Modeling Inundation Impacts on Transportation Network Performance: A GIS and Four-Step Transportation Modeling Analysis

by

Michael Dowd

Bachelor of Arts, City University of New York – Hunter College, New York, NY 2011

Submitted to the Department of Urban Studies and Planning and the Department of Civil and Environmental Engineering in partial fulfillment of the requirements of the degrees of

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Signature of the Author...
Department of Urban Studies and Planning and Department of Civil and Environmental Engineering
May 21, 2015

Certified by ....
P. Christopher Zegras
Associate Professor, Department of Urban Studies and Planning
Thesis Supervisor

Certified by ....
Mikel Murga
Research Associate, Department of Civil and Environmental Engineering
Thesis Supervisor

Accepted by ....
Dennis Frenchman
Professor, Chair MCP Committee
Department of Urban Studies and Planning

Accepted by ....
Heidi Nepf
Donald and Martha Harleman Professor of Civil and Environmental Engineering
Chair, Graduate Program Committee

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Abstract

The world's leading climate scientists have reached a consensus that "[w]arming of the climate system is unequivocal" (IPCC, 2007). This warming will carry with it a host of consequences for the global community, including increased occurrence of flooding. Little focus has been placed on the operation of transport systems during, or shortly after inundation events.

Inundation affects the availability and quality of network assets (i.e. Transportation Supply) and inhabitable land, which produces and attracts transportation users (i.e. Demand). In this thesis, I apply an altered four-step transportation modeling method to allow for the analysis of impacts in a single set time: modeling an event rather than a future equilibrium scenario.

I show how traditional four-step models can be used to produce valuable metrics describing performance of the disrupted transportation system. Such metrics contribute to understanding potential consequences and planning for mitigation and response.

Using the Boston Metro Region as a case study, and a four-step model for the year 2010, I demonstrate a method (Inundation Impact Assessment) for quantifying transport network impacts under six different inundation levels, one-foot to six-feet. The results indicate that inundation has widespread impacts on the ability of persons to complete trips and the performance of both the auto and transit networks.

I then demonstrate how this method can be applied to examine different infrastructure projects in the future, modeling two different demographic scenarios for the year 2030 with two different BRT alignments. The goal is to evaluate potential contribution of BRT to recoup trips lost by the impact of inundation on other transit links.

The methods and approaches used in this work show how such four-step models can be used to plan for inundation events. This method provides significant amounts of data that can be used to assess the value of potential interventions, such as the protection of mobility or the reinforcement of transportation network performance.

Thesis Supervisor: P. Christopher Zegras, Assistant Professor, Department of Urban Studies and Planning

Thesis Supervisor: Mikel Murga, Research Associate, Department of Civil and Environmental Engineering

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Thesis Supervisor: Mikel Murga

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1 Introduction

The world's leading climate scientists have reached a consensus that "[w]arming of the climate system is unequivocal" and that such warming will carry with it a host of consequences for the global community (IPCC, 2007). The expected consequences of such warming vary by region, but droughts; flooding; more high temperature days and heat waves; fewer low temperature days in winter; melting of the arctic ice; increased extreme precipitation events; increased intensity of hurricanes; sea level rise and a host of other consequences are expected (TRB, 2008)(IPCC, 2014).

Furthermore, major weather events like heat waves in Europe and California; Hurricane Katrina in 2005; Hurricane Irene in 2011; and Hurricane Sandy in 2012 have raised awareness of the vulnerability of coastal cities to such events. While the direct attribution or causation of climate change's role in these recent events is difficult to identify, researchers have identified evidence that suggest significant direct links do exist (Peterson et al., 2013). Regardless of direct attribution of recent events, the consensus among scientists is that the climate is warming, and the minimal success in global efforts to stem the tide of GHG emissions has led to an acceptance that it is likely already too late to avoid considerable warming. With this acceptance, a new wave of research has developed, focused less on the causes and mitigation of GHG emissions, and more on planning for the attendant consequences of a warmer planet.

Consequences vary drastically depending on location, but one of the clearest threats for coastal urban areas in the coming century is that of increased flooding events due to increases in extreme weather exacerbated by sea level rise. There is a clear understanding that increased sea levels coupled with increased major precipitation events and increased intensity of extreme weather events, such as hurricanes, point to the need for planning for inundation events in our coastal cities.

Multi-modal transportation networks are especially susceptible to failure and degradation under such events. Subways often operate in underground tunnels that can flood from both rain and storm surge; in addition, many cities have major highways built along their coastlines adjacent to old docklands that have induced new development. Planning for the consequences and developing adaptation strategies for each sector involves a broad spectrum of professions from science and engineering to social sciences.

One area of importance that has received only limited attention is planning and anticipating the operations of transport systems in the face of inundation events. This includes the corollary, systemwide effects of degraded, or disabled, segments. People interpret inundation events as a form of catastrophe where even somewhat normal operation of the system is not expected. Therefore, most research has focused on network performance under evacuation and the evaluation of evacuation scenarios and plans. This thesis argues that inundation events may come to be a regular part of habitation in a coastal environment. Higher sea levels, higher levels of precipitation and more extreme weather all bolster such an interpretation. Furthermore, some scientists believe it is possible for the planet to reach a tipping point, whereby sudden arctic ice melt could trigger sea level rise in an abbreviated period, resulting in serious challenges for the transportation networks.

This thesis seeks to demonstrate the application of transportation modeling tools to estimate potential network impacts of inundation events. Traditionally, these tools are used to forecast traffic conditions in different possible futures with alternate infrastructure, but they can also be applied to modeling impacts of climate change, including inundation events. By applying transportation modeling to alter the modeling process to allow for the analysis of impacts in a single set time, rather than forecast future operations of the transportation system, we can develop an understanding of the effects of inundation events. This initial analysis will provide a framework for applying traditional forecasting tools to analyze the impacts of an inundation event in the future year 2030 under different demographic scenarios. To demonstrate an application of the framework, I examine two alternative infrastructure options, to highlight how such an approach could be used to gauge projects' relative resiliency in terms of providing mobility and accessibility, in the face of inundation. I do not intend to shed light on the long-term impacts to those "under water", as those impacts are relatively obvious from an operations point of view. Nor do I intend to further the understanding of actual infrastructure damage. Rather, I focus on estimating the total number of trips that cannot occur in an inundation event and the *upstream* effects on the inundated networks, thus demonstrating how this analysis can inform future planning efforts.

To accomplish this task, transportation performance will be modeled in the Cube Voyager Transportation Planning Package using the Boston Metro Region MIT-Four Step Model (M.Murga, 1.254 Transportation Modeling, Civil Eng, DUSP – MIT). I incorporate inundation into this model using six sea level rise scenarios for the Boston Metropolitan Region, from the one-foot to six-foot levels. The Boston Metropolitan Region offers an exemplary case because it is a major coastal metropolitan region with a vast and mature multimodal transit system susceptible to inundation impacts.

Although this analysis focuses on the Boston Metro Region, it demonstrates a method for applying transportation models to short and long-term inundation modeling that should be broadly applicable to other regions. The results and metrics produced illustrate the types of information available as outputs from the modeling tools used. Ultimately, however, this thesis offers a demonstration of the approach. Any application of this method intended for use in policymaking or decisions would require teams of different experts and custom data sources specific to the region being modeled.

1.1 Research Objective and Measurement Method

1.1.1 Objective:

This thesis demonstrates how *existing* Four-Step Transportation Models can be used to plan for major disruptions to a transportation network and the users of that network. The major disruption modeled is a large-scale inundation event and the impacts. Inundation affects the availability and quality of network assets (i.e. *Transportation Supply*) and inhabitable land, which produces and attracts transportation users (i.e. *Demand*). These models produce valuable **metrics** describing **performance** of the transportation system given the disruptions described above. Such metrics can aid our understanding of potential consequences and inform planning for mitigation and response. This, in turn, can help us answer many specific questions about inundation impacts in the model region, including:

- What levels of inundation severely impact the system?
    - This is measured in terms of:
        - Infrastructure
        - Inability to complete trips
        - Extreme travel times
- What modes are most impacted? Is there a marked difference for those who have access to cars and those who do not?
- What are the accessibility impacts of inundation, both by mode and by different types of accessibility?
- How will users of the transit system respond to inundation along certain transit routes?
    - Do alternative routes exist? If so, can we identify these routes?
- How does system degradation impact people and accessibility?
    - This is measured in terms of:

        - Travel time
        - Changes to route
        - How many people can no longer complete their trips
- What are the "upstream" network effects of inundation on non-inundated links?
- How can we use this information to assist in better assessing infrastructure projects?

To assist in answering the above questions performance metrics will be used.

1.1.2 Performance Metrics

Performance metrics provide means for comparing impacts across different situations. The metrics can be used, for example, to estimate costs and/or benefits, as well as broaden our understanding of the operation of the inundated system relative to a baseline condition. I have divided the metrics into three broad categories: Impact and General Measures; Auto; and Transit.

Impact and General Measures are the broadest and include: simple counts and quantities of impacted assets given inundation; total number of trips that cannot occur due to inundation; as well as changes in accessibility given inundation. The auto and transit metrics represent, for the most part, standardized measurements, readily comparable to a baseline no-inundation scenario.

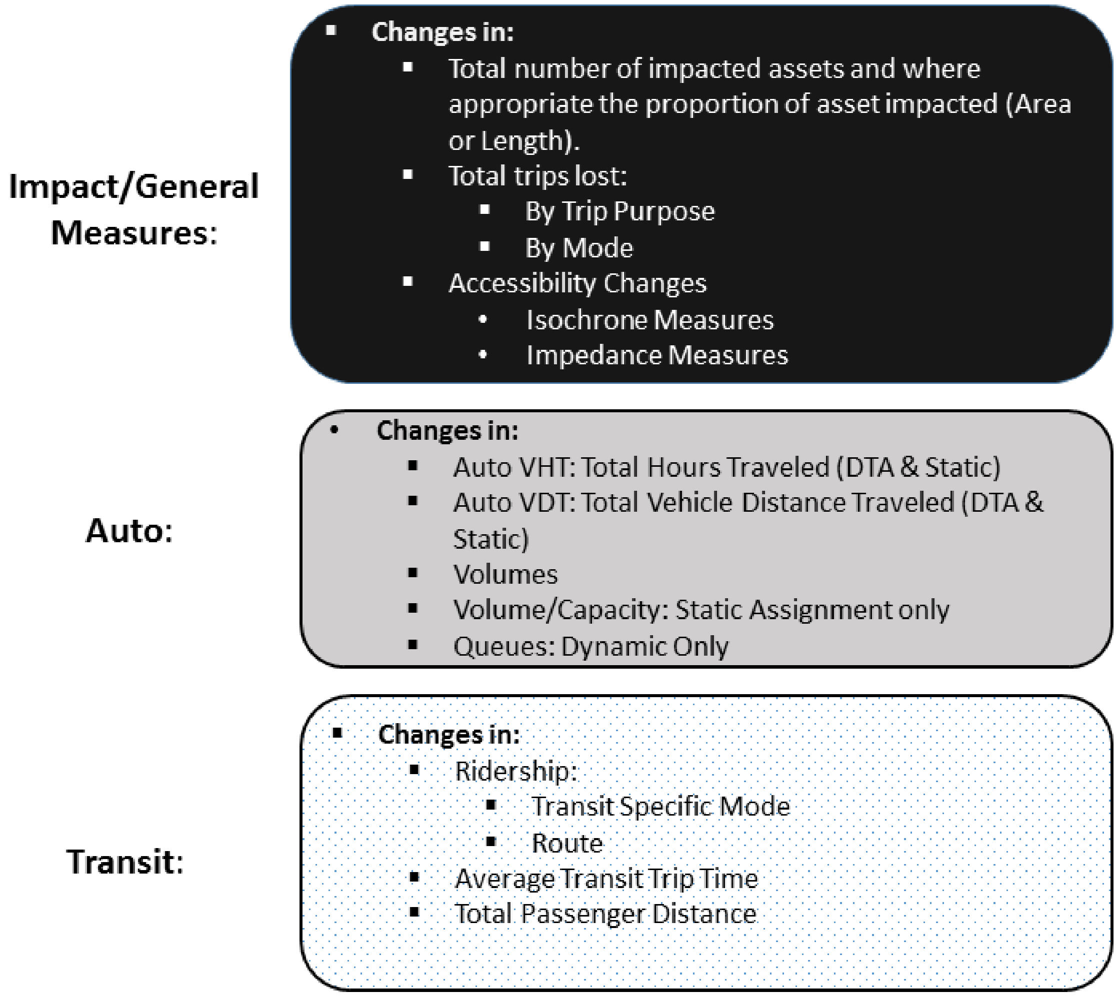

Figure 1: Performance Metrics

The metrics in Figure 1 primarily derive from outputs of the Boston Metro Region MIT-Four Step Model (MIT-FSM). The total number of impacted assets is an output of a separate GIS analysis.

The performance metrics have broad possible usage. These metrics provide comprehensive information regarding the potential impacts of inundation events, for multiple modes' networks and operations. However, in highlighting these impacts, the metrics can also be used both to plan for events - how an agency might intervene to mitigate the effects of inundations – and to assist operational interventions during or after an inundation event.

1.2 Methodological Summary

The overall thesis consists of three related but independent analyses. I will briefly introduce each of these analyses here.

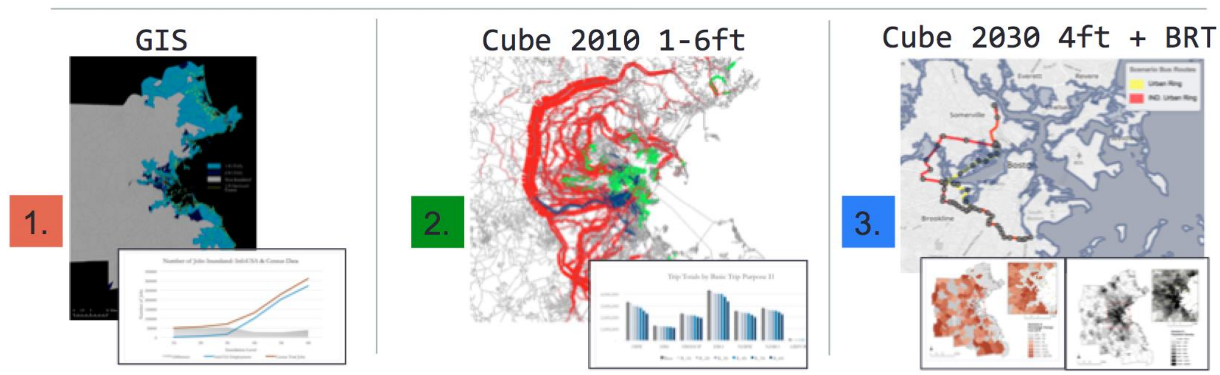

Figure 2: Research Steps

1) **Inundation Assessment**: The first step in the analysis consists of a geographical analysis (GIS) to locate and identify where and to what extent transportation and transportation-related assets are impacted at each inundation level.

2) **Impact Assessment Modeling**: The second step integrates the inundation assessment into the transportation-modeling suite to examine impacts on the baseline (2010) system. The baseline, non-inundated system, provides an equilibrium origin/destination (OD) matrix and that serves as an input to subsequent inundated models. Inputting the baseline OD into the different inundation scenarios provides an understanding of network congestion, speeds, capacity, ridership, travel times, and lost trips. Inundated impacts are conceivably temporary, therefore, these models are not run to equilibrium.

3) **Scenario Modeling**: Step three applies the step 2 modeling approach in what I have termed "Scenario Modeling." In the demonstration, I characterize the scenarios by varying demographic conditions; although with more time and resources other scenario dimensions could be included to increase the number of scenarios. I then analyze two possible transportation infrastructure projects. I evaluate how these projects contribute to transit network performance and resilience:

which of these two transportation infrastructure projects offers both the greatest possible resiliency to inundation events and services the greatest number of users.

My overall goal is to provide foundational understanding of how these models can help evaluate infrastructure projects in an uncertain future. Calls for such analysis have already been made, with the Obama administration requiring major infrastructure projects to plan for the impacts of climate change (Eilperin, 2015). Eventually, the steps developed and demonstrated in this thesis could be adapted to consider a suite of policy and investment alternatives, providing a new tool to complement and enrich traditional project evaluation in the era of climate change risks.

1.3 Major Assumptions

In this work, I model an inundation event as a single stable inundation level that has degraded or disabled the transportation network (transport supply). This inundation has broader impacts, including areas of lost land, i.e. homes and jobs (sources of transport demand). In the Impact Assessment Modeling, I model six events corresponding to the height of inundation (one-foot to six-foot levels). When modeling these events, I made certain assumptions concerning the trip making behavior of users of the transport system. A more detailed explanation of the modeling methods used may be found in 6.1 Method and 7.1 Methodology Summary: Scenario Modeling. I introduce the assumptions here to facilitate a thorough understanding of my intentions and a proper interpretation of the results of this work.

1.3.1 People Attempt to Make Regular Trips

Modeling the impact of an inundation event is complicated, both technically and conceptually. One can presume that currently the majority of regions across the world, including the Boston Metro Region, would have advanced knowledge of an impending event. The exact magnitude of impact may not be known, but the expectation of some negative consequences would result in people choosing to stay home, businesses to close and transportation networks to preemptively shut down. I am interested in modeling a situation where users of this system will attempt a trip if completing that trip is possible. I define a trip as "possible" if the origin and destination are not inundated, the network links connecting the origin and destination are not disabled and the travel time between the origin and destination is less than three hours. I am not modeling an evacuation scenario; rather, I model the current trip making patterns under some level of inundation.[1]

1.3.2 Two States Modeled

1. **Fixed - Trip Distribution/Mode Split**

In this state, I assume that trip distribution (flows of trips between different zones) and mode split (choice of transportation mode) remain constant. My justification for this assumption is that people will have already made their decision on what trips they wish to make and the mode(s) they will use. Furthermore, certain types of trips cannot easily have their destinations altered, specifically the location of people's homes, jobs, and schools (a person cannot chose to have their work or home in a different location immediately). The majority of the analysis presented in later sections focuses on the results of the fixed distribution and mode split model runs, although I present examples that allow some trips and corresponding modes to change given inundation. I further justify this choice in the Conceptual Justifications section.

2. **Semi-Variable -Trip Distribution/Mode Split**

I do model a semi-variable trip distribution and mode split situation whereby I allow the trip distribution for all trip purposes except work trips from home (Home Base Work) and trips to school from home (Home Based School) to be altered by a certain factor. I also allow all mode choice, other than school bus, to be altered by other certain fixed factors. I present these factors and the actual method in 6.1 Method.

1.3.3 Not a New Equilibrium Situation

A new equilibrium condition would reflect changes in the long-term decisions of model agents and would likely affect their location decisions. I modeled an event; therefore, the agents do not have long-term options to relocate their jobs or homes. Similar to the above comments, I modeled a fixed or semi-variable trip distribution and mode split. The origin destination matrices are held constant or only slightly changed. Generally, as described in Four Step Transportation Modeling (FSM) Methods and Software, I run the models until trip distribution has stabilized and does not change greatly between iterations. This approximates long-term decision making by agents in the model region, which

[1] Current patterns will depend on the target year and demographic scenario being modeled.

remains in the fixed state. When I model the fixed state, I remove trips that cannot occur due to inundation and then load trips on the network given updated network attributes. In the semi variable inundation event, I run the model from Trip Distribution to the assignment modules once.

1.4 Conceptual Justifications

1.4.1 Acclimation

Other than permanent sea level rise, the expected causes of flooding due to climate change include the increased frequency of extreme precipitation events. Climate scientists agree that those storms once considered rare will become much more normal in the future (Lin et al., 2012). Storms of an intensity expected to occur once every hundred years may occur once every ten years, or even more frequently. This raises the question: at some point in the future, will there be a shift in the response to these events? If a major storm becomes something that occurs twice a year or more, one can assume an acceptance of these impacts, resulting in the transition to a new response to such events. In other words, people will travel immediately after the event has occurred regardless of whether flooding has subsided, assuming it ever subsides. The New York City Climate panel recently released a report stating that they expect increased frequency of major storms, major sea level rise and the city's current flood zone to double in size by the end of the century (Horton et al., 2015). This leads to the conclusion that flooding events may become commonplace in some major cities. In my thesis, I explore a hypothetical scenario where the future residents of these cities have become acclimated to some level of flooding and attempt to complete their journeys if their origin or destination is not inundated. I believe people are adaptable and if (what are now defined as) rare flooding events become commonplace, people will change their behavior and attempt to complete their trips. Clearly, those persons and jobs located in inundated regions will not be able to continue with their travel per usual.

Figure 3: Flooding Threat | sources: Left, The NY Daily News, Right. Reuters

1.4.2 Timeframe Impacts

The effects of an inundation event extend beyond the immediate impact of the storm. Flooding and its damage continues to impact infrastructure for days to months, even once the water has receded. One can logically assume that the comprehensiveness of the infrastructure damage will be relative to the concentration of inundation in an area. This is the scenario witnessed in New York City during and after Hurricane Sandy. Hurricane Sandy seriously damaged the NYC transport system. The Metropolitan Transportation Authority (MTA) acted decisively and wisely in relocating trains and buses to locations outside of flood plains (Kaufman et al., 2012). Nonetheless, there was broad flooding of fixed infrastructure, such as rail tracks and tunnels. Within a week, they had restored 80 percent of subway service. Without mitigation planning, one can image a situation where the delay in the restoration of service could take much longer.

Roads can withstand flooding and storm damage better than fixed rail, although they still face the potential for washouts and debris that can inhibit travel after the water has receded.

The modeling I present can be applied to understand how the transport system would operate in situations where the transport infrastructure is impacted for days or weeks at a time.

1.4.3 Utility of Assumption:

I believe that it is valuable to compare how the transport system currently operates to how the transport system could operate given severe degradation. I believe it is interesting and useful to develop such an understanding in that it can lead to better response plans and more resilient transport networks. It can shed light on portions of the system that would benefit from improvement and allow for the adoption of operational interventions to mitigate impacts during and after an event.

1.4.4 Method is Flexible

A final detail worth highlighting is that the method is flexible. If one wanted to model other situations such as an evacuation or a new equilibrium, the method can accommodate such goals. Evacuation scenarios are generally modeled based on the assumption that evacuation fully occurs before the networks are impacted by whatever event is being modeled. Such exercises require different data and assumptions.

New equilibrium situations could also be modeled with this method. Such an application would require an in-depth investigation into the expected long-term behavioral response of persons and firms in the area given permanent inundation. If integrated with a land use model, one could approximate the number of persons that chose to relocate, leave the area, or stay in their current location, as well as identify possible new commerce centers given inundation of the traditional centers (assuming we are examining a city like Boston).

Finally, inundation is not the only type of event to which this analysis can be applied. The model could investigate any event that causes large areas of land to be inaccessible and/or large segments of the transport network to be degraded or disabled. Such events include chemical spills, major infrastructure failure, urban conflict, and large-scale forest fires.

Given these justifications, I believe that modeling the inundation events with the approach I develop provides a reasonable way of understanding some of the network impacts on users of the system not directly in inundated areas, and quantifying the total number of trips that would no longer occur both due directly to inundation and due to network degradation.

1.5 Thesis Structure

This thesis contains nine chapters, including this Introduction.

Chapter Two reviews relevant literature on network resiliency and other relevant literature, as well as analysis that has been done in relation to sea level rise impacts across various sectors, including a review of specific case studies conducted by municipalities and regional planning authorities.

Chapter Three introduces the empirical setting of this analysis as well as the Four Step Modeling process and tools. It also presents the MIT-Four Step Model (MIT-FSM) used in this analysis

Chapter Four presents the baseline, no inundation, MIT-FSM model results for the year 2010.

Chapter Five presents the method and results of the Inundation Assessment Analysis.

Chapter Six presents the method and results of the Inundation Impact Assessment Analysis (Inundation from one foot to six feet in the 2010 baseline model).

Chapter Seven presents the method and results of the Scenario Modeling exercise.

Chapter Eight assesses Limitations and Further Research, including: next steps and conceptual improvements that could be made to the methods developed and demonstrated; and recommendations for the application of this approach given more resources.

Chapter Nine concludes.

2 Literature Review

The research addressing climate change and the transportation sector has mostly focused on mitigation – that is, attempts to reduce the release of carbon dioxide into the atmosphere. However, CO_2 concentrations in the atmosphere have continued to rise, with levels reaching 400 parts per million in the earth's atmosphere (http://climate.nasa.gov/400ppmquotes/). Cohesive worldwide efforts to pass meaningful mitigation legislation has not had significant impact. The focus on mitigation has more recently been matched with a newly adopted acknowledgement of the need to research adaptation measures. To reiterate this point, the European Union published a white paper highlighting that mitigation strategies are needed but that it will take more than 50 years to see the effect of any such policies (Evangelos Mitsakis et al., 2014). With this shift in research has come a broader political acceptance of the inevitability of climate change: Koetse further supports this change remarking recently, "a tendency can be observed that policy makers accept the fact of climate change and explore adaptation strategies such as the implementation of policy measures to reduce potential damage costs related to climate change."(Koetse et al., 2012). To prepare effectively for the potential effects of climate change, adaptation research has included predicting potential impacts. The transportation sector specifically, and urban planning and engineering in broader terms, must use predictive modeling to support infrastructure resiliency. In this research, my goal was to look at a city such as Boston, located on the coastline, and find and analyze the impact of inundation due to sea level rise (whether a sudden inundation event, i.e. a hurricane, or long-term/gradual. i.e. melting ice caps). This kind of predictive modeling is still nascent.

Within climate adaptation research, focuses vary broadly, including within the transportation sector. Some of this research can be characterized as examining the "day-to-day," or cumulative small-scale effects of a warmer world, in terms of the impacts on infrastructure, operations and safety. In other words: how certain potential consequences of climate change, such as warmer temperatures or more rain, impact transportation. The impacts are expectedly broad and the research range reflects this expectation, from analysis of the long-term heat impact on asphalt to the impacts of more rain on accident frequency, and road congestion in networks. The majority of this research has focused on road transport, with some examples of the public transit impacts (Koetse, 2012). Such research highlights some of the major complications of planning for climate change – mainly the divergent impacts that can occur in different locations and their varying effect. Some impacts of climate change may actually be beneficial in certain locations, such as increased precipitation events in dry areas, or, oppositely, decreased precipitation events in wet areas, while others are decidedly negative (wide-scale flooding, home loss, etc.).

In this research I focus specifically on the possible dramatic and sudden impacts of climate change, under events that scientists expect to become more frequent in the future, i.e. sea level rise and major weather events. This, too, has received some attention in the literature, but to a lesser degree. There are, of course, broader implications of researching specific events, such as major storms, in that we can expect a relationship between links or networks affected by a singular devastating event and more gradual environmental changes.

Certain terms related to this research require definitions as they relate to broadly adapted and specific use. Terms such as "resiliency," "robustness," and "accessibility" have specific denotations and connotations as they relate to planning, engineering and the transport sector.

Historically, resiliency is a concept used in transportation modeling and analysis to describe the functionality capability of a network to withstand some shock and return, or remain close, to its initial state. Reggiani et al further investigate broader definitions as they have been described across the literature – the question is about network resilience as it relates to the efficient ability of public and private transport to continue to operate given major network impacts (Reggiani et al., 2015).

Within the literature, robustness is treated as the ability of the system to withstand even major events. A definition provided by Holmgren states: "Robustness signifies that the system will retain its systems structure (function) intact… when exposed to perturbations (Reggiani, 2015)." I would argue that it could be coupled with the term redundant, as a network with great redundancy could be seen as robust, or the opposite of vulnerable. A hypothetical example is if a major bridge was closed due to construction but many other crossing are easily available. Thus, the impact of this closing is minimal. The reciprocal linkage between robustness and vulnerability is particularly acute when we consider robustness of a system within the context of climate change. A dense road network may be robust but if it is at all susceptible to certain inundation, then it is, in fact, proven vulnerable.

I prefer to focus on the ability of a system, or processes in that system, to rebound from a shock. The differences between these terms, resilient and robust, are subtle. I favor "resilient/resiliency" as my modeling focuses on the aftermath of the event that caused the inundation, not the event itself: not transportation during a hurricane, but, rather, transportation given recent or continued flooding.

Given inundation of the network at a certain level, will users be able to complete their journey by the same, or possibly, altered routes and modes?

I aim to answer this question by offering an analysis method that can assist in developing solutions that allow transportation to be *resilient* to an environmental event. Assuming global climate change and a rise in water level, we need to plan for a future system that can withstand and evolve to meet changing road and travel conditions. A system will be resilient if it can continue to function, even if that function is an ever-changing definition of "normal."

Furthermore, within the larger framework of transportation modeling, my research also considers the concept of "accessibility." From a mobility perspective, accessibility represents "the ability to reach desired goods, services, activities and destinations" (Litman, 2010, p. 1). The use of accessibility measures has become increasingly recognized as important, and "best practice" in planning and decision-making for sustainable transportation (Condeço-Melhorado et al., 2014; Geurs et al., 2012). In examining inundation impacts to better plan responses, I use the accessibility optic to assess how we can plan more resilient transport networks.

Some existing research relate to this idea of modeling for disaster events, post-disaster resiliency and accessibility. Zhu & Levinson (2012) highlight a recent review of 16 studies on the transportation presumed behavioral responses after various disasters (including natural disasters and infrastructure failure). They conclude that planning for these events and their aftermath must include models of human behavior. They recommend demand modeling to take into account traffic dynamics, accessibility, chance, decision, etc. Van Exel and Reitveld highlight the point that certain events will disrupt travel patterns so completely that it could lead to new permanent/equilibrium changes in travel patterns (Van Exel et al., 2001)

Vulnerability and exposure represent other important concepts in this research. Jenelius and Mattsson (2015), in a recent review of vulnerability studies, outline how the impact on a single user, or a group of users (for instance, defined by those living in a certain region), under a certain disruption scenario represents the exposure of the user to that scenario. In this way, groups of individuals severely affected by a certain disruption scenario can be identified. From a general perspective, we can measure the importance of a system component according to how much a disruption to this component impacts the performance of the transport system as a whole (such as through the total increase in travel time in the network).

Interestingly, vulnerability studies mainly concern road infrastructure networks, "because of the extensive road coverage and the network robustness in maintaining the connectivity of urban systems:" after disaster events, the road network is considered more viable (i.e. resilient) than other modes (such as rail) (Kondo et al., 2012). Transit must be part of vulnerability analyses, however. Flexible or adaptable transit modes such as the bus enhance resilience. In addition, predictive modeling could facilitate the development and implementation of operational measures that could preserve at least partial functionality of the transit systems in the event of inundation.

2.1.1 Optimization Approaches

Much of the earlier research in network performance has concerned itself with traffic incidents, construction activities, infrastructure failure and special conditions (events, etc.) on network performance (Taylor, 2008), with a strong focus on mathematical programming and network optimization methods. The complexity of the methods tends to limit the analyses to smaller networks or subsets of overall networks, such as the consequences to the system as a whole of losing a specific link. Antunes et al. (2003) provide an example, incorporating an accessibility-based optimization analysis with nonlinear combinatorial optimization methods. The computational intensiveness of these methods tends to limit their application to "toy networks." Network resiliency analyses face similar constraints. He et al. (2014) examined the impact of multiple link failures in a toy network to identify those links with the greatest impact on network operations. They used a genetic algorithm to quantify the impact of the link closures.

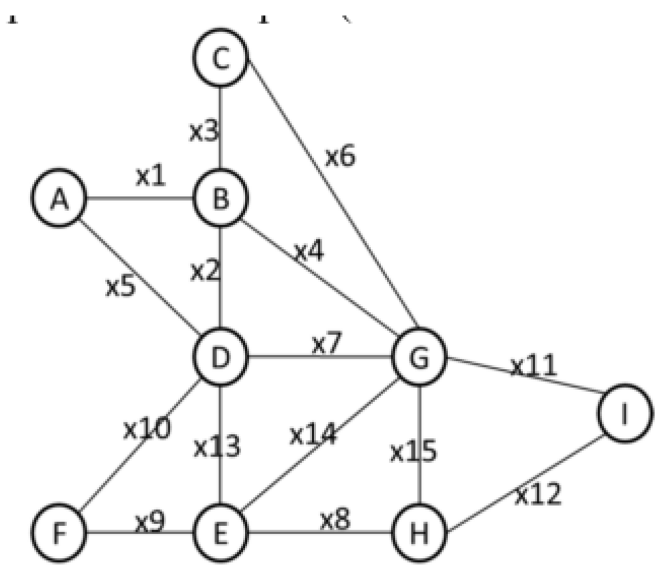

Figure 4: Toy Network in (He, 2014)

These approaches have been adapted to modified or simplified transit or road networks, but not entire systems, given the dense and complex matrix of an entire network's road/transit/walk model. Some current advances have utilized raster-based GIS and graph theory to analyze complex networks at a larger scale, such as a state level major route network (Schintler et al., 2007); again, however, a state level major route network is much sparser than a region-wide full multimodal transport network. Such approaches hold great future promise given the inevitable increases in computational power.

Microsimulation models offer another promising method. Cats et al. (2015) use graph theory analysis coupled with a microsimulation transit model, BusMezzo, to model general disruptions(i.e. reductions in capacity) the public transit network in Stockholm. They identified important links, particularly overcrowded links, and implemented specific disruptions to these important (critical / overcrowded) segments and calculated differences in travel times. The model includes congestion within the public transit network. No trips are "lost" in their analysis, so travel times increase in degraded scenarios (unlike in my approach where trips are considered "lost" at a certain determined time threshold). They then modeled different "capacity enhancements" to estimate the benefits given different impact scenarios – aiming to find which "enhancement" would best serve the degraded link, i.e. reduce travel time. Their main interest is in identifying network lines or links that would benefit from reserve capacity, or the ability to increase capacity given some event. They provide very detailed analysis of time and transfer impacts within the network. Their technically and theoretically sophisticated and forward-thinking work provides a critical foundation for my research. The focus on transit and transit congestion are of particular interest especially considering the potential transit congestion impacts of degraded networks due to inundation.

The significance of this kind of research is supported by real life events, such as Hurricane Sandy and its broad impact to New York City's transit system (MTA). Given the inundation and inoperability of several lines following the storm, the MTA introduced "Bus Bridges", a select bus service to transport persons from Brooklyn to midtown Manhattan. These buses were desperately crowded.

