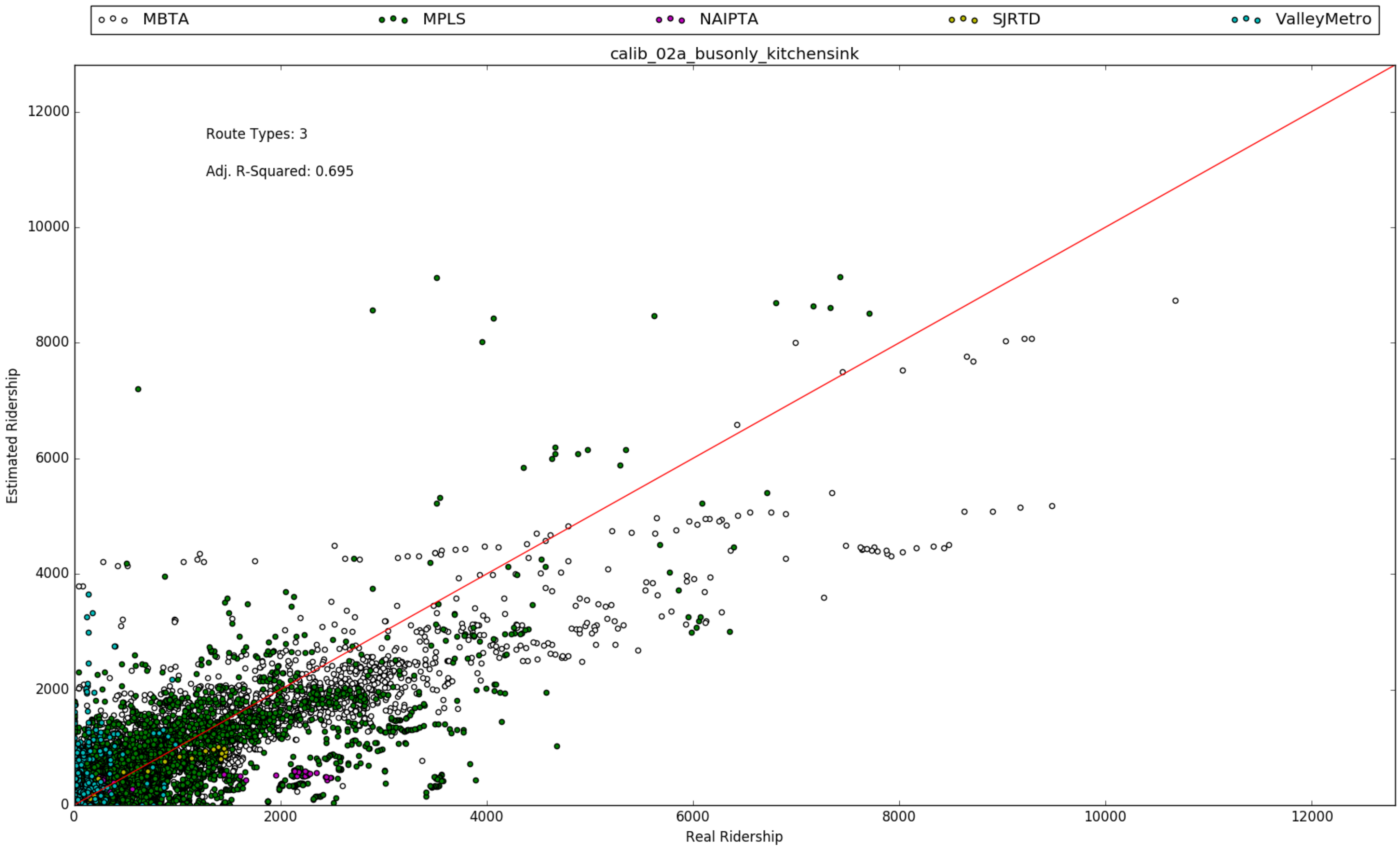


Figure 7: Measured (real) versus estimated ridership for buses for all case study agencies.

Accuracy and predictive power of model iterations

Table 2 below shows the complete set of adjusted r-squared values for each calibration, comparing not only the overall data set against itself (as is shown in the figure), but also for each agency individually. So, for example, all agency data and all calibration features were used in calibration 2a, which yielded an r-squared of 0.695. However, as shown in the table below, the fitted model's effectiveness varied when used to estimate ridership for each agency individually.

Table 2: Model goodness-of-fit for various calibration conditions.

		Adjusted R-Squared							
Calibration ID	**Number of Parameters**	*All Data*	*BART*	*LIRR*	*MBTA*	*Metro Transit*	*NAIPTA*	*SJRTD*	*Valley Metro*
1 (all data)	37	0.327	0.358	-0.005	0.351	-0.806	0.586	-0.392	-232.205
2a (bus only)	37	0.695	---	---	0.792	0.558	0.758	0.804	-13.172
2b	28	0.695	---	---	0.791	0.557	0.548	0.792	-13.277
2c	25	0.695	---	---	0.791	0.557	0.478	0.783	-13.263
2d	**24**	**0.695**	**---**	**---**	**0.791**	**0.556**	**0.451**	**0.781**	**-13.298**
3 (rail only)	37	0.737	0.818	0.358	0.766	1.033	---	---	---
4a (bus w/o Valley Metro)	37	0.708	---	---	0.797	0.554	0.789	0.648	-18.556
4b	27	0.708	---	---	0.797	0.553	0.573	0.621	-18.859
4c	24	0.707	---	---	0.797	0.551	0.510	0.616	-18.499
4d	23	0.707	---	---	0.797	0.551	0.486	0.614	-18.678

The model performed well when bus and rail data were separated. For the bus-only calibrations (2a-d and 4a-d), the overall models achieved adjusted r-squared values of roughly 0.70. In particular, the model accurately predicted ridership for the Boston (MBTA) and Stockton (SJRTD) systems. Interestingly, the Flagstaff system (NAIPTA) achieved strong explanatory power when more variables were included, but as insignificant factors (for the entire data set) were removed, the adjusted r-squared fell significantly (from 0.758 to 0.451 between 2a and 2d, and from 0.789 to 0.486 between 4a and 4d). This suggests that at least some of the parameters which were removed during those iterations were important predictors for the NAIPTA system but not for other systems. However, collinearity issues (as described below) make this difficult to ascertain.

The model also achieved a good fit for the rail case study agencies, with an overall adjusted r-squared slightly better than that for bus (0.737 versus 0.695). Notably, LIRR performs much more poorly than the other agencies, suggesting that the commuter rail LIRR system is subject to different demand patterns than the other subway/light rail systems. (Again, note that the 1.033 adjusted r-squared value for Metro Transit is due to the small quantity of rail data for that system and should not be considered a robust value.)

Some sets of calibration coefficients do not produce accurate results for certain agencies. In particular, Valley Metro has extremely poor fits across all the calibration sets. The model estimates are much worse than a simple average of *only the data describing Valley Metro's ridership*. Since Valley Metro contributes relatively little data to the calibration process, the larger systems (namely MBTA and Metro Transit) dominate the resulting calibration coefficients. A calibration using only Valley Metro's data produces a reasonable model fit (adjusted r-squared of 0.621) but the coefficients are entirely unlike those produced in calibrations 2a-d or 4a-d. This suggests that the tested predictors affect ridership differently at Valley Metro than other agencies, or that there are other major factors affecting ridership for Valley Metro far more than other agencies that are not considered in this model.

Self-calibration of model runs

For model iterations 1 through 3, the project team did not attempt to avoid testing the model on systems that were used to calibrate the same model. In these cases, the overall model was calibrated on all available data (all systems, all bus systems, or all rail systems depending on the iteration) and tested on all available agencies. This means, for example, that the coefficients predicting NAIPTA's ridership were calibrated in part using actual NAPITA ridership data. This obviously increases the predictive power of the model and does not fully reflect a real-world scenario where measured ridership is not known in advance.

However, given the limited case study ridership data available, the desire to create calibration parameters that are a composite of many agencies, and the general goal to demonstrate a proof-of-concept rather than a fully production-ready model, the project team deemed this acceptable. Model run 4 attempted to separate out Valley Metro as a way to show the potential predictive power of a naively calibrated model, but unrelated differences in Valley Metro's results limited the usefulness of this iteration. Because there is more overall data from larger agencies like MBTA and Metro Transit, this potential over-prediction effect would be greater for them and lesser for agencies like NAIPTA or SJRTD. However, the results show that while the model generated consistently accurate estimates for MBTA, the model predicted NAIPTA and SJRTD at a better or similar accuracy to Metro Transit.

Effect of individual predictive variables

In a well-specified model, the individual parameters of the model provide insight into the results produced by the model. For example, two input parameters that are similar in magnitude but have dramatically different coefficients assigned to them by the optimization routine can be differentiated in importance to the ultimate result of the estimation. Similarly, positive and negative coefficients indicate that input parameters are positively or negatively correlated with the result of the estimation.

Throughout this modeling effort, an ordinary least squares optimization within the *statsmodels* Python package is used, which automatically examines the calibration parameters. The function, *ols*, also examines the underlying data and results to produce a simple report which includes statistical tests on the fitted calibration. In every case for this analysis, the results indicate that there are strong collinearities within the data, both among the ridership data itself and among the model inputs. This is expected especially for ridership data given its nature. Ridership at each segment along any transit line is highly dependent on the ridership immediately upstream. Furthermore, riders often use multiple lines to reach their destination, so the connection points between routes also have collinearities.

Beyond collinearity issues within the calibration ridership data, several of the input parameters are also correlated with one another. For example, total population, population age 25+, and working population 16+ are all closely related. This makes individual parameter interpretation difficult, but does not affect the overall performance of the model.

For the purpose of examining individual variables, strong collinearity significantly limits the ability to understand how each individual parameter is related to ridership. Table 3 is included below to show only the *sign* of each coefficient (or 'o' if the parameter was not included in the particular calibration). In some cases, these relationships seem reasonable, such as frequency of service which is always positively correlated. Given that these data are from existing agencies that regularly adjust supply (i.e. re-plan routes) to respond to demand, routes where there is greater demand have higher frequency service.

Stability can be considered – coefficients that are always positively or negatively correlated are likely more stable and meaningful than those which change sign. For example, the number of jobs that are categorized as 'professional, scientific, or technical' (NAICS Sector 54) is both positively and negatively correlated in various models, and ultimately falls out of significance for the last several models. If the underlying models were well specified, this would be meaningful. Given the strong collinearity issues within the data, it is difficult to say whether people in this category of jobs tend to interact with transit significantly differently than workers in other categories. Coefficients that are stable suggest that the relationship is more robust – more frequency *always* means more overall ridership and should always be a factor in the model.

The magnitude of each coefficient cannot be directly examined as an indicator of 'strength' both because of the collinearity issues described above, but also because the underlying parameters fall in different ranges. Table 4 shows minimum and maximum values for each input parameter based on data from all systems combined. Values that range between higher values but which are more important within the model may nevertheless have smaller coefficients (in absolute terms).

Table 3: Correlation summary of calibration parameters to estimated ridership: positive (+), negative (-), or not included in calibration (o).

	Calibration ID									
Calibration Parameters	*1*	*2a*	*2b*	*2c*	*2d*	*3*	*4a*	*4b*	*4c*	*4d*
Frequency of service	+	+	+	+	+	+	+	+	+	+
Number of serving routes	-	-	-	-	-	+	-	-	-	-
Total population	-	+	+	+	+	-	+	+	+	+
Percent minority population	+	+	+	+	+	+	+	+	+	+
Number of households	-	-	-	-	-	+	-	-	-	-
Percent households under poverty line	-	-	o	o	o	+	-	o	o	o
Population age 25+	+	-	o	o	o	+	-	o	o	o
Population with high school degree	+	-	o	o	o	-	+	o	o	o
Population with college degree	+	+	+	+	+	-	+	+	+	+
Population with advanced degree	+	-	-	o	o	-	+	o	o	o
Number of housing structures	+	+	+	+	+	-	+	+	+	+
Number of 1 unit dwellings	-	-	-	-	-	+	-	-	-	-
Number of 2-4 unit dwellings	-	-	-	-	-	+	-	-	-	-
Number of 5-19 unit dwellings	-	-	-	-	-	+	-	-	-	-
Number of 20+ unit dwellings	-	-	-	-	-	+	-	-	-	-
Working population (age 16+)	-	-	-	-	-	-	-	-	-	-
Working population using transit for commute	+	+	+	+	+	+	+	+	+	+
Percent working population using transit	-	+	+	+	o	-	+	o	o	o
Number of households which are renting	-	+	+	+	+	-	+	+	+	+
Median age	-	+	o	o	o	-	+	+	+	+
Median household income	-	+	+	+	+	+	+	+	+	+
Median rent	+	+	o	o	o	-	+	+	+	+
Percent of households without a vehicle	-	+	+	+	+	+	+	+	+	+
Number of jobs	+	-	-	o	o	+	-	+	o	o
Jobs with $1250 monthly income or less	-	-	o	o	o	-	-	-	-	-
Jobs with $1251 - $3333 monthly income	-	-	-	-	-	+	+	o	o	o
Jobs with $3334 monthly income or more	+	+	+	+	+	+	+	+	o	o
Jobs in NAICS sector 51 - information	-	+	o	o	o	-	-	o	o	o
Jobs in NAICS sector 52 - finance and insurance	-	-	-	-	-	+	-	-	+	+
Jobs in NAICS sector 53 - real estate, rental and leasing	-	-	o	o	o	-	-	-	o	o
Jobs in NAICS sector 54 - professional, scientific, and technical	-	+	+	+	+	-	+	o	o	o
Jobs in NAICS sector 55 - management	-	-	-	-	-	+	-	-	-	-
Jobs in NAICS sector 56 - administrative and support	+	-	-	o	o	-	-	-	-	-
Jobs in NAICS sector 61 - education	-	-	-	-	-	-	-	-	-	o
Jobs in NAICS sector 62 - health care	-	+	+	+	+	-	-	o	o	o
Number of ARNOLD intersections	-	+	o	o	o	-	+	+	+	+
Annual ridership reported to NTD (by mode)	+	+	+	+	+	+	-	o	o	o

Table 4: Calibration parameter minimum and maximum observed values.

Calibration Parameters	Minimum Value	Maximum Value
Frequency of service (daily)	1	722
Number of serving routes	1	34
Total population	0	12295
Percent minority population	0%	99.6%
Number of households	0	5096
Percent households under poverty line	0%	85.4%
Population age 25+	0	8777
Population with high school degree	0	4891
Population with college degree	0	3527
Population with advanced degree	0	3086
Number of housing structures	0	5751
Number of 1 unit dwellings	0	1106
Number of 2-4 unit dwellings	0	2837
Number of 5-19 unit dwellings	0	2126
Number of 20+ unit dwellings	0	4860
Working population (age 16+)	0	6068
Working population using transit for commute	0	3994
Percent working population using transit	0%	78.9%
Number of households which are renting	0	4727
Median age	0	77
Median household income	0	250001
Median rent	0	2001
Percent of households without a vehicle	0%	84.7%
Number of jobs	0	101941
Jobs with $1250 monthly income or less	0	21753
Jobs with $1251 - $3333 monthly income	0	23199
Jobs with $3334 monthly income or more	0	75190
Jobs in NAICS sector 51 - information	0	12841
Jobs in NAICS sector 52 - finance and insurance	0	34868
Jobs in NAICS sector 53 - real estate, rental and leasing	0	7439
Jobs in NAICS sector 54 - professional, scientific, and technical	0	28013
Jobs in NAICS sector 55 - management	0	8974
Jobs in NAICS sector 56 - administrative and support	0	23853
Jobs in NAICS sector 61 - education	0	19834
Jobs in NAICS sector 62 - health care	0	33160
Number of ARNOLD intersections	0	212
Annual ridership reported to NTD (by mode)	57384	14961417

Maps of Model Results

Because the model algorithm ties both the model results and the measured ridership data from case study agencies to the ARNOLD network, it is possible to compare the results spatially. The figures below show the measured ridership data for the Boston area provided by the transit agency, the estimated ridership from the model, and a ratio of both figures showing where the model may be overestimating or underestimating ridership.

The project team used these maps during the project to identify areas where additional data could help improve the accuracy of the model. For example, underestimation of ridership in employment centers such as downtowns led the team to use incorporate employment information from the Census's LODES dataset into the model.

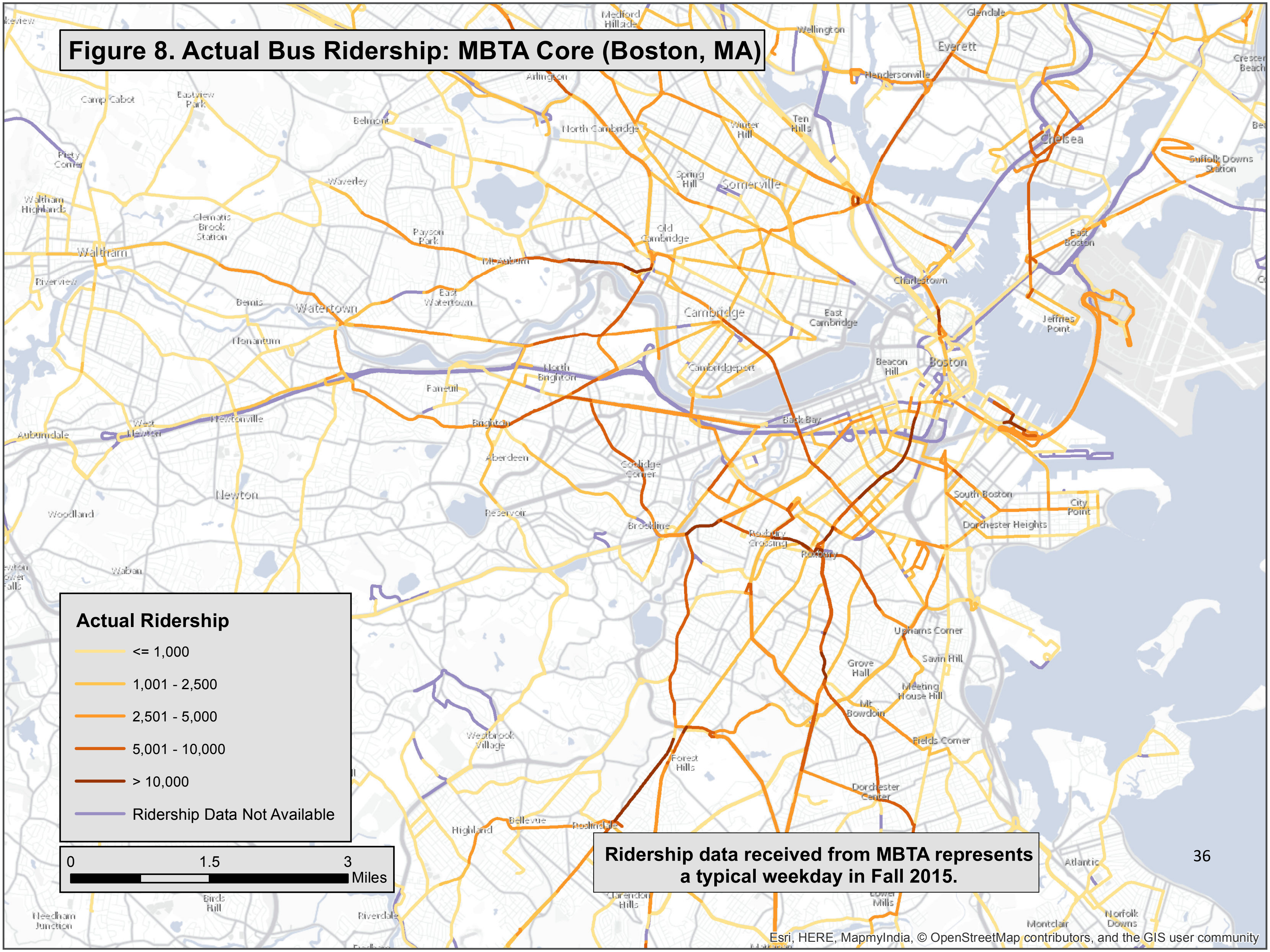


Figure 8. Actual Bus Ridership: MBTA Core (Boston, MA)

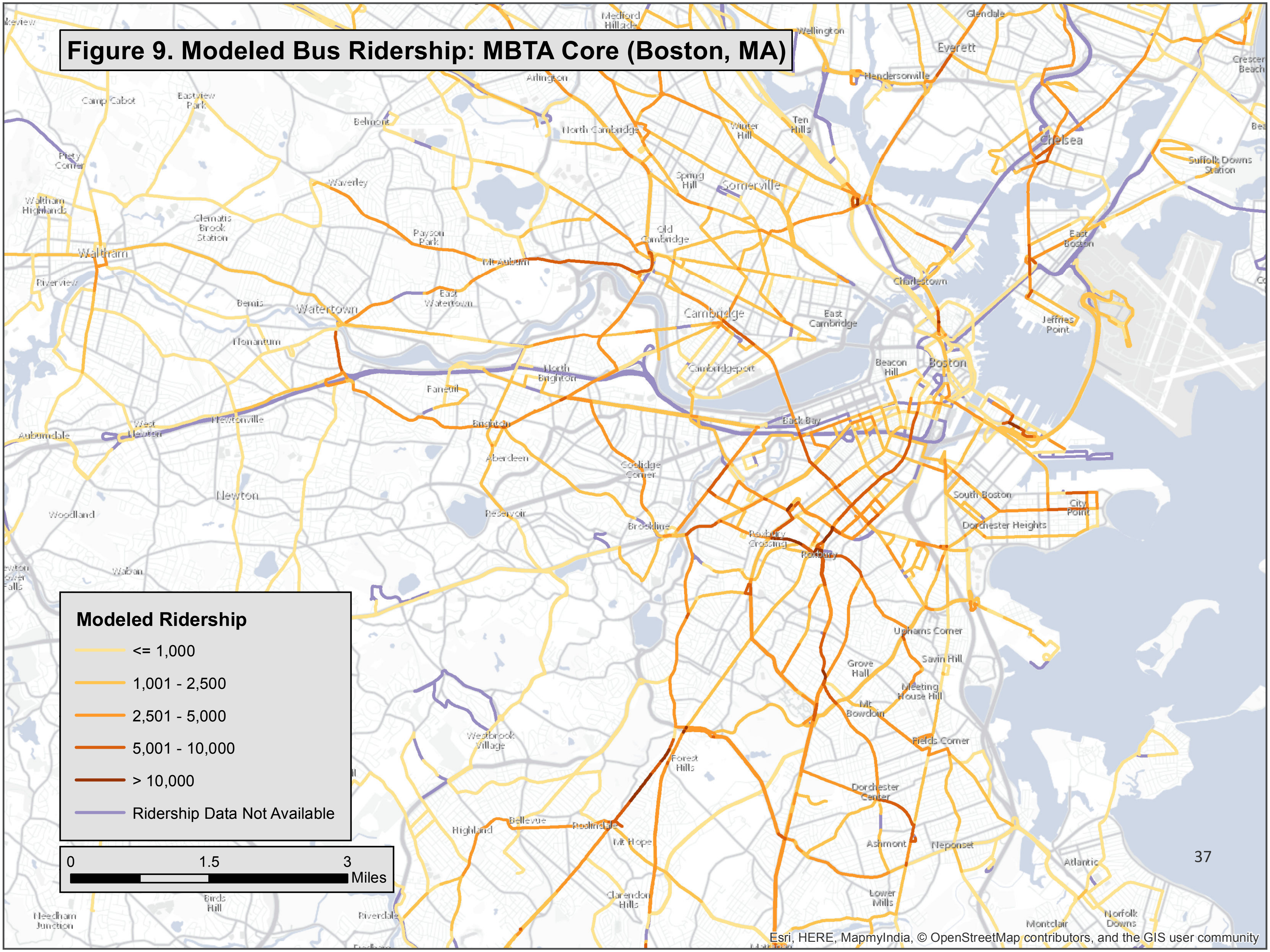


Figure 9. Modeled Bus Ridership: MBTA Core (Boston, MA)