Figure 5: Line for Boarding MTA Bus Bridge | source Gothamist.com

2.1.2 Empirically Based Approaches

Other examples exist of empirically based work to predict and analyze the effects of inundation events or other climate change initiated disturbances to transport (de Groot et al., n.d.) (Cambridge Systematics, 2012) (Hodges, 2011) (National Research Council [U.S.] Committee on Climate Change and U.S. Transportation., 2008). Most research on sea level rise and flooding impacts has concerned itself with locating and quantifying the impacts, generally adopting a GIS approach with LIDAR data to locate and determine the extent of the assets threatened by inundations. Given the limited goal of identification and quantification, many of these studies include detailed analysis of the actual infrastructure being studied. Actual soil conditions, road grade, local drainage, and other relevant details are often included (Bloetscher et al., 2014). Though much of this analysis has focused on the impacts to road networks, some focus on transit infrastructure as well (Oswald et al., n.d.).

Specific cities have attempt to model, in varying degrees of detail, the potential effects of climate change on transit. In Portland, Oregon, for example, Chang et al (2010) analyzed network expansion under flooding impacts, utilizing hydrological models, along with a framework for identifying "critical" linkages in the region. (Chang et al., 2010). They modeled the different scenarios with the regional MPO's transport model and computed changes in vehicle hours traveled (VHT). Their modeling assumes no lost trips; instead, minor flooding along certain rivers results in users modifying routes chosen in the system. The combination of hydrological models, qualitative infrastructure prioritization and a transport model makes this research highly relevant. They do not incorporate dynamic traffic assignment, however, instead assuming that persons have perfect knowledge of the situation and that the degradation represents a new equilibrium condition. Furthermore, they do not incorporate any analysis of the impact on transit in their flooding scenarios.

In 2005, a Suarez et al (2005) published results of a study examining the Boston case, a direct precedent application of transportation modeling methods and software to analyze possible system performance impacts of inundation events (Suarez et al., 2005). They assume that extreme weather events, coupled with increased sea levels, will lead to overall increased frequency of inundation events in the future. Their target outputs identified the number of trips that would not occur due to flooding of the origin or the destination zone or the necessary transportation infrastructure. Of the trips that do occur, some will take much more time. The goal of their analysis was to estimate the economic cost associated with these delays and the lost trips. They modeled different future population and land use patterns. They assumed that commuting trips to a flooded area do not occur, all trips from flooded residential areas do not occur, and shopping trips redirect to the nearest other shopping area. They consider a link non-usable if touched by an inundation layer. While providing a direct empirical and methodological foundation for my work, Suarez et al (2005) model two inundation scenarios only for "surface transportation," i.e. the road network. They do not consider transit services, do not analyze accessibility impacts, nor do they use the analysis to measure the impact of infrastructure in providing relief. Finally, they analyzed a much smaller network, less than 10 percent of the total number of links in the region.

In New Jersey, the state contracted Cambridge Systematics under a Federal Highway Administration Grant to create an inventory of assets, analyze potential climate scenarios, and identify the potential vulnerability or resiliency of critical assets. They used standard GIS analysis and contracted hydrologists and a climatologist to develop site-specific models of potential sea level rise, as well as storm surge areas. Of direct relevance, they use a four step model to create a criticality metric for certain assets and zones. They compute zonal criticality scores from the output of a modified highway assignment and based on the number of persons and jobs in a given zone (TAZ). They then use these zonal scores in the modified highway assignment, assigning the score for trips between a given origin-destination pair to each network segment used. They kept a cumulative running total of all scores by link.

The New Jersey analysis highlighted the links in the system that had large amounts of traffic and the links between zones that can be considered "important." The researchers did not delve into the actual network impacts of inundation or other types of network impacts linked to climate change. The analysis represents a well-developed, high-level investigation into the types of assets that may be impacted, providing an inventory of vulnerable/valuable assets and developing site-specific models of potential climate change and sea level impacts. Yet, the work did not fully capitalize on the potential benefits and outputs of the four-step model. This was partially due to the lack of a consistent regional state-wide modeling platform.

2.1.3 Policy Level Analysis

Additionally, examples exist of cities making prescriptive or predictive suggestions, utilizing anecdotal or local knowledge to inform policy decisions. This sort of research, qualitative instead of quantitative, incorporates on-the-ground expertise of people who can attest to things like the resiliency of the network to withstand inundation. While a model might assume certain conditions, such as the operational conditions of transport lines, a transit operator (e.g., conductor) or local engineer who interfaces, operationally, with the network daily, might have a more nuanced or informed idea. He/she could provide insight into how the train line or road works, will operate, and/or will withstand inundation, etc. (including pointing out weak parts of the track and historically bad roads).

Lindgren et al (2009) provide an example this qualitative approach using the Swedish railway system to address the issues of specific vulnerabilities and possibly necessary adaptation strategies. They obtain information from interviews with key personnel in the Swedish Railway administration (Lindgren et al., 2009). The researchers argue that climate related events are already one of the leading causes of railway disturbances and that flooding is a major threat to such infrastructure and operations.

Some of the key recommendations offered through this interview process included the "Systematic Mapping" of vulnerable infrastructure and the likely consequences. Such information can then inform the development of adaptation strategies and assist in the prioritization of interventions. Lindgren et al (2009) advised that climate changes consequences and adaptation be considered in all stages of planning, risk and vulnerability analysis, especially in early stages. They also advised awareness of possible goal conflicts in the design of adaptation measures. The report underscores that the impacts of higher water levels and more high precipitation events are among the most important climate change-related consequences. The report's adaptation strategies focus heavily on bolstering engineering standards to withstand extreme temperatures or changes in ground permafrost. It also underscores the importance of identifying areas lacking network redundancy, defined in terms of alternative routes and links that cross the same (potentially vulnerable) geographic features. Finally, Lindgren et al (2009) emphasize that the character of railway systems, in general, make them more vulnerable to impacts. Rail systems, the outcome of long-term planning and investment decisions, use fixed facilities that cannot be changed easily, economically, or quickly.

A final observation concerning Lindgren et al's (2009) interviewing process is that it reveals certain "weaknesses" in system oversight. The interviews revealed a low general awareness of the threats of climate change and the need for adaption planning. Additionally, current inspection practices do not include analysis of unlikely events; i.e. a section of track can pass inspection for normal operating conditions but given a flooding event may succumb to failure. Such an approach can clearly inform policy-making, providing pointed advice on networks to watch and maintain carefully in preparation for an inundation event. Mixing qualitative and quantitative assessment techniques would be mutually beneficial.

2.1.4 Measuring Impacts

Different researchers have measured the impact of network disruptions in many different ways. Some using traditional four step modeling tools focus less on quantifiable network attributes and rather focus on higher-level model outputs such as mode shift. Stamos, Mitsakis, Salanova, & Aifadopoulou (2015) quantified the impact of extreme weather events by investigating the impact on mode choice for travel between three European cities. Mitsakis (E. Mitsakis et al., 2014), previously used various mathematical tools to quantify impacts on traffic flow as well. Suarez et al. (2005) measured the impact as the number of trips lost due to sea level rise and the estimated cost of increased travel time. Chang et al. (2010) used a similar method but also incorporated metrics such as changes in vehicle distance traveled. They found minimum impact on these measures, although the extent of the flooding modeled in their work was constrained to two river watersheds, with relatively small impacts on the region. Lu & Peng (2011) examined network vulnerability in south Miami by utilizing accessibility change from no inundation, baseline, to two different sea level rise levels (0.3 Meters & 0.6 Meters.) A similar accessibility change approach was used to identify links that would disproportionately impact network robustness by examining the impacts of car breakdowns, crashes, and major congestion in Adelaide, Australia (Taylor, 2008). Cats & Jenelius (2015) used changes in average travel time, transfers and a generalized travel cost (which they termed traveler welfare), including all components of travel time and cost. My research attempts to coalesce these various quantitative assessments into one metric by which the success/accessibility/resiliency of a network can be evaluated.

2.1.5 My approach

In this research, I look for a practical way to assess inundated networks using universally adoptable tools. My work provides an empirical examination of region wide and transport system wide impacts utilizing existing transportation analysis tools that are readily available to most planning agencies. Many other analyses have examined the impacts of climate change (such as increased rainfall, etc.) in terms of specific incidents, for particularities of specific cities, or with specialized models specific to certain modes (Swedish Stockholm PTN). My approach is adaptable to address less extreme impacts, such as increased rainfall, on both auto and public transit networks with a broad geographic scope. Using widely available models, my methods can be relatively easily applied elsewhere, given the right technical expertise and resources.

3 Empirical & Experimental Setting

3.1 Boston Metro Region

The Boston Metropolitan region is the tenth largest metropolitan region in the United States when categorized as a Metropolitan Statistical area. It is located in the New England region of the United States between Rhode Island, Connecticut, New Hampshire and New York. Boston's metropolitan planning organization (MPO) considers its principal jurisdiction to be the 101 towns of eastern Massachusetts, but for travel demand modeling purposes they include a further 63 towns. The specific area of focus for this analysis coincides with the MPO's travel demand modeling extent, 164 towns of western Massachusetts. Due to its unique history and age, the city of Boston is only a small piece in a larger patchwork of cities and towns. The region is relatively monocentric with a transportation system that spreads radially out from the inner core of Boston (Matsuo, 2011). The historic Central Business District (CBD, located in Boston, continues to be the principal center of commerce, but in the past decades Cambridge, too, has developed major hubs of commerce. The inner core region encompasses around 21 towns immediately surrounding Boston proper (MAPC, n.d.).

Boston leads all other towns in the region in terms of jobs, population, vehicles, land use mix, etc. Figure 6 shows population density in the region and Figure 7 shows job density in the region. The inset map in both figures highlights the inner core, which possesses both higher population and job density.

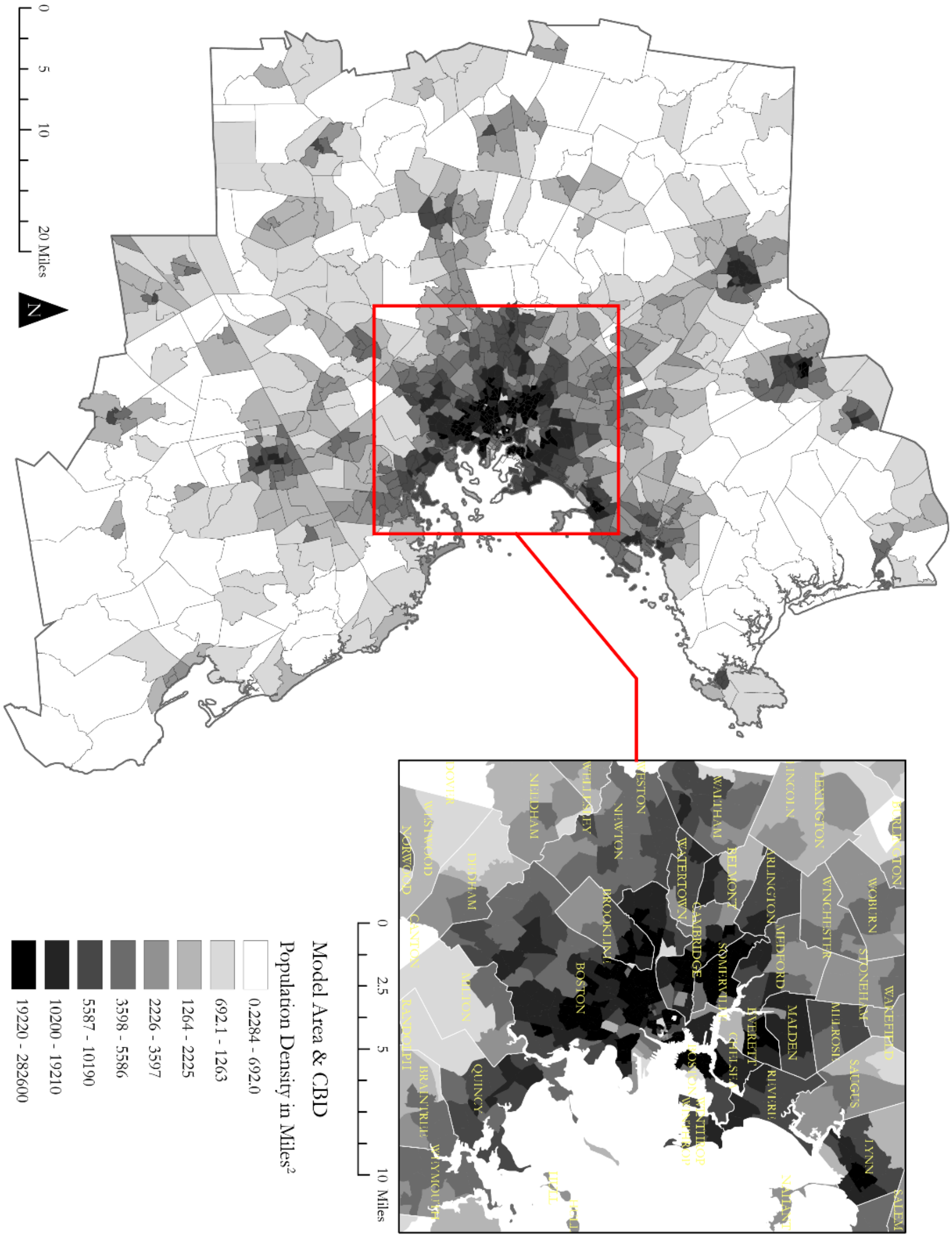

Figure 6: Population Density: Model Area & CBD

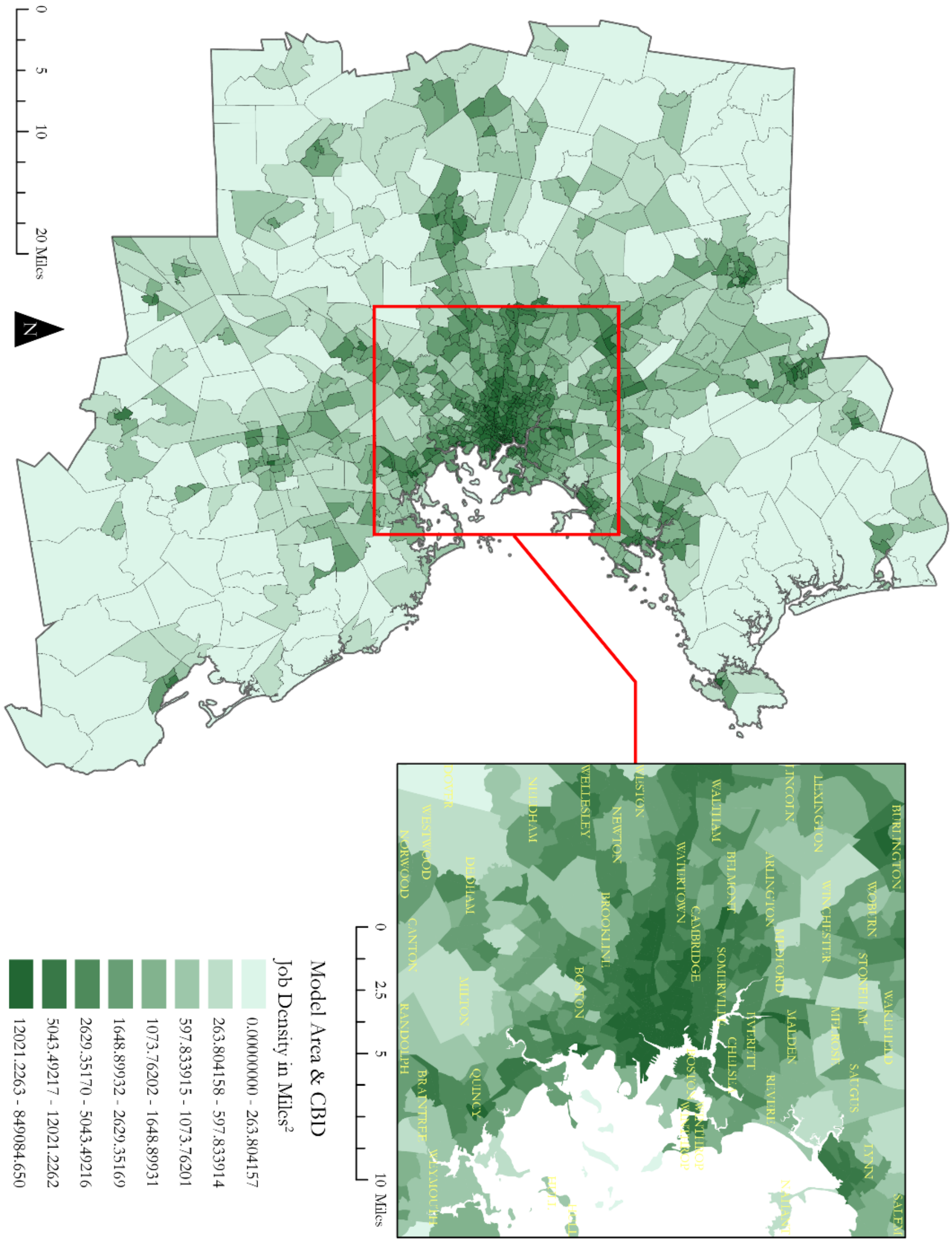

Figure 7: Job Density: Model Area & CBD

The region is home to a mature multimodal transit system, which consists of four heavy rail lines, one branching light rail with five different alignments, a large bus network of about 110 different lines, commuter rail lines and ferry service.

Figure 8: MBTA Subway / Rail Map

3.1.1 Boston Region and Sea Level Rise

The Boston metro region is especially threatened by sea level rise and possible flooding events (Douglas et al., 2010). Much of the inner core area of Boston was built on infill and is generally only a few feet above sea level. Furthermore, the region has a high rate of subsidence, the sinking of land over time. Reports by the Boston Harbor Foundation estimate that sea level will increase by two feet by 2050 and possibly six feet by the end of the century (Douglas, 2010).

Given that Boston has a highly developed radial transit system and is severely threatened by the impacts of inundation and sea level rise, it provides an exemplary test case for this research.

3.2 Four Step Transportation Modeling (FSM) Methods and Software

The traditional four step modeling method is a way of forecasting transportation demand to estimate performance of a city or region's existing or proposed transportation infrastructure and services. Traditional four-step models are "Mesoscopic", generally used at a relatively large scale, usually regional; the models generalize space into zones (traffic analysis zones or TAZs) and demand into aggregated agent types. Agent types vary across models but the usual unit of measurement is the number of households by zone, stratified by different demographic characteristics. Depending on implementation, these flexible models can be used to provide information on peak, off-peak and average daily flows of people and vehicles on pedestrian, highway and transit networks. Abridged versions of the process have also been used for evacuation modeling or modeling the impacts of major special event such as the impact on operations of a city hosting the Olympic Games.

The FSM produces outputs in the form of demand loaded on the different networks (auto, transit, pedestrian). These outputs can also feed into other models to estimate, for example, regional vehicle emissions (output data fed into packages such as MOVES or EMFACs) or detailed traffic movements via microsimulation. Various model extensions can further expand some of these outputs. For example, dynamic traffic assignment, which more accurately estimates network congestion, can provide the number of vehicles stuck in traffic on a given link during a modeled time period. Furthermore, the mesoscopic model outputs can be fed into microsimulation models where the agent types are disaggregated, the geographic extent of the analysis is far smaller, and modeled flows and network congestion are generated at higher temporal detail. Mesoscopic models are not appropriate for modeling minor operation interventions such as the effect of altered signal timing or the introduction of short contraflow lane in a city center. Such detailed analysis use micro simulation models that work at the unit of a vehicle or pedestrian.

Travel in four step models is measured by trips. Different types of trips have different characteristics, such as average travel time, average travel time distribution, and time of day distribution. Trip Purpose refers to the classification of person trips into categories, such as:

- HBW – Home Based Work: A trip from home to work.
- HBS – Home Based School: A trip from home to school.
- HBShop – Home Based Shopping: A trip from home to a shopping location.
- NHBW – Non Home Base Work: A trip from some location other than home to work.
- HBO – Home Based Other: A trip from home and to a miscellaneous location (personal business, bank, medical, food, etc.)
- NHBO – Non Home Based Other: A trip from some location other than home and to a miscellaneous location (personal business, bank, shopping, medical, food, etc.)

Different models may have different levels of trip aggregation and classification. I will now detail what constitutes the traditional four-step model process.

3.2.1 Trip Generation

This sub-model computes the total number of person trips to and from each of the model's analysis zones. Characteristics of each zone, generally the total number of different households, stratified by different demographic characteristics types, and land use, are used to determine the total number of trips attracted to this area (i.e. nonresidents coming to this zone) and the total number produced (i.e. residents leaving the zone and creating trips). Land use is typically measured by the number of jobs by sector present in an area along with various measures of density. The number of households in a given zone by a given type is then multiplied by a specific trip rate, corresponding to the observed trip rate (e.g., from a survey) for households of that type, producing total trips. Different household types will have different trip rates, producing different numbers of trips by different trip purposes. The number of trips attracted to a zone is a function of relevant zonal attributes (such as number of jobs or floor area by sector and use). The trip attraction factors typically come from the Institute of Transportation Engineers (ITE) (http://www.ite.org/). For the traditional FSM, land use and zonal demographics are exogenous, not altered in any model step, but rather defined by the analyst as external scenarios.

The output of this process is a production and attraction matrix by trip purpose for all zones in the model region – the new unit of focus in the model is now the trip.

3.2.2 Trip Distribution

This process takes the zonal production and attraction matrix from the trip generation phase and creates travel matrices of origin destination (OD) pairs. The most common model is the so-called gravity model, which distributes trip production according to relative attractiveness and a travel time impedance function. The impedance functions should be be estimated based upon region-specific trip length distribution data obtained from travel surveys, but "off-the-shelf" impedance functions also exist. The travel times used in the impedance function should ideally reflect the trip period (e.g., AM peak congestion) (and mode) and, in theory, also varies by trip purpose and trip-maker category. . The traffic assignment section will describe the process of estimating travel times in more detail, but, briefly: the first time a trip distribution is run, free flow travel times are used, i.e. travel times that assume no traffic on the networks. Because the initial run incorporates free flow travel time, the trip distribution matrix will not be accurate. Iteration of the mode from trip distribution to traffic assignment will eventually provide the accuracy needed.

The output of this process are origin and destination matrices by trip purpose.

3.2.3 Mode Split/Mode Choice

The origin-destination matrices created in the trip distribution step do not have a defined mode of transportation. Some models may only contain a single auto mode, in which case, the mode choice step can be skipped. In models with multiple modes, especially models that include various forms of transit, the mode choice step is based upon disaggregate discrete choice models, estimated on survey data, and which predict mode choice a trip purpose based on attributes of the alternatives, the traveler, and the origin or destination zone. These mode choice models should be estimated at the level of observation used in the early stages of the four-step process, generally households, but could be individuals. Though the mode choice model is estimated at the level of household, the entire household is not bound to utilizing a single mode. Rather, the mode choice model provides the probabilities of use of a specific mode for a particular household type making a specific type of trip between the same OD pair. If the mode probabilities for a single Home Base Work trip between a particular OD pair are (75 percent Auto, 15 percent Transit, 10 percent Walk) then 75 percent of trips of the same household type, purpose and OD pair will use auto, 15 percent will use transit and 10 percent use walk.

The output of this process are origin and destination matrices segmented by trip purpose and mode.

3.2.4 Assignment

Once the total number of trips have been determined by different trip purposes and distributed across the various OD pairs with mode assigned, the trips must be loaded (assigned) to the various networks represented in a given model. Assignment estimates which links will used to complete a given trip for all trips modeled. If auto is the only mode, then all trips will be assigned to the road network. In models with multiple modes and specific networks, there may be multiple assignments. For instance, there would be an assignment of pedestrians on the portions of the road network available to them and on pedestrian-specific routes. Additionally, transit users would be assigned to a transit network, which may include walking and transit-specific links if the transit mode does not operate on the regular road network (i.e., subways, dedicated busways, commuter rail). Assignment to the network is completed via various optimization algorithms that generally minimize either system travel time or user travel time. These algorithms iterate until some predefined level of convergence is reached.

Once trips are loaded on the network, travel time matrices should be recalculated and the process should repeat from the trip distribution phase. The assignment algorithm will iterate until whatever convergence criteria is met. This convergence is specific to the OD trip matrix that is an input to the assignment module. Since the trip distribution phases requires congested travel times, we must return to trip distribution and update the OD matrices, then re-estimate the mode split with updated travel costs and then run the assignment module again. This iteration will continue until either for a predefined number of iterations (user best judgment) or some convergence criteria is set on the changes in the output trip-distribution-matrix is reached. This is iteration, considered the final, or fifth, step of the four-step model.

The goal of any model is to create a representation of a system that is less complicated than the actual system but is nonetheless able to reasonably approximate aspects of the larger system and provide valuable insight into future trends and responses to various forms of intervention. Once the model has iterated either a predetermined number of times or until some measure of convergence is reached, outputs must be verified against actual real world data to ensure that the model is approximating reality (or, at least, approximating whatever aspect of the that system is of interest). The final activity required for these FSM models is to examine actual observed travel patterns in the modeled region, compare them to the model outputs, and modify different model components (trip distribution impedance measures, mode-choice-model-coefficients, etc.) to attempt to approximate observed patterns.

The general outputs of this process are:

- Auto network file reflecting loaded traffic on the network, with outputs including:
    - Volume/Capacity Ratios (VC) (Derived)

    - Vehicle Hours Traveled by link (VHT)
    - Vehicle Distance Traveled by Link (VDT)
    - Volumes (V)
    - Congested Capacity by link
    - Congested Speed by link
- Transit network file reflecting loading on the transit network, with outputs including:
    - Ridership by Line
    - Passenger Hours Traveled by Line
    - Passenger Distance Traveled by Line
- Pedestrian network file reflecting pedestrian loadings on the highway network, with outputs including:
    - Vehicle Hours Traveled by link (VHT)
    - Vehicle Distance Traveled by Link (VDT)
    - Volumes (V)

These outputs can then be aggregated to derive total metrics for the entire network.

A variety of software packages are available to modelers that include modules and methods for completing each of the steps outlined above. Examples include TransCAD, EMME/2 and Cube Voyager. For this research I use Cube Voyager, as a baseline Boston model was already developed and available at MIT courtesy of MIT-Lecturer Mikel Murga (M.Murga, 1.254 Transportation Modeling, Civil Eng, DUSP – MIT).

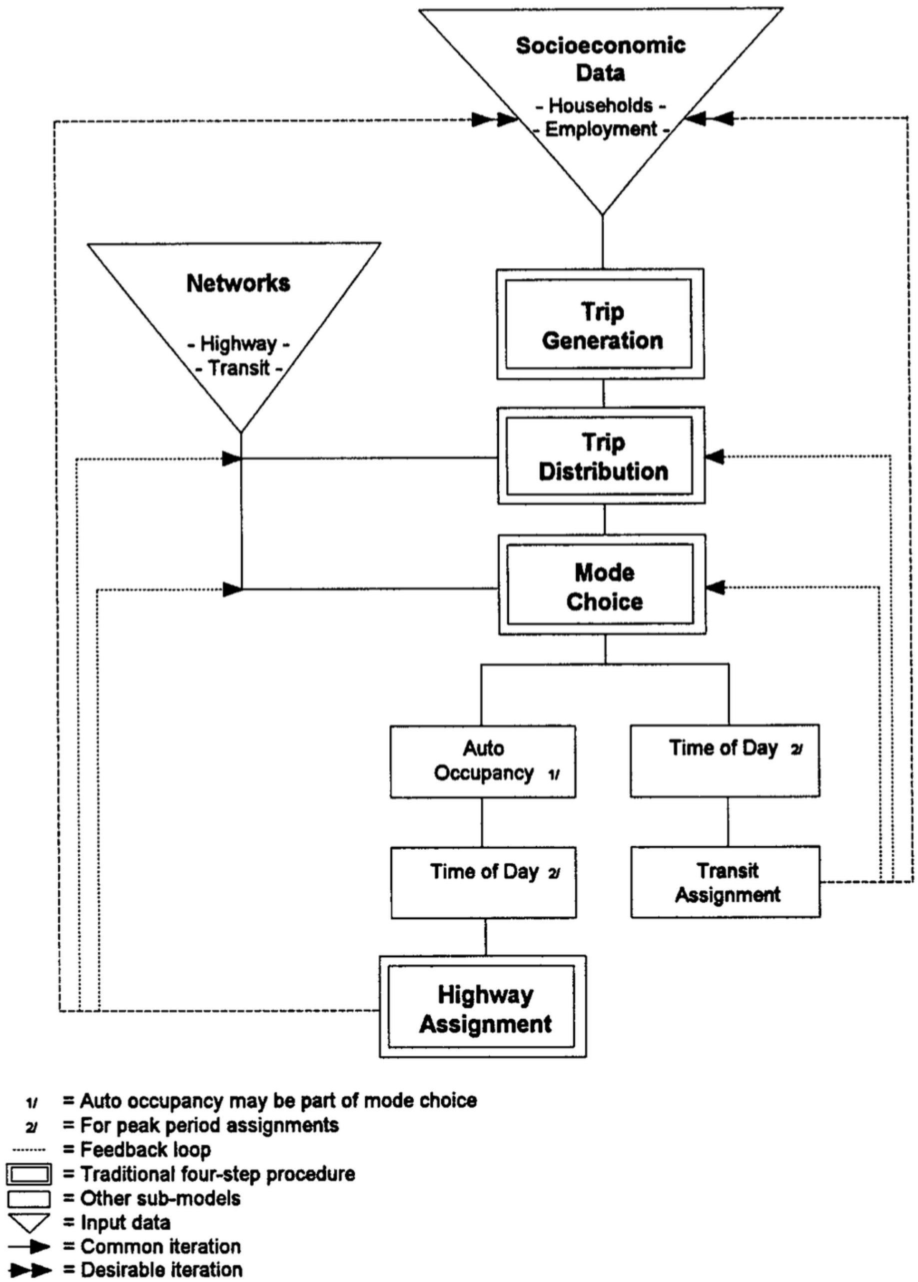

Figure 9: Example Four Step Model Flow Diagram | source: NCHRP 365

3.2.5 Four Step Model Limitations / Weaknesses

The FSM has well-known shortcomings, both theoretical and practical. These include:

- **Freight**: Typically, freight is poorly represented, if at all, in such models. Freight requires large amounts of disparate data, not collected as consistently or broadly as demographic data; furthermore, underlying behavior of relevant agents tends to be poorly understood. Cube, and other transport modeling platforms, do offer freight modeling but they are far less utilized than the four step models.
- **Pedestrians and cyclists**: The FSM was originally developed primarily for road traffic and then extended to transit. Although pedestrians and cyclists can be, and are, modeled, FSMs tend to poorly represent such travel for a host of reasons. These include the sizes of the analysis zones, poor data, and basic or nonexistent bike-pedestrian specific travel networks. Furthermore, FSMs typically simply cannot account for many characteristics of relevance – such as cyclist safety perceptions, route attractiveness, street crossings, personal safety, etc.
- **Land Use**: As discussed above, land use is exogenous to the FSM. Yet, land use and transportation are undeniably linked, as transport levels of service influence development and location attractiveness of different zones. Land Use models do exist that attempt to make the land use-transport link explicit (e.g., (Martínez, 1996) (Brown, 2012)), but these tend to be exceptions in most practice, due in part to data shortcomings and model complexity. In addition, local level land use and built environment characteristics can influence travel demand and relative attractiveness of different modes; the FSM framework tends to fall short of being able to represent such conditions.
- **State of Practice, not State of Art:** Newer activity- and tour-based models, currently state of the art, are beginning to be deployed in the metropolitan regions. Such models use trip chains, or tours, as the unit of measurement rather than single purpose trips. While the FSM predicts aggregate zone-to-zone trips, activity or tour-based models attempt to simulate individual level trip making decision processes. This reflects more nuanced, sophisticated, and ultimately more realistic representations of actual travel behaviors compared to the traditional FSM. Such models are computationally intensive and require more data (disaggregate data/synthetic population) than traditional four-step models. Practical deployment can be challenging. The Transportation Research Board (TRB) reported that, as of 2012, 14 major American cities had either developed or were in the process of developing some form of activity-based model (Vovsha et al., 2012). A cursory internet search of the respective MPO's responsible for these models reveals that many of them are still in the development phase today (2015) (In

Development = Atlanta, Seattle, Boston, Chicago; Deployed = San Francisco, New York City, Phoenix).

3.3 MIT Boston Metro Region Four Step Model (MIT-FSM)

Based in the Cube Voyager modeling software platform, the MIT-FSM consists of 986 zones covering 164 towns of western Massachusetts. The 986 zones reflect the model structure of the regional MPO, the Central Transportation Planning Staff (CTPS), although the current CTPS model has 2,272 zones. The smaller number of zones compared to the MPO's model allows for large decrease in run time while still maintaining high spatial resolution in areas of high density, such as the urban core and in outlying regional cities such as Lowell and Lawrence.

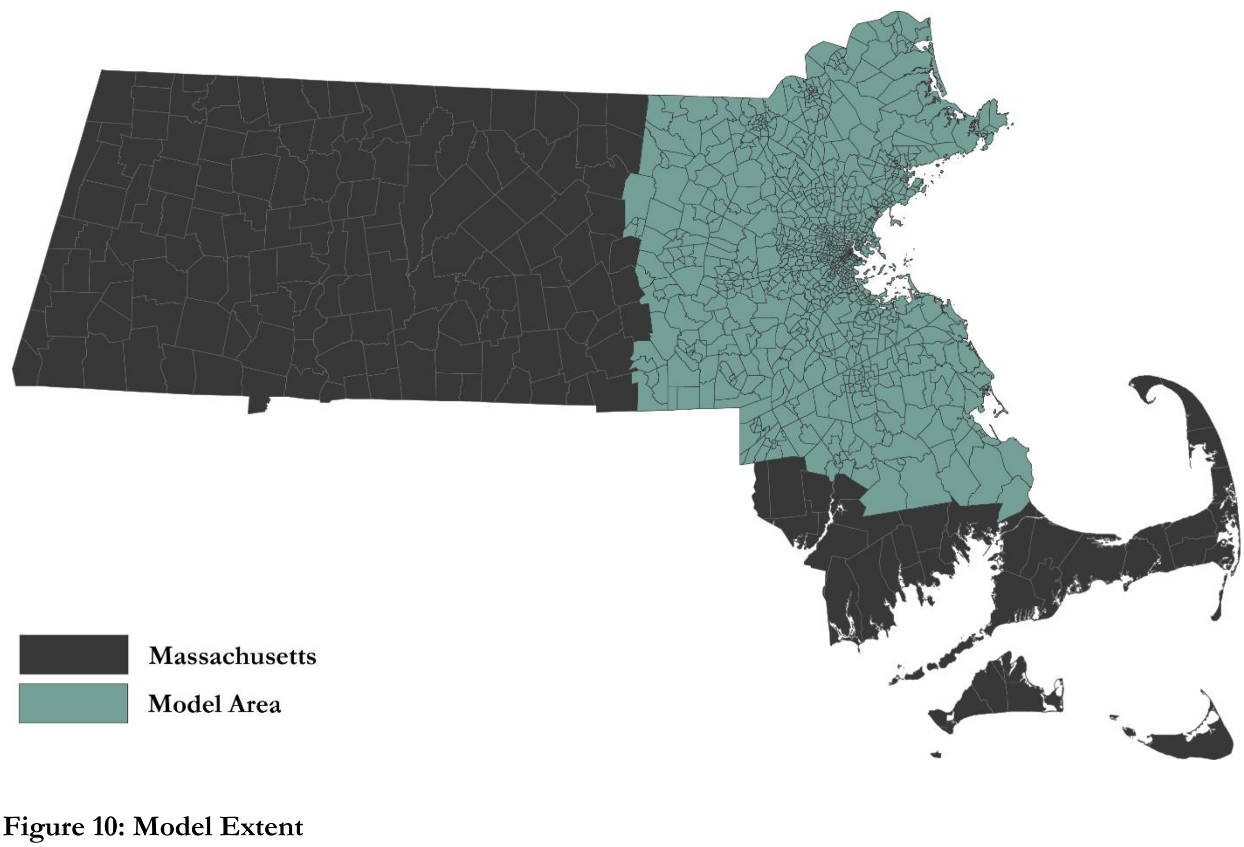

Figure 10: Model Extent

3.3.1 Computing Environment

Four step models are computationally intensive. The key factors in model run times are the number of zones present in the model, the auto assignment method used and the settings of the transit assignment method. All model runs performed for this thesis were run on a machine with 20 dual core I7 chips (40 threads) that allowed extensive parallelization of model processes. Previously, I ran this model on an I5 dual core laptop running Windows 7. The increase in computing power decreased the processing time of a single full model run to equilibrium (about six iterations) from 16 hours to about six.