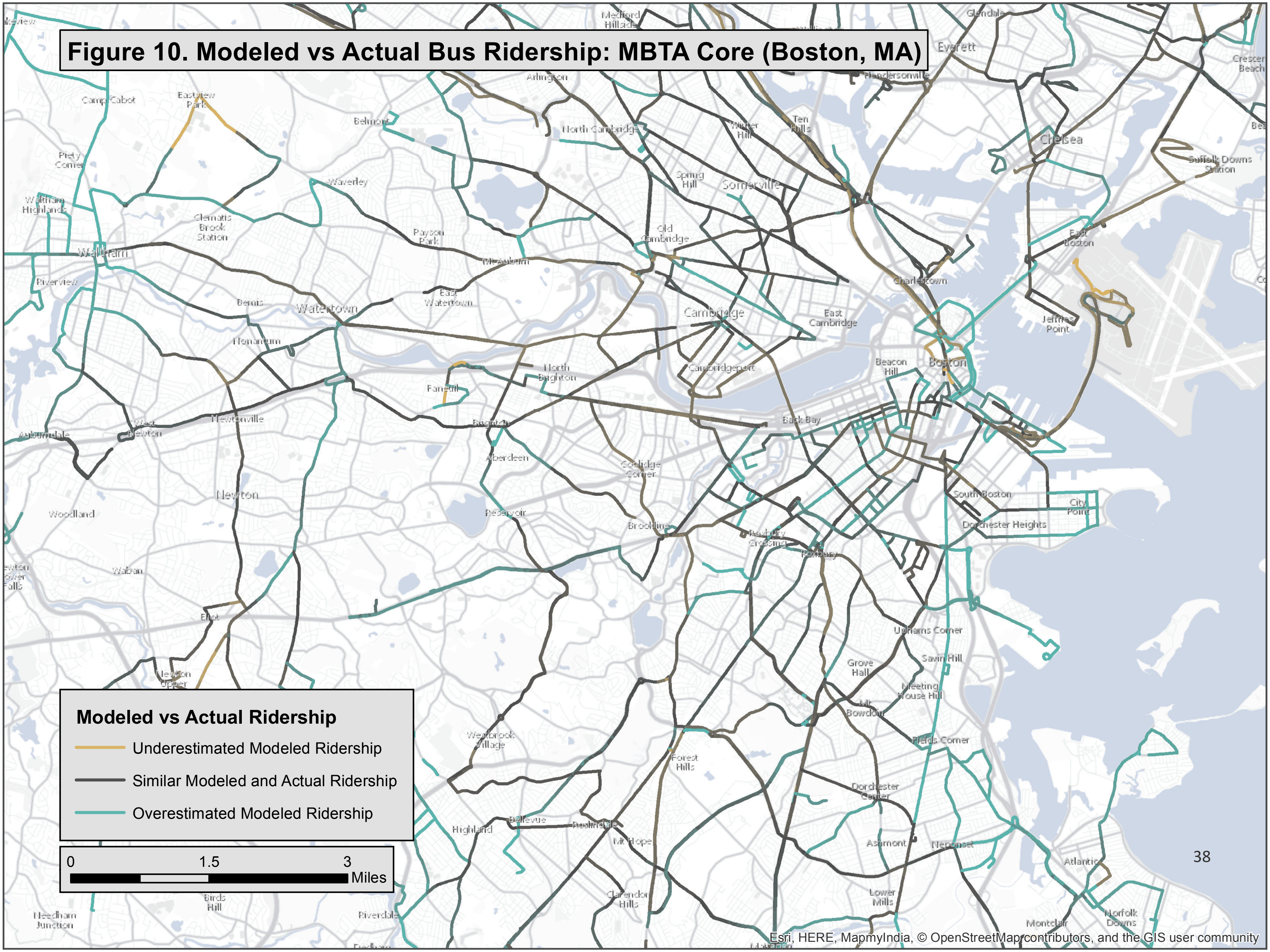


Figure 10. Modeled vs Actual Bus Ridership: MBTA Core (Boston, MA)
Modeled vs Actual Ridership
Underestimated Modeled Ridership
Similar Modeled and Actual Ridership
Overestimated Modeled Ridership
0
1.5
3
Miles
Esri, HERE, MapmyIndia, © OpenStreetMap contributors, and the GIS user community

Multimodal performance measures

The main multimodal measures developed for this project are the **percentage of total motorized road users on transit** and its intermediate measure of **total motorized road users.** This project calculates both at the road segment level. It is possible to use either modeled or measured data to calculate this measure, but the project team focused on results using measured data from case study transit agencies.

The limitations of the percentage of total motorized road users on transit measure comes primarily from potential mismatches between the inputs. For example, it is possible that the AADT, GTFS, and transit ridership data were all measured or recorded in separate years. If, for example, a transit agency rerouted a bus route (and updated its GTFS to match) after collecting ridership data, it would create a mismatch where transit riders, and hence transit riders as a percentage of road users, could not be calculated for that portion of the route. Similarly, if older AADT data does not reflect traffic growth or newly-added routes present in GTFS/ridership data, it would inflate transit's share of total road users.

However, even with these limitations, the project team believes this measure has advantages that could be incorporated into the national performance management baseline measures. These measures rely on region-wide transit vehicle occupancy rates, which gloss over considerable differences between corridors. But data from this project allows for reporting and analysis at the corridor or even road segment level, similar to the scale of AADT data available through HPMS.

Maps of Performance Measures

The figures below show percentage of motorized users on transit for Boston using measured ridership data. Comparing these maps to the ridership maps from earlier in the report indicates that the highest ridership transit corridors are not always those where transit riders make up the largest portion of road users. However, some of these roads where transit riders make up a high percentage of users are not corridors at all, such as where a bus route that primarily follows an arterial road loops around in neighborhood streets near the end of a route (this is most evident in the Metro Transit maps in the appendix). In addition, these performance measures require both ridership data and AADT information on a road segment to function. Where one or both of those is not available, the maps indicate that there is no data. As discussed above, the quality of GTFS, measured ridership data, and AADT varies by transit agency and State.

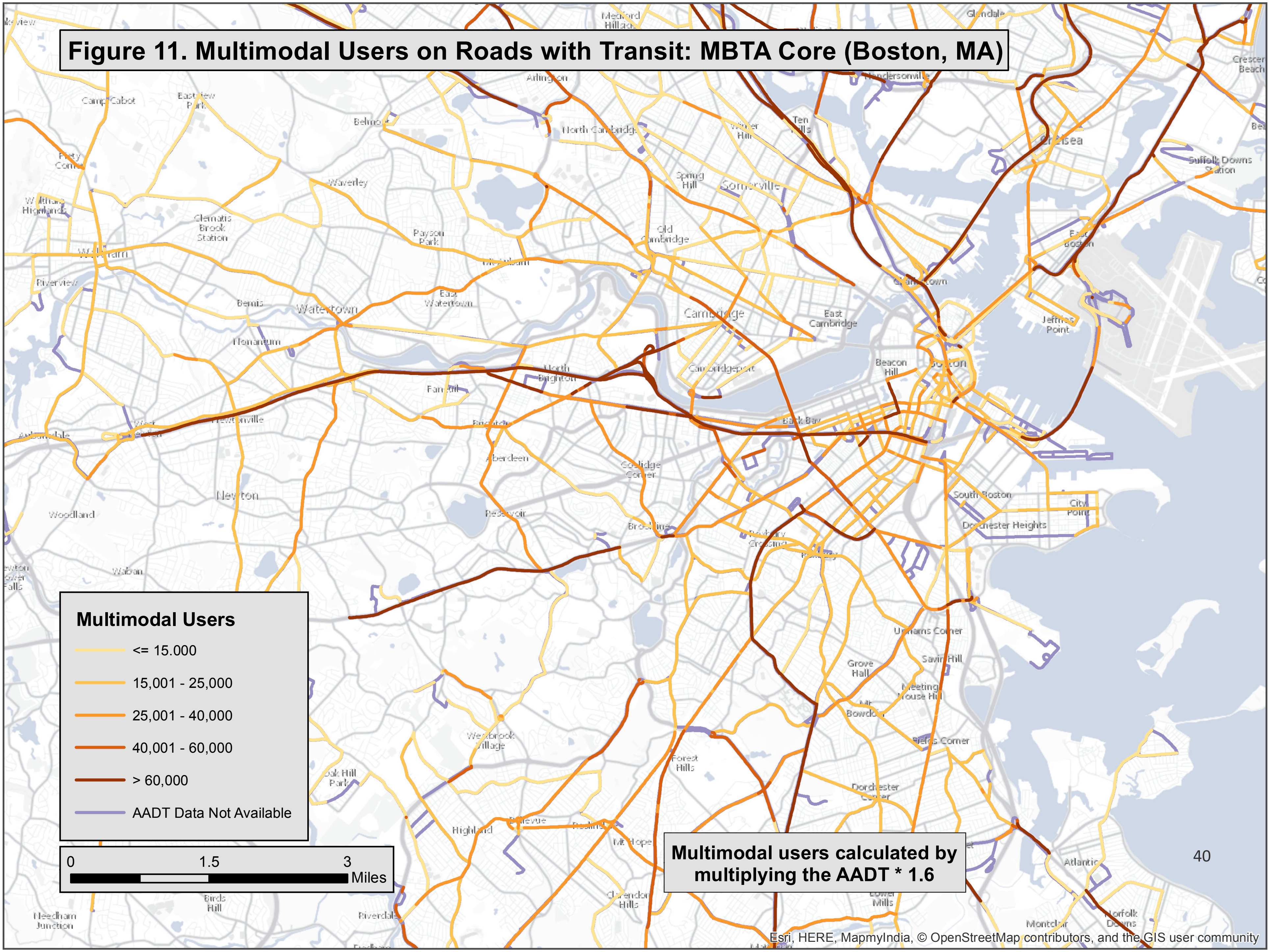
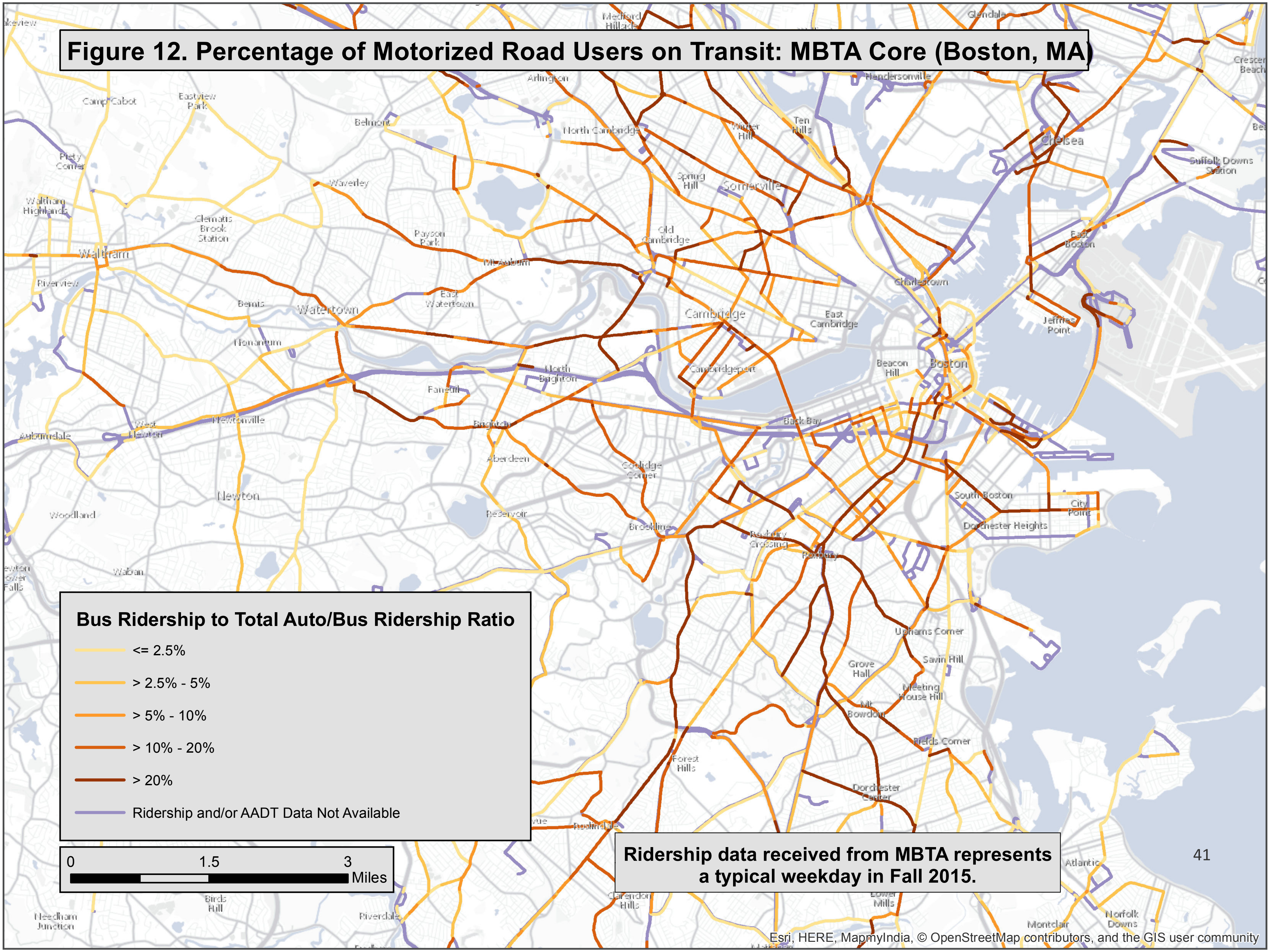


Figure 11. Multimodal Users on Roads with Transit: MBTA Core (Boston, MA)

Figure 12. Percentage of Motorized Road Users on Transit: MBTA Core (Boston, MA)



Non-Street-Running Transit

Programmatically calculating the percentage of motorized users on transit requires road and transit data to be aligned in the ARNOLD framework. Although this is not possible for non-street-running transit, an alternative is to manually compare vehicle occupants on a road with the corresponding transit service.

Figure 13 makes this comparison for a portion of the Metro Transit Green Line light rail line between Minneapolis and St. Paul. Although this a more straightforward rail comparison since the Green Line operates along University Avenue for almost the entirety of its route, it does highlight challenges around the definition of a corridor. For example, Interstate 94 also runs parallel to the Green Line and University Avenue, and may serve some—but not all—of the same transportation needs as the Green Line. It is possible to try and programmatically or manually match service like the Green Line to roads like University Avenue, but for rail or ferry systems that do not align so closely with the road network, it could be difficult to find the right corresponding road. And, as demonstrated with Interstate 94, there is not always one directly corresponding road. These issues are present for bus services as well, but become more complex with rail, ferries, and other non-street-running transit, especially when they are less clearly aligned with the road network than the Green Line, e.g. MetroRail in Washington, D.C. or the MBTA subway in Boston.

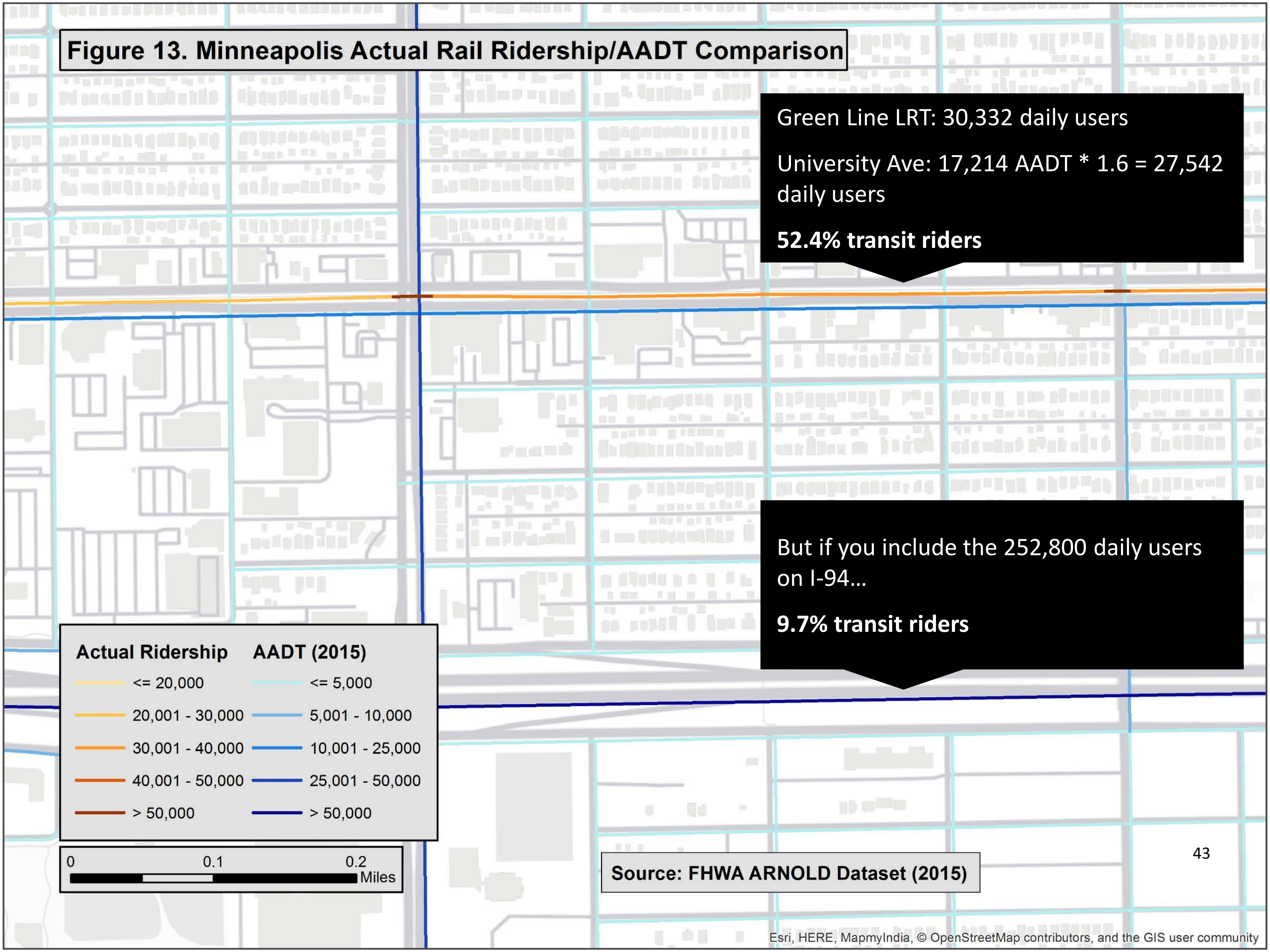


Figure 13. Minneapolis Actual Rail Ridership/AADT Comparison

Revenue vehicle miles traveled and passenger miles traveled

As part of the route snapping process, characteristics such as system-wide transit Revenue Vehicle Miles Traveled (transit VMT) along the ARNOLD network can be calculated from GTFS. The project team calculated these for two agencies as a secondary goal of this project and compared them to the same performance indicators as reported in the NTD. These serve primarily as a proof-of-concept for using GTFS and ridership estimates to calculate required NTD fields, but also highlight some differences between the results of this project and NTD-reported data.

Vehicle Revenue Miles Traveled

When routes are snapped to a road network, the length of a road segment can be multiplied by the number of trips that traverse that segment to calculate the transit VMT for that road segment. These calculations can be summarized at the system level, resulting in a measure similar to the Vehicle Revenue Miles reported in the NTD. The following table compares these calculations for an average weekday bus VMT (based on 2016 GTFS data) to the corresponding 2015 NTD system-wide bus VMT. While estimated transit VMT for the MBTA was very similar to what is published in the NTD, VMT for Metro Transit was about 32.3% higher. There are a variety of factors that could result in this mismatch, including:

- Different years of analysis (2016 for GTFS vs. 2015 for NTD)
- Differences between service offered on the selected typical weekday and the average of services offered on all weekdays throughout the year
- Quality or completeness issues with the underlying road network, especially ARNOLD dual carriageway issues

While further work and investigation would be needed, the results do suggest the possibility of calculating revenue VMT from readily available GTFS feeds. This could be useful for transit agencies, which must report this information to NTD and to other stakeholders.

Table 5: Comparison of GTFS-calculated and NTD-reported bus VMT

Transit Agency	Revenue Vehicle Miles Traveled (2016 GTFS bus data Snapped to ARNOLD)	Revenue Vehicle Miles Traveled (2015 NTD, Bus Only)	Percent difference vs NTD
Massachusetts Bay Transportation Authority (MBTA)	78,495	76,951	+2.0%
Metro Transit	103,738	78,398	+32.3%

Passenger Miles Traveled

Similarly, system-wide Passenger Miles Traveled (PMT) can be estimated as part of the route snapping process, based either on the actual ridership data provided by the transit agencies or the ridership estimates output by the model. These values can in turn be compared to the passenger miles traveled reported in the NTD. For the MBTA, actual and modeled passenger miles traveled are around 15-17% lower than what is reported in the NTD. For Metro Transit, passenger miles traveled estimated based on actual ridership data are approximately 38% higher than what is reported in the NTD, but passenger miles traveled based on modeled ridership are only about 5% higher. Like VMT, PMT differences could be due to a variety of different factors, including the different year of analysis (2016 GTFS data and 2015 NTD data) and the accuracy and completeness of the ARNOLD data, which is the basis for the mileage for each passenger.

Depending on the further development of this project's ridership estimation capabilities, this method for calculating PMT could help agencies that do not currently have measured ridership report this required NTD element without conducting additional, expensive rider surveys or estimating from outdated surveys.

Transit Agency	Passenger Miles Traveled (Actual Ridership Data, GTFS routes snapped to ARNOLD—bus only)	Passenger Miles Traveled (Modeled Ridership Data, GTFS routes snapped to ARNOLD—bus only)	Passenger Miles Traveled (2015 NTD, Bus Only)	Percent difference Actual vs NTD	Percent difference Modeled vs NTD
Massachusetts Bay Transportation Authority (MBTA)	961,083	940,588	1,126,438	-14.7%	-16.5%
Metro Transit	1,154,807	878,512	834,648	+38.4%	+5.3%

Finally, this project's tools can calculate VMT and PMT at a segment level. While not currently useful (they are largely a different way of displaying the frequency and ridership measures already discussed in this report) this may be an opportunity depending on the future development of other data systems. For example, if transit crashes could be reported at the segment level an agency could also report segment-level crashes or injuries per VMT or PMT, similar to common measures for highway safety.

Opportunities and Insights

The National Transit Map is a relatively new data resource and this project is among the first efforts to explore the GTFS data housed in the NTM and see how it can feed into other departmental priorities such as performance management. Because of this, the project team ensured that it noted insights and opportunities for the NTM, other data sources, and the products of this effort. The team also held discussions with staff from FTA, BTS, and other stakeholders throughout the project, and these conversations helped shape the discussions below.

Opportunities

Based on discussions with stakeholders, the project team outlined some possible further opportunities for use of GTFS in multimodal planning, and for use of this project's analytical tools in other ways.

Multimodal planning

By combining transit and roads data structures, products from this project could help planners better understand and account for multimodal use of roads. The specific measure and tool used may depend on the data available or particular local needs.

State and local identification of road/transit improvement opportunities

For example, a regional planning organization could calculate the percentage of motorized users riding transit using ridership data from its transit agency as well as State DOT AADT data. It could use this information to identify corridors where transit riders make up a large percentage of road users. These could be corridors where it would make sense to allocate additional road space to transit (e.g. bus lanes, pullovers). Because the data is attached to ARNOLD, agencies may also be able to combine it with local data on road condition or congestion to understand to what degree transit riders are affected by these issues.

Even for simple data such as frequency, the maps generated by this project differ from typical agency route maps since they show the total level of transit service available along the road system rather than route-by-route frequencies. This may be useful as a basic data source for road planners identifying where additional road space could be allocated for transit users (e.g. bus lanes, enhanced stops).