3.3.2 Demographic Representation

The MIT-FSM has 26 household types, based on household size, number of workers and number of vehicles. The classification scheme goes from 1-3+ people, 0-3+ workers and 0-3+ vehicles in a household. Households with 1 person but 2 cars would be collapsed into the 1-person-1-car category since the relationship of interest is how many people in the household have access to a car. Households for each of the 26 types were drawn from the 2010 Census Transportation Planning Package (CTPP).

Households are further segmented based on a designation of "Captive" or "Choice." This designation refers to mode choice, reflecting whether all workers in the household have access to a vehicle or not. A household with more workers than vehicles is classified as captive. A portion of captive household trips will face different mode choices estimated with different mode choice models than the choice households. In the model choice and captive users have different travel time sensitivity. We expect choice users to have a higher value of time compared to captives given their larger choice set of transport options. The MIT-FSM operationalizes this assumption with different travel time skims used for mode choice and transit route selection for each group.

3.3.3 Road Network

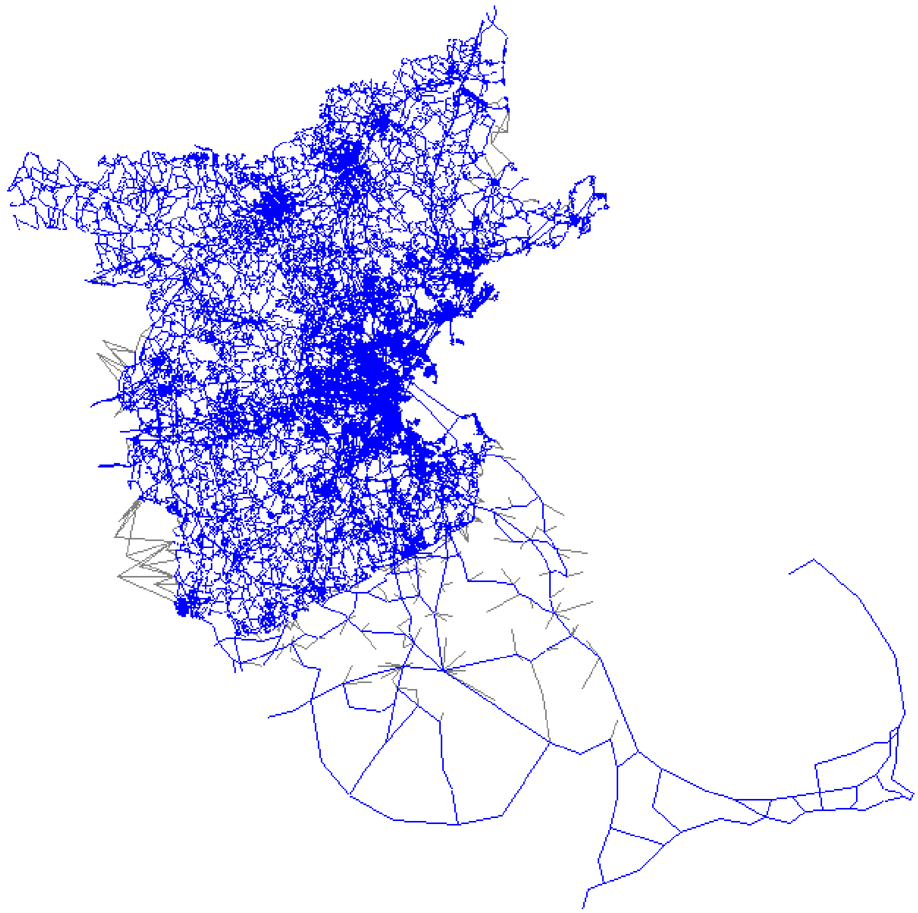

Figure 11: Road Network

The road network (Figure 11) in the MIT-FSM has over 265,000 links, and almost 138,000 nodes with specific attributes describing the capacity, speed, and free flow travel time needed to traverse links by different modes as well as "functional parameters" describing the type of the link and the specific modes that can use it for travel. Link-classes group similar links together by type and speed determine which modes can use specific links (Table 1).The network was modified from a GPS navigational system network for modeling purposes, and, therefore, the level of detail in the primary model area is very high. In Figure 11, one can see the southern area of the model region has a sparse network. This area was not initially included in the MIT-FSM. A "sketch" network of major highways represents these "feeder" cities and towns that are attracted to the inner core area of the model region. Centroid connectors link the network to the zone centroids, where all trips begin or end.

- Expressways – 65 mph (Link-class=1 thru 3)
- Expressways – 55 mph (Link-class=4)
- Expressways – 50 mph (Link-class=5)
- Interchanges - 40 mph (Link-class=6)
- Main Arterials - 50 mph (Link-class=11,12,13)
- Minor Arterials - 45 mph (Link-class=15,16,17)
- Distributors - 25 mph (Link-class=14,20,21)
- Minor Distributors - 25 mph (Link-class=18,25,26)
- Local Streets - 15 mph (Link class=31)
- Subway Rail (Link-class=40) and Commuter Rail, (Link-class=42)
- Light Rail Track Links (Link-class=41) and Bus-Lanes (Link-class=45)
- Navigational channels (Link-class=47)
- Walk Access to Rail Stations (Link-class=50)
- Walk Connections Across Rail Platforms (Link-class=51)
- P&R Drive Access to Commuter Rail (Link-class=52)
- Centroid Connectors (Link-class=53)

Table 1: Link-Classes

The MIT-FSM uses a sub-area network in Dynamic Traffic Assignment (DTA). This sub-area network includes 520 out of the 986 model region TAZs. Figure 12 shows the extent of the sub-area network. The only differences between this network and the regular MIT-FSM are its extent and a few attributes used in the application of DTA. Though smaller, it does cover the most important regions of the model area.

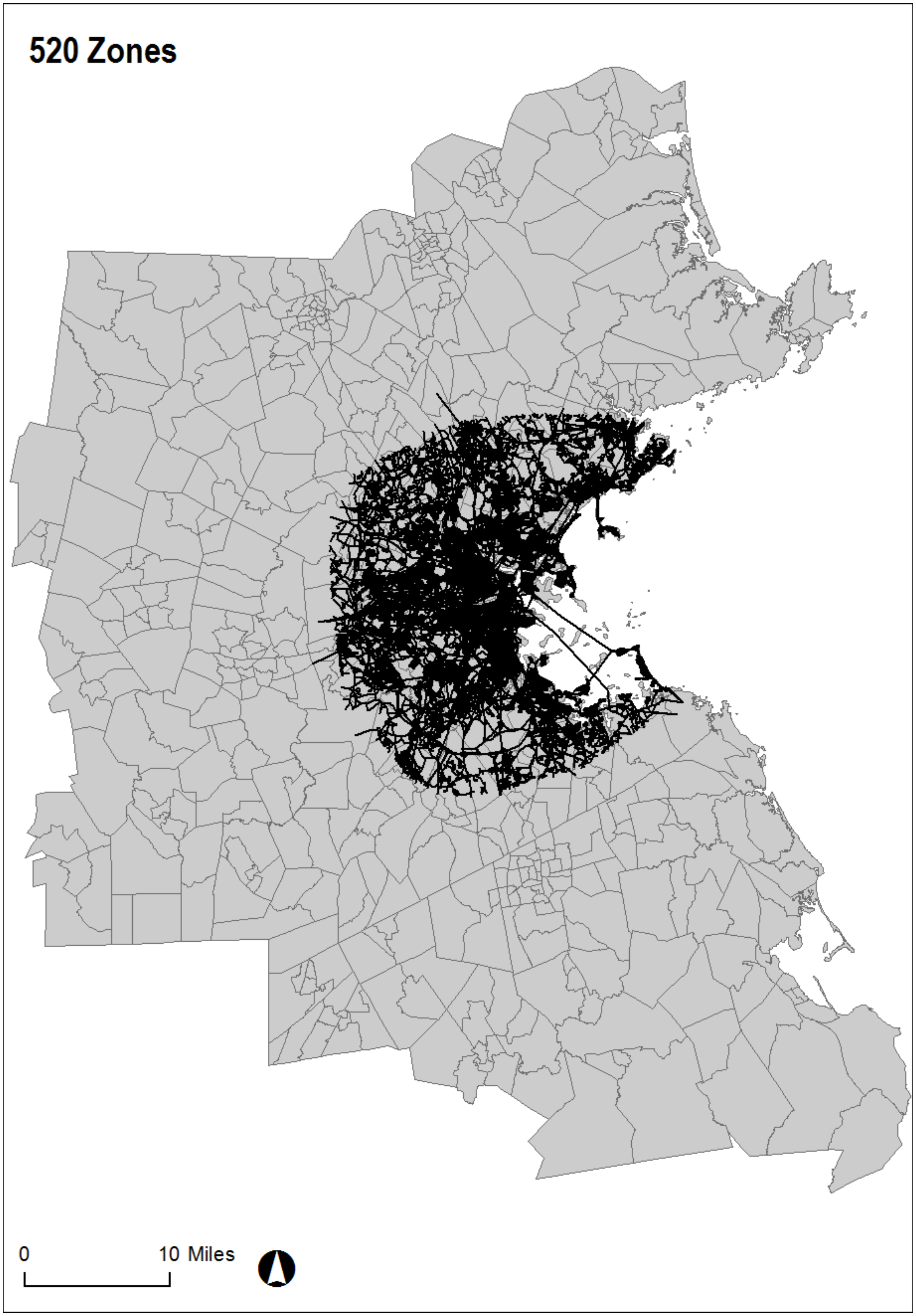

Figure 12: MIT-FSM Sub Area Network

3.3.4 Travel Modes Represented

The MIT-FSM represents three distinct transportation modes: 1. Auto, 2. Transit, and 3. Walk. All modes utilize the same overall network, but the link-classes ensure that different modal vehicles can only access those links on which they are allowed to travel. For example, cars and buses can travel on expressways, while trains and persons walking cannot.

Automobiles may access any link that is not transit or pedestrian specific. Since the auto network was derived from an auto navigation network, it accurately approximates the real world auto network of the Boston Metro Region.

Pedestrians travel on the roadway network, specifically on any link that is not a dedicated highway/tunnel, a dedicated transit link, or navigation channel. Some pedestrian specific links exist in the model, but, in general, walk trips share paths with vehicles. Pedestrian trips do not face capacity constraints on any links.

Transit represents the most complicated mode in the model. As discussed Section Boston Metro Region, the MBTA transit system consists of urban heavy rail, urban light right, buses, commuter rail and ferries. The MIT-FSM includes all these modes:

- All rail
    - Urban Heavy Rail: Red Line, Orange Line, Blue Line
    - Urban Light Rail: Green Line
- Ferries: Hingham/Rowe, Hull-Pembroke/Long Warf, Charleston Navy Yard/Lovejoy
- Buses: 90 percent of the MBTA bus routes, representing about 95 percent of bus demand.

3.3.5 Model Structure

The MIT-FSM is a traditional four-step model, with an iterative loop specified to allow for convergence of distribution, mode split and assignment. Each sub-model utilizes a range of variables, but the primary input is a zonal table with demographic and land use/built environment attributes for each of the 986 zones. The land use/built environment attributes are limited to available data on parking capacity and cost, density of persons, and jobs.

Figure 13 summarizes the main characteristics of the MIT model.

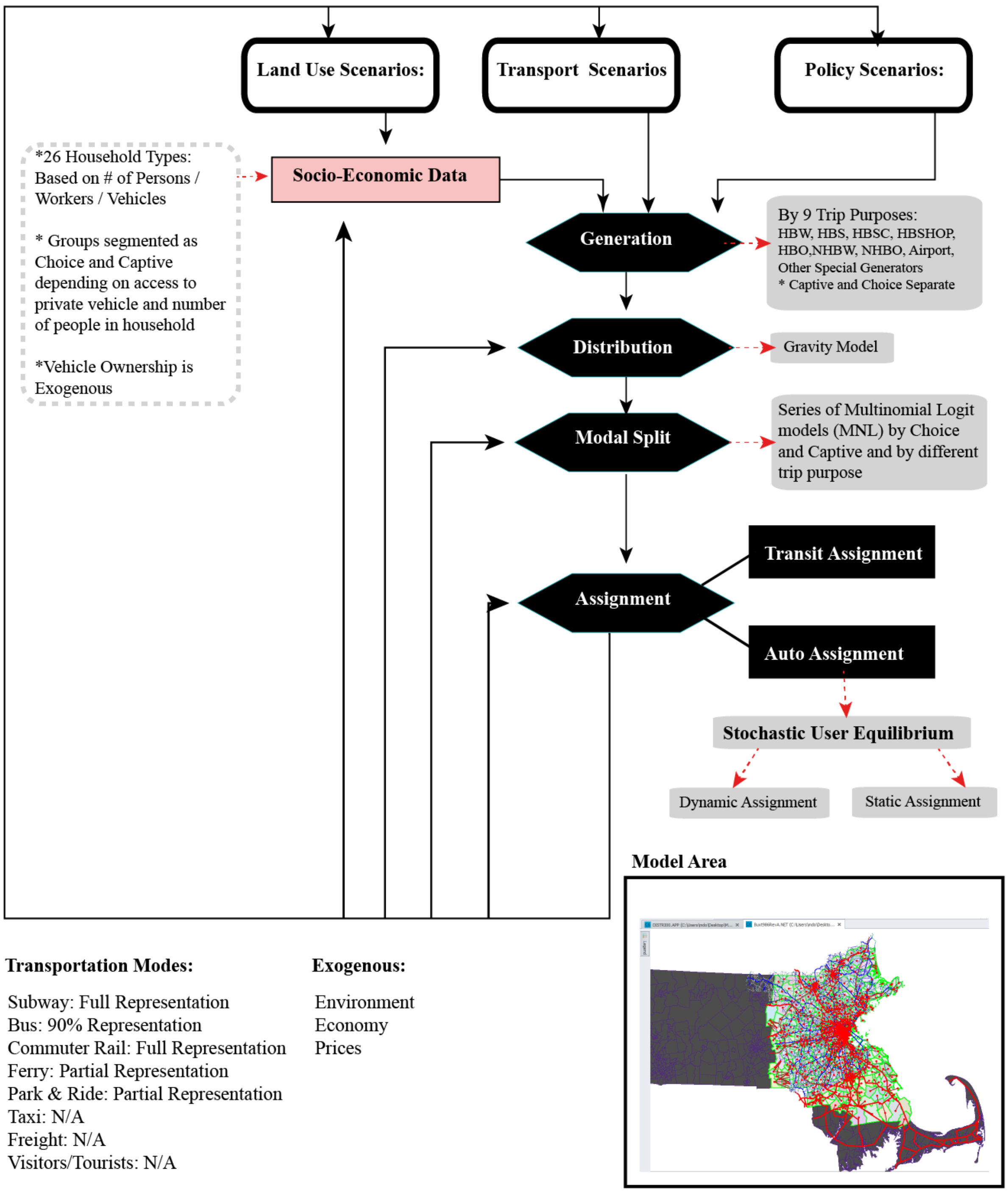

Figure 13: Diagram of Model Structure

I will now briefly describe each of the four steps as implemented in the MIT-FSM.

3.3.5.1 Generation/Attraction

As mentioned, the trip generation sub model uses 26 household types and their respective trip rates for different purposes, along with data for each zone on total employment. The household and trip rate information is the basis for estimating the trips produced in each zone, while the total number of jobs by sector is the basis for estimating the total number of trips attracted to each zone for all purposes except school trips. School trips were estimated separately by zone based on school enrollment data. The MIT-FSM represents trips by nine separate trip purposes: Home Base Work (HBW), Home Based School (HBS), Home Based Shopping (HBSHOP), Home Based Other (HBO), Non Home Based Work (NHBW), Non Home Base Other (NHBO), Logan Airport (LOGAN) and other special generators. The trip rates by trip purpose and by captive or choice trips, are derived from the 1991 Boston Regional Travel Survey. They were estimated by stratifying survey respondent households into groups based on the number of people, vehicles and workers to match the household types used in the model. Once stratified, the aggregated and average trip rates were estimated.

3.3.5.2 Trip Distribution

The trip distribution module is calibrated from the 1991 Boston Regional Travel Survey using a standard gravity model as seen in Equation 1.

$$T_{ij} = P_i \left(\frac{A_j F_{ij} K_{ij}}{\sum_{k=1}^{zones} A_k F_{ik} K_{ik}} \right)$$

where

T_{ij} = the number of trips from zone i to zone j,
P_i = the number of trip productions in zone i,
A_j = the number of trip attractions in zone j,
F_{ij} = the friction factor relating the spatial separation between zone i and zone j, and
K_{ij} = an optional trip-distribution adjustment factor for interchanges between zone i and zone j.

Equation 1: Gravity Calculation, Source: NCHRP 365

The friction factors (F_{ij}) used in this gravity model were determined from the 1991 Boston Regional Travel Survey as well. The friction factors are generated through the use of a gamma function

(Equation 2), adjusted and iterated until the model trip length distribution approximates the trip length distribution observed in the travel survey.

$$F_{ij} = a \times t_{ij}^{b} \times e^{c \times t_{ij}} \tag{4-2}$$

where

F_{ij} = the friction factor between zones i and j,
a, b, and c = model coefficients; both b and c should, in most cases, be negative; a is a scaling factor and can be varied without changing the distribution,
t_{ij} = the travel time between zones i and j, and
e = the base of the natural logarithms.

Equation 2: Gamma Function

Intrazonal Trips

Intrazonal trips begin and end in the same zone. Most intra-zonal trips in the MIT-FSMl, with the exception of some school bus trips, are modeled as walk trips. This assumption fits in the dense urban areas of the region and is acceptable in the larger and less dense zones in the outer regions as the absolute number of intra-zonal trips generated there are quite small. Intra-zonal travel times can be calculated in various ways, but, generally, they are a function of the size of the zone, e.g., as an equivalent radius (Equation 3):

$$Intrazonal\ Walk\ Distance\ (Miles) = \frac{\sqrt{Area_Z}}{\pi}$$

$$Intrazonal\ Walk\ Time\ (Minutes) = \frac{\sqrt{Area_Z}}{\pi} * 20$$

$$Where\ z = Zone\ where\ trip\ occurs$$

Equation 3: Intrazonal Travel Distance & Time Calculation

Given that all trips begin or end at zone centroids, a larger zone will have a higher intra-zonal travel time compared to a small zone. These time calculations are independent of the road network.

3.3.5.3 Mode Split/Mode Choice

Trips take place via one of the modes represented in the MIT-FSM. Estimated multinomial logit models determine the mode choice for these trips. The choices available include the possibility to utilize multiple modes. Auto drivers and auto passengers are treated as separate modes. The mode choice models differ based on trip purpose, and on whether the trip corresponds to a *choice* or *captive*. Captives have three mode choices:

- Walk Access Transit (PT_Walk)
- Walk
- Auto Passenger (AutoPax)

Choice users have four mode choices:

- Walk Access Transit (PT_Walk)
- Auto
- Walk
- Drive Access Transit (PT_Drive)

The variables used in the mode choice models vary by trip purposes and choice/captive type, but generally, they include attributes of the different modes and zonal data on density at the trip destination (in Figure 14 provides an example).

Walk Access Transit is available in all zones containing a transit stop or within a half hour walk of a transit stop. Auto, Walk, and Auto Passenger are available in all zones. Drive Access Transit is only available in zones accessing the inner core from outside the inner core, representing the fact that most users of this mode live in the suburbs of the region and drive to regional transit stations, generally commuter rail.

HBW-Choice

$\boldsymbol{P(Walk)} = 0.5 - 0.25 * TravelTime$

$\boldsymbol{P(PT\_Walk)} = 1.5 - 0.05 * TravelTime - 0.1 * WalkAccessTime - 0.18 * WaitTime - 0.18 * TransferWaitTime - 0.15 * Fares - 0.31 * NumTransfers$

$\boldsymbol{P(PT\_Drive)} = -1.5 - 0.05 * TravelTime - 0.18 * WaitTime - 0.18 * TransferWaitTime - 0.15 * Fares - 0.31 * NumTransfers - 0.35\ AccessEgressTime$

$\boldsymbol{P(Auto)} = -2.5 - 0.10 * TravelTime + .79 * CarsPerWorker - 0.1 * AutoAccessTime - 0.1 * AutoEgressTime - 0.3 * (Fuel\ Tax * Distance) - 0.3 * ParkingCost - 0.3 * DestinationDensity(Job\ \&\ Res)$

HBW-Captive

$\boldsymbol{P(Walk)} = 0.5 - 0.17 * TravelTime$

$\boldsymbol{P(PT\_Walk)} = 4 - 0.07 * TravelTime - 0.1 * WalkAccessTime - 0.2 * WaitTime - 0.2 * TransferWaitTime - 1.1 * Fares - (5 * -0.07) * NumTransfers$

$\boldsymbol{P(AutoPax)} = -2.5 - 0.24 * TravelTime + 3.6 * CarsPerWorker - 0.24 * AutoEgressTime - 0.24 * AutoAccessTime - 3.5 * (Fuel\ Tax * Distance) - (0.24 * 3.5) * ParkingCost$

Figure 14: Example Mode Choice Equations - Home Based Work (HBW)

3.3.5.4 Assignment

The MIT-FSM estimates assignment outputs by different times of day. The trip distribution and mode choice outputs are 24 hour trip matrices by different modes. Time of day factors are then applied to estimate the share of trips that occur during specific time periods: AM Peak, PM Peak, Midday and Rest of Day. Time of day factors were calculated based on the trip departure time distribution by different trip purposes from the Boston 1991 Travel Survey. The MIT-FSM produces a representative hour of each time period. In other words, only one hour of AM, PM, Midday and Rest of Day is modeled. The Boston 1991 Travel Survey provides us with the length of these periods, therefore if one wants to calculate the total daily traffic volumes one can multiply each time period by its specific factor and then sum them together. The AM peak and Midday are each three hours long, the PM Peak is four hours long and the Rest of Day is eight hours long.

3.3.5.4.A Auto Assignment

Stochastic User Equilibrium

The MIT-FSM uses a stochastic user equilibrium assignment algorithm that finds the minimum travel time routes having the highest probability of use; higher travel time routes may also be assigned traffic, stochastically. This approach attempts to minimize the travel time for all users. This assignment algorithm is implemented in Cube Voyager as a "Static Assignment," simultaneously assigning all auto trips in a modeling period to the networks. That is, assignment is time-invariant within a model period (AM, PM, MIDDAY, Rest of Day). The congestion caused by vehicles on the roadway at the same time (or before) is not a variable in the assignment algorithm. The contribution of more trips on a link does not dissuade the use of that link in any single model run. Congestion is estimated by the BPR formula (Equation 4):

$$Congested\ Time = \frac{\text{Distance}}{Current\ Speed} * \left(1 + 0.3 * \left(\frac{Volume\ on\ Link}{Capacity}\right)^{15}\right)$$

Equation 4: Link Time Calculation

This approach may initially produce links with very high volume to capacity ratios. Iteration mitigates this. Once the assignment converges, a new network file is created with updated speed and travel time values reflecting the level of service on each link. This network is then used to update travel time costs in the trip distribution phase. The process repeats until network links reach volumes that allow reasonable travel times on most links. I found iterating six to ten times, consistent with professional practice (Murga. M, 2014), provides stable trip distribution matrices.

Assignment Outputs:

The various link-based values (e.g., volumes, speeds) can then be summed to provide network-wide summaries. Cube Voyager's "skimming" modules uses the network file containing the link information to produce travel time matrices for a total of 972,196 origin-destination (OD) pairs (for the 986 zones). OD matrices are produced for auto, walk, and transit, segmented by time of day (AM, PM, Midday and Rest of Day) and by different user classes. User classes, as described in the previous chapter, refer to different types of people and their respective values of time.

Dynamic Traffic Assignment

Dynamic Traffic Assignment (DTA) aims to provide a better estimate of network congestion during each modeling period (AM, PM, MIDDAY, Rest Of Day). Cube Voyager implements DTA with the Cube Avenue extension package. The DTA method has time variant loading with time varying costs for each modeling period. OD Trip matrices are split, or "sliced", into a user specified number of sub-period time segments. My implementation of DTA splits the matrix into five-minute slices. Essentially, DTA is a series of individual static assignments of each slice of the model sub-period matrix. DTA is more computationally intensive than static assignment. One method for reducing the runtime of the DTA-sub model is to assign traffic to an extracted portion of the overall highway network. The MIT-FSM subarea network (Figure 12) is assigned all trips from the model region that pass through any link within the 520 zones in the subarea network; the DTA does not include trips not passing through any of these 520 zones.

While in a regular static assignment we assign all trips for a model period and then update the network costs (travel time on links, speed, etc.), in DTA:

- a single slice is loaded on the network,
- network costs are updated,
- the next slice is loaded on the updated cost network, and
- the process repeats until all matrix slices are loaded on the network.

In contrast to static assignment, DTA tracks all vehicles in the network. Individual vehicles traveling between the same OD pair may be grouped together and loaded onto the network. Up to 1000 vehicles can be grouped together and assigned to the network. Groups that begin their journey in later periods are subject to congestion created by vehicles loaded on the network in earlier periods. Furthermore, vehicles that do not arrive at their destination in a given internal "slice" period may change route, if the minimum time path has changed, once the network is updated. A file is created tracking the flow of traffic over the model period. These data can be animated on a map to examine flows.

Static assignment differs from DTA in the way in which the model handles vehicle trips. For static assignment, the model forces all trips through the network within that hour, regardless of congestion. Conversely, DTA does not allow volume to exceed capacity. As a result, DTA more accurately models congestion, with fewer vehicles arriving at their destination during the period modeled.

3.3.5.4.B Transit Assignment: "Probabilistic Multimodal"

The MIT-FSM uses a probabilistic route enumeration and evaluation algorithm that first identifies all the routes available (enumeration) and then determines the routes available with the highest probability of use (evaluation). The Cube Voyager platform has a multitude of different path enumeration/evaluation settings that alter possible route search space based on different criteria including maximum walk time, maximum number of transfers, maximum number of routes enumerated, maximum cost, and many others. Different settings can cause large variations in the output. For example, setting the minimum walk time to access transit too low can lead to a zone having no transit access whatsoever. On the other hand, increasing all max settings to allow full enumeration of all possible routes is extremely computationally intensive and produces multiple output files up to 120 gigabytes apiece. Therefore, one must carefully examine the travel time matrices to ensure that zones that "should" have transit access do. This requires some judgment by the modeler; I generally adjusted route enumeration parameters to ensure that a zone has transit access if it has a transit stop. The main parameters of interest are the maximum walk time, which I set to 30 minutes and the total number of transfers which I set to a total of 3.

The route enumeration files feed into the transit assignment algorithm, which assigns riders to routes based upon the probabilities of use, as generated in the enumeration and evaluation process. The probabilities are based on the different travel times associated with different routes. Voyager does not make very clear the exact estimation of the probabilities. Since it is probabilistic, one will find that a mode with the highest probability of use will have the highest ridership for a specific OD pair, but higher travel time routes may also be assigned traffic. The model does not report specific transit pathing from origin to destination by zone, so if ridership changes across different modeling scenarios, or runs, determining which routes people have diverted to requires exploration.

Transit assignment outputs include ridership by route and network link; total volumes by route and link; passenger distances by route and link; boardings and alightings at stops by route; total walk access time; walk egress time; walk transfer time; and in vehicle time. Again, the model does not report these metrics by individual OD trip pair, but by network link and route.

Weaknesses of the current transit implementation in the MIT-FSM model include: transit vehicles have unlimited capacity; subway stations and transit do not suffer from pedestrian congestion; and buses do not contribute to auto network congestion. Regarding the last point, transit assignment takes place after auto assignment, so bus travel times do reflect congested network times although the don't contribute to it.

Table 2 summarizes the general inputs, parameters/methods and outputs of the various MIT-FSM sub models.

Hierarchy	FSM Modules	Primary Inputs	Exogenous Parameters | Methods	Primary Output
Core Four Step Model Sub models	Trip Generation	Number of Jobs by sector & Households by type per zone	Trip Rates for households & Trip production rates for job types	-Matrices of Produced and Attracted trips for each zone
	Trip Distribution	Matrices of Produced and Attracted trips for each zone	Impedance factors	-Origin and destination matrices by trip purposes
	Mode Choice	Origin and destination matrices by trip purposes Demographic information per zone	Logit Model Coefficients	-Origin and destination matrices by trip purposes and modes
	Auto Assignment	Auto Network OD Matrix of auto trips Traffic Signal Information	Congestion Estimation (BPR Formula) Assignment Algorithm Assignment Method(Static or Dynamic)	-Congested Network File -VHT per link -VDT per link -Volume per link -Volume/Capacity per link -Congested Travel time on each link -Congested Speed
	Transit Assignment	Auto Network Transit Network OD Matrix of all Transit Trips	Max walk time to access transit Max transfers	-Loaded Public Transit Network File. -Ridership by transit specific mode (Bus, Urban Rail, Ferry, Commuter Rail, etc.) and route. -Boardings and Alightings by transit stop. -Passenger hours traveled by route and link.
Sub Models	Travel Time Skim Modules	Network File (Auto or Transit)	--	Travel time matrices by mode

Table 2: FSM Summary Primary Inputs, Exogenous Parameters/Methods and Outputs

3.4 NOAA Sea Level Rise Layers

The National Oceanic and Atmospheric Administration has recently released coastal sea level rise data for the United States. I obtained the data for the sea level rise in one-foot increments from one-foot to six-feet from the NOAA data portal in GIS format

NOAA created these layers using a "modified bathtub" model with specific local and regional data on the water features along US coastlines and the connectivity of other hydrological features. A "bath tub model" is, essentially, a digital elevation model of the region's land overlaid with data on the elevation and extent of water. The tidal surface provides the height of water as of 2012. To model sea level rise, the tidal surface is combined with potential sea level rise values from one to six feet, increasing the elevation of water by those values. The sea level rise values (one foot to six feet) represent the range of possible sea level rise totals for the year 2100, but the data include no probabilities of, nor timetables for, occurrence. NOAA analyzed the digital elevation model and the tidal surface to determine where the tidal surface exceeds land elevation and inundated areas are identified. Areas of non-coastal land adjacent to coastal land that is inundated is also considered inundated, as the water would flow down into these areas.

I treat these sea level rise data layers as potential inundation flood zones. This simplifying assumption does not take into account the difference between incremental sea level rise and a storm surge. A storm surge could have different extents and depths because of many other weather-related factors and tide height. I chose the NOAA data because it is the highest quality data available specific to the Boston Metro Region with the largest range of inundation values. The latter point suits well my objective of highlighting an approach to examining the impacts of inundation events across a spectrum of inundation values. If an agency were conducting such an exercise to inform actual decision-making, different datasets may be preferable/required. Figure 15 presents the NOAA data layers and their extent.[2]

[2] The data for all US coastal regions can be found at: http://coast.noaa.gov/dataregistry/search/dataset/B6C0D28D-EB05-4857-AC6A-A219B59B2241.

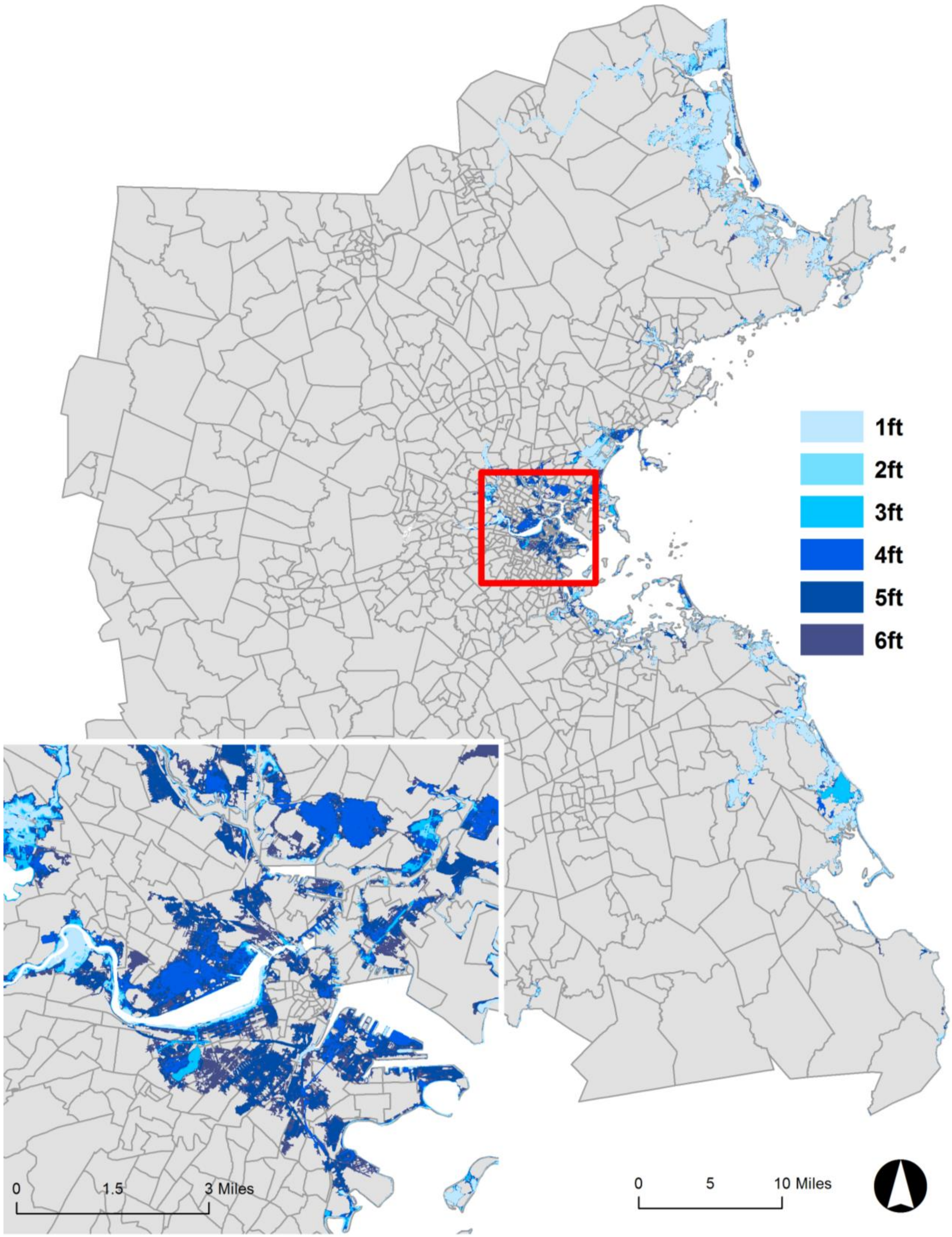

Figure 15: NOAA Sea Level Rise Data from 1ft to 6ft

4 Model Baseline Results

In this Chapter, I present baseline 2010 model outputs of the MIT-FSM, including basic model outputs and metrics and their respective baseline values.

4.1 2010 Baseline Model Results

4.1.1 Trips

The baseline 2010 model predicts that about 16.4 Million trips for all trip purposes occurring in the model region during an average day. The majority, 69 percent of trips in the region, are auto trips. Walking trips account for 26 percent of all trips and transit trips only account for roughly five percent (Table 3).

MODE	TOTAL TRIPS	PERCENTAGE	MTS[3] TOTAL TRIPS
AUTO	10,265,427	62.6%	8,718,011
AUTOPAX	1,049,129	6.4%	3,242,318
WALK	4,259,798	26.0%	1,652,464
PT_WALK	760,167	4.6%	424,840
PT_DRIVE	72,486	0.4%	230,480
TOTAL	16,407,006	100%	14,268,113

Table 3: Baseline 2010: Trip Total and Mode Split

The low predicted transit share for all trip purposes corresponds to reality in Greater Boston, where the automobile dominates like in all other metropolitan areas in the USA. Transit still plays a key role on certain corridors and for the urban core, illustrated by the predicted 13% transit HBW mode share (Table 4). The model seemingly over predicts walking trips, perhaps due to the method for calculating intrazonal trips. Furthermore, the model greatly under predicts Park and Ride (PT_Drive). There is noticeable variation between the most recent travel survey and the model outputs. I believe some of this is due to how the modes and transit services are included in the MIT-FSM model; the MTS includes all regional transit while the MIT-FSM does not. The variation in PT_Drive is likely due to the constraints present on where PT_Drive can originate from, and that the model does not contain "drop off public transit," also known as "Kiss and Ride." Finally, the vast difference in walk trips is likely related to the intrazonal trip calculation, whereby all intrazonal trips are walk trips.

[3] Massachusetts Travel Survey 2011 (MTS) : Source MassDOT

MODE	TOTAL TRIPS	BASE2010	MTS TOTAL TRIPS
AUTO	2,428,523	74.12%	1,658,850
AUTOPAX	216,232	6.60%	140,934
WALK	152,923	4.67%	121,540
PT_WALK	424,539	12.96%	267,953
PT_DRIVE	54,163	1.65%	136,027
TOTAL	3,276,380	100.00%	2,325,304

Table 4: Baseline 2010: HBW Total Trips and Mode Split

Table 5 displays the total number of predicted trips by different trip purposes. The most common trip purposes are Home Based Other, at 26 percent of all trips; Home Based Work, at 20 percent; and Non-Home Based Other, at 16%. Relative to figures from the expanded 2010 travel survey the model overpredicts HBW and HBShopping trips and NHBO. Some of these differences may be due to changing trip rates over time (Han, 2015).

PURPOSE	TOTAL TRIPS	PERCENTAGE
HBW	3,276,380	20.0%
HBS	1,243,061	7.6%
HBSHOP	2,259,043	13.8%
HBO	4,259,490	26.0%
NHBW	2,522,716	15.4%
NHBO	2,763,319	16.8%
AIRPORT	82,998	0.5%
	16407005	100.0%

Table 5: Baseline 2010: Total Trips by Trip Purpose

Choice users account for almost 73 percent of the trips in the model region (Table 6). Captive trips more likely use transit or walk compared to choice trips (Table 7). The most common mode across all trip purposes for choice trips is auto followed by walk. Captive trips most commonly use the walk mode followed by the auto passenger mode.

	TOTAL TRIPS	PERCENTAGE
CHOICE	11,900,709	72.5%
CAPTIVE	4,506,297	27.5%
TOTAL	16,407,006	100.0%

Table 6: Choice and Captive Trip Split

MODE	BASE2010	CHOICE	CAPTIVE
AUTO	60.1%	79%	0.0%
AUTOPAX	6.4%	0%	32.4%
WALK	26.0%	16%	51.3%
PT_WALK	4.6%	4%	7.4%
PT_DRIVE	0.4%	1%	0.0%
SCHOOLBUS	2.4%	0%	8.9%
TOTAL	100%	100%	100%

Table 7: Baseline 2010: Choice and Captive Mode Split

Both groups have some form of auto travel as their most likely mode, while the Captive group has more than twice the share of trips by transit compared to choice.

HBW MODE	CHOICE	CAPTIVE
AUTO	83.6%	0.0%
AUTOPAX	0.0%	58.4%
WALK	3.4%	14.4%
PT_WALK	11.1%	27.2%
PT_DRIVE	1.9%	0.0%
TOTAL	100%	100%

Table 8: Home Based Work Choice & Captive Mode Split

4.1.2 Auto Assignment Metrics

Table 9 shows the baseline (2010) auto assignment metrics for the AM period for only the sub area network where DTA also applies. In the baseline scenario, static assignment returns a maximum VC equal to just over four. This extreme value reflects a single link in the network. The average of all links with volumes was only 0.16. The static versus dynamic assignments produce different metrics, with DTA metrics consistently lower than the static metrics. This result makes sense in light of the DTA method, whereby not all trips arrive during the model period.

2010	TYPE	BASE
STATIC	Volumes	14,023,798
	V/C (MAX)	4.06
	VDT	1,228,486
	VHT Static	42,087
DTA	Volumes	10,494,896
	VDT	828,954
	VHT	39,902
	Queue Total	185,173
	Block Total	74,396

Table 9: Baseline 2010: Auto Assignment Metrics – All values are Sums except V/C (Maximum).

4.1.3 Transit

Table 10 presents the transit metrics. The model predicts over 1,449,399 passengers use the different transit modes on an average day. The total number of passengers exceeds the total number of transit trips seen in Table 4 because some users transfer to other transit modes and log as a passenger again (that is, the results in Table 10 correspond to “unlinked” trips). The predicted average time for all transit rides is about 31 minutes and the average distance is about 5 miles.

METRICS	BASE
TOTAL UNLINKED PASSENGERS	1,449,399
TOTAL DIST MILES	3,599,251
TOTAL PASSENGER HOURS	207,452
AVG DIST (TOTAL DISTANCE / LINKED TRIPS) - MILES	5
AVG TIME (TOTAL TIME / LINKED TRIPS) - MINUTES	31

Table 10: Baseline Model: Basic Transit Metrics

Table 11 shows the top routes by ridership for transit. The urban rail lines carry the highest demand, with the Red, Green and Orange lines carrying at least four times the ridership of all other routes.

RANK	ROW LABELS	MIN OF MODE	SUM OF PASS_YEAR 2010
1	Red	Heavy Rail	275,114
2	Green	Light Rail	259,869
3	Orange	Heavy Rail	241,823
4	Blue	Heavy Rail	61,199
5	66	Bus	28,394
6	39	Bus	24,197
7	9	Bus	22,591
8	86	Bus	20,199
9	SILVER	Bus	32,277
10	Needham	Commuter Rail	16,756
11	111	Bus	16,046
12	Attleboro	Commuter Rail	15,674
13	Franklin	Commuter Rail	14,105
14	57	Bus	13,789
15	1	Bus	13,775
16	Framingham	Commuter Rail	13,039
17	93.2	Bus	11,766
18	88	Bus	11,540
19	96	Bus	10,673
20	71	Bus	10,207

Table 11: Baseline 2010: Top 20 Transit Routes by Ridership

Though there is variation between the MTS and the MIT-FSM outputs, I believe that the variations do not negate the value of the model. The results are reasonable and the MTS is, itself, a sample of a much larger population. Further verification using the CTPP would benefit this, and any modeling effort.

5 Inundation Assessment Analysis

5.1 Inundation Assessment Analysis Method

The Assessment Analysis utilizes ArcGIS intersection tools. A GIS intersection, or overlay, analysis is a procedure where one examines two or more geographic layers in the same spatial area to identify areas of overlap. For this analysis, this provides the ability to develop an initial understanding of inundation's impacts on transportation system performance.

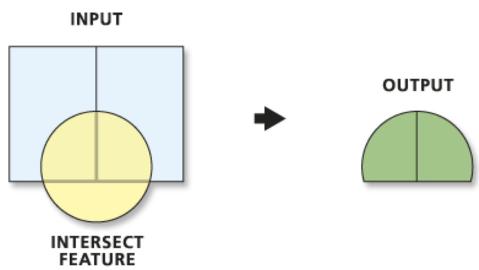

Figure 16: Intersection Analysis: Source ESRI

The simplest output of this type of analysis is the area of overlap between features, such as point information like the location of a bus stop. Line or polygon data, such as streets and parcels, can also provide information on the amount of overlap of features. This type of analysis has a long history; accuracy depends on the data available. A simple intersection analysis investigates two-dimensional space, i.e. in an X and Y or latitudinal and longitudinal plane. More advanced analysis would add a Z plane, which would generally reflect elevation. For the purposes of this research, I am interested in where transportation and transportation-related assets overlap with inundation layers. The water layers used in this analysis simulate elevation in that they reflect the XY extent of water on land given a sea level rise. But they do not reflect the actual elevation in relation to other features or assets.

My analysis is not a comprehensive inquiry into the exact spatial interaction of the modeled water layers and the real world infrastructure. Without elevation data on various assets some bridges may be marked as inundated when, in fact, they are not. For the Inundation Assessment analysis, line features have two measures of impact: the total count of features and the total length of features impacted. I present only one measure, counts, for point level data.

I conducted intersections analysis in ArcMap GIS software and in the Python programming language. ArcMap provides tools to automate and customizes GIS analysis with Python, specifically ArcPy (http://resources.arcgis.com/en/communities/python/) provides a method for accessing ArcMap analysis tools from a Python scripting environment. I created a series of Python scripts that:

- Computed the intersection between assets and the inundation layers;
- Updated the input features with attribute information to reflect whether or not a specific asset was inundated, and, where applicable, the extent of the inundation.

These scripts are available for examination and use at https://github.com/mdgis/md_scripts. The scripts output updated Shapefiles for point level intersection and DBF tables for polygon or line intersections where the extent of inundation was calculated.

Most demographic data in the region are only available at the zonal level. I used a proportional split procedure to estimate the impact of inundation on demographic data. A proportional split determines the percentage of shared area between overlapping zones (TAZs) and water areas and then applies this percentage to the demographic data. This method assumes that the demographic data (Jobs, People, Households) are distributed uniformly across space.

5.1.1 Inundation Assessment Data

The Boston metropolitan region has a wealth of data readily available for use in GIS. Demographic data include population, households and jobs. I also use land uses because, while the MIT-FSM does not include actual land use as an input (see Four Step Transportation Modeling (FSM) Methods and Software], the data are available and of interest to planners and policy makers. I also include data on transit and road infrastructure and the CUBE highway network.

The types of data selected for such analysis depends upon the specific question. This type of analysis could focus on, for example, health care access, or sidewalks, or pipelines, etc. Some open source websites have begun automating and disseminating this form of analysis for coastal cities in the United States (climatecentral.org).

5.1.2 Cube Road Network

Road network links are generally very short, so a basic intersection is relatively accurate for links located on land. I processed the inundation layers to remove existing water areas in an attempt to increase the accuracy of inundation estimates. I "cleaned" inundation layers to remove sections that covered preexisting water; that is, a simple intersection would identify bridges over water and tunnels below the water as being inundated. I further inspected the Cube Voyager model networks manually and marked bridges and tunnels as inundated only if the connecting land-based link (e.g., ramp) was inundated. I use the road network overlaid on aerial photos to visually identify tunnel entrances, as no GIS Shapefiles existed for this feature.

5.2 Inundation Assessment Results

5.2.1 Introduction

As described in the previous section, I intersected many transportation-specific or transportation-related geographic information system layers with each of the six inundation layers. I now present the results of this analysis, grouping the impacts into broad categories: Demographic; Transit; Highway & Roads; and Land & Land Use. I then present the results of the accessibility analysis.

5.2.2 Demographic Impacts

Demographic data come from the census transportation planning products (CTPP), aggregated to the Traffic Analysis Zones (TAZs) used by the Cube Voyager model.

5.2.2.1 TAZ Impacts

The total area of inundation by TAZ for each inundation level provides a baseline understanding of inflection points across the different inundation levels. For example, at a large increase in inundated land at the three-foot level we would expect a relative increase in inundated workers at that same level. This analysis may highlight specific areas of impact or critical levels of inundation with a disproportionately larger impact compared to the TAZ area. Figure 17 shows a fairly linear increase in inundated areas, with slight changes at two feet, four feet and five feet. The amount of land inundated ranges from ~50 square miles to ~92 square miles. Figure 18 shows the inundation layers overlaid onto TAZs. Table 12 presents the total number of inundated TAZs.

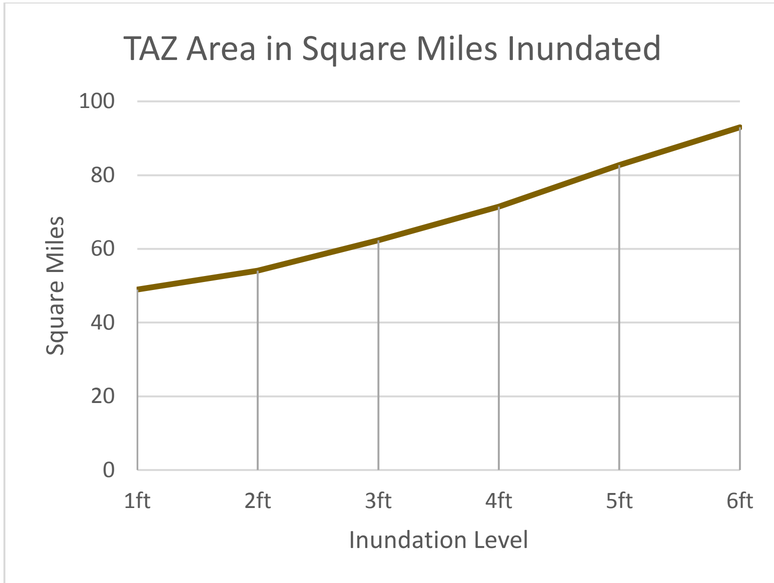

Figure 17: TAZ Area

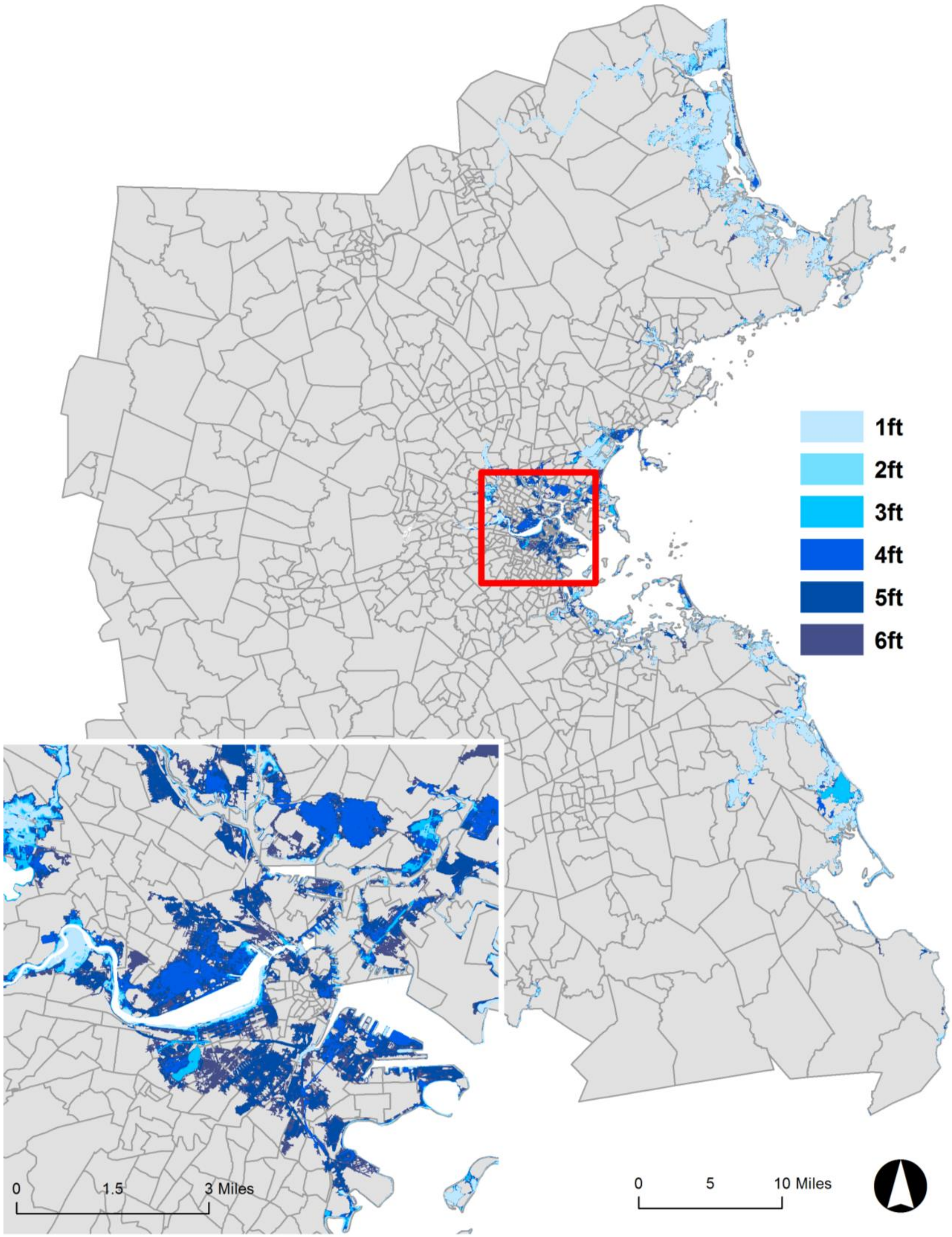

Figure 18: One Foot and Six Foot Inundation TAZs

At the one-foot level, 232 TAZs are inundated. Not surprisingly, the majority of the TAZs initially inundated at some level are along the coastline.

INUNDATION LEVEL	NUMBER OF TAZS
1FT	232
2FT	234
3FT	251
4FT	279
5FT	322
6FT	338

Table 12: Number of Inundated TAZs

I analyze the extent of the inundation and estimate the quantities likely impacted, but not the actual physical impacts to these areas. Flooding can cause enormous and divergent damage to homes, infrastructure, businesses and the environment. The calculation and quantification of such effects are beyond the scope of this work. Instead, I simply account for the people, jobs, roads, and transit infrastructure in these areas in order to assess effects on the overall accessibility of the modeled area.

5.2.2.2 Population & Households

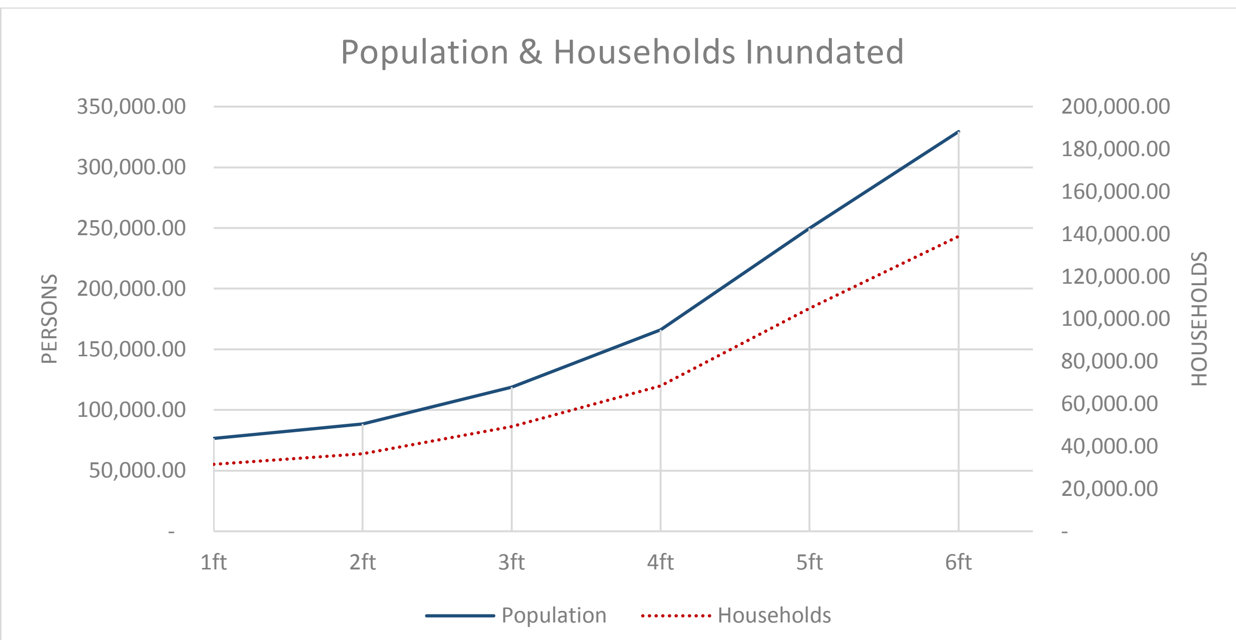

Figure 19: Population and Households by Inundation Level

The number of impacted persons and households (Figure 19) increases almost linearly, with only a slight upward increase until the four-foot scenario. At this point, there is marked change in the number of people impacted that continues to increase through the six-foot scenario. Unfortunately, we do not know the exact distribution of persons and households in a given TAZ, but in the densely settled areas in the inner core, the proportional split assumption is more reasonable. The rate of increase for population is slightly higher than that of households, but the overall trend is similar. Of model area total population of 4,457,779, 7.3% is impacted at the six-foot level is 7.3%. At this level, 8.6% of the model area households is impacted.

5.2.2.3 Total Jobs & Jobs by Sector

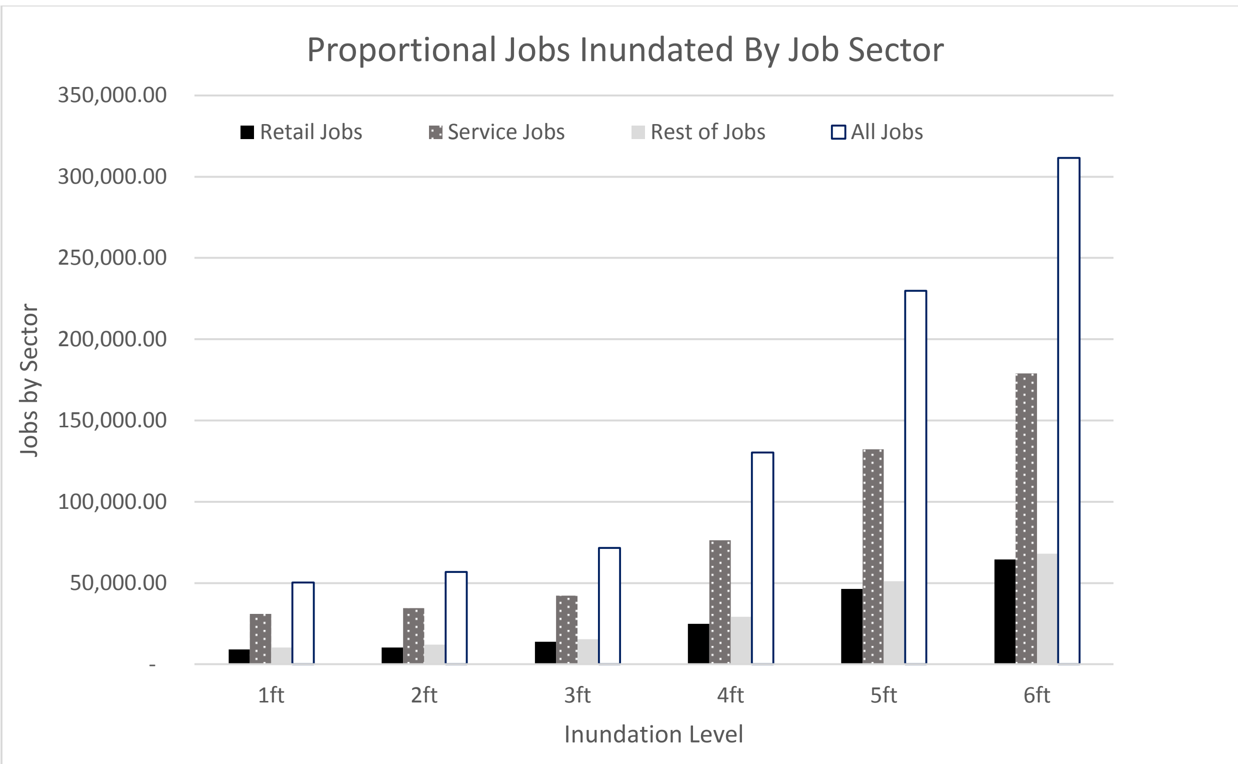

Figure 20: Proportion of Inundated Jobs by Sector

In Figure 20, the total number of jobs impacted has two inflection points: at the three-foot level and at the four-foot level. Similar to population and households, the four-foot inundation scenario marks the point of the greatest change of slope. After the four-foot level, the increase appears to continue linearly. There are no clear differences in impact across the different job sectors.

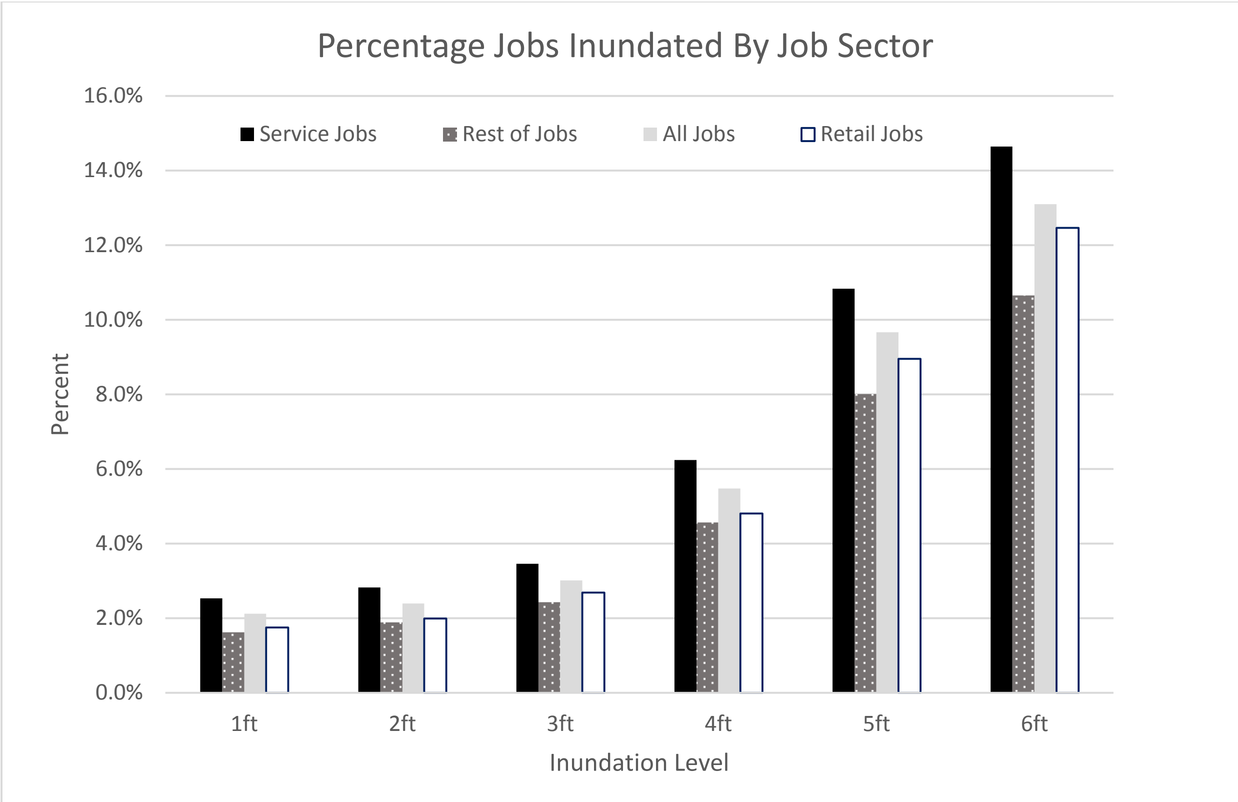

Figure 21: Percentage of Jobs Inundated by Sector

Figure 21 shows the proportional impact of inundation levels on jobs by sector. Inundation impacts service jobs more than any other job type and more than all jobs combined, which should be concerning given the importance of service jobs to the modern American economy.

Job categorizations are necessary for the travel demand model and influence the rates of production and attraction of a given zone. The model areas has about 2.4 million jobs and at the six-foot scenario, nearly 13 percent of them are in areas impacted by inundation. This highlights the importance of the inner core area as an economic and job center of the region.

5.2.2.4 InfoUSA Firms and Jobs

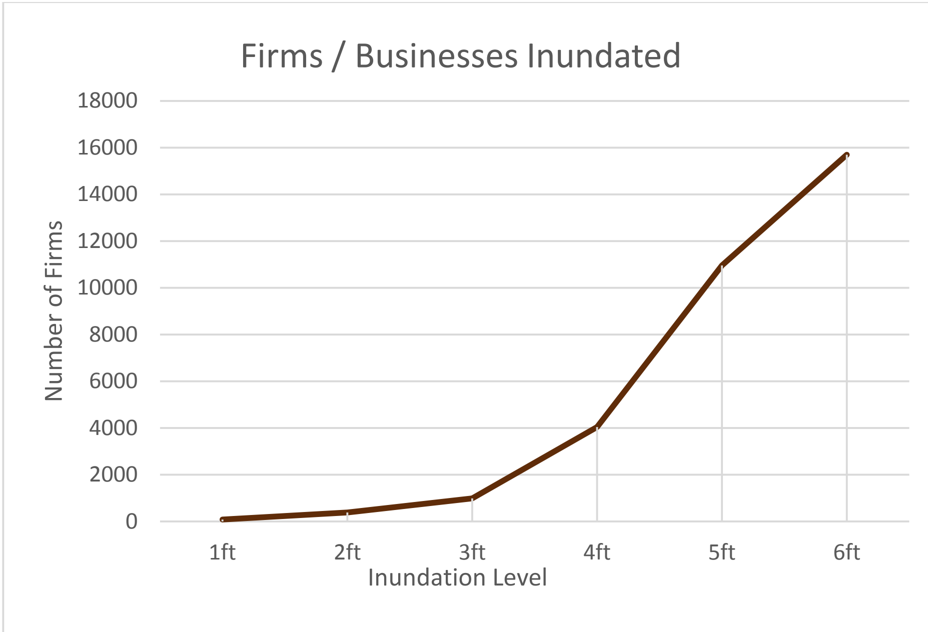

Figure 22: InfoUSA Firms and Jobs

InfoUSA Business/Firm data provides information on the location of businesses in the Boston Metro region. Although these data are not used in the four step model, I include them here because they provide an opportunity to examine specific point-level impacts (as the firm data have geo-located addresses or latitude/longitude coordinates) and provide an alternative estimate of job totals in the region. The firm data reveal the same inflection point as the jobs data at the four-foot inundation level, however far fewer firms are impacted compared to jobs. The number of firms impacted firms remains quite low until the three-foot level. Several explanations exist for this difference relative to the jobs data: the point level data may represent locations inconsistent with the proportional split assumption for the zonal data; the relatively few firms impacted at low inundation levels may have a large number of jobs; and/or the InfoUSA may inaccurately represent the firm population (presuming the CTPP-based job data are more accurate).

The InfoUSA data provide estimated employment. Some of these values were estimated by calling actual businesses and inquiring about the total number of employees; and others come from proprietary statistical models not available to users. As a result, the data come from something of a "black box" in terms of quantifying employment. Nevertheless, its geographic precision (more than

80% of the observations locatable at the street block level) provides an interesting comparison to the zonal based data.