Table 6 shows the main outputs of potential value to multimodal planners as well as tradeoffs such as data needs and uncertainty.

Table 6: Summary of key multimodal measure outputs

Measure	Required Data	Uncertainty	Notes
On-road transit frequency	GTFS and ARNOLD	Low	Differs from typical route-focused frequency and could be used to understand key bus corridors.
Transit riders as % of all multimodal road users (modeled ridership)	GTFS, ARNOLD, AADT, and model inputs	High	Truly multimodal measure, but relies on estimated transit ridership.
Transit riders as % of all multimodal road users (measured ridership)	GTFS, ARNOLD, AADT, and measured ridership	Low	Truly multimodal measure based on measured data, but project code needs to be adapted to each transit agency's ridership data format.

As other data systems increase in sophistication, GTFS and this project's tools could be the basis for calculating other segment-level performance measures such as breakdowns per VMT/PMT or crashes per VMT/PMT. Transit agencies could use this data to identify routes, road segments, or general areas where additional investments in safety would be most effective.

While the project team released the code to develop these measures as open-source software and performed outreach to stakeholders as part of this effort, it may be useful for DOT to work more extensively with partners to understand the measures that could be useful to them and explore opportunities for refinement.

National transportation performance management

However, the primary goal of this project is to explore potential inputs into national performance measures in federally-required transportation performance management (TPM). While FHWA rulemakings have defined performance measures for multimodal congestion and delay using region-wide transit data from NTD, States and MPOs may request to use more detailed methods instead.

As a potential next step from this project, FHWA, FTA, or other stakeholders could refine this project's outputs so that there is a clear method for using GTFS-linked estimated or measured ridership data as inputs for existing, defined national TPM measures. This would require enhancement to the tools developed for this project and new calibration inputs. For example, this project focuses on daily ridership and service, but the Annual Hours of Peak-Hour Excessive Delay requires data that is narrowed to peak commuting hours. Similarly, this project can calculate transit trips as a percentage of all road users, but the non-SOV Travel measure may need to take into account non-motorized users as well.

To help States and MPOs generate these more detailed measures, FHWA and FTA would also need to describe in more detail how to use tools like those developed for this project to generate national TPM measures. As GTFS and segment-level ridership data become more widely available, this could elevate the nationally-available information on multimodal performance for TPM.

Further refinement of ridership model

Because this was a proof-of-concept project, the team was only able to develop a basic model demonstrating the possibility of using GTFS to estimate segment-level ridership. This ridership model was developed as a proof-of-concept for demonstrating the possibility of using GTFS to estimate segment-level ridership, and the exploratory results are fit for their purpose of being an initial approach to estimate road segment level ridership for TPM measures. Although discussed at length in the appropriate sections above, the limitations of the current ridership model include:

- No mechanism for addressing collinearity between stops along the same road or route, i.e. ridership on stop 11 of a route is usually highly correlated with ridership on stop 12.
- Limited number of case study agencies to provide calibrating ridership data and the related need to validate the model on agency data also used to partially calibrate input coefficients.
- A data structure based around road segments rather than routes. While this may be a strength for comparisons with road-based data like AADT, it makes it challenging to incorporate other potential inputs like scheduled transit speed.
- A focus on bus transit systems rather than rail
- Idiosyncrasies in the ARNOLD network that may interfere with correct matching of transit routes to roads (see below discussion of ARNOLD and OpenStreetMap)

However, the project team identified a number of enhancements to the ridership model in particular that would be possible with additional time and resources. These could help increase the accuracy of ridership estimations and make them more useful for real-world performance measurement and reporting.

The team identified the following data sources as ridership predictors not fully accounted for in the current model:

- Intermodal Passenger Facilities
- Land use patterns
- Street design characteristics (e.g. sidewalks)

Other refinements would not require new data:

- Calculating scheduled speed of transit service (from GTFS) and using it as a model input
- Accounting for proximity to alternative transit options (e.g. bus service that replicates parallel heavy rail service)
- Using ridership from previous stop as a predictive input for subsequent stops

Accounting for collinearity of ridership data

Regarding ridership from previous segments (the last bullet above), the model could either be adjusted to work from the *change in ridership* along each portion of a route instead of absolute ridership, or a lagged variable could be incorporated into the model which accounts for upstream ridership, possibly in the form:

$$R = \gamma_0 + \sum_{i=1}^{n} \gamma_i x_i + \boldsymbol{y_l r_{s-1}}$$

where r_{s-1} is the ridership of the previous segment. A more significant restructuring of the data could also be explored where ridership along each route is treated as panel data, allowing for examination of serial correlation effects.

Alternatively, the underlying structure of the model could be altered. A linear combination model, while simple to implement and understand, may not be the best choice for modeling ridership. Instead, a more traditional demand generation approach could be taken using the same demographic data already incorporated into the model. Origin-destination data could be produced for every stop pair, and routing could be performed using the transit system, with service characteristics such as frequency being used to adjust or weight these estimates.

Road snapping refinements

Although not an input into the ridership model itself, validating ARNOLD data with OpenStreetMap (OSM) could help reduce issues related to ARNOLD snapping and enable road characteristics in to be used as model inputs.

Estimation for particular dates or times of day

Finally, the model could be adjusted to calculate service characteristics and ridership by time of day or different seasons. For example, it would be possible to calculate peak-hour headways along all routes on a system or estimate peak hour ridership. However, only a handful of transit agencies report ridership at the hourly scale, so more calibration data from transit agencies would be needed.

Summarizing transit service in the National Transit Map

Relatedly, another opportunity from this project may be the ability to describe transit service across the United States in a more detailed and coordinated way. Currently, the National Transit Map has some basic national maps based on the submitted GTFS feeds, including the location of transit stops across the country and participating agencies. BTS or partners could adapt code from this project to generate more detailed information on these services, such as on-road frequency or operating hours.

While the ARNOLD snapping process described in this report is not without challenges, most could likely be resolved by supplementing ARNOLD with OpenStreetMap and a small amount of case-by-case review of snapping results to ensure that resolved routes match each agency's network.

Creating public online maps of estimated ridership is possible, but the public-facing character of the NTM could risk implying that estimated ridership is more reliable than it actually is. However, implementing ARNOLD or OSM snapping in the NTM would allow BTS to easily map ridership data from a potential future GTFS-based ridership data standard (see below).

Transit agency ridership forecasting

The results of the predictive models described in previous sections show that reasonable estimates of transit ridership can be developed using widely available data and a GTFS feed for a given region. Such models could possibly be used for planning purposes when rerouting, adding, or removing service to estimate the ridership impact along key corridors. Additionally, if predictions for changes in development, land use, employment, and demographics are available, future year conditions could be modeled to predict ridership changes over time. While they both function very differently than the model in this project, Florida DOT provides future ridership estimation in its Tbest tool, and FTA's Simplified Trips-on-Project Software (STOPS) model helps transit agencies evaluate potential fixed-guideway investments.

Ridership estimation using partial data

An alternative use case that was considered for preliminary analysis was an agency using a subset of measured data to extrapolate ridership across their entire system. As smaller agencies are able to upgrade their buses and trains, automatic passenger counters or fare tracking mechanisms can be installed. However, due to cost, this is generally done in a slow roll-out across an agency's fleet rather than all at once.

A predictive ridership model, calibrated using a wider set of measured data (from, for example, a one-time ridership survey) could then inform both which routes and areas within an agency should be prioritized for data collection, and the subset of data from those systems could be used to provide a complete, albeit estimated, picture of ridership for the entire agency. The project team looked into testing this approach on this project's model, but partial estimation is challenging under the road segment data structure the model uses. E.g., it is difficult to handles cases where one route has data and is used for calibration but it shares road segments with other routes that must be estimated.

Route snapping tool for transit agencies

Accurate GTFS shapes in the "shapes.txt" table are important for development of the multimodal measures in this project, but also have value for sharing digital traveler information with transit riders. However, creating and maintaining route shapes may be a challenge for systems with limited geospatial technology resources, and even the route shapes of larger agencies may become inconsistent as routes are updated over time.

FTA, the American Public Transportation Association (APTA) or another stakeholder could adapt this project's ARNOLD snapping code (possibly altered to use OSM) into a tool for transit agencies that could help them turn basic or outdated route shapes into accurate routes snapped to an authoritative road network. This tool could be a GIS toolset for agencies that already have geospatial resources, but a web-based interface could enable a larger number of agencies to benefit, especially those that lack the expertise or resources for GIS software.

GTFS-based ridership data standard

While the multimodal measures based on estimated ridership can be useful depending on the context and need, more and more transit agencies have at least some actual, measured stop/route-level ridership data. The project team encountered first-hand the lack of a standard format for this granular ridership information as it processed data volunteered by the case study transit agencies.

Each calibrating transit agency that contributed ridership data to this effort used a different format to share the information. While this project developed automated scripts to standardize these into a common format for the ridership model, these will likely be of only limited use since current ridership data formats appear to essentially be agency-specific. Projects like this one help place segment-level ridership data in the context of other modes (e.g. highway AADT) and highlight the benefits of sharing this information with planners outside of the transit agencies themselves. However, while modeling can fill the gap for systems with limited resources, the lack of a unified format for ridership makes it more difficult for States and local governments to calculate multimodal performance measures using stop or segment-level data some agencies already collect.

The NTM and the current focus on performance management may be an opportunity to pilot a stop or segment-level ridership reporting format that is embedded into GTFS, perhaps as an optional table. BTS could give agencies the option to submit this table along with their usual GTFS submission. This would build up the level of information in the NTM available for national-level planning, similar to the AADT usage data in HPMS. It could also be used as calibration data for a ridership estimation model like the one developed in this project. FTA and partners could explore benefits to transit agencies such as automatically calculating some NTD report items (already possible using existing GTFS for fields like Revenue Vehicle Miles Traveled) or the availability of this same level of data for adjacent transit agencies.

This is an opportunity to collaborate with and build on the work of State and local stakeholders. Oregon DOT has identified the need for a common ridership data standard and has developed a scope of work in coordination with Oregon State University. They have developed a prospective ridership standard as an extension to GTFS that they were circulating for comment and review at the time this report was under development. Florida DOT also uses a supplemental "stop_ridership.txt" table in GTFS to help the State's transit agencies model ridership for planned service.

Data insights

Using National Transit Map data

Although GTFS is well-studied and has been a de facto standard for transit schedules for a number of years, this project is among the first to take advantage of the 2016 launch of the National Transit Map, the first official agglomeration of GTFS data at the national level in the United States. Because of this, the Volpe/OST-P team worked closely with BTS so that the project team could understand the opportunities of this new data source and BTS could receive feedback about use of the feeds in a research project.

Based on this feedback, BTS released the original GTFS feeds that transit agencies submitted to DOT as a supplemental format to the single, nationally aggregated feed. This gives NTM users flexibility in the type of GTFS data that meets their research or analytical needs. This still provides an advantage over obtaining feeds directly from the agencies, due to licensing issues and also because NTM collects GTFS from all agencies on the same day, increasing consistency of the time period covered by the various GTFS feeds. A future opportunity could be aggregating the seasonal feeds that agencies usually provide into a full year of data.

GTFS shapes and calendars

Though not specific to the National Transit Map, the project team also noted some challenges in working across GTFS feeds that may be relevant to other researchers. In particular, agencies were not consistent in the use of the "shapes.txt" table as well as the calendar tables.

Shapes availability

As discussed in the methodology section, the GTFS specification does not actually require agencies to submit line shapes for transit routes, and shapes.txt is an optional table. Typically, commercial trip planners will try to approximate route shapes as close as possible by connecting the required latitude/longitude locations for stops along a route, either in as-the-crow-flies lines or by calculating the shortest road network path. However, both of these methods are prone to misrepresent actual route shapes, especially for express routes where stops may be far apart.

Although this project's route snapping algorithm can theoretically resolve stop-by-stop as-the-crow-flies shapes, the project team chose not to do so because of accuracy concerns. To help other researchers, the NTM could include a flag for individual feeds or trips within the national feed that do not have an associated shape. And as discussed below, tools developed for this project could be adapted to help transit agencies improve their shapes by snapping them to the road network.

Formats for describing calendars

Similarly, although dates of service are obviously required in GTFS schedules, there are two competing ways to describe them. The recommended use, described in Google's online GTFS reference, is that agencies should specify general service availability by day of the week in the calendar.txt table and exceptions in the calendar_dates.txt table. For example, calendar.txt would specify the services typically available on Mondays, and calendar_dates.txt would specify the (potentially reduced) services available on a holiday such as Memorial Day. However, agencies can (and do) bypass the calendar.txt file entirely (although they do provide an empty file since calendar.txt is strictly required by the specification) and instead use calendar_dates.txt to describe the service availability on every individual day in the schedule. This dramatically increases the amount of information that must be parsed to compile service characteristics.

While potentially appropriate for some systems, researchers should be aware of these different uses when working with NTM or other GTFS data. The project team encountered this use in one of the case study systems and was able to account for it in the analysis code. However, it may be worth investigating whether these two uses work compatibly within NTM's nationally aggregated feed.

ARNOLD data inconsistencies and alternatives

As described in the methodology section, the format of official DOT ARNOLD data posed a few challenges for the purposes of this project. In particular, data is currently only available within DOT and only on a State-by-State basis. This reflects the process where each States submits its ARNOLD data to FHWA. The quality of the ARNOLD network and the level of detail can hence vary significantly from State to State, with some States only including major roads (such as the National Highway System) and omitting smaller roads where many local transit services operate. There can also be conflicts at State borders where the same road may not align on either side of the border due to spatial projection or other issues. This was not a major factor for the case study agencies in this project, but could be an obstacle in future applications of these tools.

The project team discussed using OpenStreetMap as a potential alternative network to ARNOLD. OSM is an open-source, community-edited map database that is the basis of many private-sector trip planners and mapping services. Unlike ARNOLD, it is available to the general public on a national scale. And its network in the United States appears to be fairly complete, accurate, and consistent across State boundaries. The team chose to use ARNOLD since it is easily tied to HPMS AADT data, but OSM may be an appropriate choice for other applications of this work. Alternatively, it would be possible to try matching data from ARNOLD onto the OSM network.

Conclusions and Next Steps

While exploratory in nature, this project suggests that matching GTFS schedule data to the authoritative road system can help agencies and DOT estimate transit ridership and understand multimodal performance. Attaching transit usage data (either modeled or measured) to GTFS/ARNOLD, enables agencies to make multimodal comparisons at a very fine level and make the most of data sources that already exist (i.e. GTFS and AADT). This could also be the basis for future refinement of national TPM performance measures.

The OST-P and Volpe project team highlighted the following potential next steps for making use of GTFS in multimodal planning and performance management:

- **Refine ridership model and add additional calibration data**: Additional calibration data (i.e. measured segment-level ridership) could enhance the ridership estimation model greatly, to the point where DOT might be comfortable encouraging its use for performance measures.

- **Integrate Oregon DOT's GTFS ridership addendum (or another format) into the National Transit Map**: Settling on a national standard for segment-level ridership data would help lay the groundwork for transit usage data that is as readily-available nationally as highway usage is today. In addition, measured data from additional agencies could help refine the ridership model.

- **Apply road snapping or ridership estimation for all National Transit Map data**: Although it would require some amount of manual preparation, BTS or a partner could apply this project's tools to all or some National Transit Map agencies. This could be a way to create publicly available maps about the nation's transit network or provide a benefit/incentive for participating transit agencies (i.e. smaller agencies would have an incentive to submit feeds since they will receive routes and ridership estimates snapped to their road network).

- **Document an alternative way of calculating proposed national performance management measures using this project's tools**: This project provides proof-of-concept that public agencies can use GTFS data to calculate performance measures generally. Particularly for transit agencies that do not collect robust ridership information at the route level, or do not have the internal capacity to leverage this information, this proof-of-concept could be a more precise estimation at the segment level compared to the baseline calculation required in the most recent national performance management rule. But to help local governments adopt this approach, DOT or its partners should pilot and document the use of these tools to calculate the specific national performance measures defined in the most recent TPM rule, which are currently based on region-wide NTD usage data.

DOT itself or external partners could pursue these steps. To this end, the project team has made the source code for all of its analytical tools publicly available as open-source software. As this project demonstrates, transit data intended for one specific use (e.g. public trip planning) can be adapted to other uses (e.g. multimodal performance management) as a way to efficient use resources. Creative companies, public agencies, and non-profits will continue to find new uses for GTFS and other emerging transit data such as the GTFS-Real Time addendum and competing formats that some agencies are already using to share live transit arrivals. DOT should continue to track these developments to see if they could further enhance the data and tools available for transportation planning and understanding multimodal system performance.

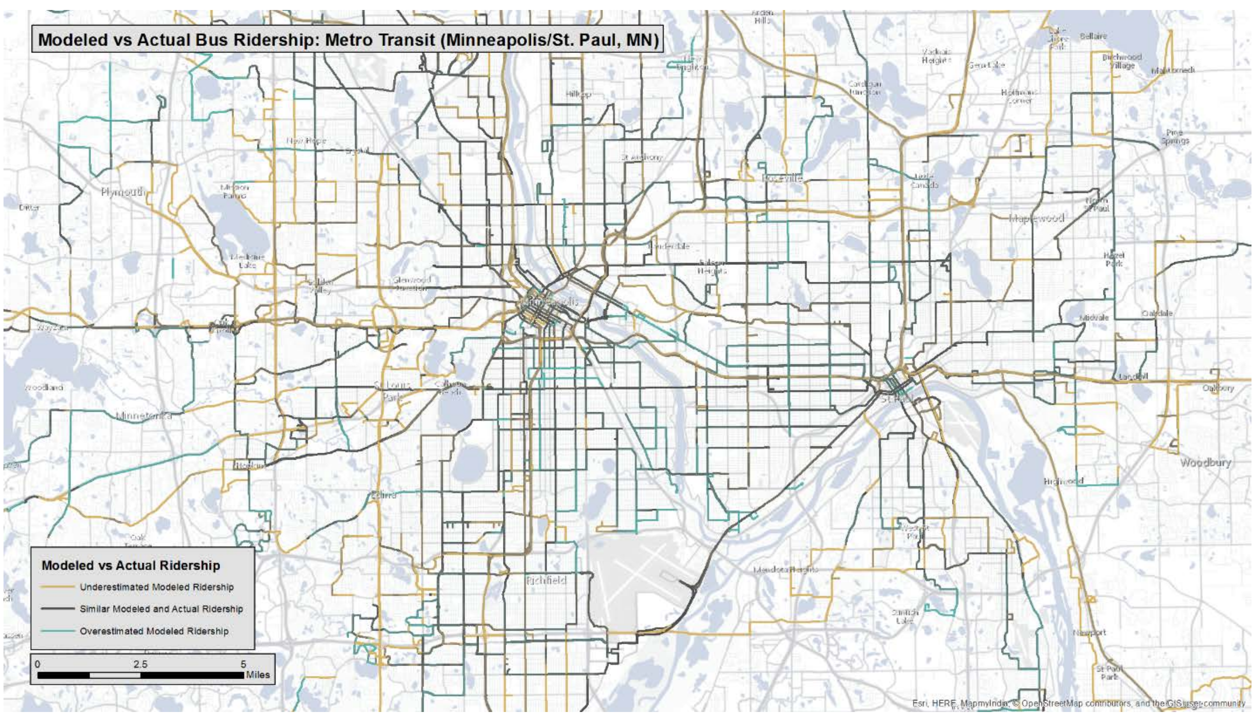
Appendix A: Maps

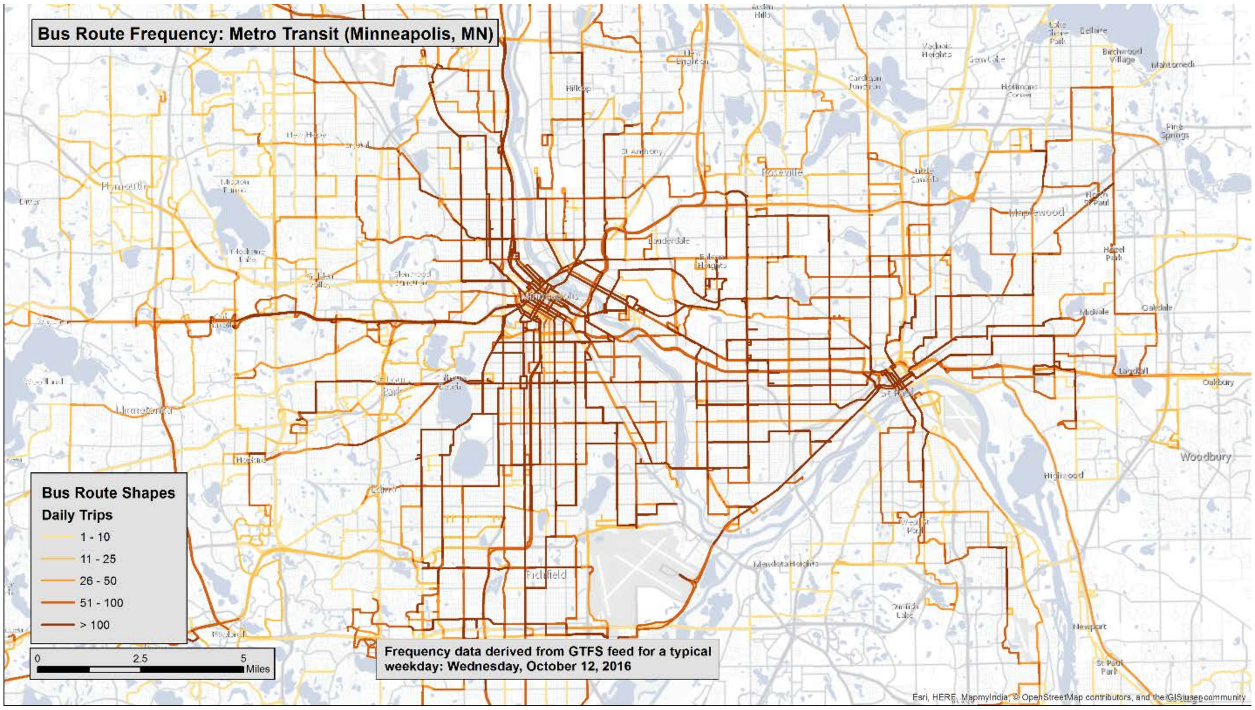
Map Notes

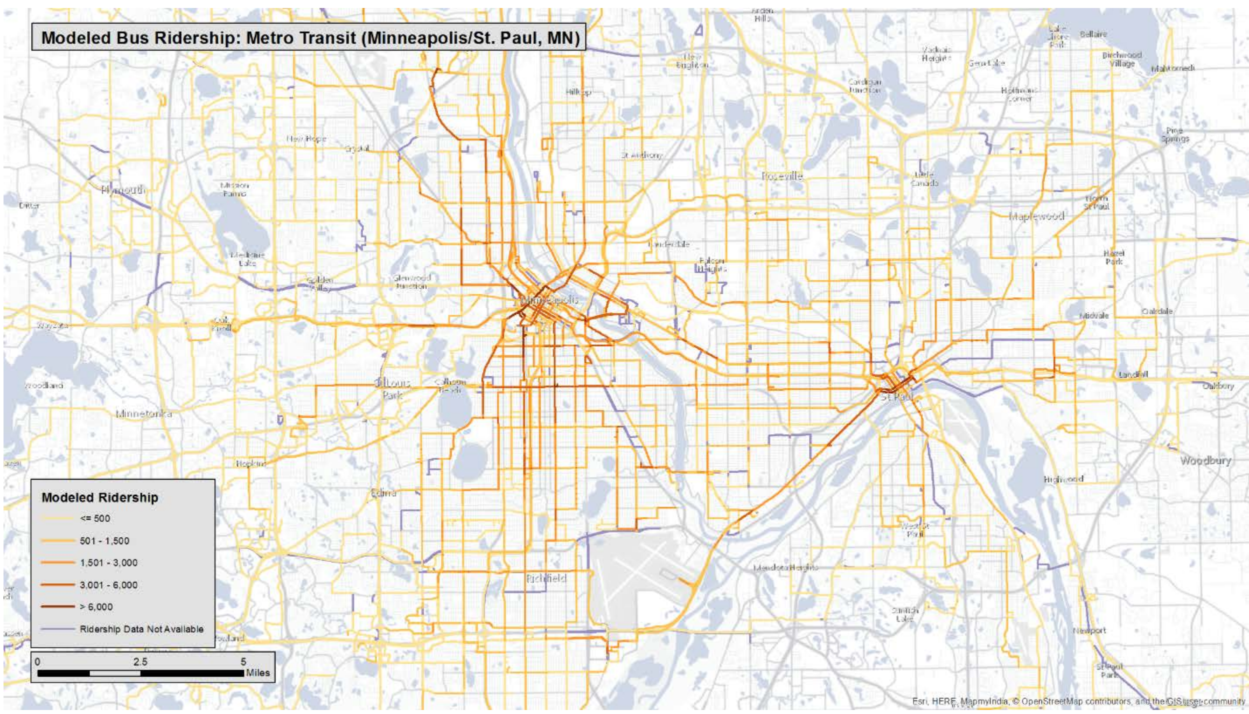
All maps show bidirectional (e.g. inbound and outbound) trips and are derived using manual classification schemes in an effort to best distinguish the variation in ridership, frequency, and road user characteristics unique to each transit system. The jenks natural breaks optimization is used as a starting point—minimizing each class's average deviation from the class mean, while maximizing each class's deviation from the means of other bins. The class breaks are then rounded to more meaningful numbers and may also be fine-tuned to ensure there is clear representation in each class. Due to the unique characteristics of each transit agency and in an effort to best show differences within a system, the class breaks vary system to system but all use the natural jenks algorithm with this basic manual rounding.