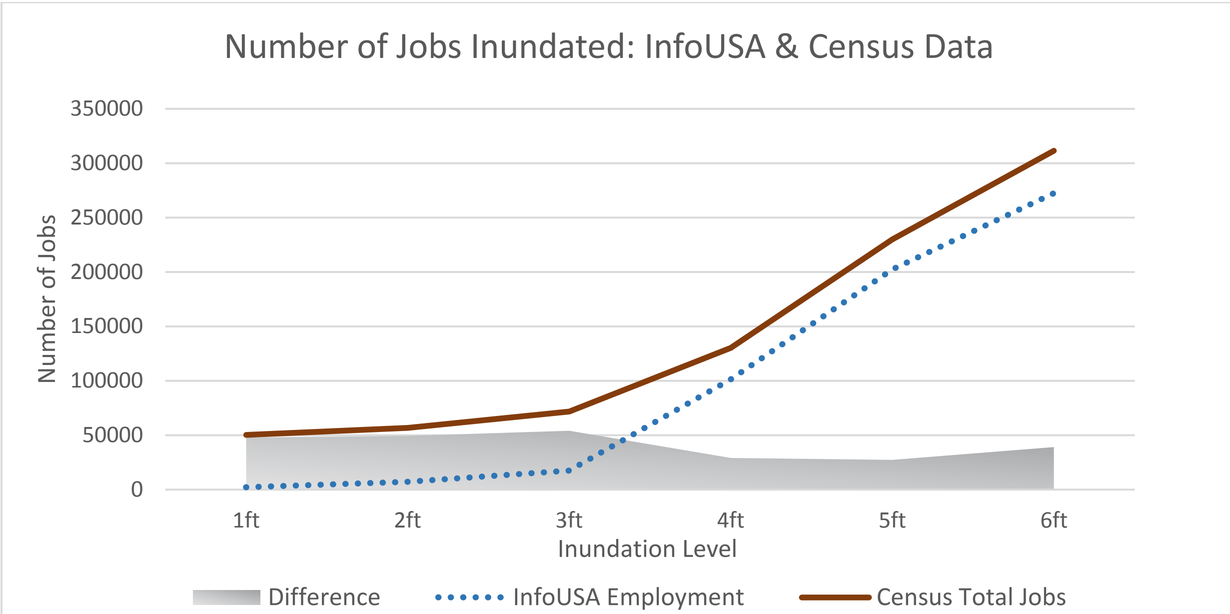

Figure 23: InfoUSA vs. Census Employment Data

Figure 23 shows noticeable differences in the total number of jobs impacted according to the InfoUSA data versus the CTPP data. The magnitude of the difference does decrease with the increase in inundation level. This may reflect the disaggregate locations of the InfoUSA data and the inaccuracies of the proportional split method at lower inundation levels. Such a finding highlights the need for data with a higher degree of spatial precision to more accurately estimate potential inundation impacts. As the inundation level increases and the proportion of the TAZ inundated approaches 100%, the numbers begin to converge. Figure 24 shows the boundaries of select TAZs in yellow: the left side has inundation levels from one-foot to three-foot; the right side has the inundation levels from four-foot to six-foot. The red squares are approximate InfoUSA firm locations, reflecting a general clustering near blocks of buildings. One can see that the areas of TAZ inundation in the one-foot to three-foot scenarios generally do not intersect actual buildings. The higher inundation scenarios inundate the majority of the TAZs and the firms. This supports the hypothesis that the proportional inundation method poses some inaccuracies in estimating the number of jobs and people impacted at a given sea level rise.

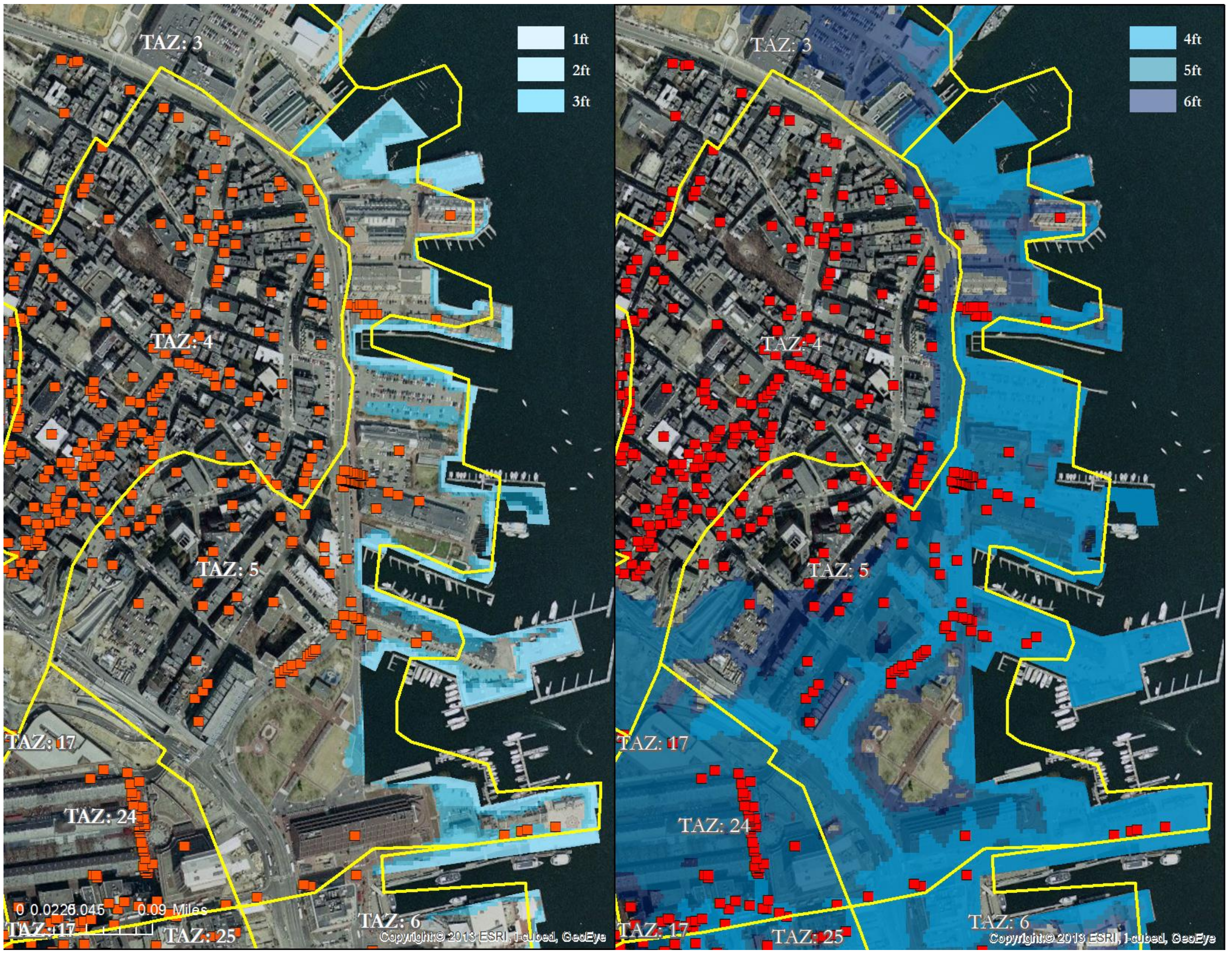

Figure 24: InfoUSA Firm Location

5.2.3 Transit System Impacts

The transit system is highly vulnerable to inundation: heavy rail lines utilize electric rails and tunnels in the center of the city can be flooded or, at very least, deemed inoperable in an inundation scenario. Furthermore, the extensive bus system faces the problem of flooded streets and stops that can compromise the provision of service. In addition, inundation can impact maintenance facilities, depots, power stations, etc. in uncertain ways. This latter uncertainty is not considered in this work. Nevertheless, the intersection analysis does provide some interesting insights into the possible impacts on performance of the transit system given different inundation levels.

5.2.3.1 Urban Rail Stations

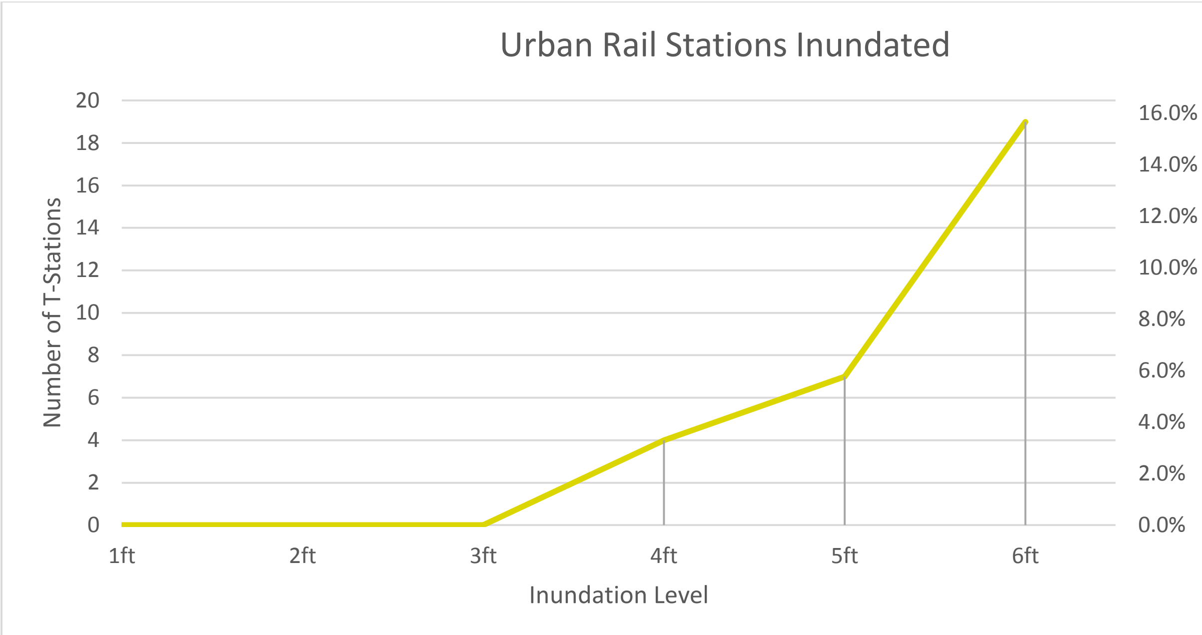

Figure 25: Number of Inundated Transit Stops

Figure 25 shows that inundation does not affect transit stations until the four-foot inundation scenario, where four stations are inundated. The five-foot inundation impacts three additional stations. At the six-foot level, the number of stations impacted nearly triples from the five-foot level. The total number of stations does not directly relate to total impact, however, since some of the inundated stations are major destinations, origins and transfer points.

Table 13 shows the levels at which different stations are inundated, together with their estimated 2013 ridership and ridership rank (MBTA, 2014). Among these, three stations merit highlighting: North Station, a major commuter rail transfer hub; Copley Square, a major shopping and business area; and Kendall/MIT. Two of the Green Line stations cannot be ranked because they are surface stations with rough approximation of boardings due to the lack of a fixed fare collection system. No data ridership data were available for Assembly Square, on the Orange Line, since the station opened relatively in 2014.

Line	Station Name	2013 Ridership	Rank	Inundation Level
Blue Total = 6	Airport	7429	29	6ft
	Aquarium	4776	45	4ft
	Orient Heights	2833	53	4ft
	Revere Beach	3197	51	4ft
	Wonderland	6105	38	6ft
	Wood Island	2507	54	5ft
GREEN Total = 5	Arlington	8655	27	6ft
	Copley	14021	10	6ft
	Northeastern	2650	NA	6ft
	Prudential	3643	49	6ft
	Saint Mary's Street	1532	NA	6ft
GREEN/ORANGE	North Station	17079	6	6ft
ORANGE Total = 4	Assembly	NA	NA	6ft
	Community College	4956	43	6ft
	Massachusetts Ave	6417	36	6ft
	Ruggles	10433	18	6ft
RED Total = 3	Alewife	11221	16	5ft
	Kendall/MIT	15433	8	4ft
	North Quincy	6975	30	5ft

Table 13: MBTA Station Boardings - Source MBTA Bluebook 2014

Figure 26 shows the locations of specific stations listed in Table 13, along with the four-foot and six-foot inundation levels. The shape of the station label icon indicates the level at which it is first inundated.

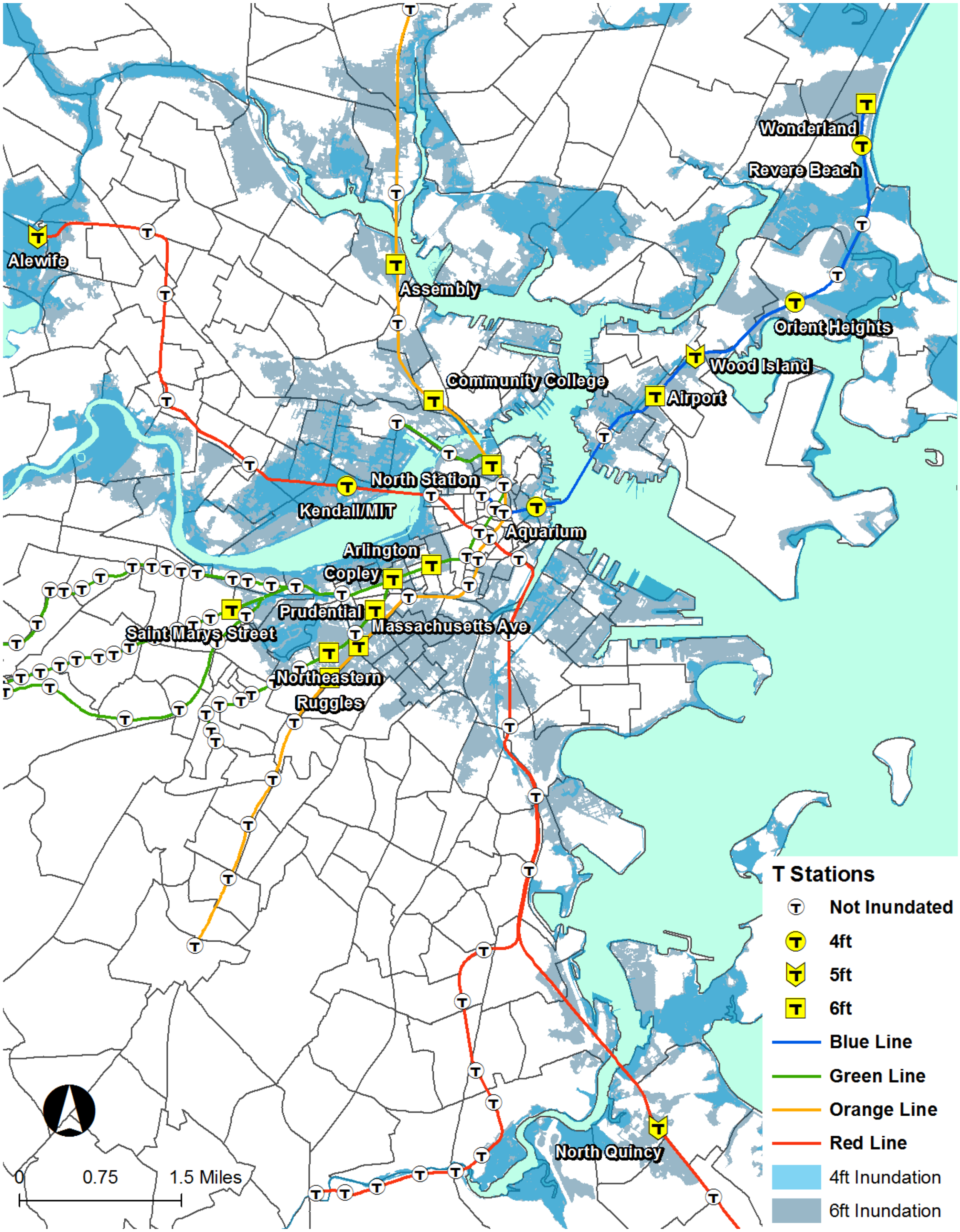

Figure 26: Location of Inundated Urban Rail (T) Stations

5.2.3.2 Urban Rail Lines

As in the roadway case, the inundation assessment initially identifies some section of each of the main four urban rail lines as inundated, even at baseline "no inundation." This is because the baseline NOAA water layer intersects line segments which cross rivers (notably the Charles River). I processed the layers to remove such areas.

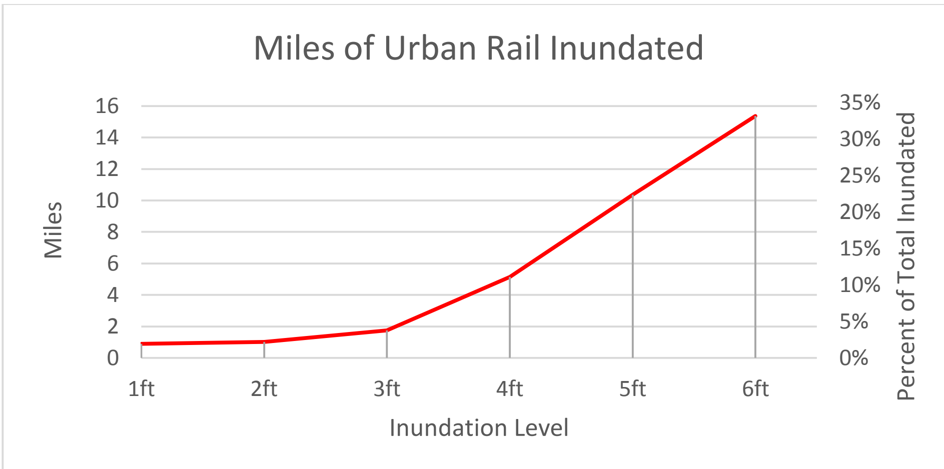

Figure 27 Percent Miles of Urban Rail Inundated

Similar to those seen in the previous inundation charts, the impacts at the one-foot and two-foot levels are rather small with a modest slope up to three feet of inundation. At the one-foot to three-foot levels, the share of total line length inundated goes from two to 4.5 percent. Though these numbers are small, if a rail line is compromised at any section, the length of the route can no longer be completed and the whole line itself may be deemed inoperable. The modeling exercise will shed more light on the impact on specific lines. At the four-foot level, we see a marked increase that continues almost linearly up to the six-foot inundation level.

Figure 28 demonstrates the difference between the miles of inundation by line and Figure 29 shows the percentage of inundation by line. In terms of miles of inundation, the Red Line is the most impacted with nearly five miles of line inundated at the six feet scenario. In terms of percentage, the Blue line is the highest with about 70 percent of the line inundated at the same scenario. Again, these results inform our expectations about accessibility impacts in the subsequent analysis. Major impacts to transit links directly contribute to drops in accessibility to the TAZs these links serve.

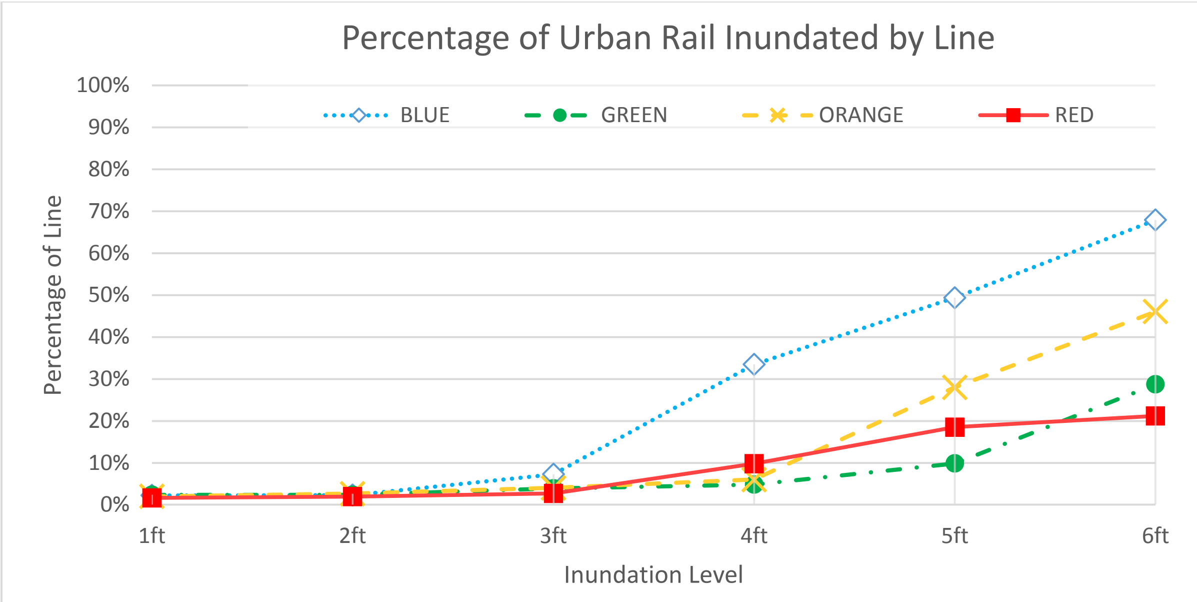

Figure 28: Percentage of Urban Rail Inundated by Line

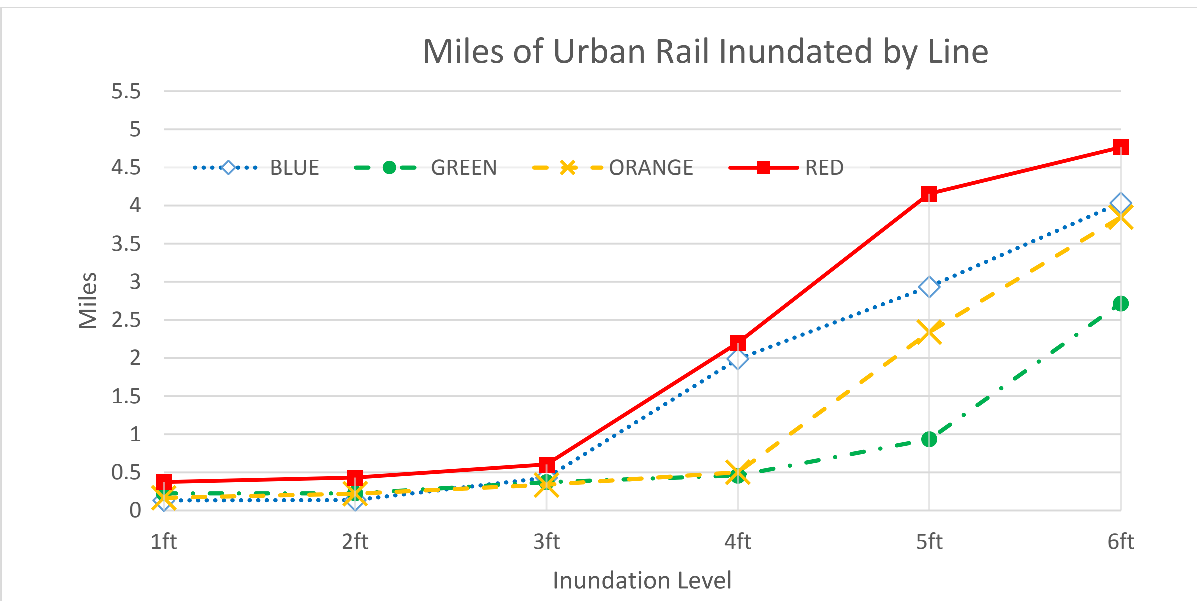

Figure 29: Miles of Urban Rail Inundated By Line

5.2.3.3 Bus Stops and Lines

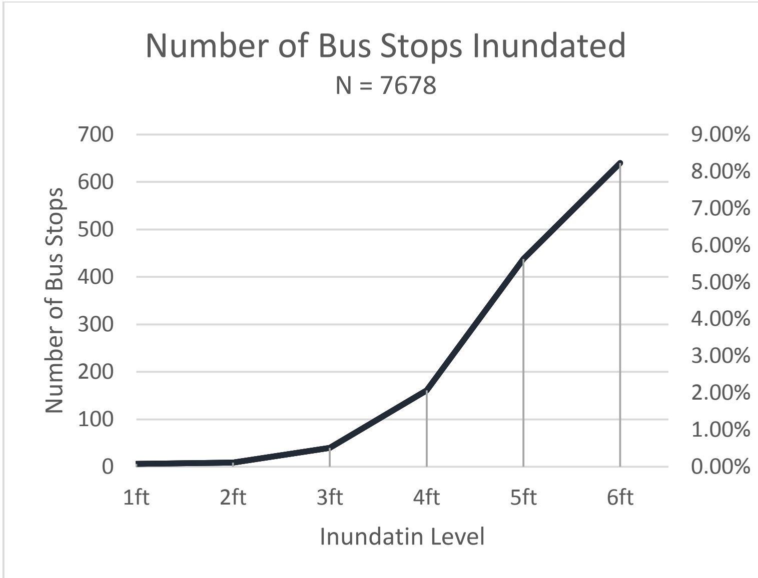

Figure 30: Number of MBTA Bus Stops Inundated

The MBTA bus stop Shapefiles include a point for each stop, including stops for routes traveling in different directions but on the same street. There are 7,678 bus stops in the region. Following the patterns seen for the other transport infrastructures, impacts start low at the one-foot to three-foot, increasing markedly at the four-foot level (Figure 30).

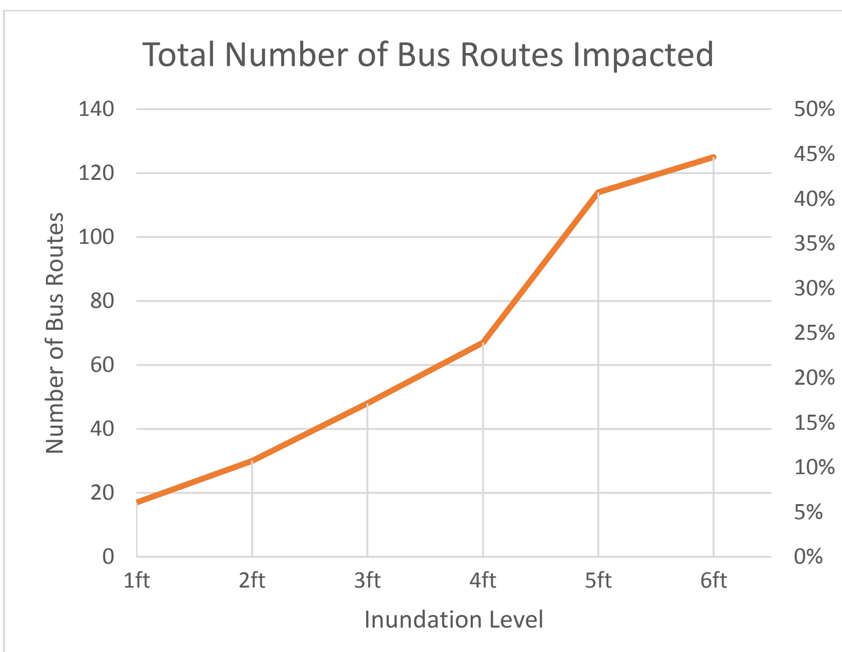

Figure 31: Total Number of Bus Routes Inundated

The total number of bus routes impacted (Figure 31) is quite high, even from the first inundation level. This is likely due to two reasons: one, these routes operate on roadways possibly inundated at very low levels, and two, the routes may simply be marked as inundated because they cross preexisting waterways over bridges or roads at a higher elevation. Though I did carefully assess the inundation impacts to attempt to clean out inaccurate inundation data, I could not eliminate all of it. I prefer to examine the total length of inundation across scenarios for a more accurate understanding of the impacts.

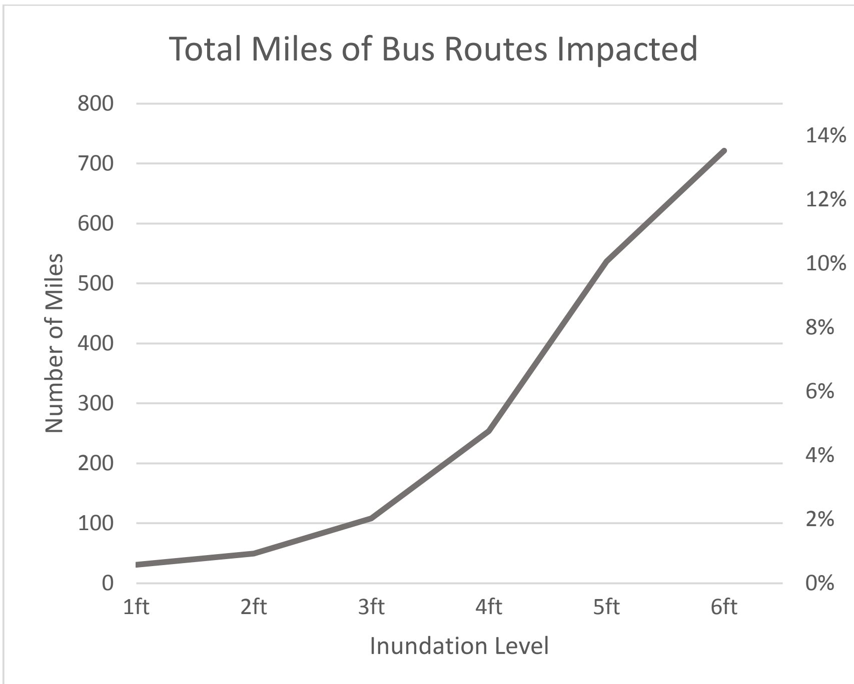

Figure 32: Total Miles of Bus Routes Inundated

Figure 32 displays total miles of MBTA bus routes inundated. Inundation impacts about 25 miles of routes in the one-foot scenario. By the six-foot level, inundation impacts over 700 miles of routes, which would substantially affect bus operations. The bus route Shapefiles include a separate line layer for each route direction as well as for each route that crosses the same area of roadway. Therefore, if an inundated link has many buses running across it in both directions, the total miles of routes impacted will increase quickly. This could imply major service impacts, although buses could possibly detour around specific links to continue operation.

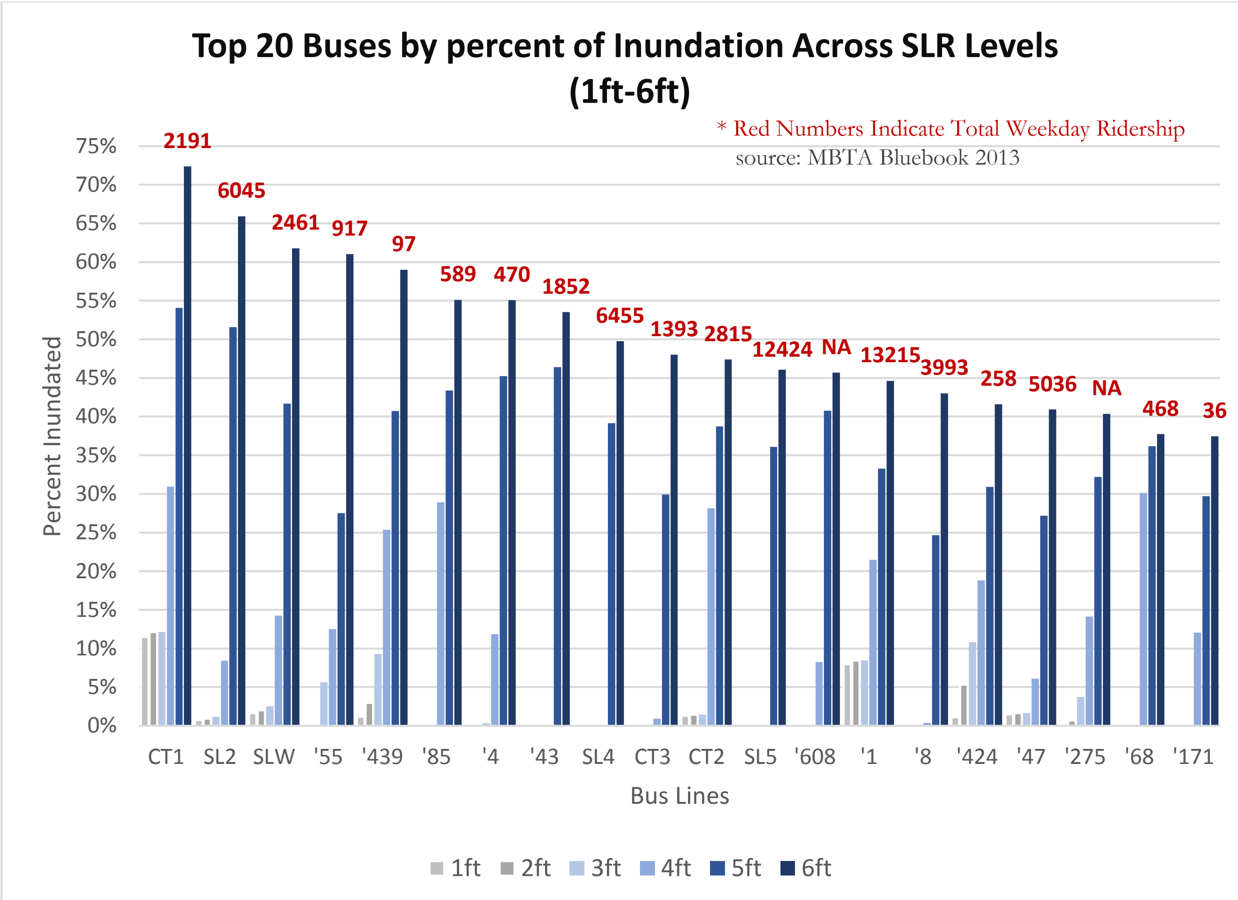

Figure 33: Top 20 Buses Based on Percentage of Inundation at Six Foot Scenario

Figure 33 shows the 20 bus routes with the highest shares of their length inundated at the six-foot scenario as well as their shares inundated at all other inundation scenarios. The routes with the highest ridership are the 1, SL2, 46, and SL4. With at least 35 percent of their routes inundated at six feet, the routes presented in Figure 33 could not likely make simple adjustments to avoid inundated links.

Some of the routes in Figure 33 have very low ridership, so while they may be disabled at high inundation, the service impacts may be relatively modest. To identify those bus routes with both high total ridership and high impacts due to inundation, Table 14 presents the 20 bus routes with the highest ridership along with their share of route miles impacted at different inundation levels.

TOP 20 ROUTES BY RIDERSHIP AND PERCENTAGE OF INUNDATION

RANK	Route	Ridership	1ft	2ft	3ft	4ft	5ft	6ft
1	39	14877	0.0%	0.0%	0.0%	0.0%	2.4%	25.5%
2	28	14057	0.1%	0.1%	0.1%	0.1%	0.1%	0.7%
3	66	13933	0.8%	0.9%	1.0%	5.5%	11.9%	13.0%
4	1	13214	8.0%	8.4%	8.4%	21.5%	33.3%	44.6%
5	23	12527	0.0%	0.0%	0.0%	0.0%	0.0%	0.6%
6	SL5	12406	0.0%	0.0%	0.0%	0.0%	36.1%	46.1%
7	111	12133	3.6%	3.8%	5.0%	7.1%	17.3%	21.1%
8	32	11020	0.0%	0.0%	0.0%	0.1%	0.1%	0.1%
9	57	10094	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%
10	22	8656	0.0%	0.0%	0.0%	0.0%	0.0%	0.8%
11	77	7799	0.1%	0.2%	0.2%	0.7%	1.7%	3.2%
12	9	6604	0.4%	0.4%	0.4%	0.6%	8.8%	22.1%
13	SL4	64444	0.0%	0.0%	0.0%	0.0%	39.2%	49.7%
14	73	6424	0.0%	0.0%	4.0%	5.5%	6.0%	6.3%
15	31	6405	0.2%	0.3%	0.3%	0.3%	0.3%	0.4%
16	15	6309	0.0%	0.0%	0.0%	0.0%	0.0%	0.9%
17	116	6054	2.3%	2.3%	2.3%	3.3%	8.0%	21.5%
18	SL2	6045	0.7%	0.9%	1.2%	8.4%	51.6%	65.9%
19	SL1	6001	0.4%	0.6%	0.7%	11.8%	25.3%	32.9%
20	86	5618	0.8%	0.8%	0.9%	5.1%	12.3%	15.4%

Table 14: Top 20 Bus Routes by Ridership and Percentage of Inundation by Inundation Level

All of the 20 high ridership routes have some level of inundation at the six-foot scenario and slightly over half of them have a percentage of inundation greater than 45 percent. Route 39, which has the highest ridership in the system, has only minor inundation at the five-foot level, but has a 25 percent of its route miles inundated at six feet. Considering these impacts together with those on the urban rail system, we can expect inundation will result in major impacts to transit system operations and to users' abilities to reach destinations by transit.

5.2.3.4 Commuter Rail Stops

STATION	SERVICE	1FT	2FT	3FT	4FT	5FT	6FT
BACK BAY	Commuter Rail & Amtrak	0	0	0	0	1	1
CHELSEA	Commuter Rail	0	0	0	1	1	1
JFK/UMASS	Commuter Rail	0	0	0	0	1	1
MANCHESTER	Commuter Rail	0	0	0	0	0	1
NEW BEDFORD	Proposed	0	0	0	1	1	1
NORTH STATION	Commuter Rail & Amtrak	0	0	0	0	1	1
RIVER WORKS	Commuter Rail	0	0	0	0	0	1
RUGGLES	Commuter Rail	0	0	0	0	0	1
WAREHAM (P)	Proposed	0	0	0	0	0	1
YAWKEY	Commuter Rail	0	0	0	0	1	1
TOTAL	--	**0**	**0**	**0**	**2**	**6**	**10**

Table 15: Commuter Rail Stops

Analysis of the commuter rail stops (Table 15) reveal patterns quite similar to the urban rail, with no impact until the four-foot inundation scenario. The total number of impacted stops across all scenarios remains relatively low: ten out of the 139 existing commuter rail stops. Many of the commuter rail lines service areas more inland, which contributes to the lower level of impacted stops. Note, however, that all commuter rail services converge on two downtown stations, North and South Station. North Station is inundated at the six-foot water level. South Station is not inundated at any of the examined inundation levels. Rail Lines connecting to these stations do suffer inundation at lower water levels which would likely severely affect operations for the entire lines. Table 15 shows the name of station, type of service available, and level at which inundated (marked with a one if inundated and zero if not).

The length of passenger line miles has minimal inundation at lower levels but reaches almost 90 miles (32 percent) at the six-foot scenario. The rail line file includes a line for each rail line in both directions, similar to the bus line file. Therefore, the actual rail right of way, in terms of a two-way direction, is probably less than half of this. Nonetheless, clearly many passenger rail routes would be impacted heavily.

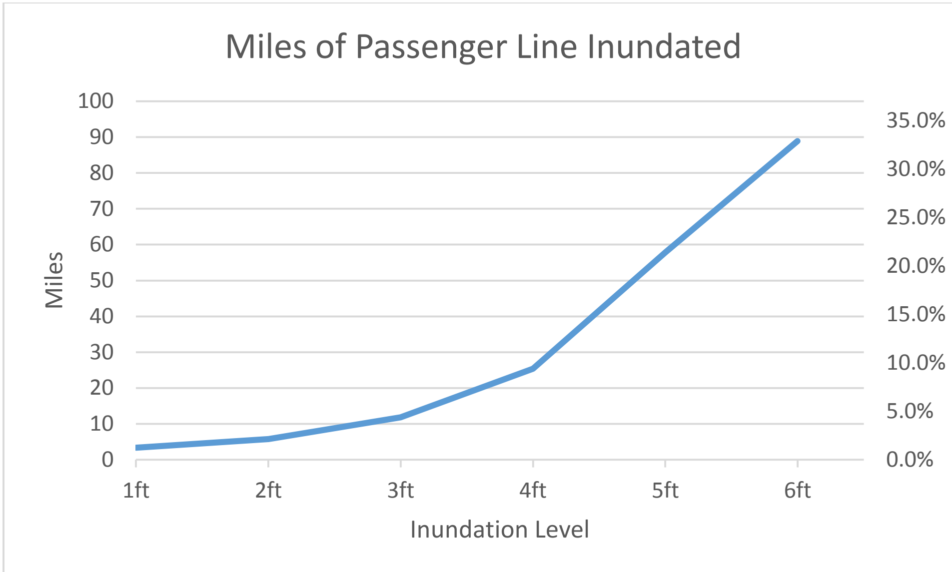

Figure 34: Miles of Passenger Rail Lines Inundated

Figure 35 shows the inundation level across different rail line segments and the routes that use these segments. The Newburyport-Rockport (NEW-ROC) line has the highest inundation after the four-foot scenario. This line uses the Beverly station, the 3rd highest station in terms of inbound boardings. The line with the highest ridership is the ATT-STO+FRANK+NEE line, which links to Providence. This line actually follows a relatively inland route and inundation does not notably affect it until the five-foot and six-foot scenarios. The Framingham-Worcester Line has the second highest ridership after Providence and it has a similar level of inundation. Since this is an inland route, its main inundation area is at South Station. Such a line could possibly continue to be utilized in inundation conditions by terminating at earlier stops, infrastructure conditions permitting. The Lowell line, also a major route, has minimal inundation across all scenarios. Figure 36 shows the percentage of miles inundated by each route segment.

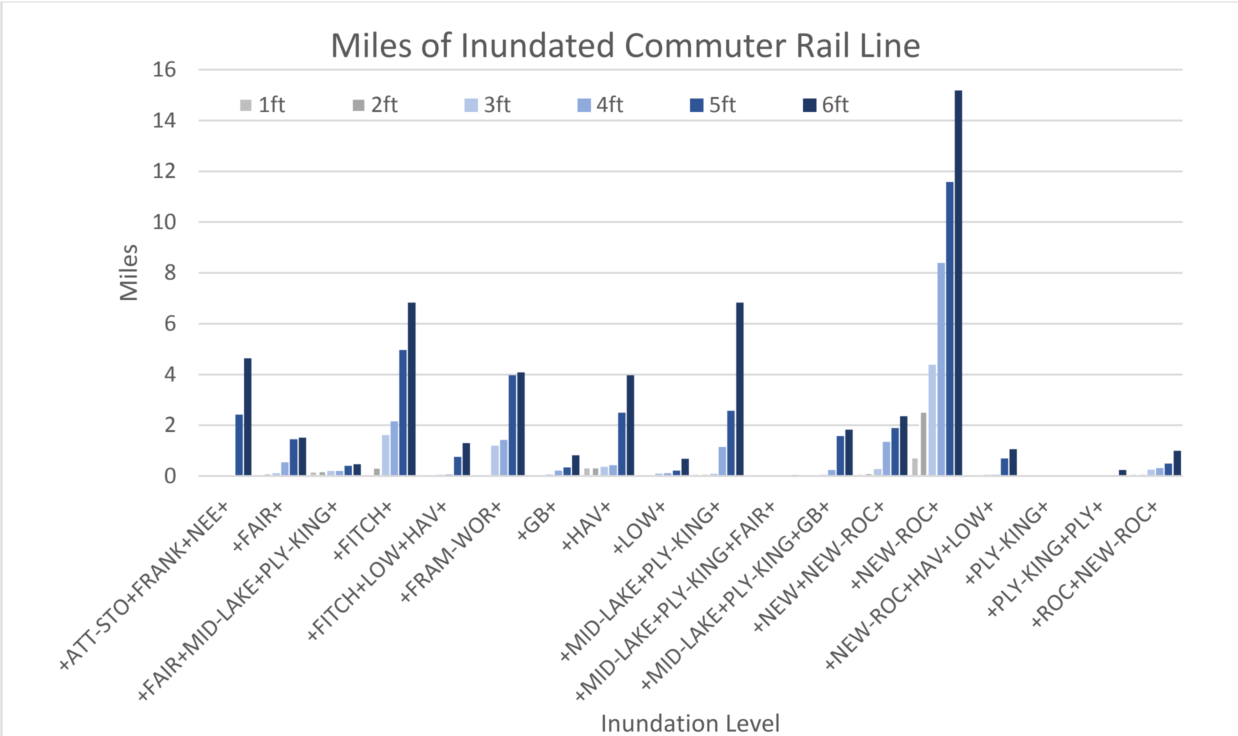

Figure 35: Miles of Inundated Commuter Rail Line by Segment

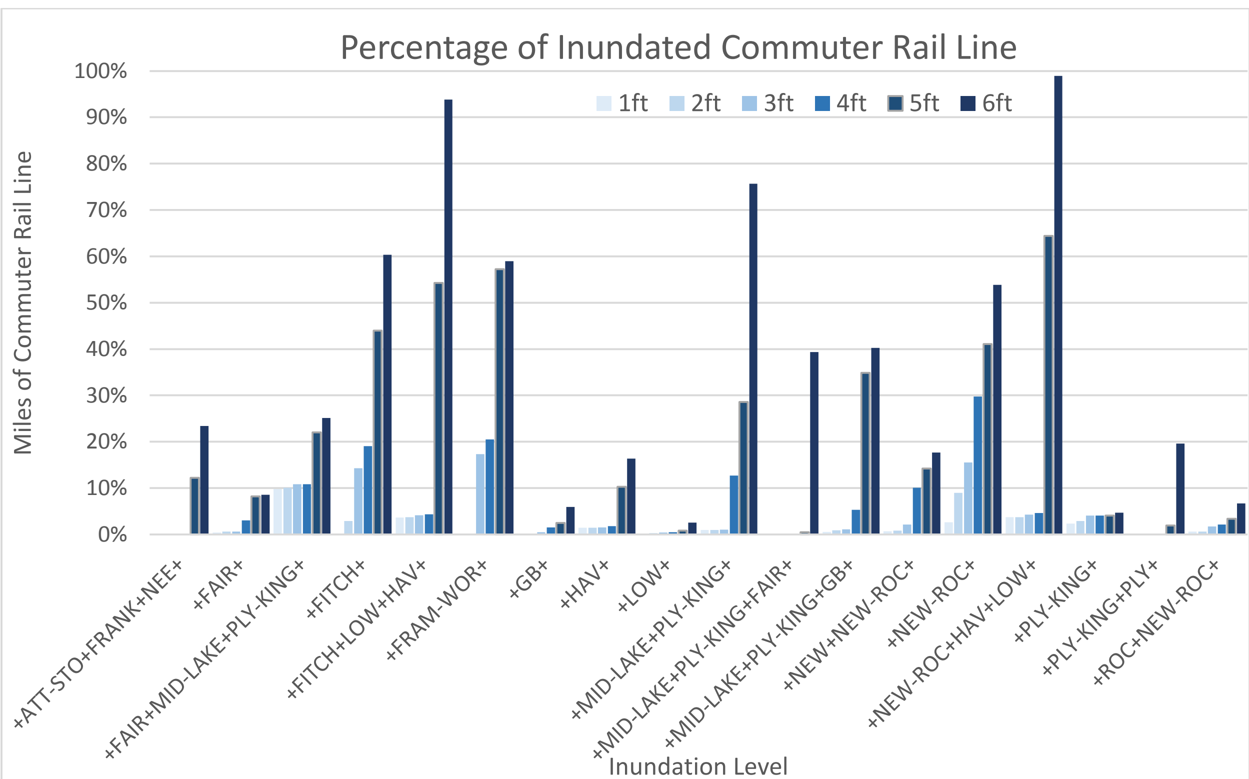

Figure 36: Percentage of Inundation by Commuter Rail Line

5.2.3.5 Freight

The total rail freight miles inundated is not as substantial as passenger rail miles, part because there are fewer total freight lines. Although I do not account for freight transportation in the subsequent analysis (the MIT-FSM currently does not include freight operations), freight impacts would be important to the region's commerce and for access to goods. At the six-foot level, inundation affects nearly 52 miles of freight line. Further modeling and analysis of freight impacts under inundation events would be an important extension to this work.

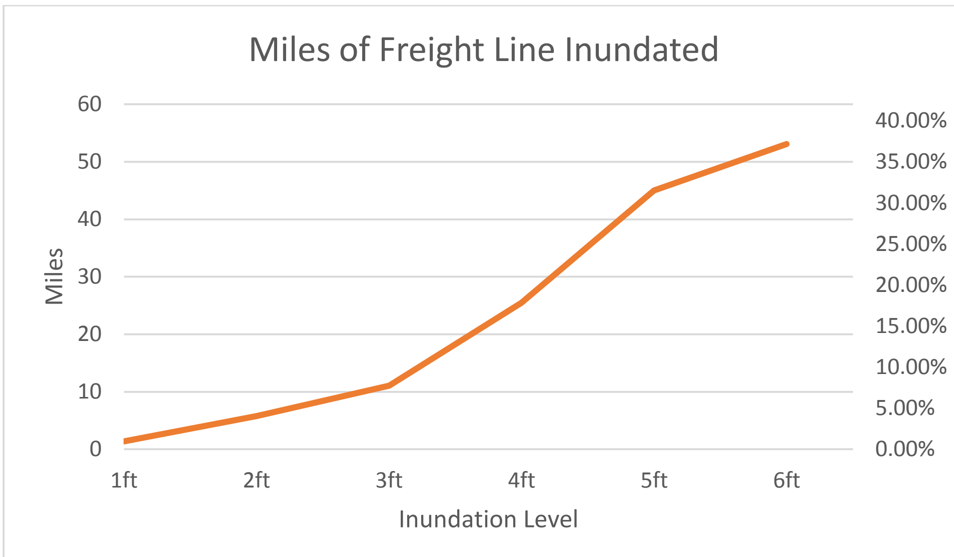

Figure 37: Miles of Freight Line Inundated

5.2.4 Road and Highway Impacts

Inundation of roads and highways will have the largest impact on transportation system performance and accessibility of the area's residents to possible destinations. Pedestrians, private vehicles, trucks, and transit buses use the road network. The Boston Metro region has a very dense transportation network that likely possesses a high degree of redundancy in terms of connections between areas; nonetheless, some links, including tunnels and major highways, are likely critical. I will discuss this in more depth in the accessibility analysis and in the Impact Assessment Modeling exercise, where I model the reaction of transportation system users to the inundation-altered network. Additionally, I identify links and groups of links that have increased utilization in response to degradation elsewhere in the network. For now, this brief discussion of the road network inundation highlights the level of inundation and assists in forming expectations of consequences. For this analysis, I use a road layer that does not have multiple links representing different direction of a street; instead, separated roadways have multiple links.

5.2.4.1 Roads

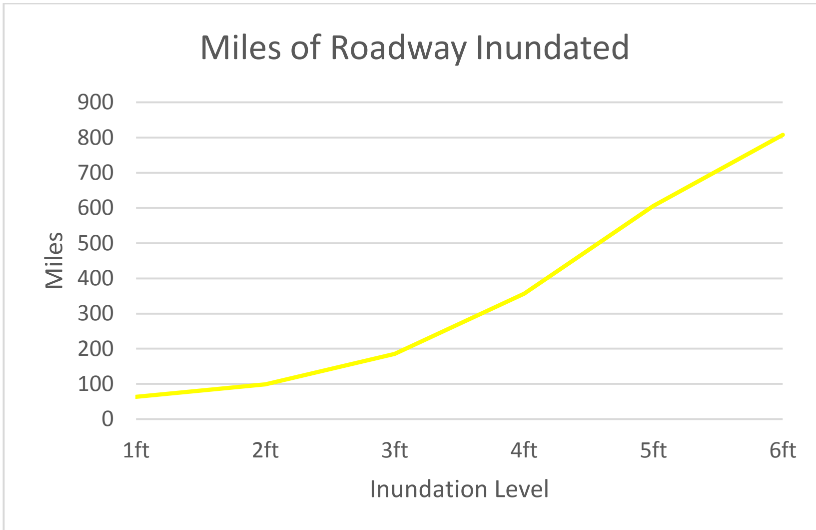

Figure 38: Miles of Roadway Inundated

At the initial one-foot inundation level, close to 80 miles of roadways are inundated, to some degree. The main inflection point appears at the three-foot to four-foot inundation level, simlar to the transit assets analyzed. Ultimately at six-foot inundation, about 800 of the model areas 24,577 miles of roadway are inundated. Though this represents only about 3.2 percent of the total roadway miles, it includes the main connector streets to the inner core of Boston, the region's hub. The hub is also home to most of the tunnels in the region, which are particularly vulnerable. Figure 39 presents the total percentage of inundation for different road types in the model region. Tunnels have, by far, the highest inundation at 62 percent in the six-foot scenario. The second highest percentage of inundation occurs with Multi-Lane Highways, suffering a much smaller percentage of inundation, only about 13 percent in the six-foot scenario.

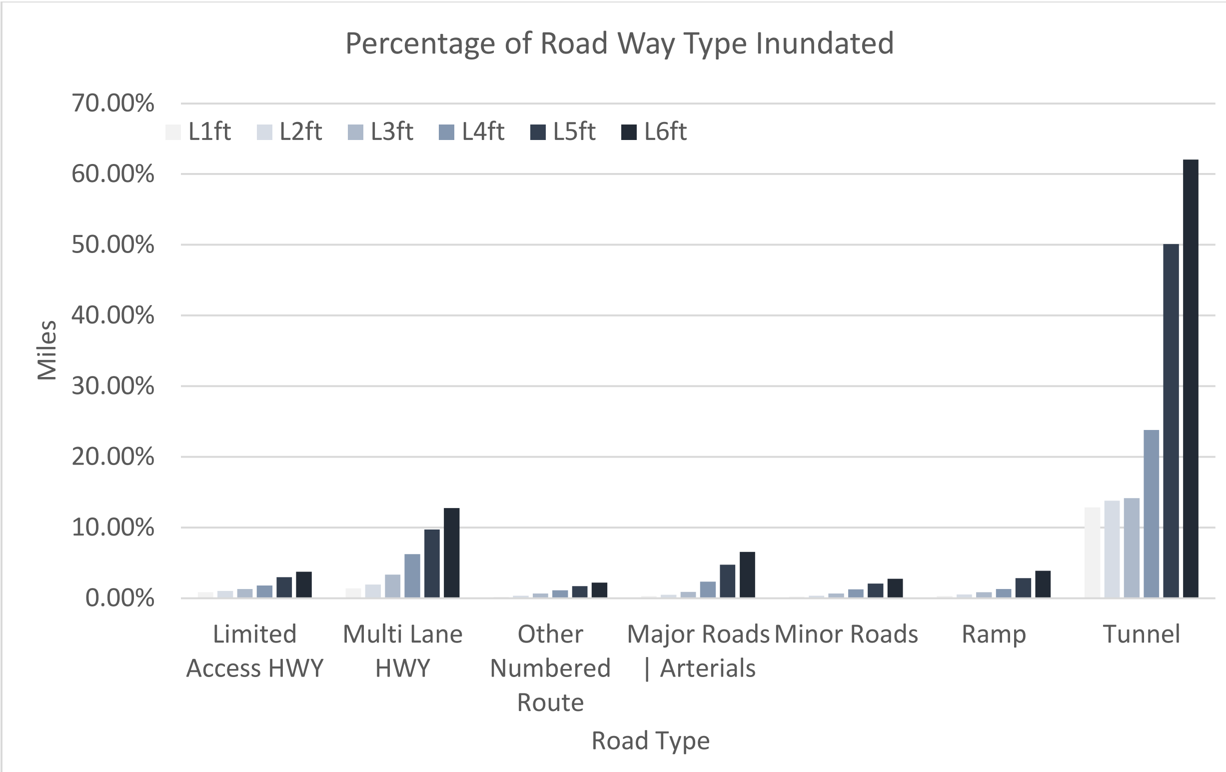

Figure 39: Percentage of Road by Type Inundated

Analyzing the inundation points for tunnels proved challenging. I assumed that once an inundation layer encompasses the entrance to the tunnel, the tunnel is compromised. This may underestimate the total length of inundated road-miles, sine the length of the tunnel link that previously passed under water is correspondingly inundated but not counted as such in the intersection analysis. Figure 41 shows the highways, major roads and tunnels in the Boston CBD.

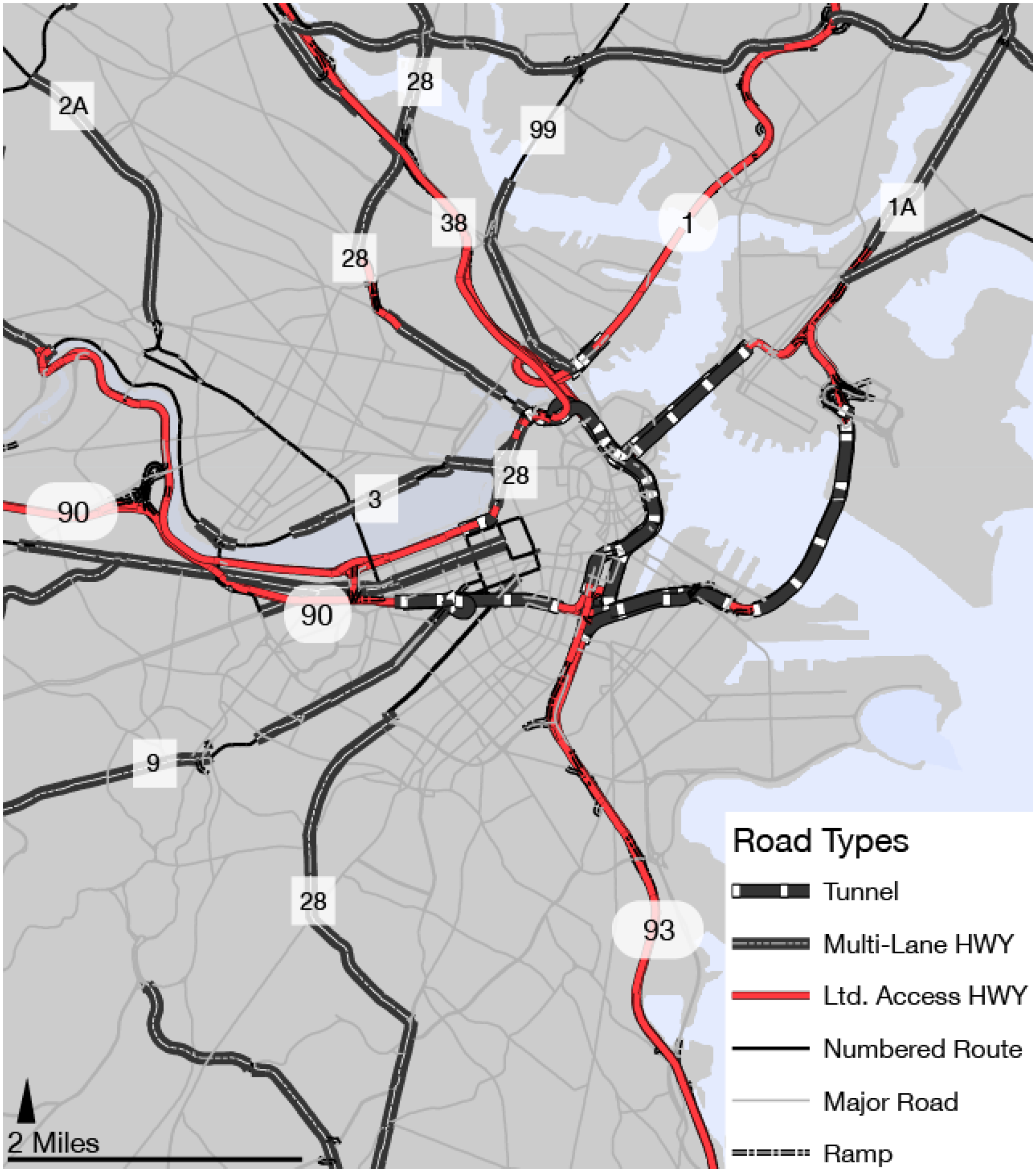

Figure 40: Highways, Major Roads and Tunnels with No Inundation

Figure 41 shows the same road information as Figure 40 but includes the four-foot inundation layer to highlight inundated routes. Highways 90, 28,1, 2A and 93 have some inundated portions.

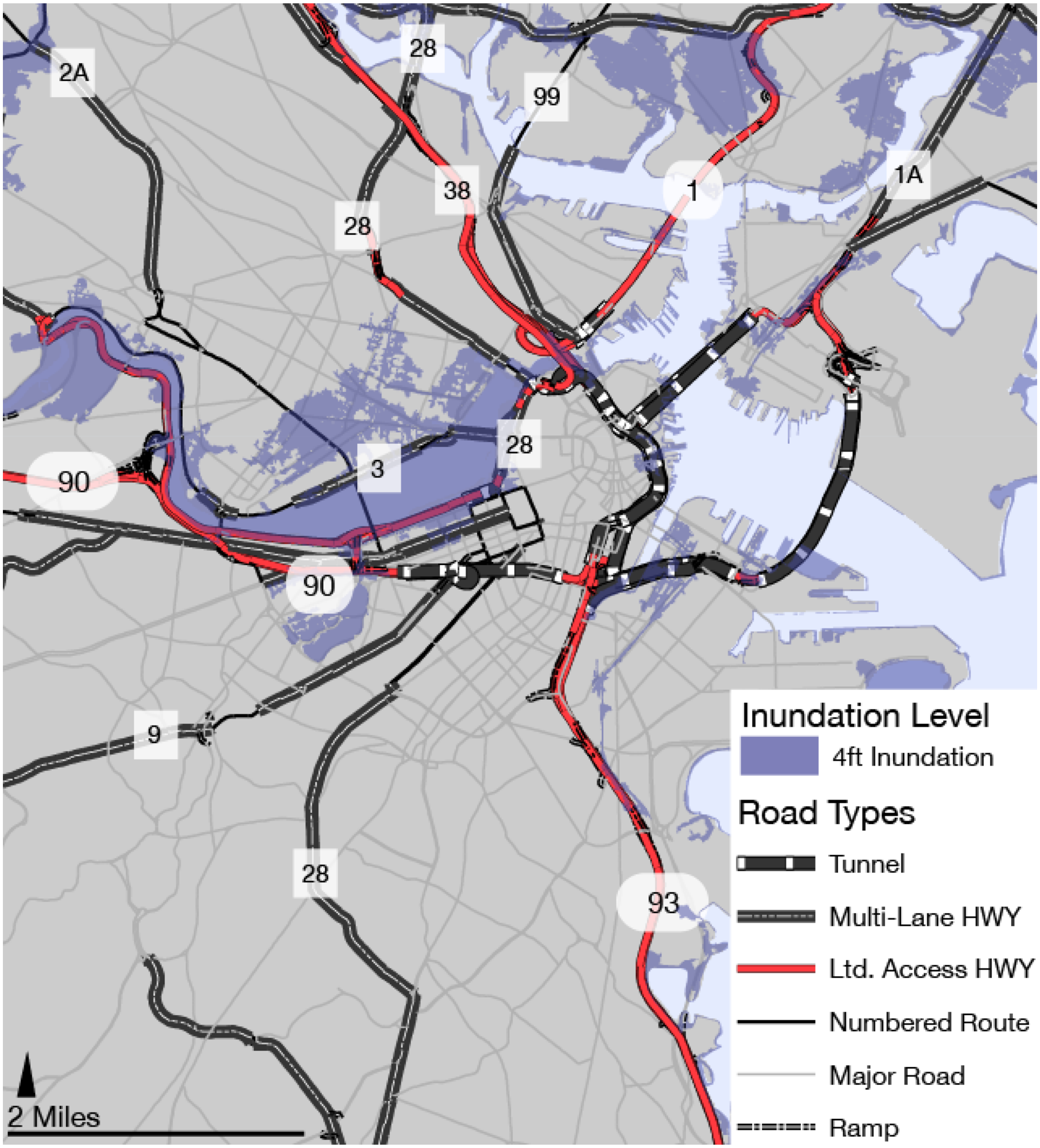

Figure 41: Highways, Major Roads and Tunnels with 4ft Inundation

Figure 42 shows the same roadways as Figure 41 and Figure 42, but at the six-foot inundation level. We can see widespread sections of all highways and most major roads and tunnels inundated at this level. The connectvity of the core to Boston, Cambridge, and East Boston (Logan Airport) appears to be threatened at the four- to six-foot inundation levels.

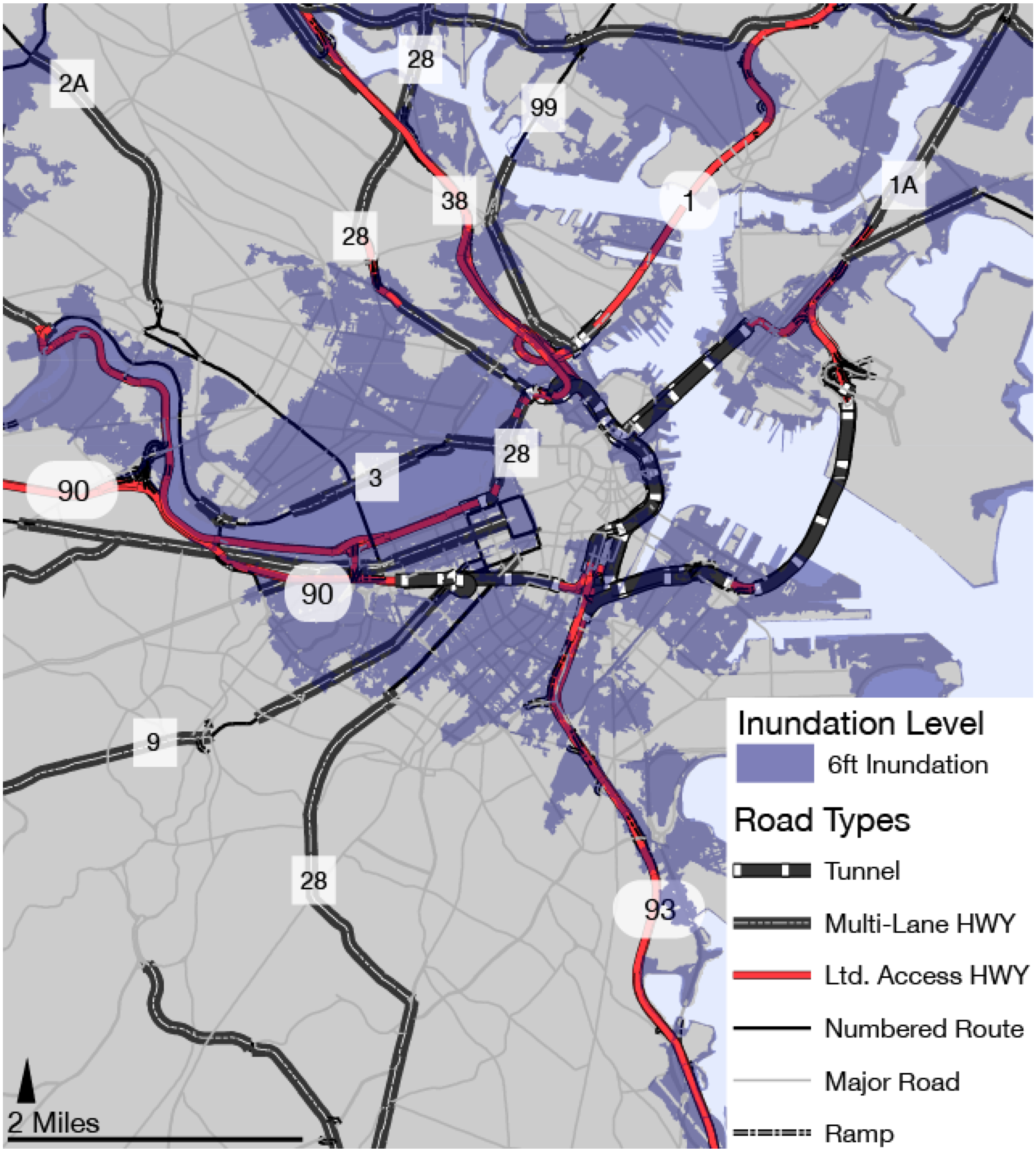

Figure 42: Highways, Major Roads and Tunnels with 6ft Inundation

The other roadway types demonstrate surprisingly linear growth across the inundation levels. Figure 43 includes the total miles of road way inundated by road type for broader context. Not surprisingly, minor streets have the most miles inundated because they account for the most total street miles. Inundation heavily impacts arterial roadways (another dominant roadway type), as well.

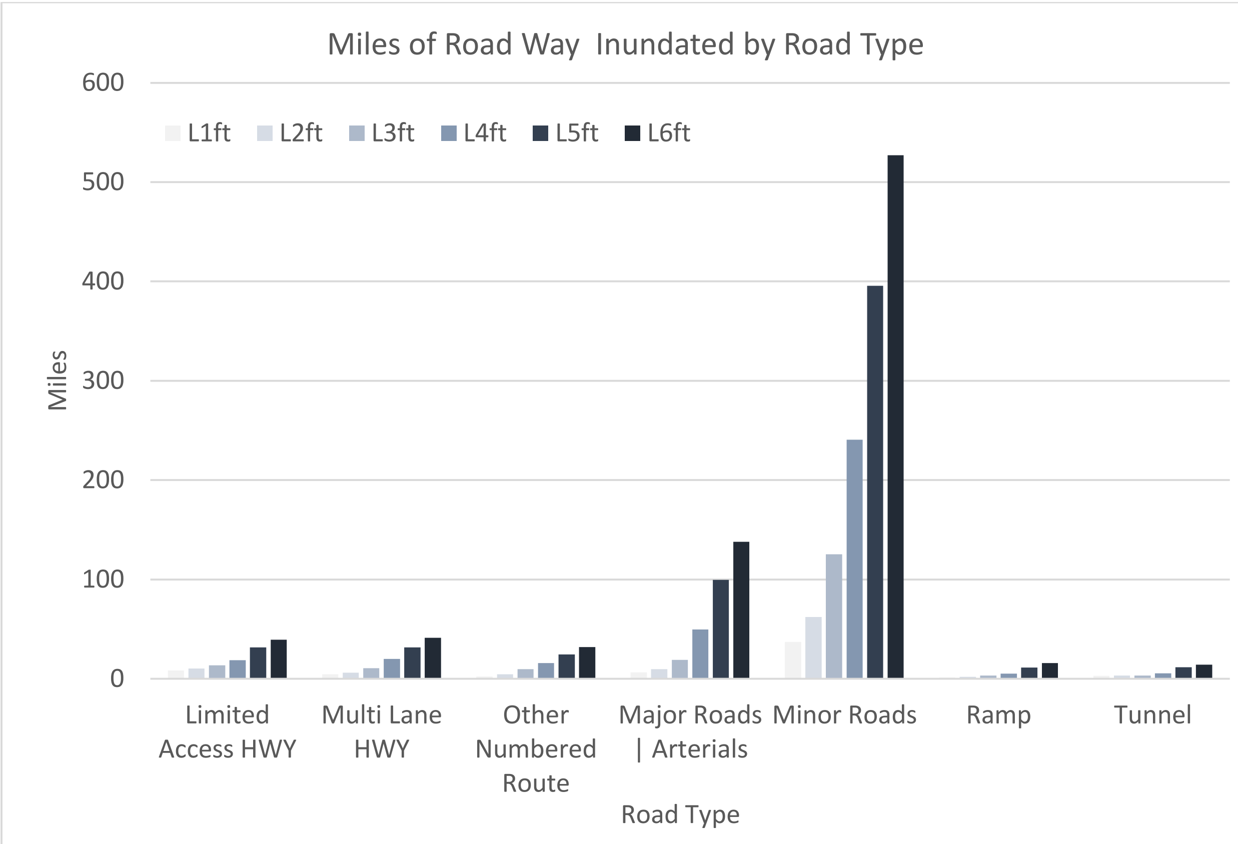

Figure 43: Miles of Road by Type Inundated

Though the total percentage of inundated roadways is not very large, the fact that the inundation is occuring in the economic and cultural hub of the region will like have drastic effects on overall urban system performance.