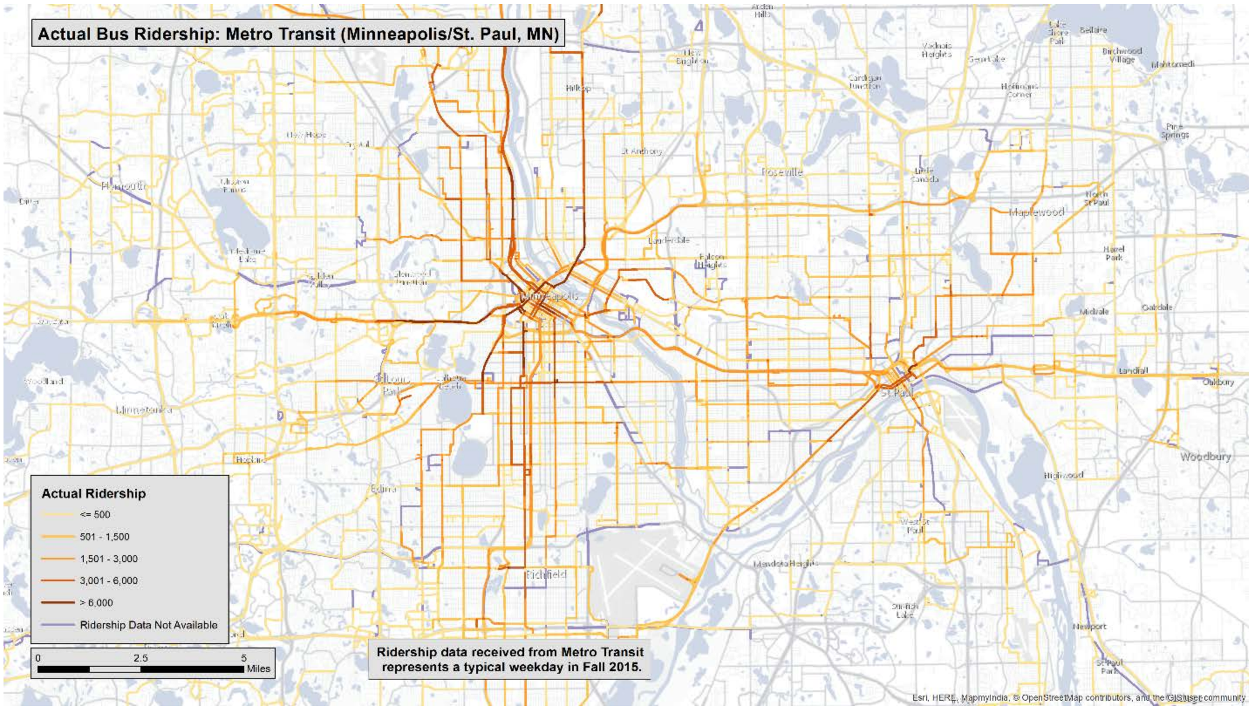
Also, the project team was unable to generate a complete set of maps for Valley Metro (Phoenix area) due to errors in reconciling its GTFS feed and the Arizona ARNOLD data.

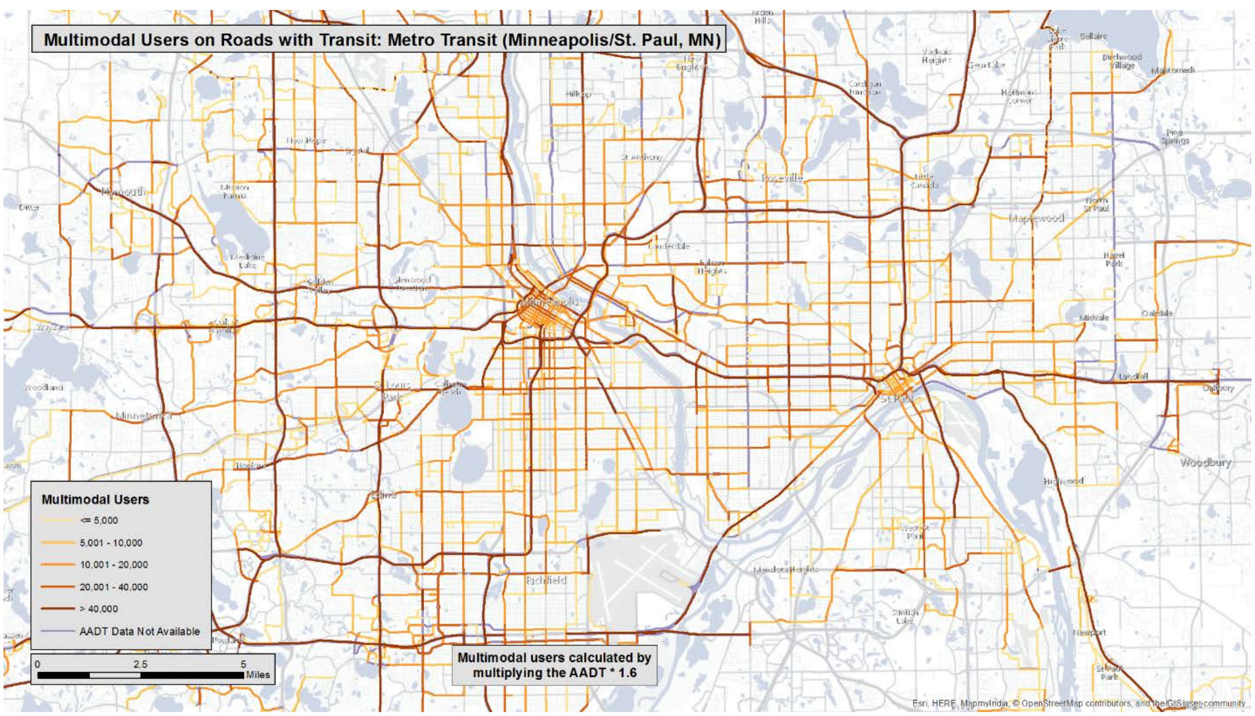
Metro Transit (MN)

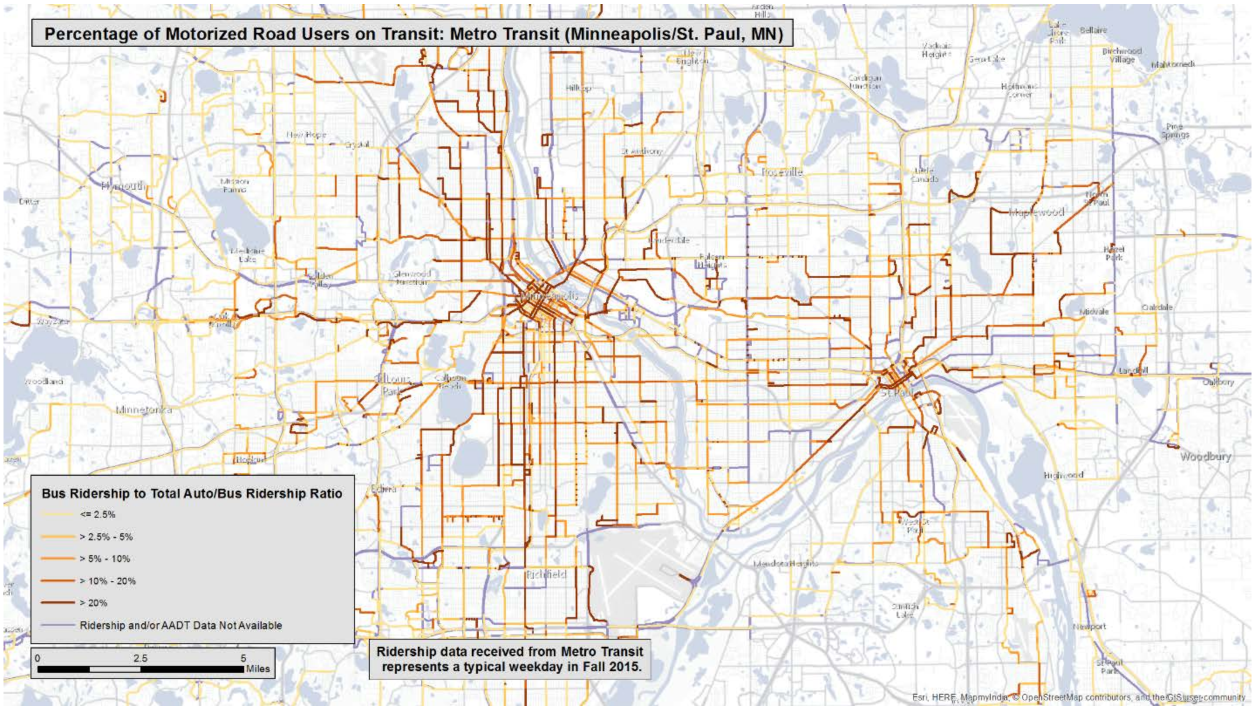



Bus Route Frequency: Metro Transit (Minneapolis, MN)
Bus Route Shapes
Daily Trips
1 - 10
11 - 25
26 - 50
51 - 100
> 100
0 2.5 5 Miles
Frequency data derived from GTFS feed for a typical weekday: Wednesday, October 12, 2016
Esri, HERE, MapmyIndia, © OpenStreetMap contributors, and the GIS user community


Modeled Bus Ridership: Metro Transit (Minneapolis/St. Paul, MN)
Modeled Ridership
<= 500
501 - 1,500
1,501 - 3,000
3,001 - 6,000
> 6,000
Ridership Data Not Available
0 2.5 5 Miles
Esri, HERE, MapmyIndia, © OpenStreetMap contributors, and the GIS user community

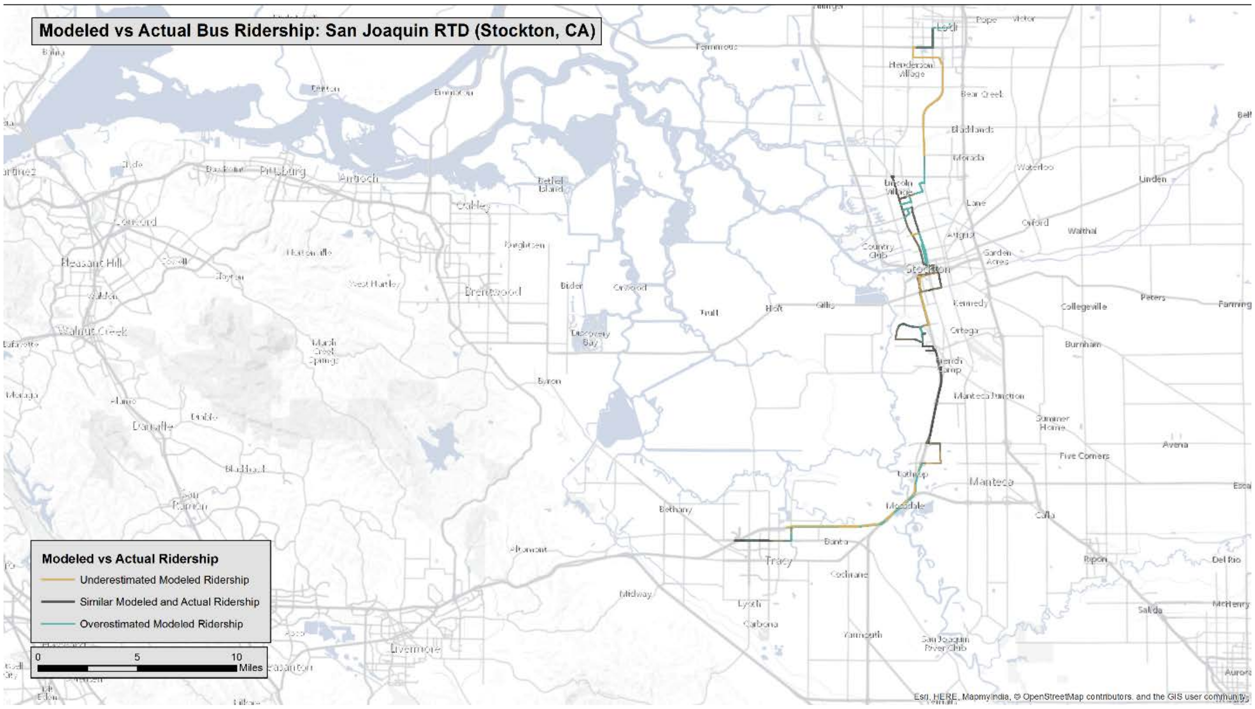

Actual Bus Ridership: Metro Transit (Minneapolis/St. Paul, MN)
Actual Ridership
<= 500
501 - 1,500
1,501 - 3,000
3,001 - 6,000
> 6,000
Ridership Data Not Available
0
2.5
5
Miles
Ridership data received from Metro Transit represents a typical weekday in Fall 2015.
Esri, HERE, MapmyIndia, © OpenStreetMap contributors, and the GIS user community

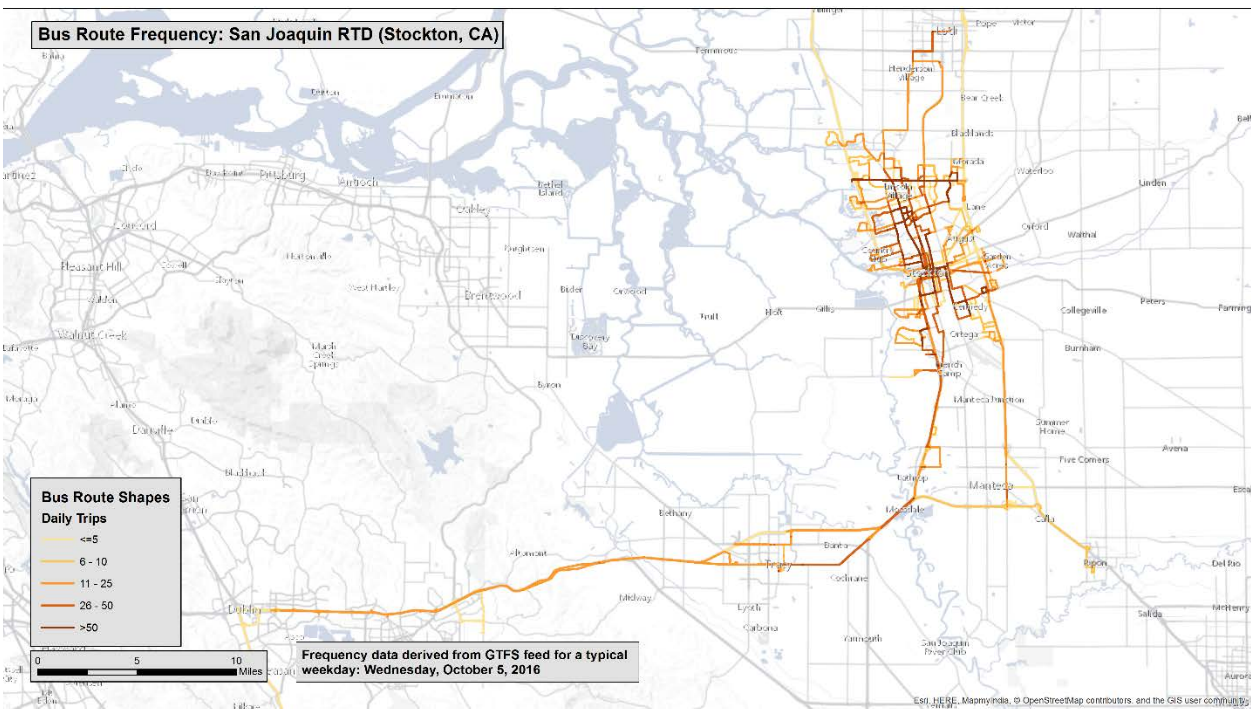

Multimodal Users on Roads with Transit: Metro Transit (Minneapolis/St. Paul, MN)
Multimodal Users
<= 5,000
5,001 - 10,000
10,001 - 20,000
20,001 - 40,000
> 40,000
AADT Data Not Available
0
2.5
5
Miles
Multimodal users calculated by multiplying the AADT * 1.6
Esri, HERE, MapmyIndia, © OpenStreetMap contributors, and the GIS user community

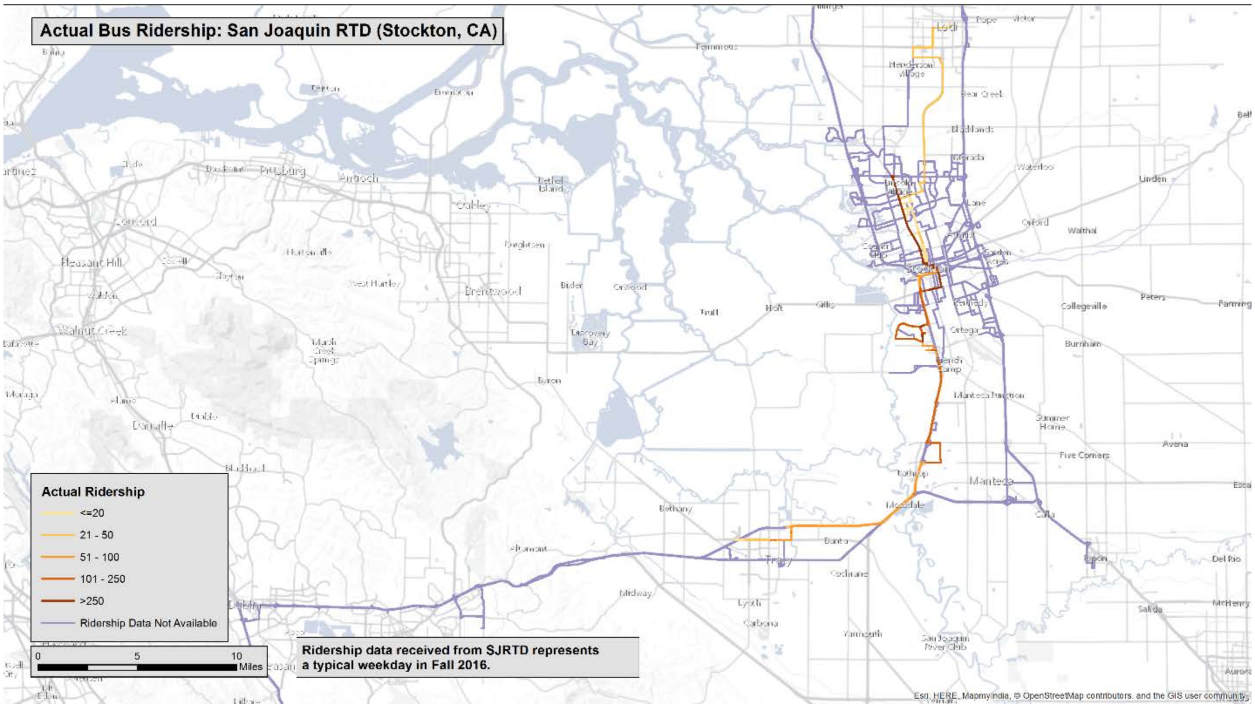


Percentage of Motorized Road Users on Transit: Metro Transit (Minneapolis/St. Paul, MN)
Bus Ridership to Total Auto/Bus Ridership Ratio
<= 2.5%
> 2.5% - 5%
> 5% - 10%
> 10% - 20%
> 20%
Ridership and/or AADT Data Not Available
0
2.5
5
Miles
Ridership data received from Metro Transit represents a typical weekday in Fall 2015.
Roseville
Woodbury
Minnetonka
Esri, HERE, MapmyIndia, © OpenStreetMap contributors, and the GIS user community

San Joaquin RTD (CA) – Not all routes have measured ridership data






Actual Bus Ridership: San Joaquin RTD (Stockton, CA)
Actual Ridership
<=20
21 - 50
51 - 100
101 - 250
>250
Ridership Data Not Available
0
5
10
Miles
Ridership data received from SJRTD represents a typical weekday in Fall 2016.
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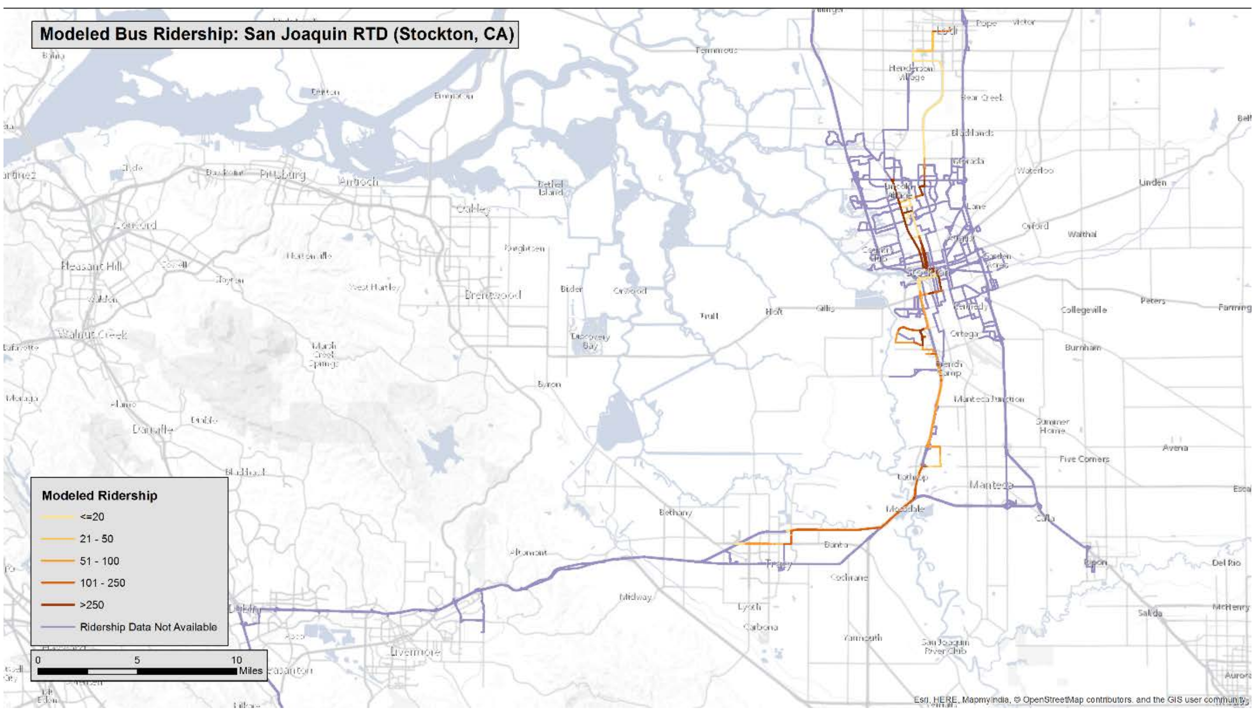
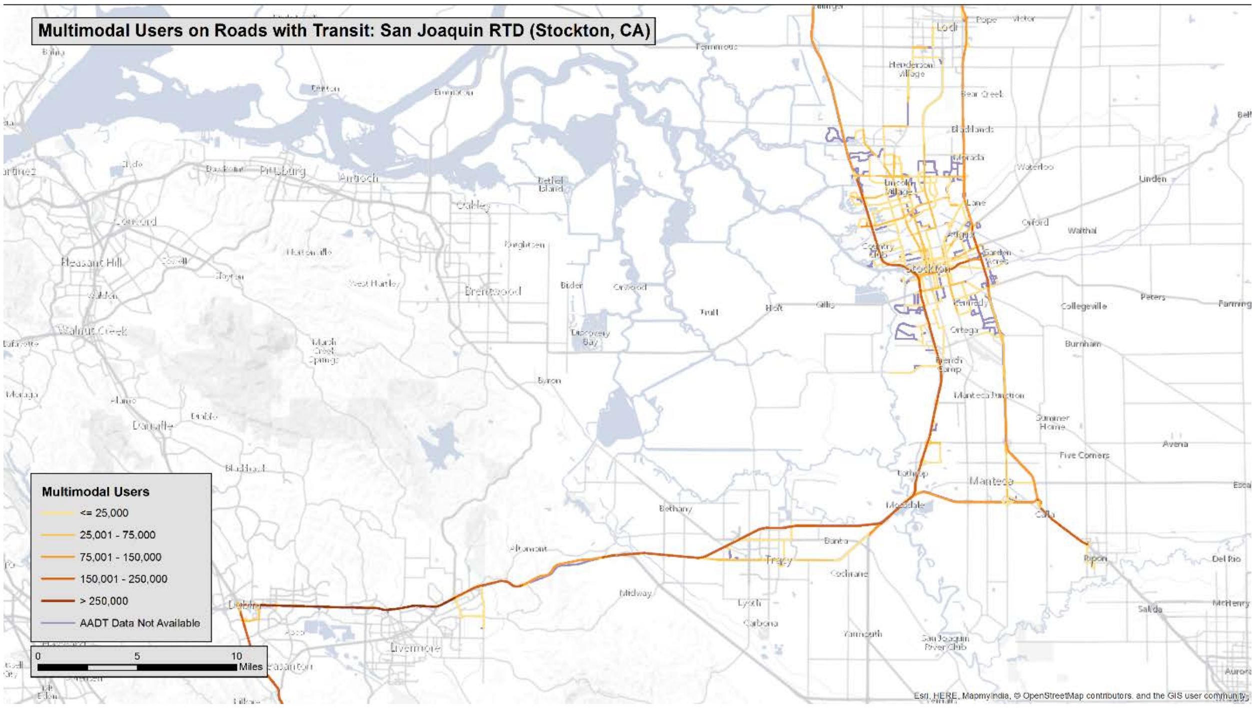
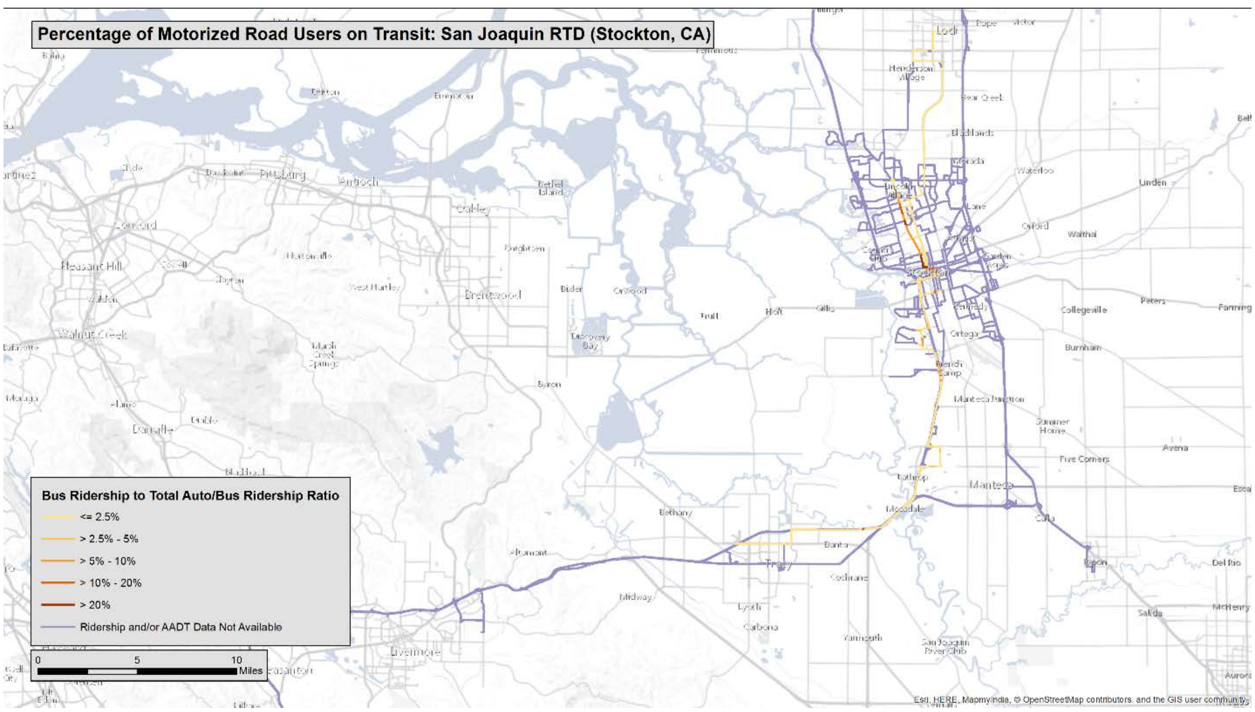

Modeled Bus Ridership: San Joaquin RTD (Stockton, CA)
Modeled Ridership
<=20
21 - 50
51 - 100
101 - 250
>250
Ridership Data Not Available
0
5
10
Miles
Esri, HERE, MapmyIndia, © OpenStreetMap contributors, and the GIS user community



Multimodal Users on Roads with Transit: San Joaquin RTD (Stockton, CA)
Multimodal Users
<= 25,000
25,001 - 75,000
75,001 - 150,000
150,001 - 250,000
> 250,000
AADT Data Not Available
0 5 10 Miles
Esri, HERE, MapmyIndia, © OpenStreetMap contributors, and the GIS user community



Percentage of Motorized Road Users on Transit: San Joaquin RTD (Stockton, CA)
Bus Ridership to Total Auto/Bus Ridership Ratio
<= 2.5%
> 2.5% - 5%
> 5% - 10%
> 10% - 20%
> 20%
Ridership and/or AADT Data Not Available
0 5 10 Miles
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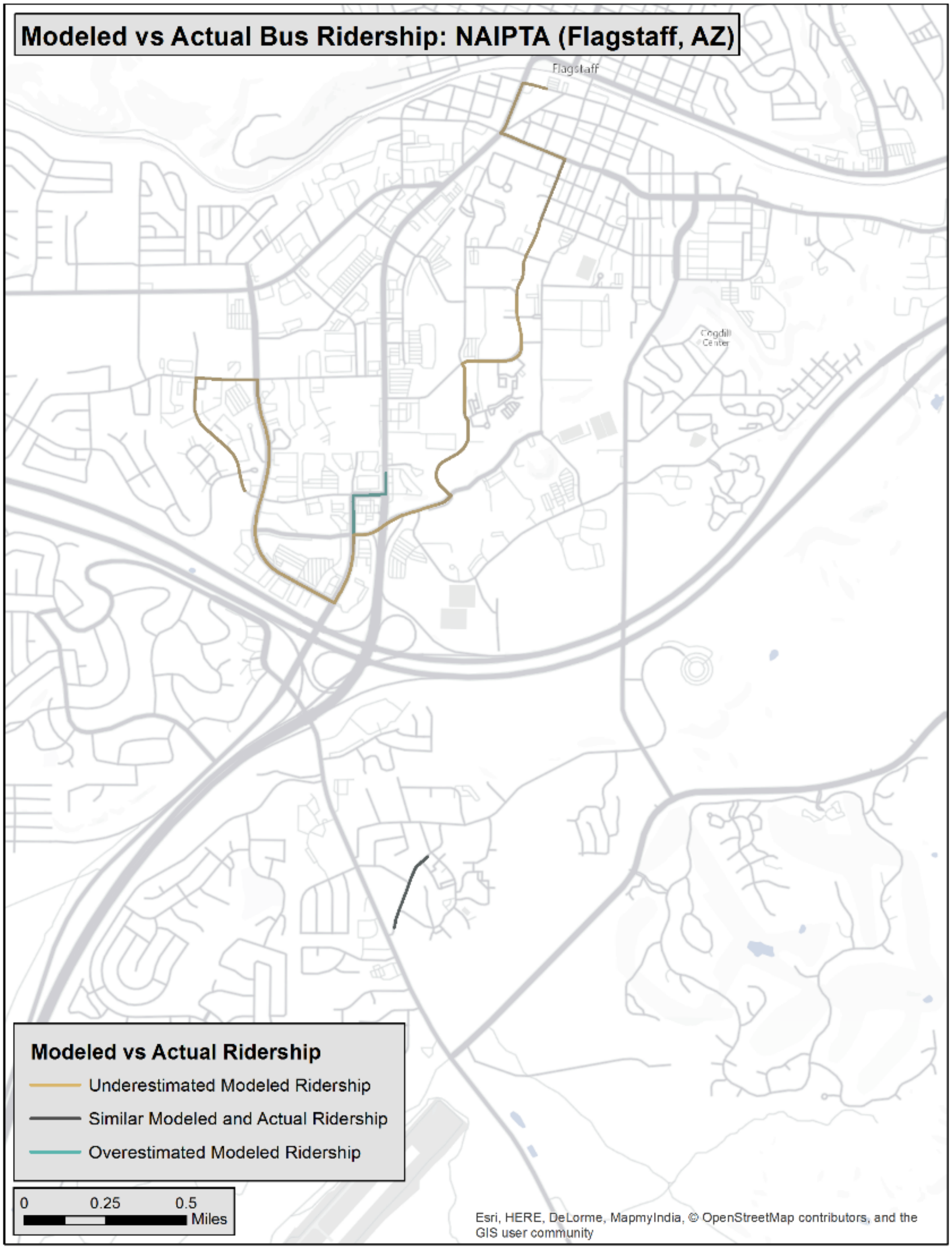
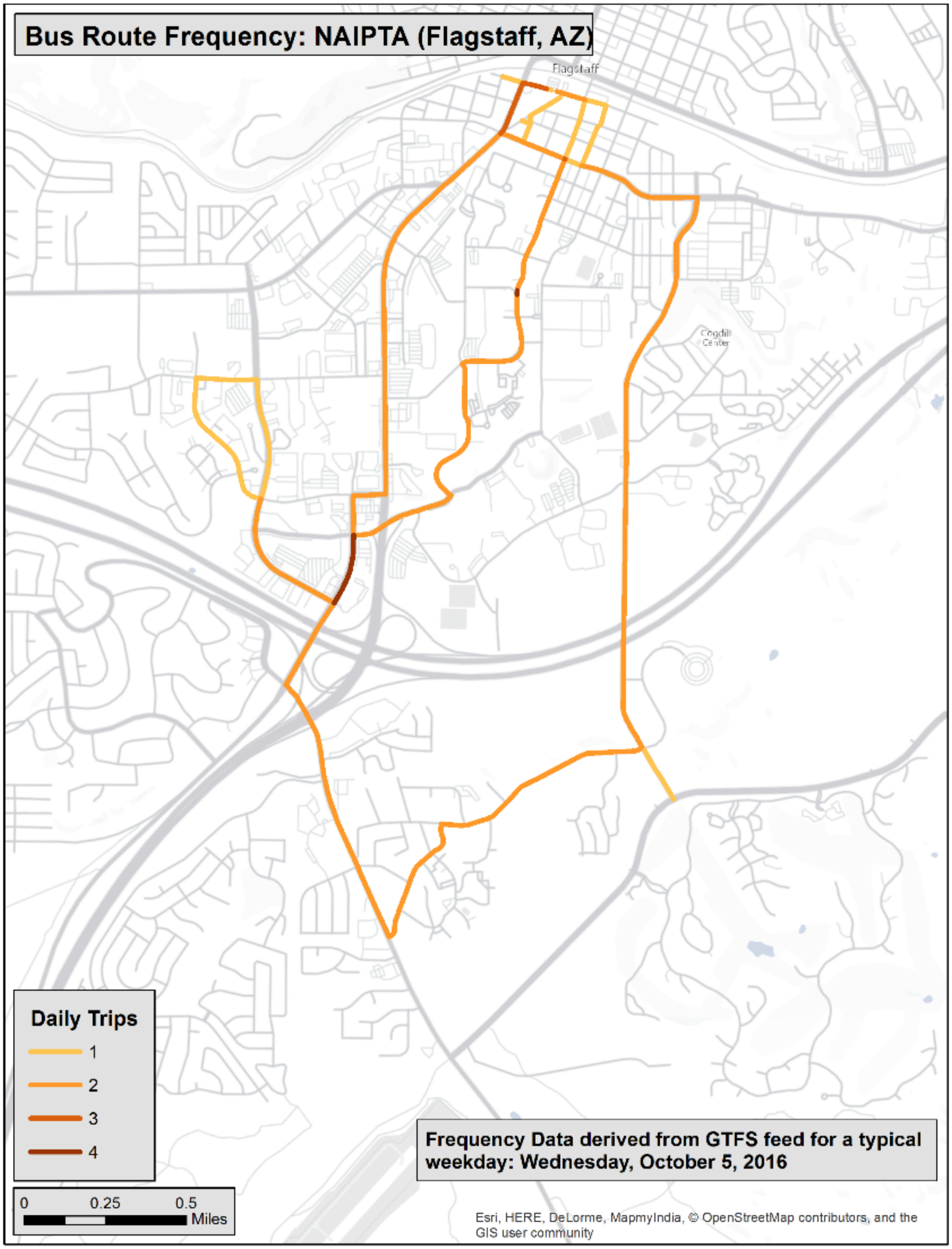
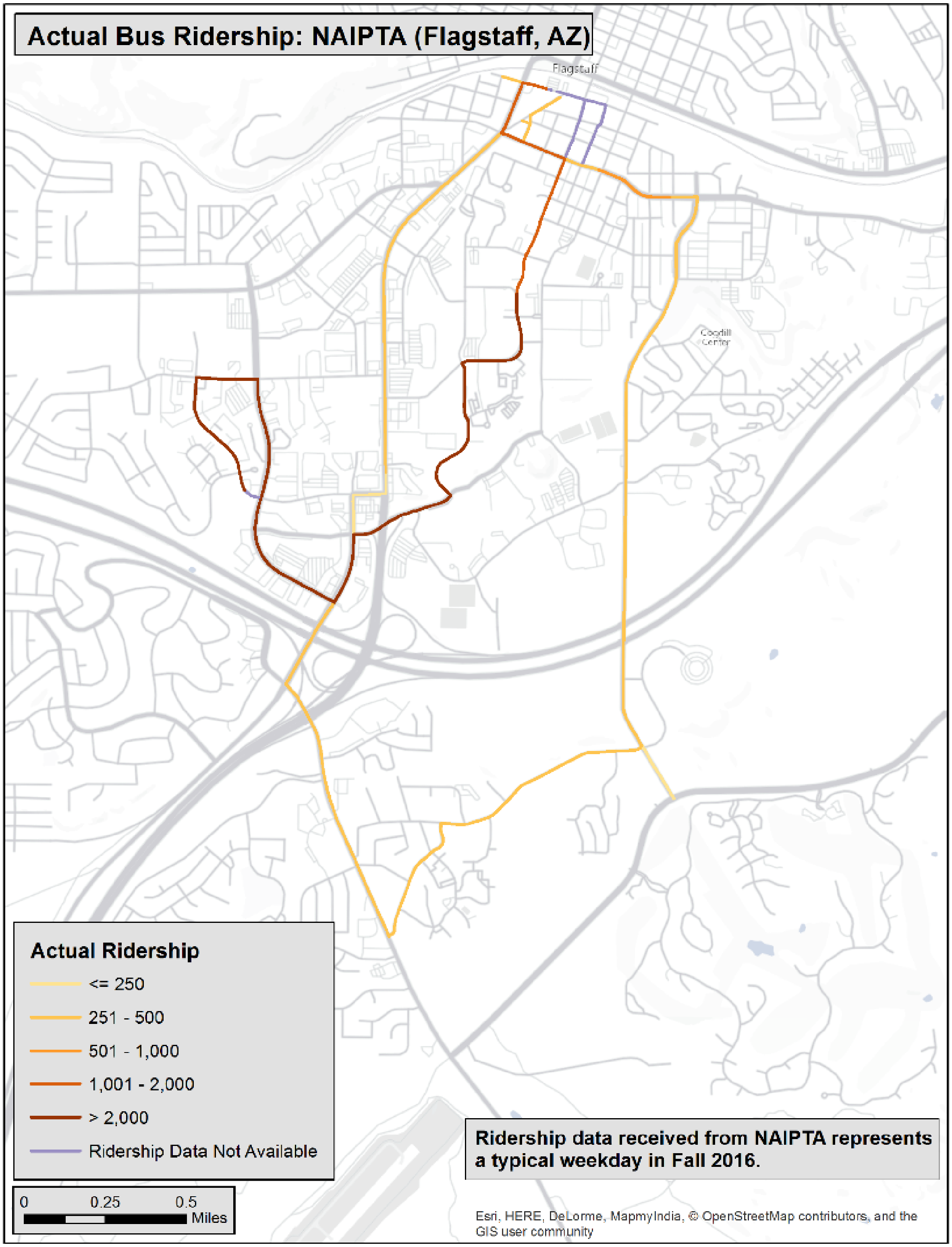
Northern Arizona Intergovernmental Public Transportation Authority (AZ)





Bus Route Frequency: NAIPTA (Flagstaff, AZ)
Flagstaff
Cogdill Center
Daily Trips
1
2
3
4
0
0.25
0.5
Miles
Frequency Data derived from GTFS feed for a typical weekday: Wednesday, October 5, 2016
Esri, HERE, DeLorme, MapmyIndia, © OpenStreetMap contributors, and the GIS user community