5.2.5 Land Use Impacts

Land uses – more specifically the distribution of jobs, homes, shops, schools, etc. – are a fundamental driver of transportation demand. Inundation impacts on different land uses will likely cause long-term impacts to the travel decisions made by model area residents. In the short-term, impacts to land uses provide information on possible economic effects to the region (although I do not directly evaluate economic effects in this thesis). Accessibility to certain types of land uses such as commercial or retail areas provides information on people's ability to access local stores, services, amenities, and jobs. We have already examined the impacts on jobs from two data sources (CTPP and InfoUSA, see Total

Jobs & Jobs by Sector and InfoUSA Firms and Jobs). The land use impact analysis provides additional information and another metric to measure accessibility in the subsequent analysis.

The number of parcels inundated across the different inundation levels is fairly linear. From among the estimated 1.34 million parcels in the model area, the number of impacted parcels is quite small (20,000 to nearly 70,000, or about one to five percent).

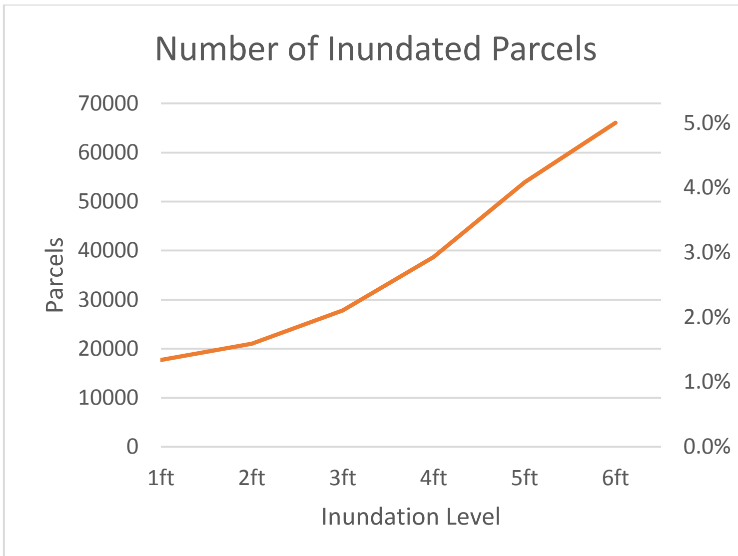

Figure 44: Number of Inundated Parcels

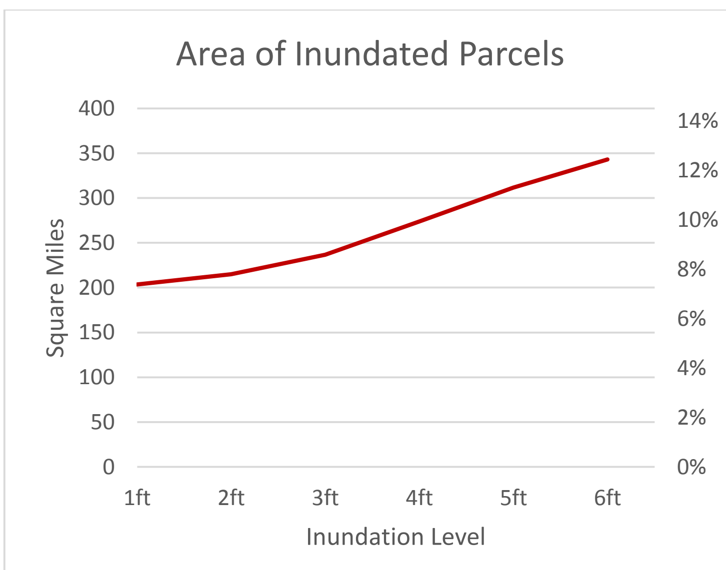

Figure 45: Area of Inundated Parcels

The total area inundated is also relatively linear but with a much flatter slope. This suggests that the parcels being inundated are generally smaller, therefore, more of them are being impacted. This follows intuition, as Boston's downtown consists of many small parcels.

Figure 46 shows the impact on different land uses by type. Residential land use suffers the most, with approximately 47,500 parcels inundated at the six-foot level. Institutional/Non Profit (i.e. governmental, non-profit and institutional uses) is the second highest impacted in terms of number of parcels. Because many of these parcels are larger than an average residential property, this parcel count may, in fact, represent a larger impact. Figure 47 graphs the total area of parcels inundated by land use.

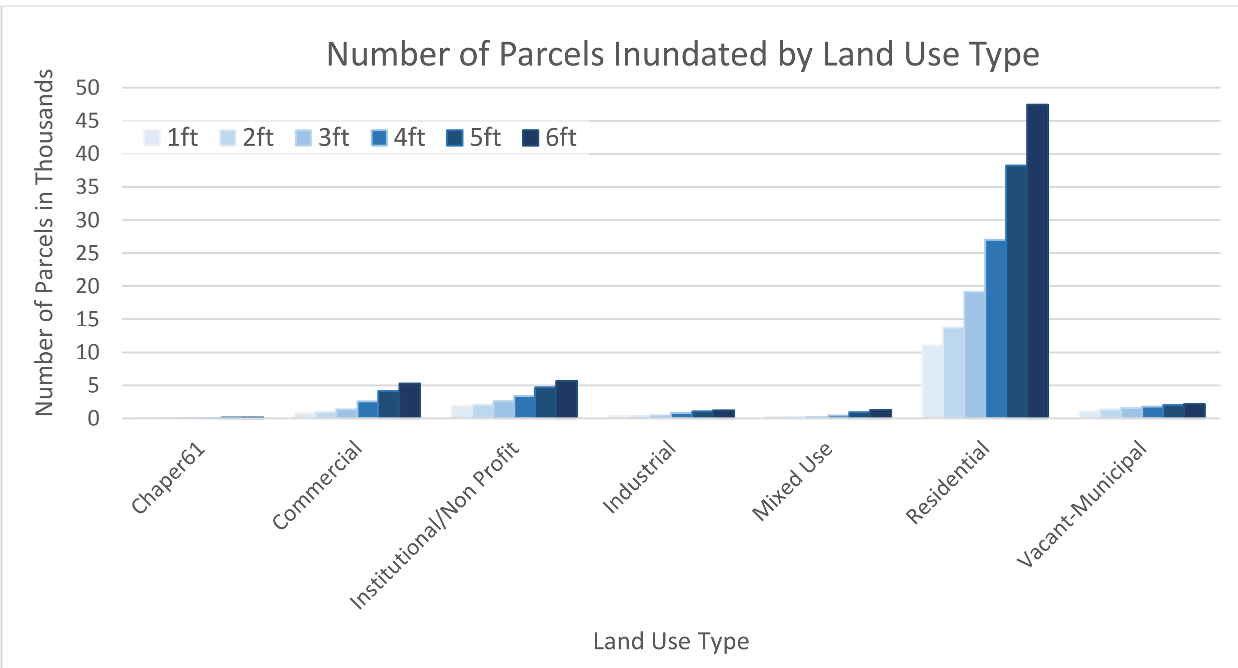

Figure 46: Number of Parcels Inundated by Land Use Type

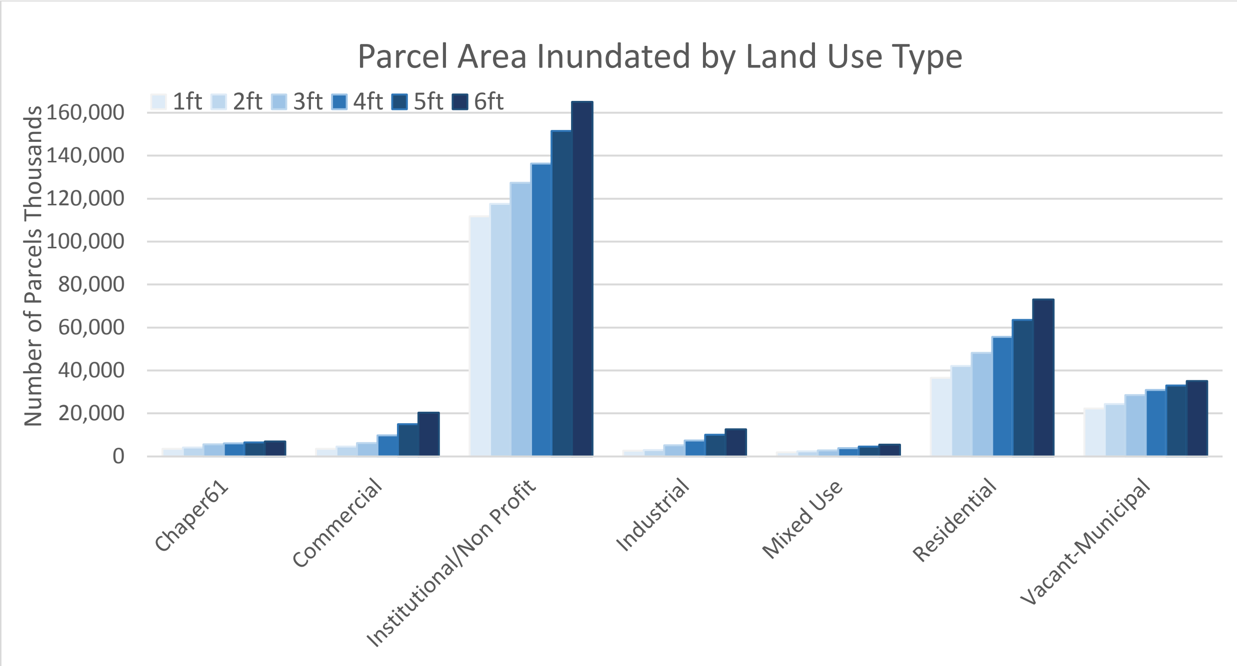

Figure 47: Parcel Area Inundated by Land Use

Figure 48 charts the percentage of total parcels inundated by each land use type and inundation level; Figure 49 shows the percentage of parcel area by each land use type and inundation level.

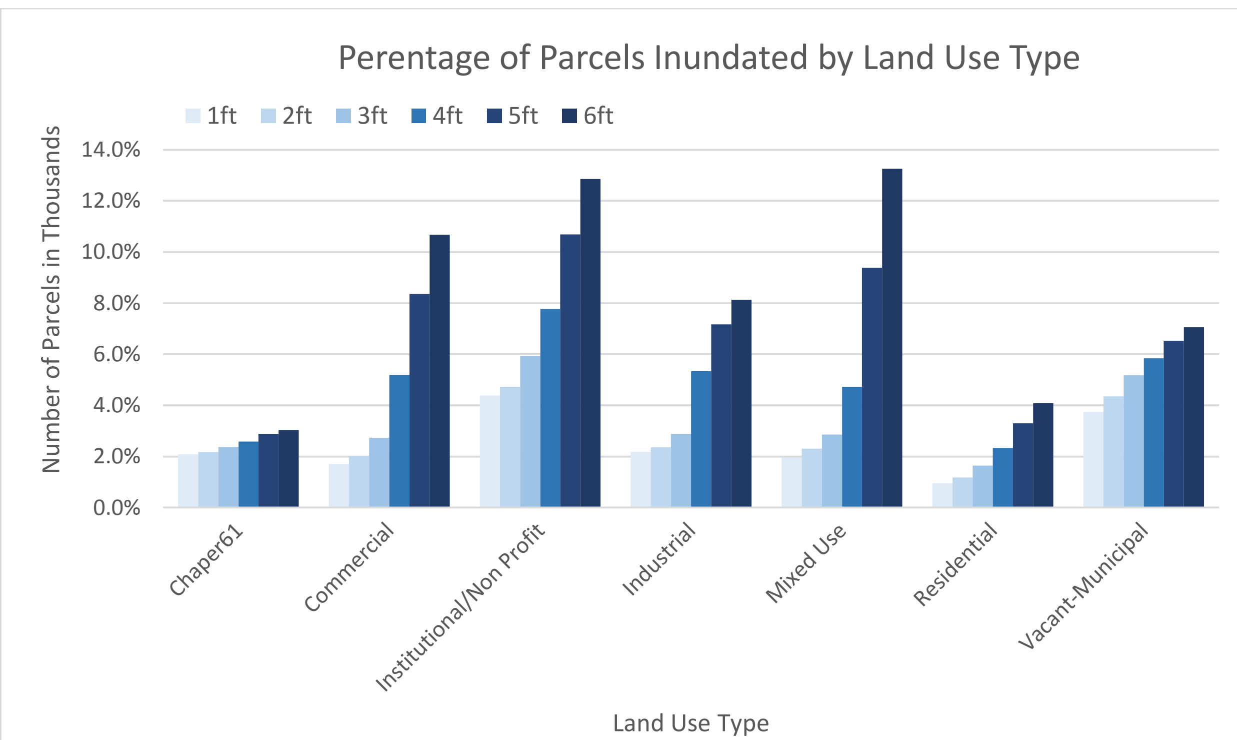

Figure 48: Percentage of Parcels Inundated by Land Use Type

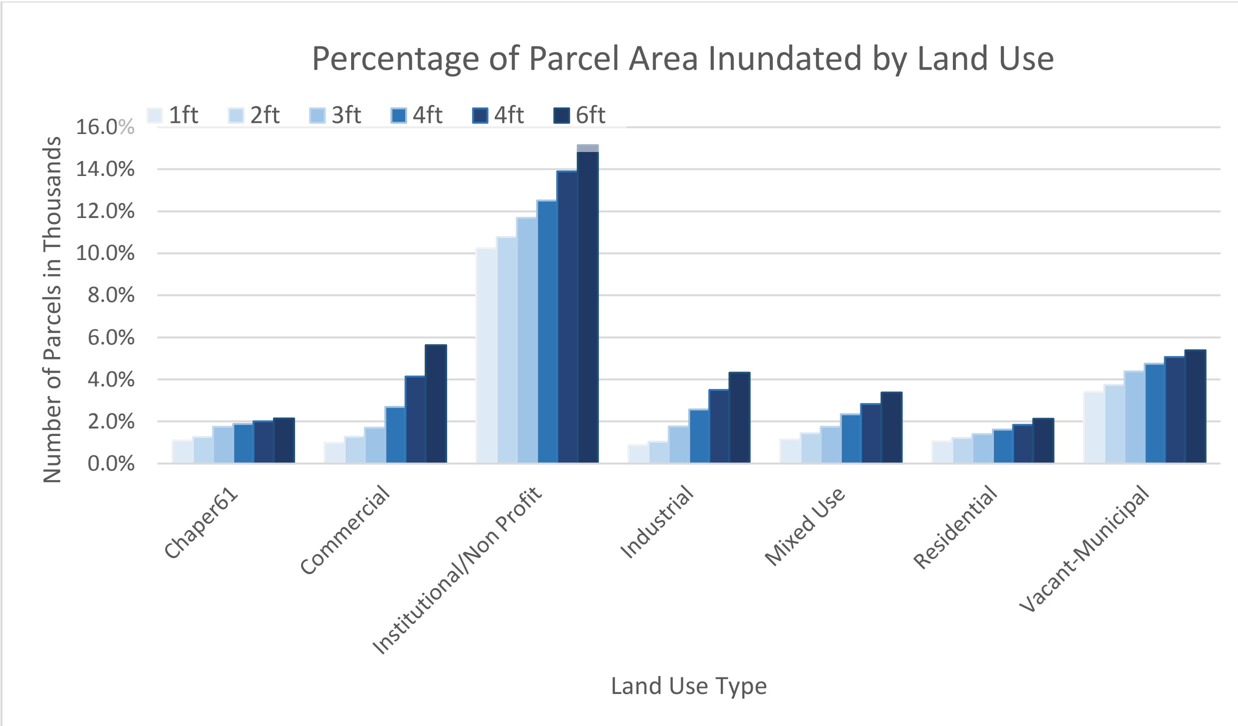

Figure 49: Percentage of Parcel Area Inundated by Land Use

Figure 46 to Figure 49 provide some interesting insights into the impacted land uses at the different inundation levels. In absolute terms, residential land use has the highest number of inundated parcels across all scenarios (Figure 46), while the land use with the highest total area inundated across all scenarios are institutional/non-profit (Figure 47). The percentage figures provide us with an understanding of the impact on land use relative to the total quantity of each of the different uses. Institutional/Non Profit uses cover the most land area (15 percent) (Figure 49) and ranks as the second-highest percent of total number of parcels (12.5 percent) (Figure 48). When examined in terms of percentage of area, the second highest use is commercial land (Figure 49). At the six-foot inundation level, mixed-use land uses suffer the highest inundation (13 percent) (Figure 48). This follows intuition – the inundation areas, largely comprised of Boston's central business district, have higher concentrations of mixed use parcels. Despite significant inundation at the six-foot level, the total percentage of mixed land use area inundated remains relatively low. Outlying regional malls or small shopping centers with much larger parcels may be responsible for this outcome. Industrial land use also suffers, with 8 percent inundated at the six-foot scenario. Finally, commercial land use parcels also face high relative inundation risk, likely linked to their concentration in the inundated inner core.

5.2.6 Summary of Results

Table 16 through Table 19 provide key summary findings for Demographic, Transit, Road and Land Use assets.

Key: C = Count, A = Area, L = Length

Figure 50: Key for Unit Field in: Table 16-Table 19

DEM. ASSET	UNIT	TOTAL	1FT	2FT	3FT	4FT	5FT	6FT
TAZ	C	986	232	234	251	279	322	338
TAZ	**C %**	--	**24%**	**24%**	**25%**	**28%**	**33%**	**34%**
TAZ	A (SQ. Miles)	2824	49	54	62	71	83	93
TAZ	**A %**	--	**1.7%**	**1.9%**	**2.2%**	**2.5%**	**2.9%**	**3.3%**
POP.	C	4,457,767	76,688	88,417	118,708	165,979	249,668	329,615
POP.	**C %**	--	**2%**	**2%**	**3%**	**4%**	**6%**	**7%**
HH	C	1718119	31,606	36,526	49,349	68,486	105,013	138,894
HH	**C %**	--	**2%**	**2%**	**3%**	**4%**	**6%**	**8%**
JOBS	C	2378384	50351	56809	71632	130212	229817	311506
JOBS	**C %**	--	**2%**	**2%**	**3%**	**5%**	**10%**	**13%**

Table 16: Demographic Asset Summary

TRANSIT ASSETS	UNIT	TOTAL	1FT	2FT	3FT	4FT	5FT	6FT
URB. RAIL STOPS	C	121	0	0	0	4	7	19
URB. RAIL STOPS	**C%**		**0**	**0**	**0**	**3%**	**6%**	**16%**
URB. RAIL LINES	L(Miles)	46.2	0.9	1.0	1.7	5.1	10.4	15.4
URB. RAIL LINES	**L%**	--	**1.9%**	**2.2%**	**3.8%**	**11.1%**	**22.4%**	**33.3%**
BUS STOPS	C	7678	6	9	40	161	438	640
BUS STOPS	**C%**	--	**0.1%**	**0.1%**	**0.5%**	**2.1%**	**5.7%**	**8.3%**
BUS LINES	L(Miles)	5351	31	50	108	254	537	722
BUS LINES	**L%**		**0.6%**	**0.9%**	**2.0%**	**4.7%**	**10.0%**	**13.5%**
COM. RAIL	L(Miles)	269	3	6	12	25	58	89
COM. RAIL	**L%**	--	**1%**	**2%**	**4%**	**9%**	**22%**	**33%**

Table 17: Transit Asset Summary

ROAD ASSETS	UNIT	TOTAL	1FT	2FT	3FT	4FT	5FT	6FT
ALL ROADS	L (Miles)	24577.2	63.7	98.8	185.0	356.3	605.8	808.1
LIMITED ACCESS HWY	L (Miles)	1057.2	8.6	10.5	13.8	18.8	31.6	39.3
MULTI LANE HWY	L (Miles)	325.1	4.5	6.3	10.8	20.2	31.6	41.5
OTHER NUMBERED ROUTE	L (Miles)	1456.3	2.5	4.7	9.6	16.0	24.4	32.0
MAJOR ROADS | ARTERIALS	L (Miles)	2114.3	6.6	9.7	19.0	49.6	99.6	138.1
MINOR ROADS	L (Miles)	19196.5	37.3	62.2	125.2	240.8	395.6	527.2
RAMP	L (Miles)	404.6	1.2	2.1	3.3	5.3	11.5	15.7
TUNNEL	L (Miles)	23.1	3.0	3.2	3.3	5.5	11.6	14.3
ALL ROADS	**L %**	--	**0.3%**	**0.4%**	**0.8%**	**1.4%**	**2.5%**	**3.3%**
LIMITED ACCESS HWY	**L %**	--	**0.8%**	**1.0%**	**1.3%**	**1.8%**	**3.0%**	**3.7%**
MULTI LANE HWY	**L %**	--	**1.4%**	**1.9%**	**3.3%**	**6.2%**	**9.7%**	**12.8%**
OTHER NUMBERED ROUTE	**L %**	--	**0.2%**	**0.3%**	**0.7%**	**1.1%**	**1.7%**	**2.2%**
MAJOR ROADS | ARTERIALS	**L %**	--	**0.3%**	**0.5%**	**0.9%**	**2.3%**	**4.7%**	**6.5%**
MINOR ROADS	**L %**	--	**0.2%**	**0.3%**	**0.7%**	**1.3%**	**2.1%**	**2.7%**
RAMP	**L %**	--	**0.3%**	**0.5%**	**0.8%**	**1.3%**	**2.8%**	**3.9%**
TUNNEL	**L %**	--	**12.9%**	**13.8%**	**14.2%**	**23.8%**	**50.1%**	**62.1%**

Table 18: Road Asset Summary

LAND USE ASSETS	UNIT	TOTAL	1FT	2FT	3FT	4FT	5FT	6FT
ALL LAND	A (SQ,Miles)	2,441	70	76	86	96	110	123
CHAPER61	A (SQ,Miles)	125	1	2	2	2	3	3
COMMERCIAL	A (SQ,Miles)	140	1	2	2	4	6	8
INSTITUTIONAL/NON PROFIT	A (SQ,Miles)	421	43	45	49	53	58	64
INDUSTRIAL	A (SQ,Miles)	112	1	1	2	3	4	5
MIXED USE	A (SQ,Miles)	63	1	1	1	1	2	2
RESIDENTIAL	A (SQ,Miles)	1,329	14	16	19	21	25	28
VACANT-MUNICIPAL	A (SQ,Miles)	251	9	9	11	12	13	14
ALL LAND	**A %**	--	**2.9%**	**3.1%**	**3.5%**	**4.0%**	**4.5%**	**5.0%**
CHAPER61	**A %**	--	**1.1%**	**1.3%**	**1.8%**	**1.9%**	**2.0%**	**2.1%**
COMMERCIAL	**A %**	--	**1.0%**	**1.3%**	**1.7%**	**2.7%**	**4.1%**	**5.6%**
INSTITUTIONAL/NON PROFIT	**A %**	--	**10.2%**	**10.8%**	**11.7%**	**12.5%**	**13.9%**	**15.1%**
INDUSTRIAL	**A %**	--	**0.9%**	**1.0%**	**1.8%**	**2.6%**	**3.5%**	**4.3%**
MIXED USE	**A %**	--	**1.1%**	**1.4%**	**1.7%**	**2.3%**	**2.8%**	**3.4%**
RESIDENTIAL	**A %**	--	**1.1%**	**1.2%**	**1.4%**	**1.6%**	**1.8%**	**2.1%**
VACANT-MUNICIPAL	**A %**	--	**3.4%**	**3.7%**	**4.4%**	**4.7%**	**5.1%**	**5.4%**

Table 19: Land Use Asset Summary

The Inundation Assessment highlights impacts on large numbers of persons, jobs, transport infrastructure and land uses. This finding informs expectations for later analysis of network performance. We should expect large impacts on the major highways and tunnels, especially coastal roadways that travel to downtown Boston. Furthermore, transit is heavily impacted, especially the urban heavy rail Lines – the Blue Line and the Red Line. In Inundation Impact Assessment, I apply the MIT-FSM to further explore the transport network performance impacts of this inundation.

6 Inundation Impact Assessment

The intent of this analysis is to gain insight into impacts of inundation events on an equilibrium system; therefore, I used outputs from the 2010 model that has reached equilibrium, specifically the number of trips by origin and destination; mode; and trip purposes. I model a situation where residents of the region have already made their travel decisions in terms of mode and destination. I model inundation scenarios, one-foot to six-foot inundation levels, to reveal the impacts on their ability to complete these trips. I introduced my basic assumptions and the justifications in sections Major Assumptions and Conceptual Justifications. To reiterate, I model a fixed trip distribution and mode split, as well as a semi variable trip distribution and mode split. I am primarily interested in the fixed distribution, as it minimizes the number of simultaneous sources of change in the model platform. This allows clear comparison to the 2010 baseline model results. I introduce select fixed vs. semi-variable results to highlight the difference between the two later in this chapter (Fixed Vs. Semi-variable).

6.1 Method

6.1.1 Impact Assessment Modeling Method

In this section, I describe the inundation impact assessment methodology. The baseline 2010 model, described in section MIT Boston Metro Region Four Step Model (MIT-FSM) of this document is altered to allow the modeling on inundation impacts.

6.1.1.1 Identify inundated links and networks:

The first step in the method is to create six different networks, one for each of the six different inundation levels. I coded the model network files in the Inundation Assessment Analysis. The network will differ across the inundation scenarios from one-foot to six-foot levels.

6.1.1.2 Estimate network impacts of those inundations

The intersection procedure provides information on inundation at each of the six inundation levels allowing the calculation of an estimated inundation at each level.

I established a strategy for degrading conditions on the link and/or preventing the use of the link once the road network was marked as inundated. Each link in the road network contains attributes, some of which I used in the calculation of travel time matrices and pathing & road assignment. There is no convenient method for altering the structure – i.e. deleting links - of the road network, and as it contains almost 265,000 links, manual methods were also not appropriate. Therefore, I allow inundated network links to continue to exist and increase travel time attributes on inundated links to a level that will ensure they are not used, since assignment (both auto and transit) uses travel time as a criterion for determining paths. This keeps trips from occurring on links inundated by more than one foot of water.

Degraded or Disabled Links: I use the predicted level of water on a link to determine if a link is degraded or disabled. I define a degraded link as one still usable by vehicles (including buses) and persons, but not by rail vehicles. Conversely, disabled links are unusable by any vehicle or person.

Inundation can affect a link at each one-foot increase of water level. However, I can only measure that between any one-foot increment inundation occurred, not the extent of that inundation. I presuppose that an expected value of inundation is the mid point: six inches. Under this assumption, if a link is first inundated at the one-foot level and I am modeling the four-foot level, the estimated inundation level would be:

$$\text{Actual Inundation} = (4\text{ft} - 1\text{ft}) + 0.5\text{ft}\,.$$

Six-inch inundation impairs but does not completely prevent travel for vehicles and pedestrians. However, electric rail-based public transit is compromised at such levels of inundation, rendering such links disabled.

Disabled and Degraded Attributes: Table 20 shows the altered network attributes, used in various areas of the model to calculate speed, time or congestions. Some model processes reference baseline 2010 congested travel time instead of calculating new values for time. Therefore, I had to change the value of the travel time, speed and capacity for all degraded or disabled links.

Attribute	Mode Type	Description
Distance	○Auto/Walk/PT	Length of link in miles
Capacity	▬Auto	Number of Vehicles Per Hour
PT Speed	►PT	Speed of Dedicated Public Transit ROW
Current Speed	▬Auto	Speed on link during current FSM model iteration. If it is the first model run Current Speed = Max Speed.

Table 20: Road Network Attributes

Degraded links have the following attributes:

- Auto Speed = 6 mph
- Auto Time = Distance / 6 mph
- Capacity = Original Capacity * 20%
- Walk Speed = 0.75 mph
- Walk Time = Distance / 0.75 mph
- Public Transit Speed (Used by Rail) = 0
- Public Transit Time (Used by Rail) = 99999 minutes

Disabled links have the following attributes:

- Auto Speed = 0 mph
- Auto Time = 99999
- Capacity = 0
- Walk Speed = 0
- Walk Time = 99999
- Public Transit Speed (Used by Rail) = 0
- Public Transit Time (Used by Rail) = 99999 minutes

The value of 99999 effectively disables the link by reflecting a greater amount of time than should ever be encountered on a link.

6.1.1.2.A Transit Special Considerations:

Because inundation often affects only portions of transit routes, I chose to allow transit lines to run in the portions of non-inundated areas. This assumption simplifies the process of modeling the inundated network. This simplification does not recognize the location of transit-specific support needs (power, maintenance facilities, operators, etc.) that may lead to a link being disabled beyond the extent of actual inundation.

6.1.1.3 Lost Trip Determination

I set a maximum travel time for 180 minutes, for two reasons: it is a likely excessively long travel time for a single trip; it better measures trips that absolutely cannot occur. Lost trips occur because:

1. They cannot be completed under the set maximum travel time of 180 minutes[4]; or
2. They have an origin or destination in a fully inundated zone.

The vast majority of trips in the model are inter-zonal trips, but the model also has some intra-zonal trips. The MIT-FSM model assumes that intra-zonal trips are walking trips, with travel time calculated as a function of the zone size and an assumed walk time. This requires a different method to estimate lost intra-zonal trips.

Inter-zonal Trips (Trips between zones):

To perform the Interzonal lost trip procedure, I created a module within the MIT-FSM to automate the process. The process runs after the MIT-FSM mode split sub model. The mode split sub model produces different OD matrices for each of the modeled trip purposes and for each mode. I identified lost trips by creating new "inundated" travel time matrices with the inundated networks.

These travel time matrices include all modes and various time of day periods. I, then, calculate lost trips for each mode and trip purpose matrix individually using these new "inundated" travel time matrices to indicate the OD pairs where travel is no longer possible. The procedure iteratively examines each matrix and the "inundated" travel time matrix sequentially, checking to see if the travel time matrix index at a given OD(i,j) for a specific set of trips is under the 180-minute time constraint. If so, the trips are copied into a new matrix; if not, the trips are lost, and not copied into the new

---

[4] Travel times exceeding 180 minutes can occur for auto or transit trips when a link is disabled and the total travel time on that link has been set to the value of 99999. It may also occur because inundation has impacted all routes that would allow the trip to complete in a time under 180 minutes.

matrix. Trips exceeding 180 minutes are removed from the new origin-destination matrices and never assigned to any mode.

Intra-zonal Trips (Trips within a zone):

$$Intrazonal\ \text{Lost}\ Trips_i = \begin{cases} \mathrm{T_i} * \mathrm{P_w}, & P_W < 0.7 \\ 0, & P_w \geq 0.7 \end{cases}$$

$$Where\ P_w = Percentage\ of\ Inundation, T_i = Number\ of\ Intrazonal\ trips\ in\ zone\ i$$

Equation 5: Intrazonal Lost Trips Calculation

At over 70 percent inundation, all a zone's trips are lost; at inundation below 70%, a zone loses intra-zonal trips in proportion to its proportion inundated.

6.1.1.4 Sequence of Model Module Runs:

The Impact Assessment Modeling process only requires re-running the model's assignment stage, as follows:

1. Network Update: Road network altered to reflect the correct inundation level.
2. Create Travel Time Matrices Network "skimming" module run to create new travel time matrices.
3. Process Lost Trips: Lost trips module run.
4. Assignment
    a. Auto
    b. Transit
    c. Pedestrian

This modeling approximates "event" impacts, assuming users do not have perfect knowledge of inundation impacts on the system. I calculate the initial skim using the congested network from the baseline 2010 model run. This means that the network contains attributes that reflect the increased costs based on the amount of usage and capacity of each link for a 2010 non-inundated network. The initial assignment and skims are generated from a loaded network for 2010, altering only the inundated links. Travel times on links near or adjacent to inundated areas will not reflect the congestion generated because of the degraded network: they will only reflect those links that are disabled or degraded. This run highlights non-inundated links that have become vital "detour" links in the inundated network. The OD matrices do not contain the new levels of congestion although some of links will likely suffer heavy congestion after running the inundated assignment sub model. Figure 51 shows the flow of steps used in the Fixed Inundation Impact Assessment Modeling graphically.