Actual Bus Ridership: NAIPTA (Flagstaff, AZ)
Flagstaff
Actual Ridership
<= 250
251 - 500
501 - 1,000
1,001 - 2,000
> 2,000
Ridership Data Not Available
0
0.25
0.5
Miles
Ridership data received from NAIPTA represents a typical weekday in Fall 2016.
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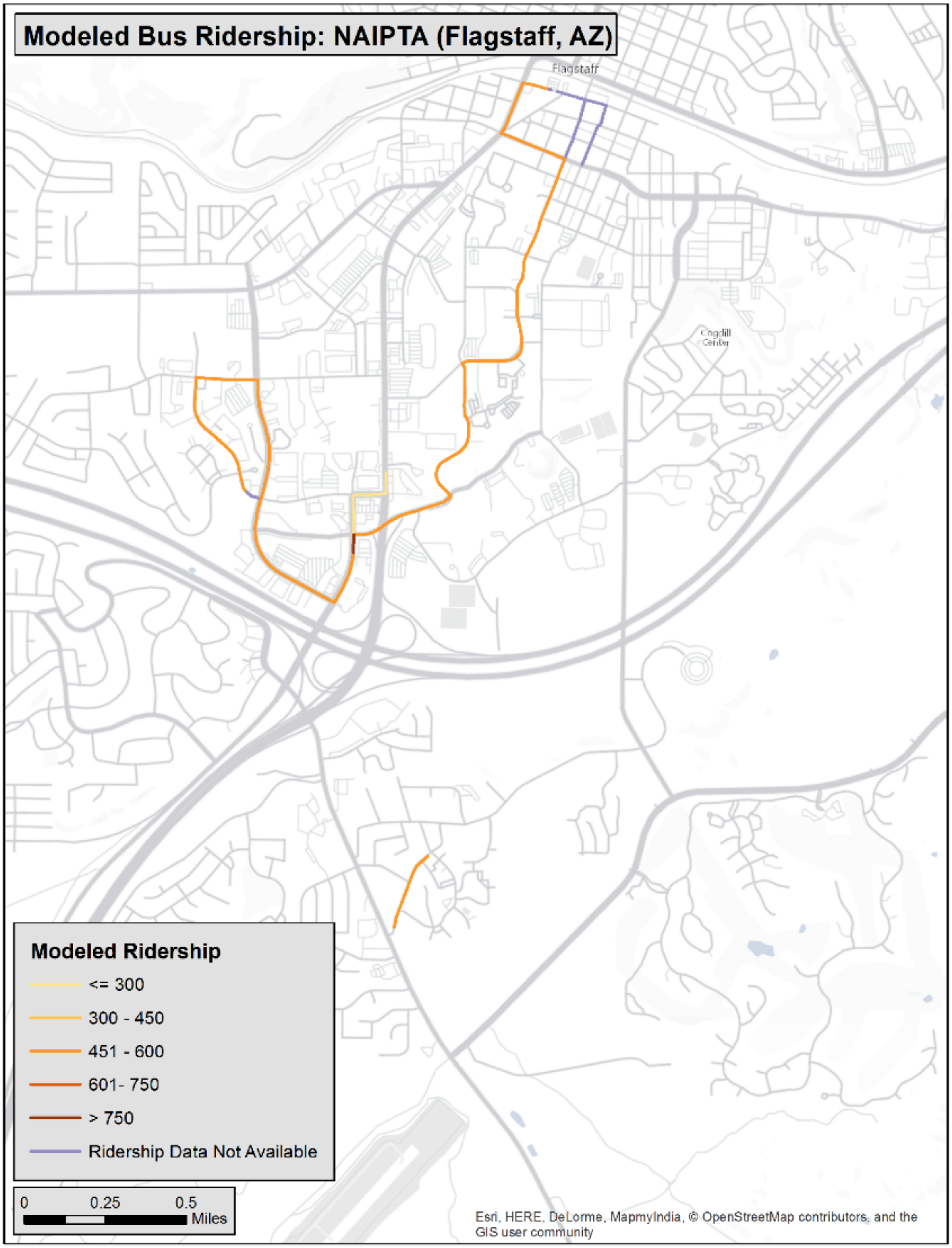
Modeled Bus Ridership: NAIPTA (Flagstaff, AZ)
Flagstaff
Cogdill Center
Modeled Ridership
<= 300
300 - 450
451 - 600
601- 750
> 750
Ridership Data Not Available
0
0.25
0.5
Miles
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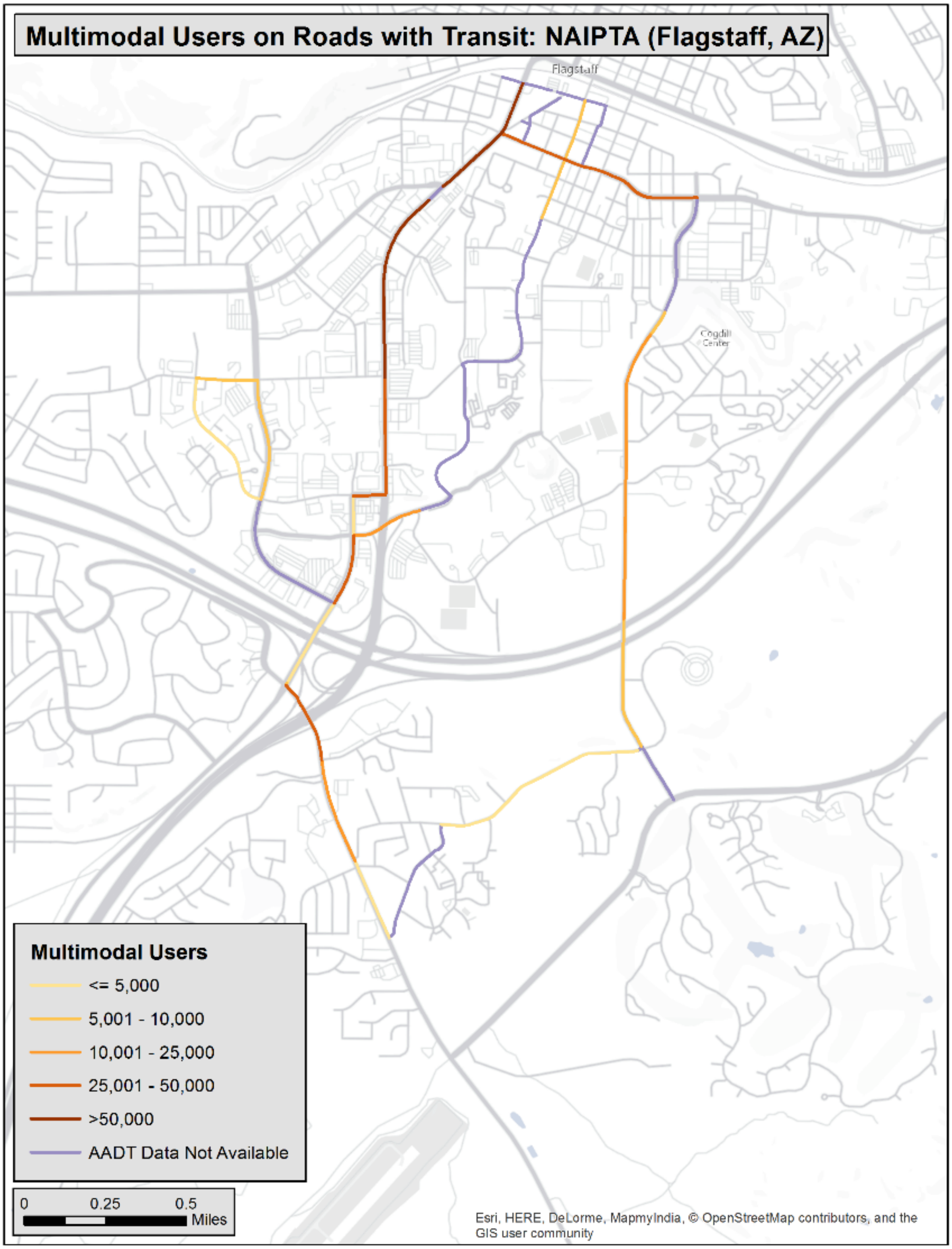
Multimodal Users on Roads with Transit: NAIPTA (Flagstaff, AZ)
Flagstaff
Cogdill Center
Multimodal Users
<= 5,000
5,001 - 10,000
10,001 - 25,000
25,001 - 50,000
>50,000
AADT Data Not Available
0
0.25
0.5
Miles
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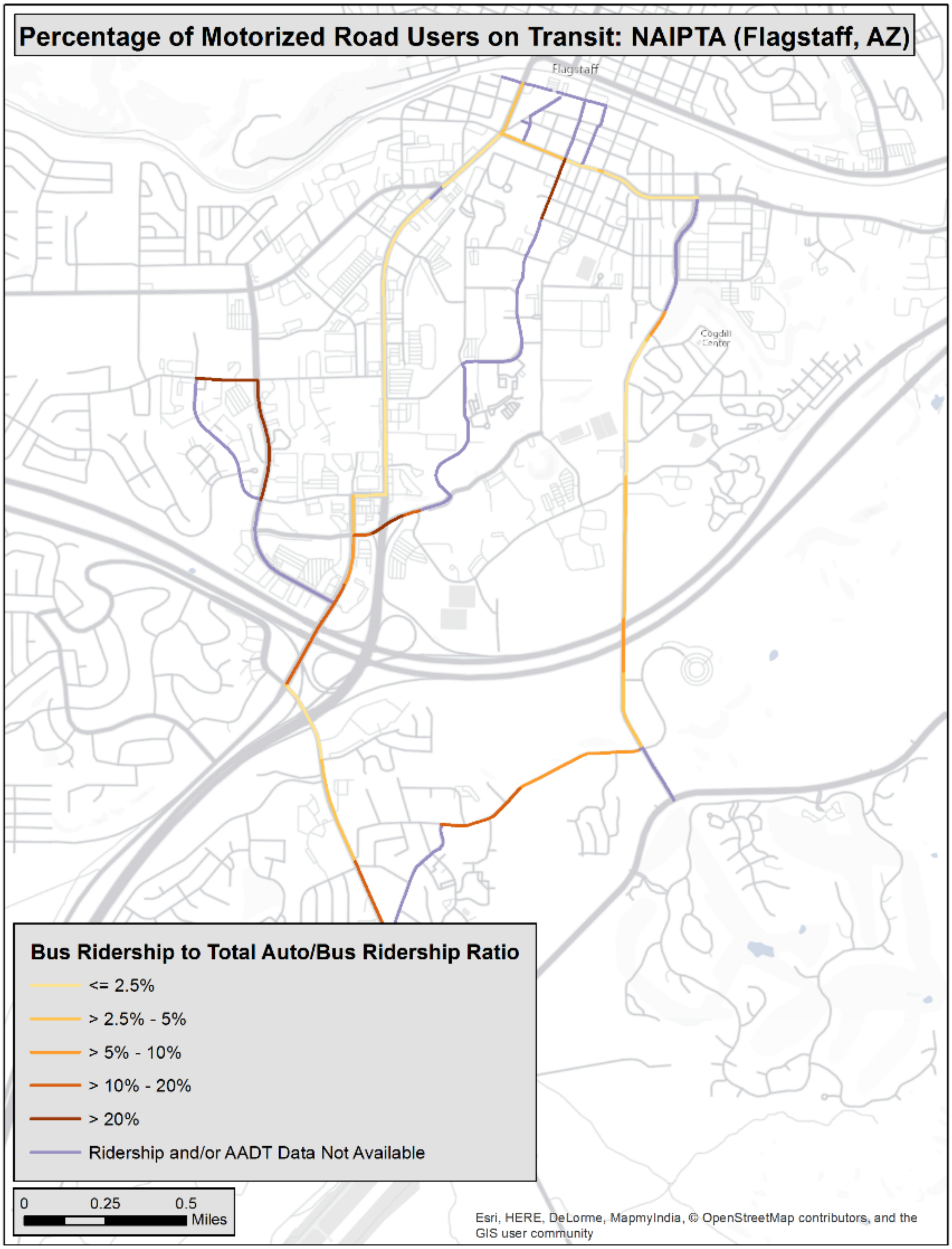
Percentage of Motorized Road Users on Transit: NAIPTA (Flagstaff, AZ)
Flagstaff
Cogdill Center
Bus Ridership to Total Auto/Bus Ridership Ratio
<= 2.5%
> 2.5% - 5%
> 5% - 10%
> 10% - 20%
> 20%
Ridership and/or AADT Data Not Available
0
0.25
0.5
Miles
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Appendix B: List of Model Input Parameters

U.S. Census American Community Survey (ACS)

- Total population
- Non-white population
- Number of households
- Households with total income under the poverty line
- Education:
    - Population age 25+
    - Population with attainment of high school diploma or lower
    - Population with attainment of some college or a college degree
    - Population with attainment of an advanced degree
- Housing:
    - Number of housing structures
    - Number of single-family dwellings
    - Number of 2-4 unit buildings
    - Number of 5-19 unit buildings
    - Number of 20+ unit buildings
- Total working-age population
- Total working-age population which use transit
- Number of households which are renting
- Median age
- Median household income
- Median rent

U.S. Census Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics (LODES)

- **Total jobs**
    - Total number of jobs
- **Jobs by earnings**
    - Number of jobs with earnings $1250/month or less
    - Number of jobs with earnings $1251/month to $3333/month
    - Number of jobs with earnings greater than $3333/month

- **Selected NAICS sectors**
  - Number of jobs in NAICS sector 51 (Information)
  - Number of jobs in NAICS sector 52 (Finance and Insurance)
  - Number of jobs in NAICS sector 53 (Real Estate and Rental and Leasing)
  - Number of jobs in NAICS sector 54 (Professional, Scientific, and Technical Services)
  - Number of jobs in NAICS sector 55 (Management of Companies and Enterprises)
  - Number of jobs in NAICS sector 56 (Administrative and Support and Waste Management and Remediation Services)
  - Number of jobs in NAICS sector 61 (Educational Services)
  - Number of jobs in NAICS sector 62 (Health Care and Social Assistance)

Other

- Frequency of transit service (daily)
- Number of serving routes
- Number of ARNOLD intersections in a .25 mile radius
- Annual ridership reported to NTD by mode and agency

Appendix C: Detailed Model Results

Note: Raw statistical package results are provided for only technical context and to assist other researches with reproducing results. For example, not all statistical tests in the raw output below are appropriate for the model approach or iteration.

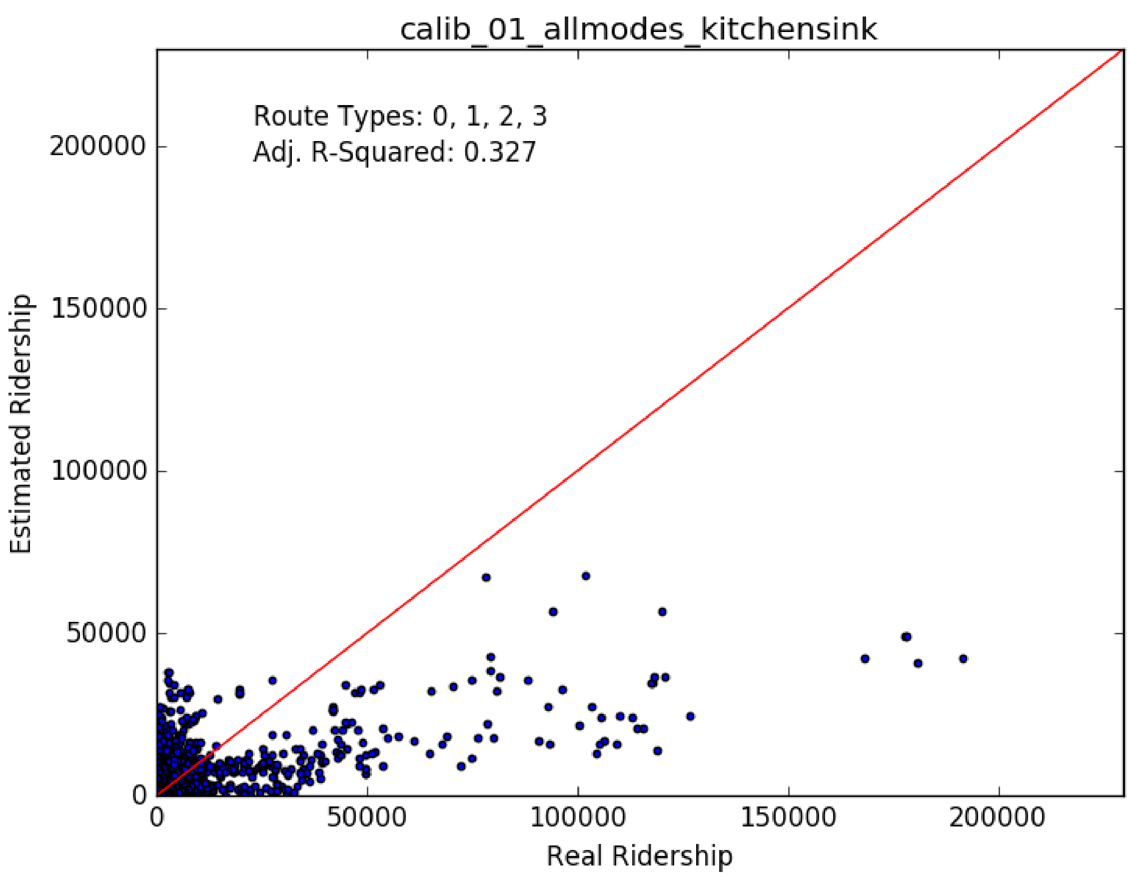
Calibration 01

Dep. Variable:	y	R-squared:	0.328
Model:	OLS	Adj. R-squared:	0.327
Method:	Least Squares	F-statistic:	317.8
No. Observations:	23489	Prob (F-statistic):	0
Df Residuals:	23452	Log-Likelihood:	-2.32E+05
Df Model:	36	AIC:	4.63E+05
Covariance Type:	nonrobust	BIC:	4.63E+05

	coefficient	std error	t	P > |t|	[95.0% Conf. Int.]	
Intercept	-4305.5574	3248.037	-1.326	0.185	-1.07E+04	2060.807
freq	53.5148	0.806	66.429	0	51.936	55.094
routes	-800.0916	28.45	-28.122	0	-855.856	-744.327
pop	-0.3271	0.133	-2.465	0.014	-0.587	-0.067
minority	1697.4612	263.034	6.453	0	1181.898	2213.024
house	-13.6213	1.152	-11.827	0	-15.879	-11.364
poverty	-658.2289	576.673	-1.141	0.254	-1788.545	472.087
pop 25+	1.091	0.253	4.309	0	0.595	1.587
high school	1435.9038	3363.017	0.427	0.669	-5155.828	8027.636
college	6048.09	3382.55	1.788	0.074	-581.928	1.27E+04
adv degree	1132.9496	3404.812	0.333	0.739	-5540.704	7806.603
housing	12.5874	0.944	13.341	0	10.738	14.437
1 unit	-1676.0519	829.644	-2.02	0.043	-3302.209	-49.895
2-4 unit	-6494.2214	877.149	-7.404	0	-8213.49	-4774.953
5-19 unit	-1978.7578	915.505	-2.161	0.031	-3773.208	-184.308
20+ unit	-2982.158	851.828	-3.501	0	-4651.796	-1312.52
workers	-0.8263	0.305	-2.711	0.007	-1.424	-0.229
workers use transit	3.0666	0.359	8.539	0	2.363	3.77
perc work transit	-5445.9748	641.483	-8.49	0	-6703.323	-4188.627
renting	-0.2298	0.389	-0.591	0.555	-0.992	0.532
age	-3.7884	6.796	-0.557	0.577	-17.11	9.533
hh income	-0.0054	0.002	-2.38	0.017	-0.01	-0.001
renting	0.0381	0.098	0.388	0.698	-0.155	0.231
no vehicle	-37.7346	583.874	-0.065	0.948	-1182.166	1106.697
jobs	0.3413	0.026	13.241	0	0.291	0.392
low pay jobs	-0.547	0.134	-4.085	0	-0.809	-0.285
mid pay jobs	-0.1954	0.151	-1.292	0.196	-0.492	0.101

high pay jobs	1.0837	0.054	20.169	0	0.978	1.189
info jobs	-3.454	0.134	-25.699	0	-3.717	-3.191
finance jobs	-1.9314	0.071	-27.369	0	-2.07	-1.793
real estate jobs	-3.4115	0.221	-15.405	0	-3.846	-2.977
professional jobs	-0.2171	0.096	-2.25	0.024	-0.406	-0.028
mgmt jobs	-1.2193	0.123	-9.881	0	-1.461	-0.977
admin jobs	1.0343	0.14	7.373	0	0.759	1.309
edu jobs	-0.8723	0.063	-13.896	0	-0.995	-0.749
health jobs	-0.9204	0.043	-21.364	0	-1.005	-0.836
ARNOLD intersections	-23.6755	2.557	-9.258	0	-28.688	-18.663
NTD riders	0.0006	2.26E-05	27.224	0	0.001	0.001

Omnibus:	42502.884	Durbin-Watson:	0.585
Prob(Omnibus):	0	Jarque-Bera (JB):	87943751
Skew:	13.155	Prob(JB):	0
Kurtosis:	301.605	Cond. No.:	1.06E+16



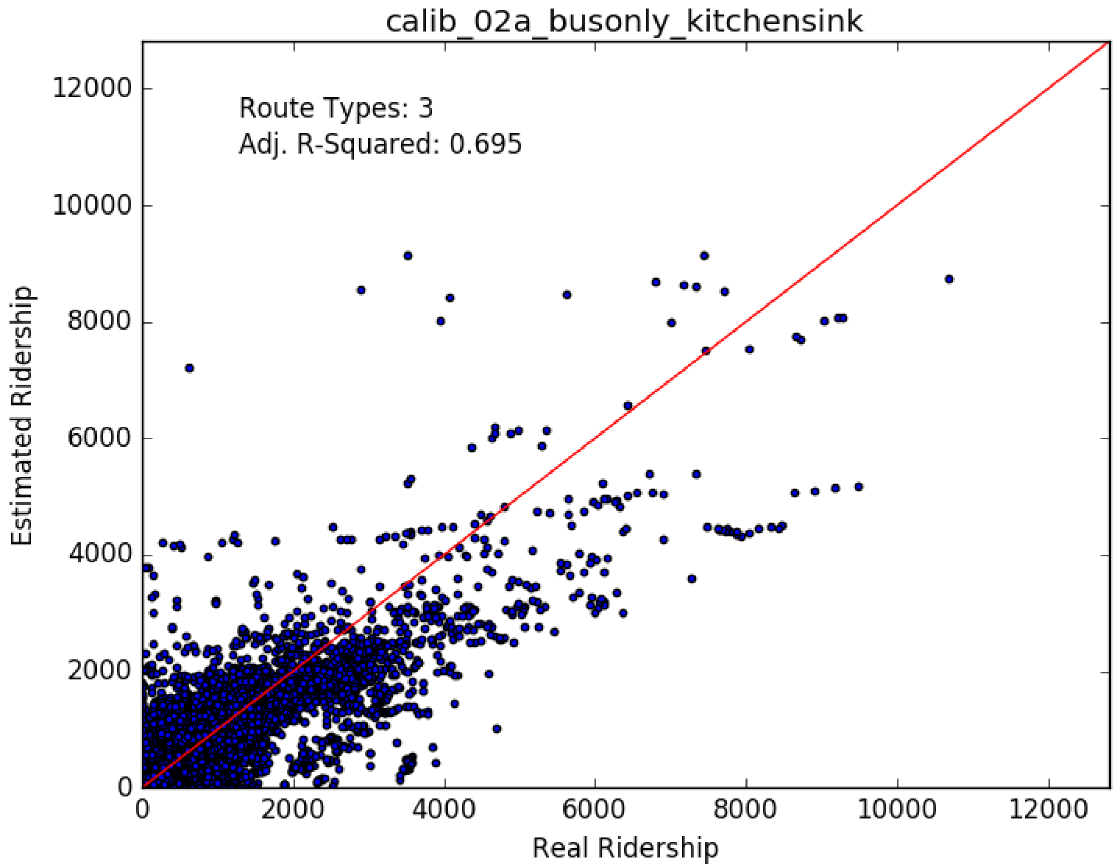
Calibration 02a

Dep. Variable:	y	R-squared:	0.696
Model:	OLS	Adj. R-squared:	0.695
Method:	Least Squares	F-statistic:	1482
No. Observations:	22707	Prob (F-statistic):	0
Df Residuals:	22671	Log-Likelihood:	-1.70E+05
Df Model:	35	AIC:	3.41E+05
Covariance Type:	nonrobust	BIC:	3.41E+05

	coefficient	std error	t	P > |t|	[95.0% Conf. Int.]	
Intercept	107.4032	65.725	1.634	0.102	-21.423	236.23
freq	13.6439	0.086	159.556	0	13.476	13.811
routes	-27.2943	2.885	-9.462	0	-32.948	-21.64
pop	0.0404	0.014	2.938	0.003	0.013	0.067
minority	102.3412	26.442	3.87	0	50.513	154.17
house	-0.8241	0.12	-6.842	0	-1.06	-0.588
poverty	-72.2492	57.045	-1.267	0.205	-184.062	39.564
pop 25+	-0.0228	0.028	-0.818	0.413	-0.077	0.032
high school	-9.2191	31.041	-0.297	0.766	-70.062	51.623
college	199.338	35.193	5.664	0	130.356	268.319
adv degree	-82.7156	40.742	-2.03	0.042	-162.572	-2.859
housing	0.6127	0.099	6.219	0	0.42	0.806
1 unit	-417.9707	80.39	-5.199	0	-575.541	-260.401
2-4 unit	-465.1916	85.712	-5.427	0	-633.194	-297.189
5-19 unit	-318.4579	89.11	-3.574	0	-493.119	-143.797
20+ unit	-611.729	82.902	-7.379	0	-774.223	-449.235
workers	-0.1017	0.031	-3.247	0.001	-0.163	-0.04
workers use transit	0.1666	0.039	4.326	0	0.091	0.242
perc work transit	142.7787	65.724	2.172	0.03	13.955	271.603
renting	0.359	0.04	8.978	0	0.281	0.437
age	0.9812	0.674	1.456	0.145	-0.34	2.302
hh income	0.0011	0	4.88	0	0.001	0.002
renting	0.0105	0.01	1.077	0.282	-0.009	0.03
no vehicle	370.0085	58.111	6.367	0	256.107	483.91
jobs	-0.0242	0.003	-8.116	0	-0.03	-0.018
low pay jobs	-0.0124	0.014	-0.887	0.375	-0.04	0.015
mid pay jobs	-0.0551	0.015	-3.568	0	-0.085	-0.025
high pay jobs	0.0433	0.007	6.164	0	0.03	0.057
info jobs	0.0035	0.019	0.185	0.854	-0.033	0.04
finance jobs	-0.0174	0.008	-2.185	0.029	-0.033	-0.002
real estate jobs	-0.0379	0.024	-1.601	0.109	-0.084	0.009
professional jobs	0.0367	0.011	3.482	0	0.016	0.057
mgmt jobs	-0.0502	0.013	-3.899	0	-0.075	-0.025
admin jobs	-0.0357	0.017	-2.089	0.037	-0.069	-0.002

edu jobs	-0.0314	0.007	-4.763	0	-0.044	-0.019
health jobs	0.0171	0.005	3.612	0	0.008	0.026
ARNOLD intersections	0.3984	0.273	1.461	0.144	-0.136	0.933
NTD riders	8.96E-06	2.43E-06	3.693	0	4.20E-06	1.37E-05

Omnibus:	9057.785	Durbin-Watson:	1.268
Prob(Omnibus):	0	Jarque-Bera (JB):	390503.19
Skew:	1.202	Prob(JB):	0
Kurtosis:	23.173	Cond. No.:	1.06E+16

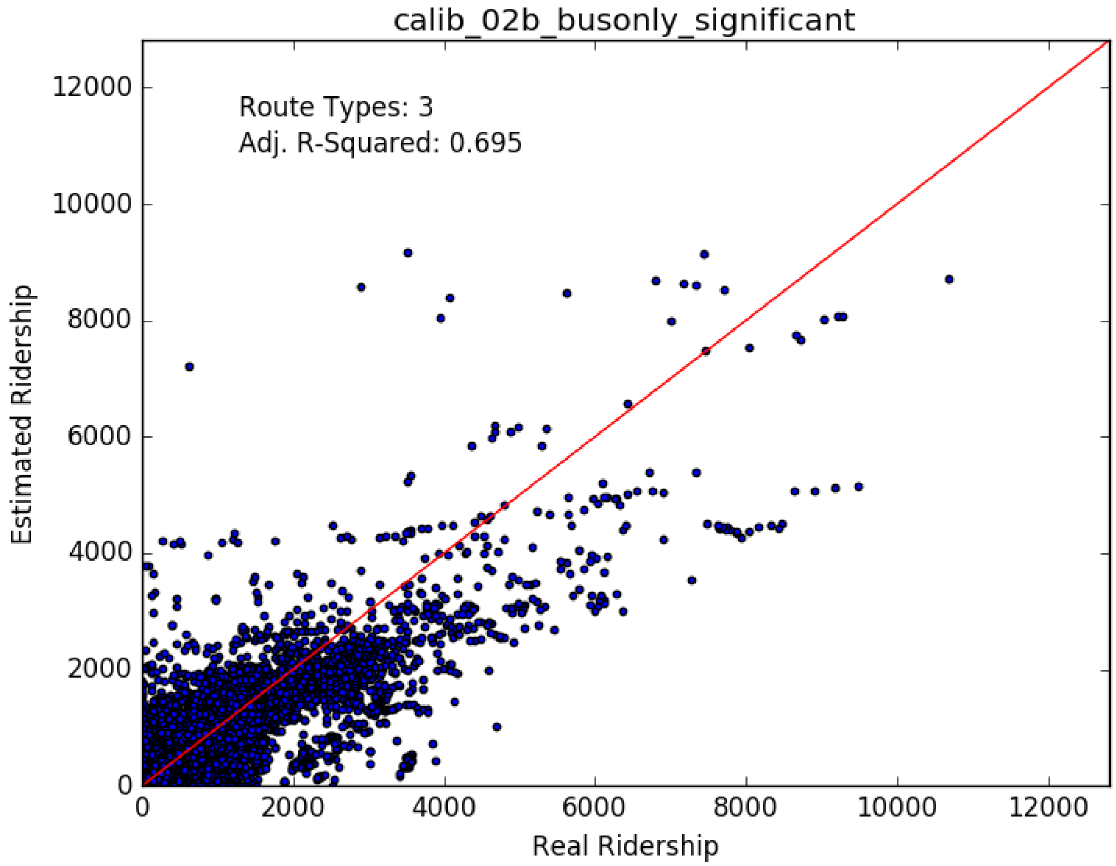


Calibration 02b

Dep. Variable:	y	R-squared:	0.696
Model:	OLS	Adj. R-squared:	0.695
Method:	Least Squares	F-statistic:	1852
No. Observations:	22707	Prob (F-statistic):	0
Df Residuals:	22678	Log-Likelihood:	-1.70E+05
Df Model:	28	AIC:	3.41E+05
Covariance Type:	nonrobust	BIC:	3.41E+05

	coefficient	std error	t	P > |t|	[95.0% Conf. Int.]	
Intercept	131.061	79.548	1.648	0.099	-24.858	286.98
freq	13.6402	0.085	160.212	0	13.473	13.807
routes	-27.2185	2.874	-9.469	0	-32.853	-21.584
pop	0.0337	0.013	2.609	0.009	0.008	0.059
minority	80.9583	23.681	3.419	0.001	34.542	127.374
house	-0.8534	0.111	-7.718	0	-1.07	-0.637
college	210.6002	46.851	4.495	0	118.77	302.431
adv degree	-68.5503	42.536	-1.612	0.107	-151.924	14.824
housing	0.6462	0.098	6.622	0	0.455	0.837
1 unit	-418.0342	80.29	-5.207	0	-575.409	-260.659
2-4 unit	-461.8632	83.856	-5.508	0	-626.226	-297.5
5-19 unit	-322.943	88.858	-3.634	0	-497.111	-148.775
20+ unit	-610.2539	82.474	-7.399	0	-771.909	-448.598
workers	-0.115	0.028	-4.084	0	-0.17	-0.06
workers use transit	0.1821	0.036	5.07	0	0.112	0.253
perc work transit	118.7757	64.557	1.84	0.066	-7.76	245.312
renting	0.3434	0.035	9.805	0	0.275	0.412
hh income	0.0012	0	5.57	0	0.001	0.002
no vehicle	352.7676	52.721	6.691	0	249.431	456.104
jobs	-0.0277	0.015	-1.845	0.065	-0.057	0.002
mid pay jobs	-0.0562	0.028	-2.037	0.042	-0.11	-0.002
high pay jobs	0.0461	0.015	3.113	0.002	0.017	0.075
finance jobs	-0.0148	0.007	-2.152	0.031	-0.028	-0.001
professional jobs	0.0305	0.01	3.194	0.001	0.012	0.049
mgmt jobs	-0.0635	0.01	-6.114	0	-0.084	-0.043
admin jobs	-0.0321	0.017	-1.908	0.056	-0.065	0.001
edu jobs	-0.0311	0.006	-5.233	0	-0.043	-0.019
health jobs	0.0185	0.004	4.619	0	0.011	0.026
NTD riders	1.15E-05	2.27E-06	5.044	0	7.01E-06	1.59E-05

Omnibus:	9025.73	Durbin-Watson:	1.268
Prob(Omnibus):	0	Jarque-Bera (JB):	392800.1
Skew:	1.19E+00	Prob(JB):	0
Kurtosis:	23.236	Cond. No.:	4.20E+08

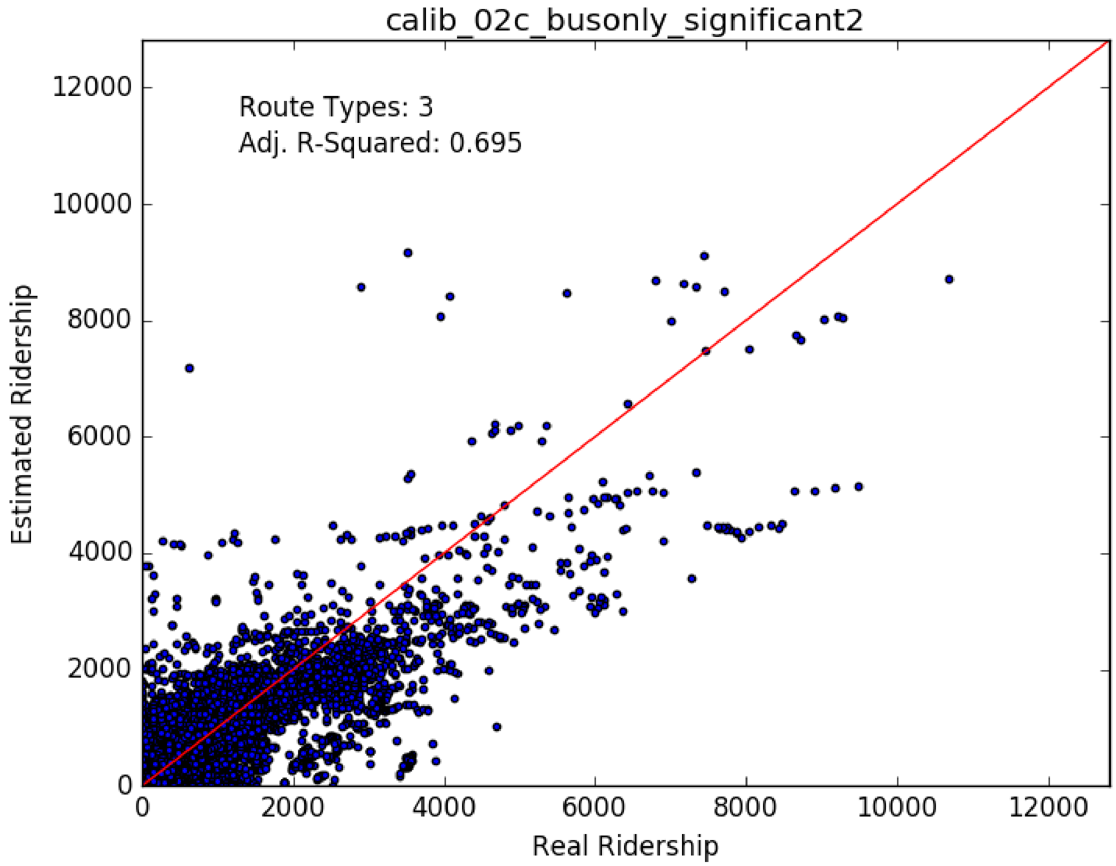

calib_02b_busonly_significant
Route Types: 3
Adj. R-Squared: 0.695
Estimated Ridership
Real Ridership
0
2000
4000
6000
8000
10000
12000

Calibration 02c

Dep. Variable:	y	R-squared:	0.696
Model:	OLS	Adj. R-squared:	0.695
Method:	Least Squares	F-statistic:	2073
No. Observations:	22707	Prob (F-statistic):	0
Df Residuals:	22681	Log-Likelihood:	-1.70E+05
Df Model:	25	AIC:	3.41E+05
Covariance Type:	nonrobust	BIC:	3.41E+05

	coefficient	std error	t	P > |t|	[95.0% Conf. Int.]	
Intercept	135.1227	79.551	1.699	0.089	-20.802	291.048
freq	13.6078	0.084	161.193	0	13.442	13.773
routes	-25.937	2.848	-9.106	0	-31.52	-20.354
pop	0.0346	0.013	2.687	0.007	0.009	0.06
minority	94.111	22.496	4.183	0	50.018	138.204
house	-0.8456	0.111	-7.649	0	-1.062	-0.629
college	228.2596	44.108	5.175	0	141.806	314.713
housing	0.6353	0.097	6.522	0	0.444	0.826
1 unit	-424.9896	80.044	-5.309	0	-581.881	-268.098
2-4 unit	-466.6783	83.441	-5.593	0	-630.228	-303.129
5-19 unit	-344.8874	86.875	-3.97	0	-515.168	-174.607
20+ unit	-634.8078	81.299	-7.808	0	-794.16	-475.455
workers	-0.119	0.028	-4.229	0	-0.174	-0.064
workers use transit	0.1945	0.036	5.457	0	0.125	0.264
perc work transit	94.8937	63.335	1.498	0.134	-29.248	219.035
renting	0.3451	0.035	9.875	0	0.277	0.414
hh income	0.001	0	6.056	0	0.001	0.001
no vehicle	345.6629	52.503	6.584	0	242.754	448.572
mid pay jobs	-0.1136	0.011	-10.478	0	-0.135	-0.092
high pay jobs	0.0229	0.005	5.03	0	0.014	0.032
finance jobs	-0.0214	0.006	-3.438	0.001	-0.034	-0.009
professional jobs	0.0246	0.009	2.633	0.008	0.006	0.043
mgmt jobs	-0.0651	0.01	-6.328	0	-0.085	-0.045
edu jobs	-0.0372	0.006	-6.739	0	-0.048	-0.026
health jobs	0.0196	0.004	4.96	0	0.012	0.027
NTD riders	1.18E-05	2.22E-06	5.328	0	7.47E-06	1.62E-05

Omnibus:	9034.028	Durbin-Watson:	1.269
Prob(Omnibus):	0	Jarque-Bera (JB):	391898.7
Skew:	1.195	Prob(JB):	0
Kurtosis:	23.211	Cond. No.:	4.17E+08

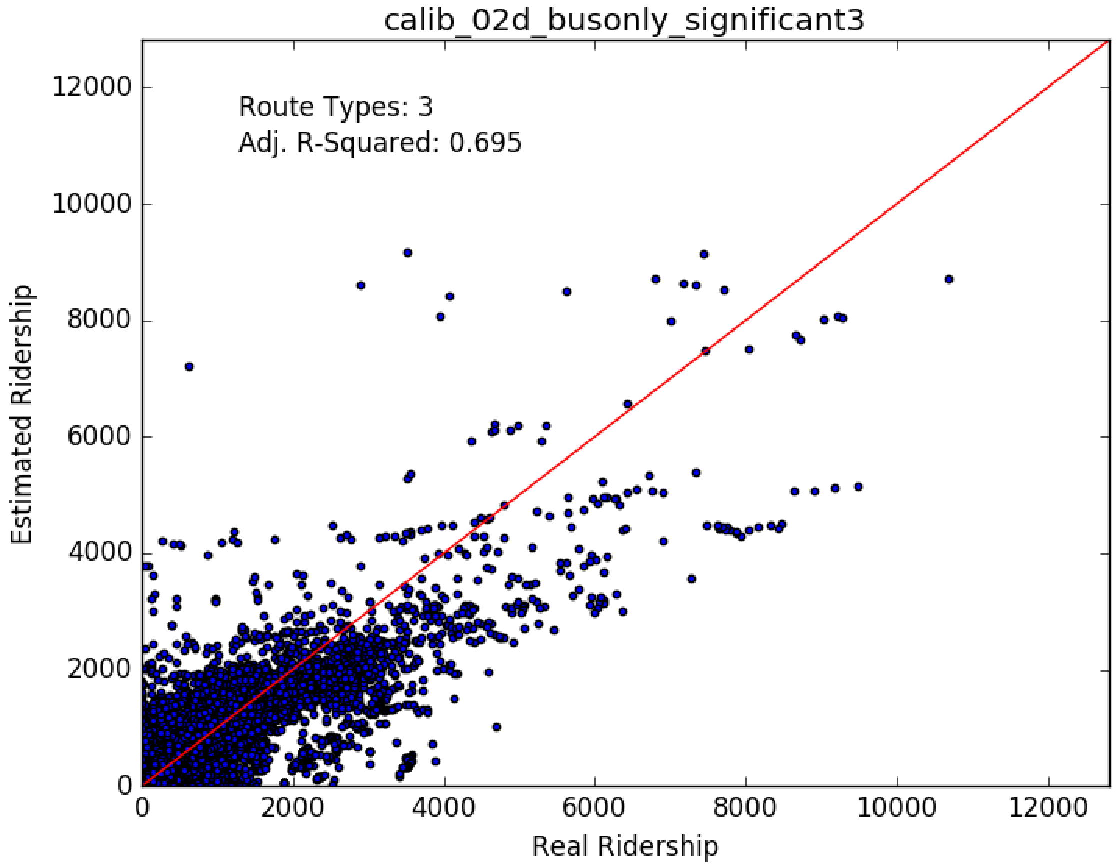

calib_02c_busonly_significant2
Route Types: 3
Adj. R-Squared: 0.695
Estimated Ridership
Real Ridership
0
2000
4000
6000
8000
10000
12000

Calibration 02d

Dep. Variable:	y	R-squared:	0.696
Model:	OLS	Adj. R-squared:	0.695
Method:	Least Squares	F-statistic:	2160
No. Observations:	22707	Prob (F-statistic):	0
Df Residuals:	22682	Log-Likelihood:	-1.70E+05
Df Model:	24	AIC:	3.41E+05
Covariance Type:	nonrobust	BIC:	3.41E+05

	coefficient	std error	t	P > |t|	[95.0% Conf. Int.]	
Intercept	126.6618	79.352	1.596	0.11	-28.874	282.198
freq	13.6306	0.083	164.139	0	13.468	13.793
routes	-26.1423	2.845	-9.188	0	-31.719	-20.565
pop	0.0326	0.013	2.541	0.011	0.007	0.058
minority	104.5818	21.383	4.891	0	62.669	146.495
house	-0.8294	0.11	-7.539	0	-1.045	-0.614
college	236.2635	43.784	5.396	0	150.444	322.083
housing	0.6289	0.097	6.462	0	0.438	0.82
1 unit	-427.3063	80.031	-5.339	0	-584.173	-270.439
2-4 unit	-456.9206	83.188	-5.493	0	-619.975	-293.866
5-19 unit	-339.5779	86.805	-3.912	0	-509.721	-169.435
20+ unit	-633.8385	81.299	-7.796	0	-793.19	-474.487
workers	-0.125	0.028	-4.487	0	-0.18	-0.07
workers use transit	0.2273	0.028	8.074	0	0.172	0.282
renting	0.3357	0.034	9.764	0	0.268	0.403
hh income	0.001	0	6.125	0	0.001	0.001
no vehicle	363.4461	51.145	7.106	0	263.199	463.694
mid pay jobs	-0.1134	0.011	-10.461	0	-0.135	-0.092
high pay jobs	0.0226	0.005	4.969	0	0.014	0.032
finance jobs	-0.0214	0.006	-3.427	0.001	-0.034	-0.009
professional jobs	0.0251	0.009	2.684	0.007	0.007	0.043
mgmt jobs	-0.0649	0.01	-6.309	0	-0.085	-0.045
edu jobs	-0.0368	0.006	-6.679	0	-0.048	-0.026
health jobs	0.0198	0.004	5.014	0	0.012	0.028
NTD riders	1.30E-05	2.07E-06	6.258	0	8.92E-06	1.71E-05

Omnibus:	9033.979	Durbin-Watson:	1.269
Prob(Omnibus):	0	Jarque-Bera (JB):	393148.6
Skew:	1.195	Prob(JB):	0
Kurtosis:	23.244	Cond. No.:	4.16E+08


calib_02d_busonly_significant3
Route Types: 3
Adj. R-Squared: 0.695
Estimated Ridership
Real Ridership
0
2000
4000
6000
8000
10000
12000

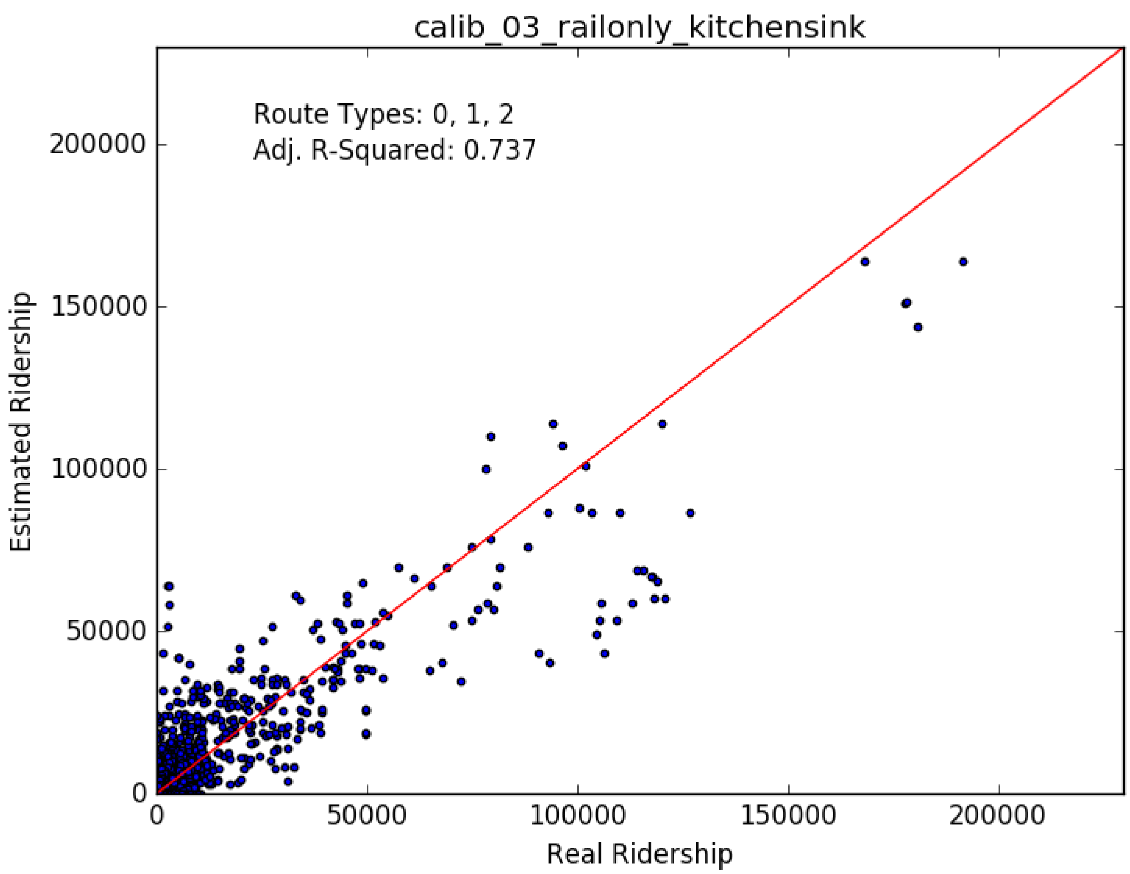
Calibration 03

Dep. Variable:	y	R-squared:	0.749
Model:	OLS	Adj. R-squared:	0.737
Method:	Least Squares	F-statistic:	61.79
No. Observations:	782	Prob (F-statistic):	3.22E-197
Df Residuals:	745	Log-Likelihood:	-8.53E+03
Df Model:	36	AIC:	1.71E+04
Covariance Type:	nonrobust	BIC:	1.73E+04

	coefficient	std error	t	P > |t|	[95.0% Conf. Int.]	
Intercept	-2.79E+04	1.01E+04	-2.76	0.006	-4.78E+04	-8069.05
freq	211.4199	8.991	23.514	0	193.769	229.071
routes	2061.4137	590.28	3.492	0.001	902.603	3220.225
pop	-1.9343	1.539	-1.257	0.209	-4.956	1.087
minority	230.4797	3688.118	0.062	0.95	-7009.86	7470.82
house	30.3802	11.704	2.596	0.01	7.404	53.356
poverty	1.59E+04	9735.478	1.633	0.103	-3214.91	3.50E+04
pop 25+	8.8861	2.069	4.295	0	4.824	12.948
high school	-1.02E+05	3.81E+04	-2.68	0.008	-1.77E+05	-2.73E+04
college	-5.07E+04	3.74E+04	-1.357	0.175	-1.24E+05	2.27E+04
adv degree	-1.20E+05	3.90E+04	-3.083	0.002	-1.97E+05	-4.36E+04
housing	-21.2162	9.68	-2.192	0.029	-40.22	-2.212
1 unit	9.08E+04	3.54E+04	2.569	0.01	2.14E+04	1.60E+05
2-4 unit	9.04E+04	3.50E+04	2.581	0.01	2.17E+04	1.59E+05
5-19 unit	1.00E+05	3.58E+04	2.797	0.005	2.99E+04	1.71E+05
20+ unit	9.33E+04	3.52E+04	2.649	0.008	2.42E+04	1.62E+05
workers	-6.5717	4.299	-1.529	0.127	-15.012	1.868
workers use transit	4.6822	3.809	1.229	0.219	-2.795	12.159
perc work transit	-5.01E+04	8062.066	-6.216	0	-6.59E+04	-3.43E+04
renting	-16.4297	4.055	-4.051	0	-24.391	-8.468
age	-287.7872	129.927	-2.215	0.027	-542.853	-32.721
hh income	0.0858	0.034	2.524	0.012	0.019	0.153
renting	-2.4901	1.486	-1.676	0.094	-5.407	0.427
no vehicle	5.31E+04	9239.267	5.744	0	3.49E+04	7.12E+04
jobs	0.5701	0.253	2.252	0.025	0.073	1.067
low pay jobs	-1.177	1.991	-0.591	0.555	-5.085	2.731
mid pay jobs	1.2462	2.008	0.621	0.535	-2.696	5.189
high pay jobs	0.501	0.459	1.091	0.276	-0.401	1.403
info jobs	-3.5548	1.368	-2.598	0.01	-6.241	-0.869
finance jobs	0.0733	0.697	0.105	0.916	-1.296	1.442
real estate jobs	-14.8335	2.699	-5.496	0	-20.132	-9.535
professional jobs	-0.2548	0.92	-0.277	0.782	-2.061	1.552
mgmt jobs	0.186	1.697	0.11	0.913	-3.146	3.518
admin jobs	-0.1706	0.999	-0.171	0.865	-2.133	1.792

edu jobs	-1.5372	0.537	-2.861	0.004	-2.592	-0.482
health jobs	-0.5908	0.381	-1.55	0.121	-1.339	0.157
ARNOLD intersections	-183.8302	32.316	-5.688	0	-247.272	-120.389
NTD riders	2.20E-03	0.00E+00	11.502	0	2.00E-03	3.00E-03

Omnibus:	155.613	Durbin-Watson:	0.684
Prob(Omnibus):	0	Jarque-Bera (JB):	1081.578
Skew:	0.701	Prob(JB):	1.38E-235
Kurtosis:	8.588	Cond. No.:	1.06E+16



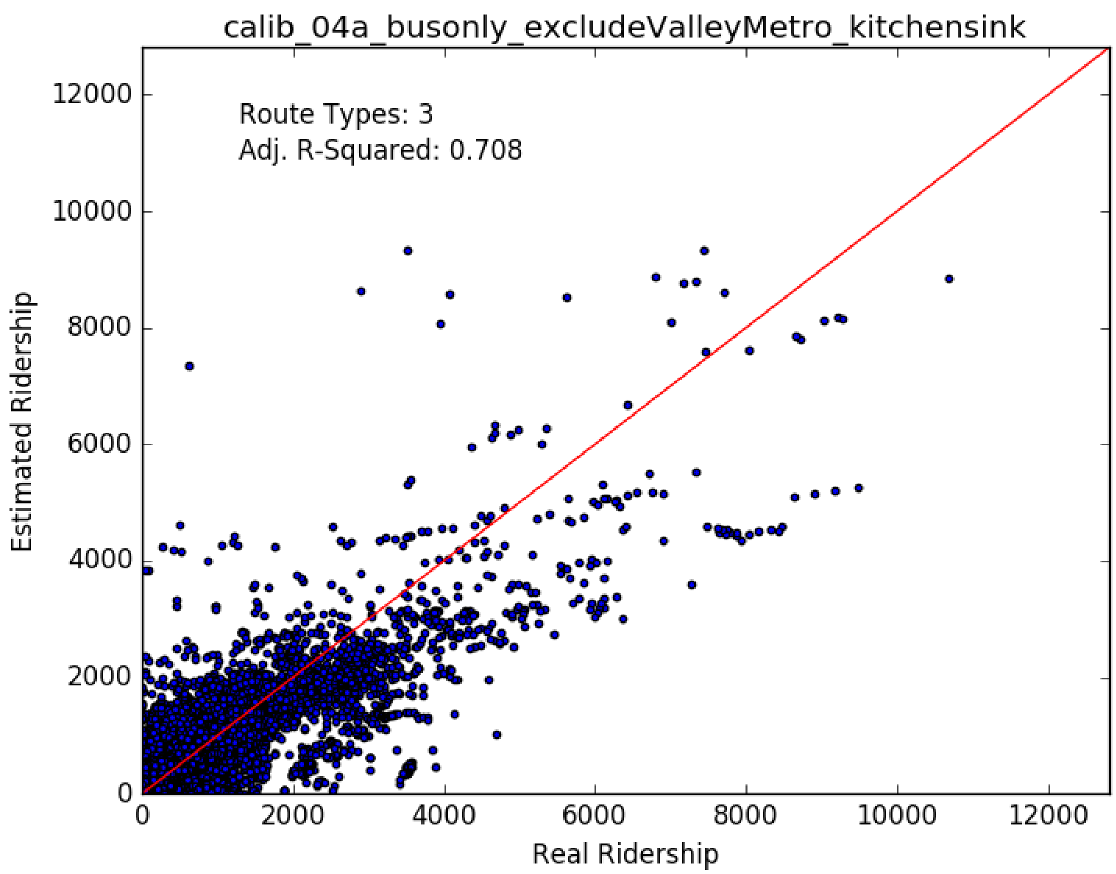
Calibration 04a

Dep. Variable:	y	R-squared:	0.708
Model:	OLS	Adj. R-squared:	0.708
Method:	Least Squares	F-statistic:	1525
No. Observations:	22017	Prob (F-statistic):	0
Df Residuals:	21981	Log-Likelihood:	-1.65E+05
Df Model:	35	AIC:	3.30E+05
Covariance Type:	nonrobust	BIC:	3.30E+05

	coefficient	std error	t	P > |t|	[95.0% Conf. Int.]	
Intercept	327.1806	70.914	4.614	0	188.184	466.177
freq	13.8538	0.086	160.196	0	13.684	14.023
routes	-22.5433	3.054	-7.381	0	-28.53	-16.557
pop	0.0533	0.014	3.848	0	0.026	0.08
minority	142.3086	26.734	5.323	0	89.909	194.708
house	-1.0272	0.123	-8.339	0	-1.269	-0.786
poverty	-0.1663	57.406	-0.003	0.998	-112.686	112.354
pop 25+	-0.0273	0.028	-0.978	0.328	-0.082	0.027
high school	49.3366	32.347	1.525	0.127	-14.065	112.738
college	259.6816	37.066	7.006	0	187.03	332.333
adv degree	18.1624	41.789	0.435	0.664	-63.747	100.072
housing	0.7579	0.101	7.467	0	0.559	0.957
1 unit	-713.942	89.187	-8.005	0	-888.754	-539.13
2-4 unit	-712.369	93.876	-7.588	0	-896.372	-528.366
5-19 unit	-503.4617	97.542	-5.161	0	-694.651	-312.273
20+ unit	-921.3264	91.569	-10.062	0	-1100.81	-741.845
workers	-0.1103	0.031	-3.514	0	-0.172	-0.049
workers use transit	0.1815	0.039	4.711	0	0.106	0.257
perc work transit	121.8641	65.8	1.852	0.064	-7.109	250.837
renting	0.3862	0.04	9.669	0	0.308	0.464
age	2.2014	0.706	3.119	0.002	0.818	3.585
hh income	0.0011	0	4.783	0	0.001	0.002
renting	0.026	0.01	2.634	0.008	0.007	0.045
no vehicle	184.8786	59.388	3.113	0.002	68.474	301.283
jobs	-0.016	0.003	-4.605	0	-0.023	-0.009
low pay jobs	-0.0808	0.018	-4.568	0	-0.116	-0.046
mid pay jobs	0.0258	0.021	1.232	0.218	-0.015	0.067
high pay jobs	0.039	0.007	5.206	0	0.024	0.054
info jobs	-0.0355	0.02	-1.773	0.076	-0.075	0.004
finance jobs	-0.0252	0.008	-2.995	0.003	-0.042	-0.009
real estate jobs	-0.0504	0.024	-2.118	0.034	-0.097	-0.004
professional jobs	0.0213	0.011	1.954	0.051	-6.79E-05	0.043
mgmt jobs	-0.0637	0.013	-4.85	0	-0.089	-0.038
admin jobs	-0.0638	0.018	-3.521	0	-0.099	-0.028

edu jobs	-0.022	0.007	-3.097	0.002	-0.036	-0.008
health jobs	-0.0011	0.006	-0.193	0.847	-0.012	0.01
ARNOLD intersections	0.8579	0.277	3.101	0.002	0.316	1.4
NTD riders	-2.86E-06	2.54E-06	-1.126	0.26	-7.84E-06	2.12E-06

Omnibus:	8864.621	Durbin-Watson:	1.279
Prob(Omnibus):	0	Jarque-Bera (JB):	413205.8
Skew:	1.198	Prob(JB):	0
Kurtosis:	24.087	Cond. No.:	1.05E+16

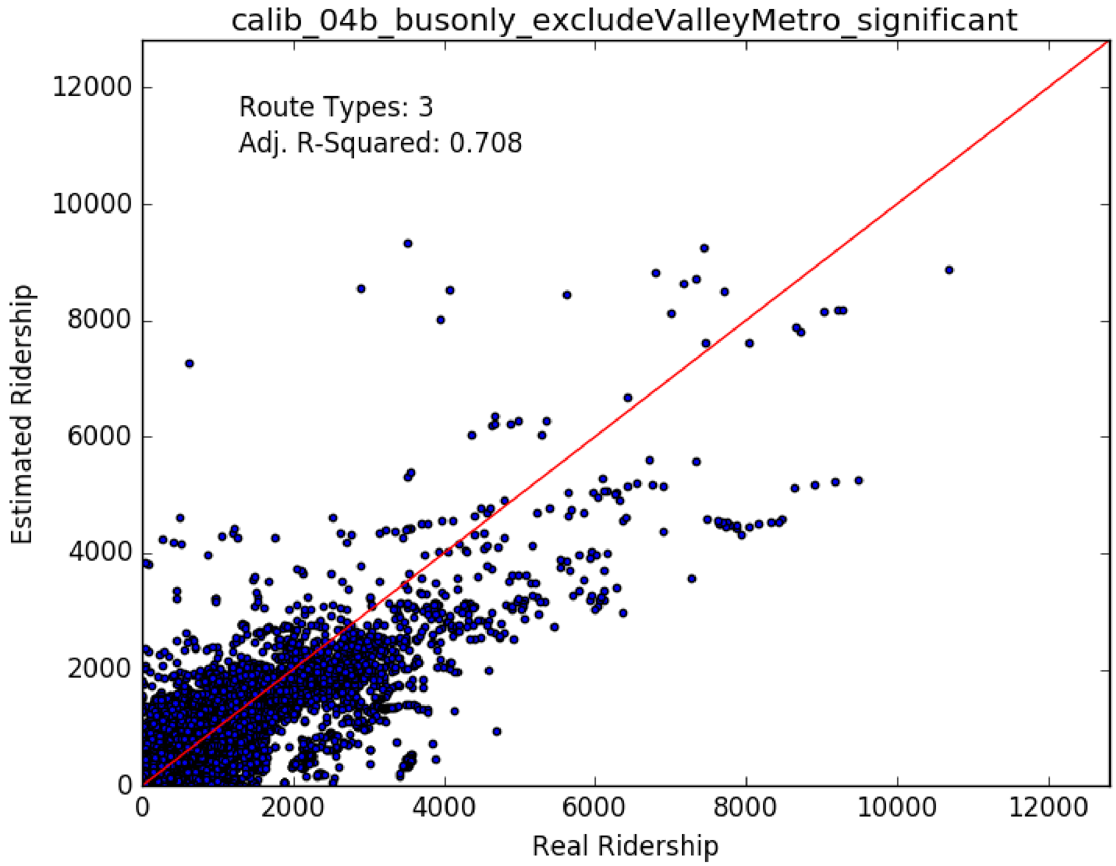


Calibration 04b

Dep. Variable:	y	R-squared:	0.708
Model:	OLS	Adj. R-squared:	0.708
Method:	Least Squares	F-statistic:	1976
No. Observations:	22017	Prob (F-statistic):	0
Df Residuals:	21989	Log-Likelihood:	-1.65E+05
Df Model:	27	AIC:	3.30E+05
Covariance Type:	nonrobust	BIC:	3.30E+05

	coefficient	std error	t	P > |t|	[95.0% Conf. Int.]	
Intercept	383.2226	91.179	4.203	0	204.506	561.939
freq	13.8947	0.084	164.543	0	13.729	14.06
routes	-23.6621	3.021	-7.832	0	-29.584	-17.74
pop	0.047	0.013	3.643	0	0.022	0.072
minority	152.0443	23.693	6.417	0	105.605	198.484
house	-1.0449	0.114	-9.197	0	-1.268	-0.822
college	238.9616	43.372	5.51	0	153.95	323.973
housing	0.7496	0.1	7.471	0	0.553	0.946
1 unit	-727.5955	88.751	-8.198	0	-901.555	-553.636
2-4 unit	-731.7234	90.871	-8.052	0	-909.837	-553.609
5-19 unit	-516.3981	95.042	-5.433	0	-702.687	-330.109
20+ unit	-943.1862	90.018	-10.478	0	-1119.63	-766.743
workers	-0.1236	0.03	-4.168	0	-0.182	-0.065
workers use transit	0.2188	0.029	7.585	0	0.162	0.275
renting	0.3893	0.035	11.017	0	0.32	0.459
age	1.7829	0.625	2.852	0.004	0.558	3.008
hh income	0.001	0	6.509	0	0.001	0.001
renting	0.0249	0.009	2.66	0.008	0.007	0.043
no vehicle	216.5226	53.693	4.033	0	111.281	321.765
jobs	0.0125	0.02	0.632	0.527	-0.026	0.051
low pay jobs	-0.1057	0.034	-3.099	0.002	-0.173	-0.039
high pay jobs	0.0078	0.023	0.336	0.737	-0.038	0.053
finance jobs	-0.0165	0.007	-2.385	0.017	-0.03	-0.003
real estate jobs	-0.0297	0.021	-1.447	0.148	-0.07	0.011
mgmt jobs	-0.0614	0.012	-5.103	0	-0.085	-0.038
admin jobs	-0.0541	0.017	-3.223	0.001	-0.087	-0.021
edu jobs	-0.0205	0.006	-3.513	0	-0.032	-0.009
ARNOLD intersections	0.896	0.265	3.377	0.001	0.376	1.416

Omnibus:	8914.058	Durbin-Watson:	1.278
Prob(Omnibus):	0	Jarque-Bera (JB):	405299.6
Skew:	1.216	Prob(JB):	0
Kurtosis:	2.39E+01	Cond. No.:	4.84E+06

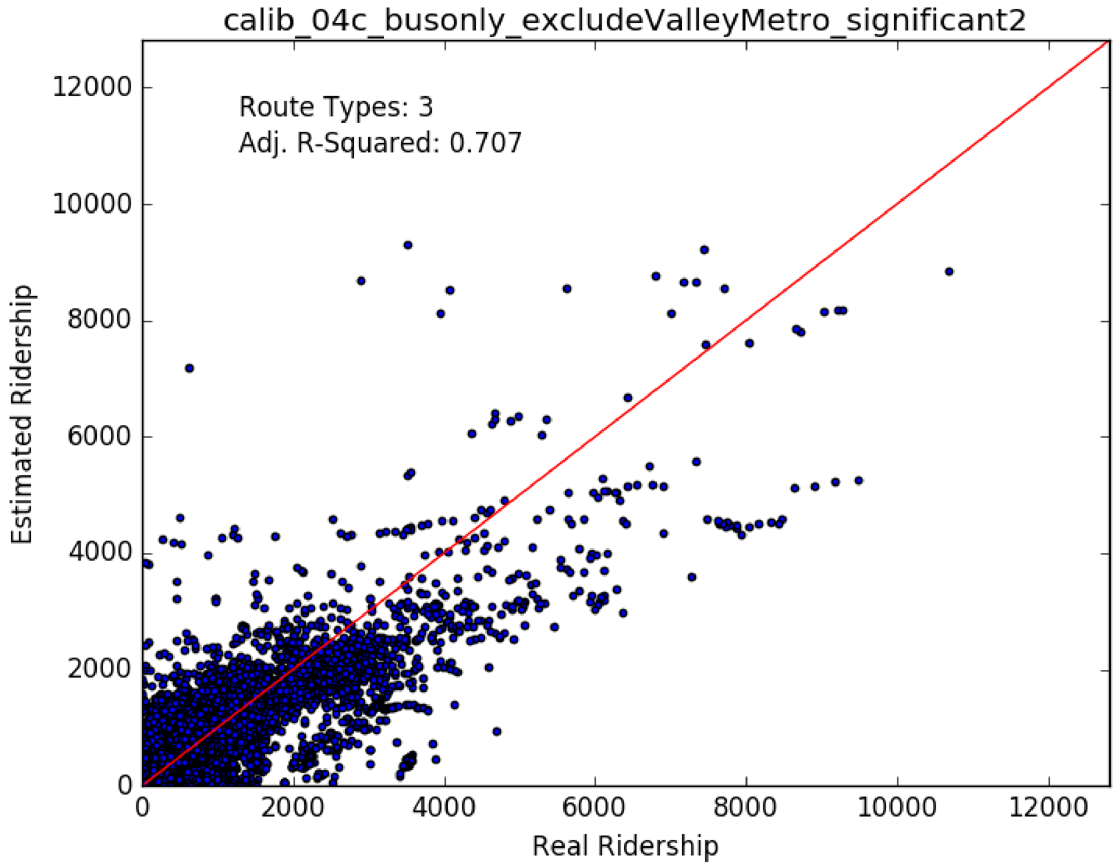

calib_04b_busonly_excludeValleyMetro_significant
Route Types: 3
Adj. R-Squared: 0.708
Estimated Ridership
Real Ridership
0
2000
4000
6000
8000
10000
12000

Calibration 04c

Dep. Variable:	y	R-squared:	0.707
Model:	OLS	Adj. R-squared:	0.707
Method:	Least Squares	F-statistic:	2214
No. Observations:	22017	Prob (F-statistic):	0
Df Residuals:	21992	Log-Likelihood:	-1.65E+05
Df Model:	24	AIC:	3.30E+05
Covariance Type:	nonrobust	BIC:	3.30E+05

	coefficient	std error	t	P > |t|	[95.0% Conf. Int.]	
Intercept	400.7734	91.269	4.391	0	221.879	579.668
freq	13.8621	0.084	164.378	0	13.697	14.027
routes	-22.4093	3.012	-7.439	0	-28.314	-16.505
pop	0.0442	0.013	3.422	0.001	0.019	0.069
minority	154.4978	23.694	6.52	0	108.055	200.94
house	-1.0029	0.113	-8.838	0	-1.225	-0.78
college	229.5346	43.401	5.289	0	144.466	314.603
housing	0.718	0.1	7.16	0	0.521	0.914
1 unit	-738.8122	88.817	-8.318	0	-912.901	-564.724
2-4 unit	-747.6193	90.901	-8.225	0	-925.791	-569.447
5-19 unit	-535.9454	95.093	-5.636	0	-722.335	-349.556
20+ unit	-944.965	90.091	-10.489	0	-1121.55	-768.379
workers	-0.1224	0.03	-4.126	0	-0.181	-0.064
workers use transit	0.2226	0.029	7.708	0	0.166	0.279
renting	0.3769	0.035	10.679	0	0.308	0.446
age	1.4088	0.624	2.259	0.024	0.186	2.631
hh income	0.0011	0	7.135	0	0.001	0.001
renting	0.0241	0.009	2.565	0.01	0.006	0.042
no vehicle	236.0861	53.574	4.407	0	131.078	341.094
low pay jobs	-0.0425	0.01	-4.096	0	-0.063	-0.022
finance jobs	0.0172	0.005	3.619	0	0.008	0.026
mgmt jobs	-0.0329	0.008	-4.031	0	-0.049	-0.017
admin jobs	-0.0681	0.016	-4.169	0	-0.1	-0.036
edu jobs	-0.009	0.005	-1.668	0.095	-0.02	0.002
ARNOLD intersections	0.9909	0.264	3.749	0	0.473	1.509

Omnibus:	8878.216	Durbin-Watson:	1.276
Prob(Omnibus):	0	Jarque-Bera (JB):	403821.7
Skew:	1.208	Prob(JB):	0
Kurtosis:	23.841	Cond. No.:	4.84E+06

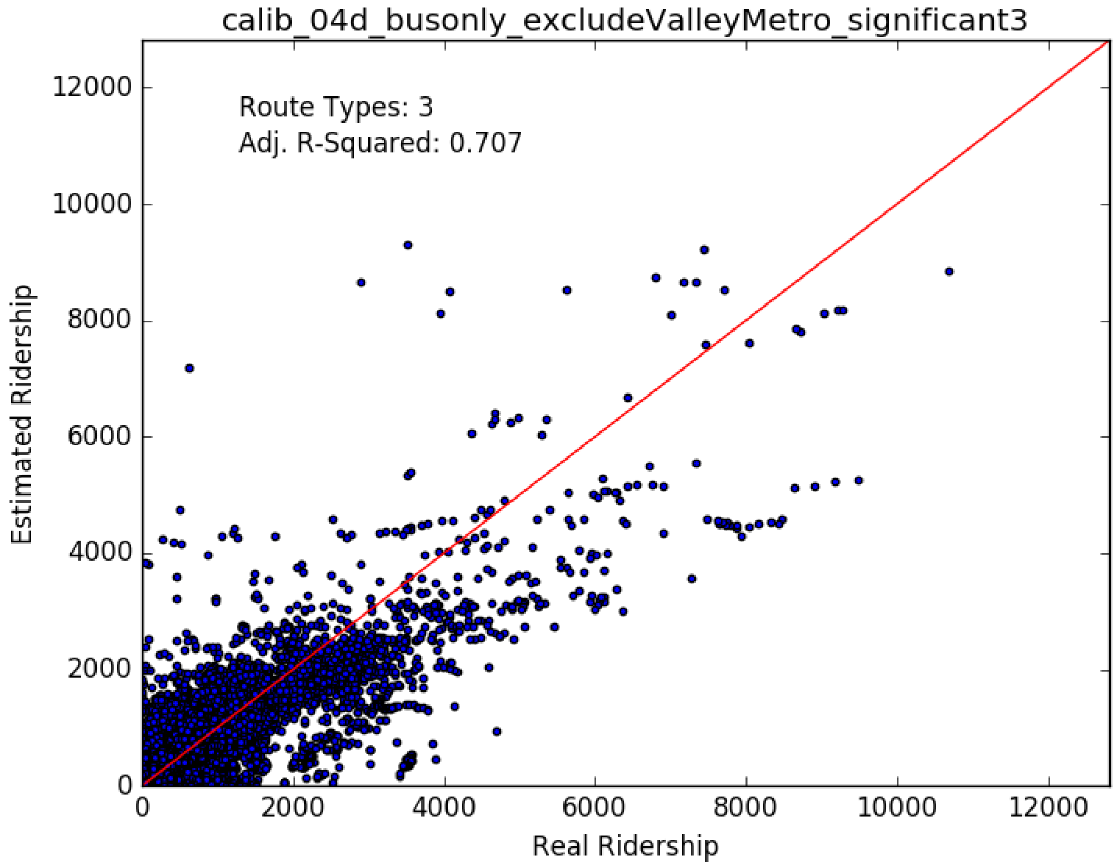

calib_04c_busonly_excludeValleyMetro_significant2
Route Types: 3
Adj. R-Squared: 0.707
Estimated Ridership
Real Ridership
0
2000
4000
6000
8000
10000
12000

Calibration 04d

Dep. Variable:		y		R-squared:	0.707
Model:		OLS		Adj. R-squared:	0.707
Method:		Least Squares		F-statistic:	2310
No. Observations:		22017		Prob (F-statistic):	0
Df Residuals:		21993		Log-Likelihood:	-1.65E+05
Df Model:		23		AIC:	3.30E+05
Covariance Type:		nonrobust		BIC:	3.30E+05

	coefficient	std error	t	P > |t|	[95.0% Conf. Int.]	
Intercept	397.6027	91.253	4.357	0	218.74	576.465
freq	13.8603	0.084	164.363	0	13.695	14.026
routes	-22.4396	3.013	-7.449	0	-28.344	-16.535
pop	0.0394	0.013	3.131	0.002	0.015	0.064
minority	159.6447	23.493	6.795	0	113.596	205.693
house	-0.9778	0.112	-8.694	0	-1.198	-0.757
college	231.2377	43.391	5.329	0	146.189	316.286
housing	0.7084	0.1	7.076	0	0.512	0.905
1 unit	-738.0075	88.82	-8.309	0	-912.1	-563.914
2-4 unit	-742.0762	90.844	-8.169	0	-920.136	-564.016
5-19 unit	-535.8075	95.097	-5.634	0	-722.204	-349.41
20+ unit	-943.4332	90.09	-10.472	0	-1120.02	-766.849
workers	-0.1265	0.03	-4.275	0	-0.184	-0.068
workers use transit	0.2276	0.029	7.927	0	0.171	0.284
renting	0.3764	0.035	10.665	0	0.307	0.446
age	1.4569	0.623	2.338	0.019	0.236	2.678
hh income	0.0011	0	7.105	0	0.001	0.001
renting	0.0238	0.009	2.534	0.011	0.005	0.042
no vehicle	228.4479	53.38	4.28	0	123.82	333.076
low pay jobs	-0.05	0.009	-5.364	0	-0.068	-0.032
finance jobs	0.0175	0.005	3.692	0	0.008	0.027
mgmt jobs	-0.0303	0.008	-3.784	0	-0.046	-0.015
admin jobs	-0.0655	0.016	-4.03	0	-0.097	-0.034
ARNOLD intersections	0.994	0.264	3.76	0	0.476	1.512

Omnibus:		8862.552		Durbin-Watson:	1.275
Prob(Omnibus):		0		Jarque-Bera (JB):	404109.5
Skew:		1.204		Prob(JB):	0
Kurtosis:		23.85		Cond. No.:	4.84E+06


calib_04d_busonly_excludeValleyMetro_significant3
Route Types: 3
Adj. R-Squared: 0.707
Estimated Ridership
Real Ridership
0
2000
4000
6000
8000
10000
12000

Appendix D: Description and availability of project code

Libraries and tools used (dependencies)

- ArcGIS
- Python
- Sqlite3
- PyGTFS

Source code availability

Source code is available here: https://github.com/VolpeUSDOT/gtfs-measures