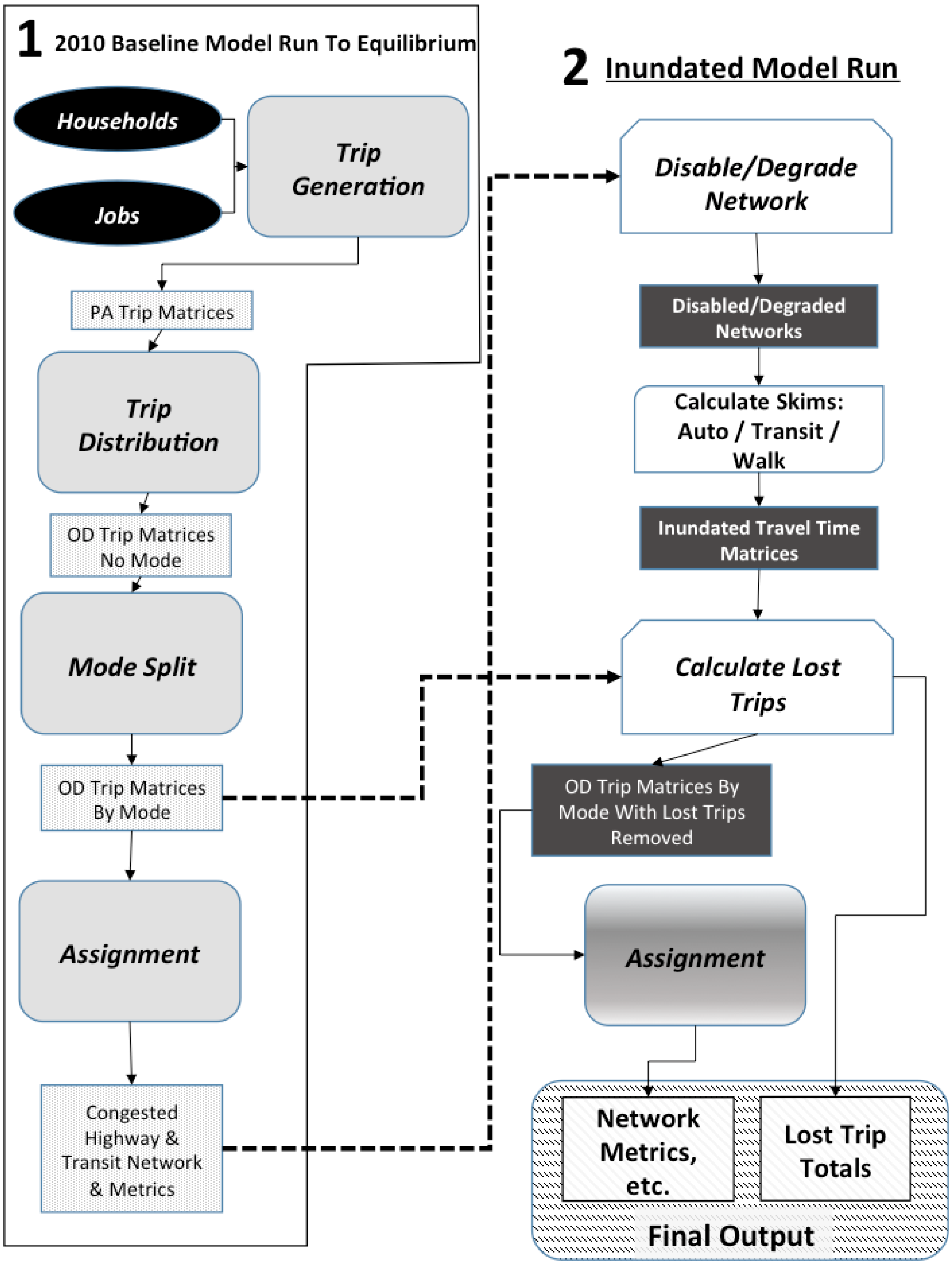

Figure 51: Illustrative Inundation Method Diagram

6.1.1.5 Semi-Variable Trip Distribution and Mode Split (SVTDMS)

I model a semi-variable trip distribution and mode split, to approximate the shifting decisions about destination choice and mode choice given inundation, by running the Trip Distribution (TD) and Mode Split (MS) sub-models within the inundation scenario. The Fixed TD and MS model runs not run the TD or MS sub-models; lost trips are removed from the baseline 2010 TD & MS output matrices. In the SVTDMS scenarios, the newly generated TD trip matrix feeds it into the MS module, producing a new series of matrices by trip purpose and mode reflecting the new inundated TD and MS.

Three arguments underlie my decision not to model fully variable TD and MS:

1. Such a model will likely over estimate the number of trips with flexible destinations;
2. Some trip purposes (Home Based Work, Home Based School) are not associated with a flexible destination (i.e., one office cannot replace another).
3. Such a model will likely overestimate Auto and especially Auto Passenger trips, given increased costs on the network.

The Semi-variable TD and MS aims to mitigate these concerns. The outputs of the fully variable TD and MS sub models create a series of trip purpose-specific matrices by mode for the specific inundated scenario. I create a single set of semi-variable trip purpose matrices by mode by multiplying each matrix by a factor and then adding each of the resulting factored matrices by trip purpose and mode. For example, the fully variable TD and MS and the Baseline 2010 TD and MS matrices include a Non Home Based Shopping – Captive – Auto Matrix. The entire contents of these matrices are multiplied by one of two factors that sum to one. Table 21 presents the factors used as ratios. This produces a matrix with an equal number of total trips but with different patterns of trip distribution and mode split.

USER TYPE	TRIP PURPOSE	TRIP DISTRIBUTION (FIXED / VARIABLE RATIO)	MODE SPLIT (FIXED / VARIABLE RATIO)
CAPTIVE	Home Based Work (HBW)	**100/0**	**70/30**
	Home Based Shopping (HBShop)	60/40	60/40
	Home Base Other (HBO)	70/30	70/30
	Non Home Based Work (NHBW)	80/20	80/20
	Non Home Based Other (NHBO)	50/50	50/50
CHOICE	Home Based Work (HBW)	**100/0**	**60/40**
	Home Based Shopping (HBShop)	50/50	50/50
	Home Base Other	60/40	60/40
	Non Home Based Work	70/30	70/30
	Non Home Based Other	50/50	50/50
	Home Based School	**100/0**	**70/30**

Table 21: Semi-variable Trip Distribution Ratios

The trip distribution factors reflect my intuition on the extent of variability possible in the destination choice of a given trip purpose. For example, Home Based Work has a ratio of 100:0, reflecting the assumption that these trips have no opportunity to change immediately. Thus the new Home Based Work matrix uses 100 percent of the baseline 2010 TD matrix and 0 percent of the variable TD matrix.

The follow process creates the semi-variable OD trip matrices by trip purpose and mode:

4) Alter the network attributes to reflect inundation.
5) Create new travel time skims reflecting inundation.
6) Run a trip distribution sub-model with the inundated travel time skims.
   a) Obtain variable OD matrices by trip purpose.
7) Feed the new variable OD matrices by trip purpose and mode into the mode split sub-model.
   a) For Home Based Work and Home Based School, discard the variable OD matrices and replace them with the fixed OD matrices
   b) Assume that choice users have more flexibility in destination and mode.
   c) For flexible trip purposes assign the ratios as in Table 21 (e.g.., for Home Based Shopping, the new output matrix would 50 percent fixed/50 percent variable for choice users and 60 percent fixed/40 percent fixed for captive users).
8) Run the mode split sub-model on the new variable matrices.
   a) Obtain fully variable OD trip distribution matrices by trip purpose and mode (except for Home Based Work and Home Based School

i) These trips have fixed trip distribution and variable mode split, with mode split varying by 30 percent for choice users and 20 percent for captive users.

9) Create a semi-variable trip purpose OD matrix by trip purpose and mode, taking the baseline matrices and the new variable matrices and multiplying them by the proportions in Table 21).
10) Combine these modified matrices to create a semi-variable OD trip matrices by purpose and by mode.

With the trip purpose matrices by mode finalized, I remove trips no longer possible (Lost Trip Determination) and run the assignment modules. The only difference in the model run between a fixed model run and a semi-variable model run is in the procedure; all output performance metrics remain the same.

6.1.1.6 A Note on the Specific determination of Lost Trips:

I apply the lost trips calculation after the mode split, creating a new Cube application to calculate lost trips based on the network impacts. This application accounts for the specificities of the MIT-FSM. When applying such a method to a different model, the exact specification would depend on how the OD matrices are created and the assumptions made about trip distribution and mode split - i.e. whether they are constant or dynamic in response to inundation.

6.1.2 Accessibility Calculation

While the majority of the performance metrics derive directly from the FSM outputs, accessibility requires additional calculation. I define accessibility to mean "the ability to reach desired goods, services, activities and destinations" (Litman, 2010, p. 1). In this specific case, I calculate a job accessibility measure, in two forms: an isochrone-based measure and an impedance-based measure. I calculate accessibility with Python in ArcMap and CUBE Voyager.[5]

Calculating the job accessibility measures requires two primary inputs: travel time matrices from each zone to all other zones in the model region by auto, walk and transit modes; and the total number of jobs in each zone.

---

[5] I calculated the accessibility values for each zone in Python and then exported to CSV files via Python PANDAS package (http://pandas.pydata.org). I, then, mapped the accessibility values by zone in Leaflet.js and D3.js, two JavaScript mapping and visualization packages.

Travel Time Matrices. I use three travel time matrices: AM peak automobile travel time; AM transit travel time; walk travel time. I do not distinguish between choice or captive in the calculation since the cost of travel is not included. Auto and transit include total travel time (e.g., in vehicle, out of vehicle). I chose AM travel time because most journey-to-work trips take place during this time and the congested conditions will produce a lower bound accessibility measure.

Data Vector. The total number jobs for each zone comes from the MIT-FSM model demographics table.

6.1.2.1 Impedance Based Measure

An impedance-based accessibility measure essentially weights access to an opportunity using an estimated sensitivity to travel time for that opportunity.

$$Accessibility_i = \sum_{j \in Z} \frac{Jobs_i}{\sum_{j \in Z} Jobs_j} * TT_{ij}^{-.503} * e^{-0.078 * TT_{ij}}$$

$$\text{Where } Z = \text{All Zones}$$

Equation 6: Impedance Accessibility (Gamma) for a Given Zone

The gamma function measure has the same specification as the gamma function measure described in the FSM Trip Distribution sub model in Chapter 3. The impedance values (-.503 and -0.078), representing sensitivity to travel time, come from the NHCRP 365, a transportation modeling reference (Martin et al., 1998).

6.1.2.2 Isochrones (Cutoff)

The isochrone-based accessibility measure represents the total number of jobs accessible from a given zone within a given amount of time. This measure is somewhat more intuitive to understand and communicate, but does not reflect the sensitivity to travel (i.e., no impedance function). Furthermore, the cutoff, which may be considered arbitrary, plays a large role in determining the results. I use 60 minutes as the cutoff.

.

$$Accessibility_i = \frac{\sum_{j \in Z} Jobs_j * TT_{ij}}{\sum_{j \in Z} Jobs_j}$$

$$TT_{ij} = \begin{cases} 1, & \text{if } TT_{ij} \text{ is} \leq 60 \text{ Minutes} \\ 0, & \text{if } TT_{ij} \text{ is} > 60 \text{ Minutes} \end{cases}$$

Where TT_{IJ} = Travel Time Between Zone I and Zone J

Where Z = All Zones

Equation 7: Isochrone Accessibility (Cutoff) for a Given Zone

6.2 Inundation Impact Assessment Modeling Results

6.2.1 Section Outline

This section presents the different output metrics and estimates how they change across different inundation levels. These performance metrics correspond to two key objectives:

1. ***Broad User Impacts* of inundation**.
    a. The total number of lost trips
    b. The number lost by mode
    c. The trip purpose
2. ***Network Performance* across modes at each inundation scenario.**
    a. The network impacts of inundation for the auto network
    b. The network impacts of inundation for the transit networks

I demonstrate the applicability of these metrics for inundation planning purposes by identifying areas of high congestion and vehicle hours traveled, determining the potential transit ridership shifts, and providing example recommendations given the results. I also provide illustrative examples of Fixed and Semi-Variable analysis results. The Impact Assessment Modeling follows the process outlined in the previous section (Method).

6.2.1.1 Performance Metrics:

Figure 52 and Table 22 present the performance metrics used in this analysis. In the following section, I demonstrate the use of these metrics using a hypothetical planning exercise for the Boston regional transportation system. The exercise and its results are a demonstration, not a concrete attempt to inform actual transportation planning possibilities under climate change risks. To do the latter would require a much broader range of expertise, resources, stakeholder input and refinement to the methods and metrics. Through this demonstration, I highlight those metrics of major interest. This demonstration intends to establish a foundation for future work. A planning agency or consultancy conducting a similar analysis may identify different specific metrics relative to its priorities or questions. This approach demonstrated can be modified to address a broad variety of concerns or questions.

Impact/General Measures:

- **Changes in:**
  - Total number of impacted assets and where appropriate the proportion of asset impacted (Area or Length).
  - Total trips lost:
    - By Trip Purpose
    - By Mode
  - Accessibility Changes
    - Isochrone Measures
    - Impedance Measures

Auto:

- **Changes in:**
  - Auto VHT: Total Hours Traveled (DTA & Static)
  - Auto VDT: Total Vehicle Distance Traveled (DTA & Static)
  - Volumes
  - Volume/Capacity: Static Assignment only
  - Queues: Dynamic Only

Transit:

- **Changes in:**
  - Ridership:
    - Transit Specific Mode
    - Route
  - Average Transit Trip Time
  - Total Passenger Distance

Figure 52: Performance Metrics

DIMENSION	METRIC	OBJECTIVE
GENERAL	Total Trips Lost	Broad User Impacts
	Total Trips Lost by Trip Purpose	Broad User Impacts
	Total Trips Lost by Mode	Broad User Impacts
	Total Trips Lost by Captive and Choice	Broad User Impacts
	Accessibility Impacts	Broad User Impacts
AUTO	Vehicle Hours Traveled	Auto Network Performance
	Vehicle Distance Traveled	Auto Network Performance
	Volume/Capacity (Static Assignment)	Auto Network Performance
	Queuing / Blocked Vehicles (Dynamic Assignment)	Auto Network Performance
TRANSIT	Ridership Changes by Transit Mode	Transit Network Performance
	Ridership Changes by Route	Transit Network Performance
	Average Transit Trip Time	Transit Network Performance
	Total Passenger Distance	Transit Network Performance

Table 22: Performance Metrics Mapped to Objectives

6.2.2 Impact Assessment Modeling - Baseline 2010 Results - Fixed Metrics

Throughout this section, many charts will utilize the label codes found in Table 23. I present the differences in terms of absolute difference or percentage difference.

CODE	DESCRIPTION
B_1FT	Difference from Baseline to 1ft
B_2FT	Difference from Baseline to 2ft
B_3FT	Difference from Baseline to 3ft
B_4FT	Difference from Baseline to 4ft
B_5FT	Difference from Baseline to 5ft
B_6FT	Difference from Baseline to 6ft

Table 23: Impact Assessment Modeling Chart Legend

6.2.2.1 Lost Trips by Trip Purpose

The baseline total number of trips (defined as trips within model region) is equal to about 16.4 million trips daily. Figure 53 shows the percentage of trips lost due to inundation. The trends are consistent with the results of the Asset Inundation analysis.

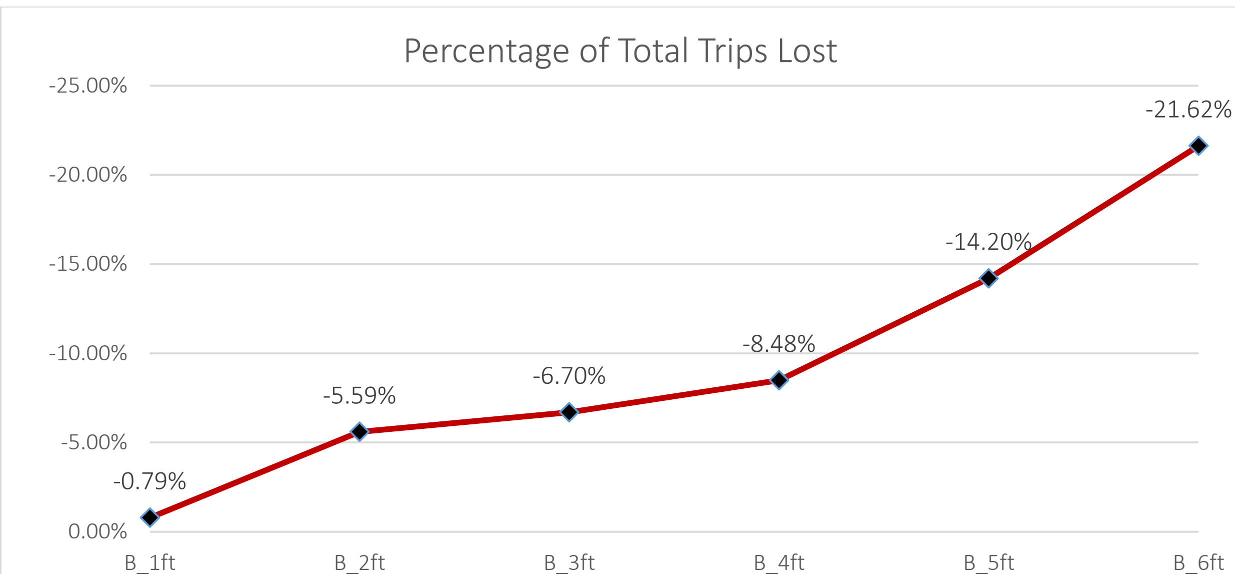

Figure 53: Percentage of Trips Lost by Inundation Level

The inflection point occurs at the four-foot mark, with the rate of trips lost continuing to increase at the five- and six-foot marks. The values range from roughly 0.8 percent of all trips lost at the one-foot mark to roughly 22 percent lost at the six-foot mark. At the six-foot inundation level, the region has close to 3.6 million trips lost due to inundation.

The Boston region's inner core concentrates the highest share of jobs, attracting commuters from throughout the metro region. As a result, I expected Home Based Work trips to be most affected by inundation impacts. Table 24, Table 25 and Figure 54, show the rate of decrease and the total number of lost trips for each inundation level. As expected, HBW has the greatest loss, totaling over 1 million work trips in the six-foot inundation scenario. Home Base Other shows near equal loss, almost 900,000 total trips. Much of the decrease is fairly liner with the HBW and HBO having major decreases at the three- and four-foot mark.

BASE TOTALS	PURPOSE	B_1FT	B_2FT	B_3FT	B_4FT	B_5FT	B_6FT
3,276,380	HBW	-31,771	-279,622	-353,987	-470,082	-713,914	-983,274
1,243,061	HBS	-14,683	-54,839	-69,644	-103,997	-137,583	-184,390
2,259,043	HBSHOP	-17,205	-97,871	-117,052	-146,026	-236,061	-328,297
4,259,490	HBO	-32,869	-196,752	-230,512	-279,381	-504,332	-896,201
2,522,716	NHBW	-11,538	-148,678	-166,911	-199,406	-329,458	-542,444
2,763,319	NHBO	-21,839	-135,460	-156,822	-188,747	-325,309	-530,362
82,998	AIRPORT	-9	-3,462	-3,668	-4,091	-82,959	-82,959
16,407,006	TOTAL	-129,913	-916,685	-1,098,596	-1,391,732	-2,329,616	-3,547,928

Table 24: Lost Trips by Inundation Level and Trip Purpose

DESC	B_1FT	B_2FT	B_3FT	B_4FT	B_5FT	B_6FT
HBW	-0.97%	-8.53%	-10.80%	-14.35%	-21.79%	-30.01%
HBS	-1.18%	-4.41%	-5.60%	-8.37%	-11.07%	-14.83%
HBSHOP	-0.76%	-4.33%	-5.18%	-6.46%	-10.45%	-14.53%
HBO	-0.77%	-4.62%	-5.41%	-6.56%	-11.84%	-21.04%
NHBW	-0.46%	-5.89%	-6.62%	-7.90%	-13.06%	-21.50%
NHBO	-0.79%	-4.90%	-5.68%	-6.83%	-11.77%	-19.19%
AIRPORT	-0.01%	-4.17%	-4.42%	-4.93%	-99.95%	-99.95%
TOTAL	-0.79%	-5.59%	-6.70%	-8.48%	-14.20%	-21.62%

Table 25: Percentage of Lost Trips by Trip Purpose

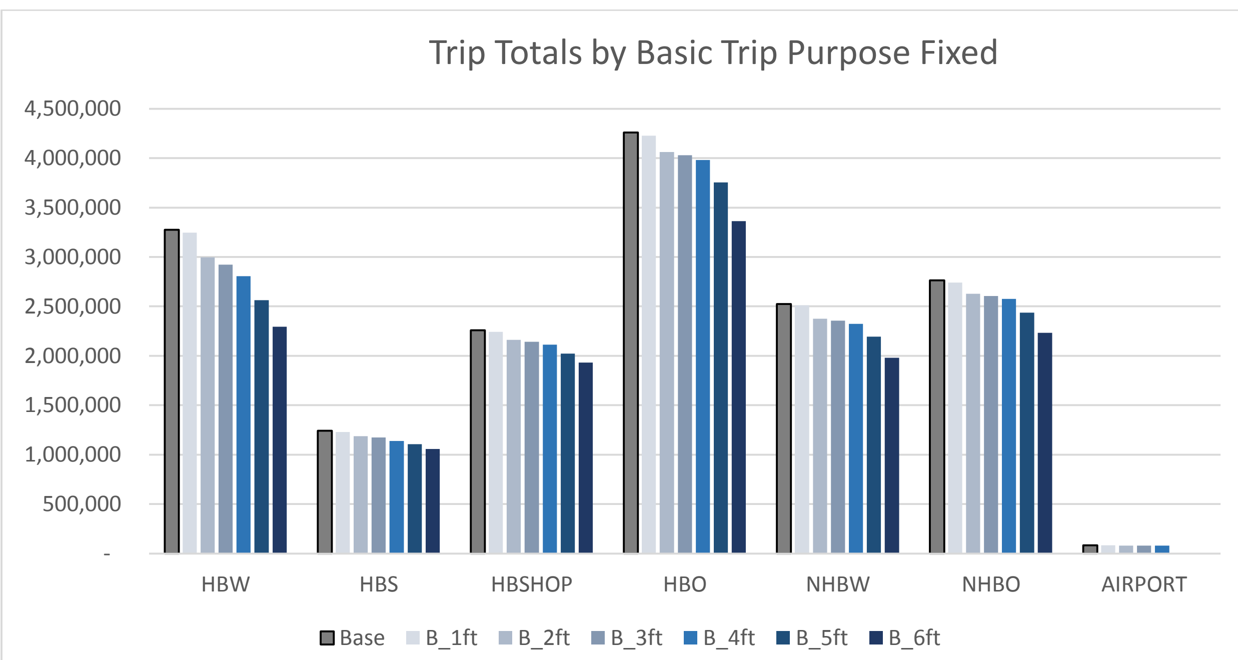

Figure 54: Trip Totals by Trip Purpose by Inundation Level

The Airport is never completely inundated, possibly due to the placement of the TAZ centroid. I did examine the location of runways with the six-foot water layer overlaid (Figure 55) and it, does, in fact, appear that the airport avoids inundation. However, the streets to the airport inundate at the five-foot mark, thus cutting it off from access.

Figure 55: Logan Airport & 6ft Inundation

Overall, there are varying rates of decline across trip purposes. This appears to be due to the concentration or dispersion of specific uses in inundated areas, as well as the sensitivity to travel for a given trip purpose, as determined in the baseline trip distribution step of the model. Referring to an earlier example, jobs concentrate in the inner core, so inundation of the inner core impacts many users. On the other hand, Home Base Shopping trips, with generally lower trip lengths, are not as impacted, although, of course, some will also be lost.

Table 26 and Table 27 provides information on the different impacts on the Choice and Captive users of the transportation system. Captive users only make up about 27 percent of all trips in the model region (2010 Baseline Model Results). As described in the Given that all trips begin or end at zone centroids, a larger zone will have a higher intra-zonal travel time compared to a small zone. These time calculations are independent of the road network.

Mode Split/Mode Choice sections of this thesis, choice riders have access to all modes and captive users do not have access to the auto drive modes. Clearly, captive riders will have a greater percentage share loss than choice users since the Auto offers the most flexibility in reaching a destination.

DESC	B_1FT	B_2FT	B_3FT	B_4FT	B_5FT	B_6FT
CHOICE						
HBW	-0.86%	-8.61%	-10.81%	-13.96%	-21.14%	-29.21%
HBSHOP	-0.48%	-5.69%	-6.64%	-7.82%	-10.79%	-13.92%
HBO	-0.59%	-5.23%	-6.00%	-6.86%	-11.33%	-20.12%
NHBW	-0.23%	-6.09%	-6.72%	-7.40%	-12.22%	-20.81%
NHBO	-0.55%	-5.67%	-6.41%	-7.32%	-11.53%	-19.11%
SUBTOTAL	-0.57%	-6.35%	-7.46%	-8.90%	-13.89%	-21.61%
CAPTIVE						
HBW	-1.83%	-7.94%	-10.76%	-17.39%	-26.91%	-36.28%
HBSHOP	-1.15%	-2.44%	-3.13%	-4.57%	-9.97%	-15.39%
HBO	-1.34%	-2.64%	-3.53%	-5.60%	-13.48%	-24.01%
NHBW	-2.28%	-4.37%	-5.80%	-11.84%	-19.67%	-26.98%
NHBO	-1.56%	-2.43%	-3.32%	-5.28%	-12.53%	-19.46%
SUB TOTAL	-1%	-3%	-4%	-7%	-14%	-22.3%

Table 26: Captive vs. Choice: Percentage Lost Tips by Inundation Level and Trip Purpose

DESC	BASE	B_1FT	B_2FT	B_3FT	B_4FT	B_5FT	B_6FT
CHOICE							
HBW	2,906,193	2,881,198	2,655,982	2,592,026	2,500,487	2,291,901	2,057,231
HBSHOP	1,318,086	1,311,723	1,243,141	1,230,505	1,215,022	1,175,810	1,134,608
HBO	3,249,977	3,230,671	3,079,856	3,055,130	3,027,119	2,881,686	2,596,192
NHBW	2,238,038	2,232,989	2,101,806	2,087,644	2,072,348	1,964,584	1,772,413
NHBO	2,105,631	2,094,048	1,986,174	1,970,647	1,951,595	1,862,761	1,703,273
SUBTOTAL	**11,817,925**	**11,750,629**	**11,066,959**	**10,935,953**	**10,766,571**	**10,176,741**	**9,263,718**
CAPTIVE							
HBW	370187	363410	340775	330366	305810	270565	235874
HBSHOP	940957	930115	918031	911485	897995	847172	796137
HBO	1009513	995950	982882	973848	952990	873472	767097
NHBW	284678	278189	272232	268162	250962	228674	207859
NHBO	657688	647432	641685	635849	622977	575249	529684
SUBTOTAL	**3,263,023**	**3,215,096**	**3,155,606**	**3,119,711**	**3,030,733**	**2,795,132**	**2,536,652**

Table 27: Captive vs. Choice: Lost Trips by Inundation Level and Trip Purpose

Table 26 shows the percentage of lost trips by inundation level and trip purpose for captive users versus choice users. A greater share of captive users is unable to complete trips in each trip purpose. The loss of Home Base Work trips by captive users is nearly 7 percent higher than that of choice users in the six-foot scenario. Surprisingly, in the two- through five-foot scenarios, choice users all have a greater percentage of trips lost for purposes other than HBW. This may be a due to choice users using autos to access destinations in inundated zones, while captive users are forced to access closer destinations that are not inundated. The total percent loss for both user groups is quite similar, with a reduction of 21.6 percent for choice and 22.3 percent for captive. Inundation disproportionally impacts the captive group for Home Based Work trips only.

Table 27 displays the total number of trips completed, organized by trip purpose, captive and choice across the different inundation levels.

6.2.2.2 Lost Trips by Mode

Though I fixed mode split in this analysis, the proportion of trips by mode will change due to differing impacts on the various networks (auto or transit). Figure 56 shows the mode shares across all inundation levels.

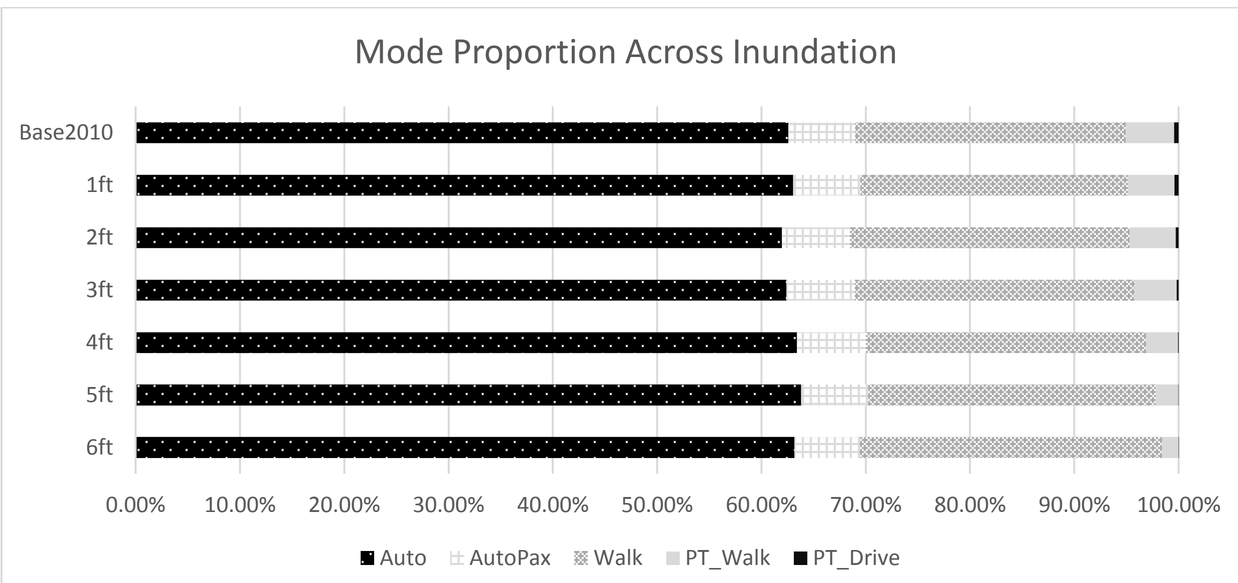

Figure 56: Mode Proportion by Inundation Level

Across all inundation levels, Auto stays relatively constant and makes up the largest proportion of trips by far. Figure 56 shows the steady decline in the percentage of trips completed using transit and a reciprocal increase in the share of walking trips. Public Transit Drive decreases consistently (although it is a very small percentage to begin with). Table 28 shows the proportional share of each mode at each inundation level: transit (PT_Walk) has a 4.6 percent share at no inundation, decreasing to roughly 1.5 percent at the six-foot inundation level. From the three- to four-foot inundation level, PT_Walk has the largest percent decrease in share, dropping from 4 to 3 percent.

MODE	BASELINE	1FT	2FT	3FT	4FT	5FT	6FT
AUTO	60.06%	60.52%	59.38%	59.77%	60.77%	61.41%	61.16%
AUTOPAX	8.91%	8.98%	9.10%	9.16%	9.24%	8.81%	8.27%
WALK	25.96%	25.66%	26.83%	26.87%	26.89%	27.59%	29.02%
PT_WALK	4.63%	4.45%	4.41%	4.01%	3.05%	2.17%	1.54%
PT_DRIVE	0.44%	0.40%	0.29%	0.18%	0.06%	0.03%	0.01%
TOTAL	16407006	16277093	15490321	15308410	15015274	14077390	12859078

Table 28: Mode Proportion by Inundation Levels

Figure 57 shows the percentage of trips lost by mode across inundation levels. Public Transit Drive has the largest decrease by percentage at every inundation level, decreasing by nearly 100 percent at the six-foot inundation level.

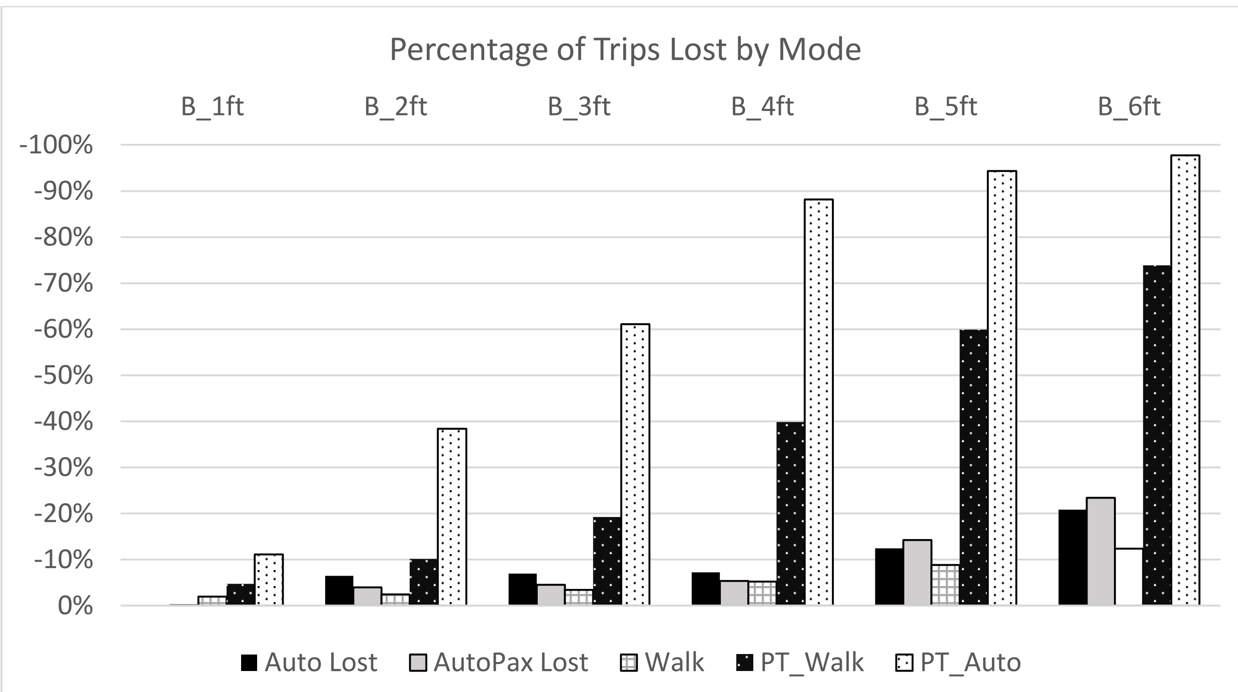

Figure 57: Percentage of Lost Trips by Mode

There are two reasons for this decrease: one, the majority of Public Transit Drive trips access inner core/Downtown destinations [i.e. Actual lost trips]; two, the loss of low travel time (single ride) transit routes forces the user to pursue multi-ride routes that utilize slower modes such as buses. This creates travel times that violate the maximum travel time I set, 180 minutes.

Mode split proportion shows variation across trip purposes. Table 29 illustrates the change for Home Based Work trips. The percentage of private vehicle usage grows across the different scenarios while transit use falls greatly.

HBW MODE	BASE2010	1FT	2FT	3FT	4FT	5FT	6FT
AUTO	74.12%	74.85%	74.53%	76.04%	78.96%	82.04%	83.56%
AUTOPAX	6.60%	6.66%	6.72%	6.85%	7.07%	7.27%	7.46%
WALK	4.67%	4.64%	4.99%	5.07%	5.12%	5.14%	5.31%
PT_WALK	12.96%	12.39%	12.66%	11.33%	8.64%	5.46%	3.65%
PT_DRIVE	1.65%	1.46%	1.10%	0.72%	0.21%	0.09%	0.02%
TOTAL	3,276,380	3,244,608	2,996,757	2,922,393	2,806,297	2,562,466	2,293,106

Table 29: Home Based Work Mode Proportion by Inundation Levels

6.2.2.3 Auto Network Performance

I ran static and dynamic traffic assignment (DTA) sub-models for each of the different inundation levels.

	TYPE	BASE	1FT	2FT	3FT	4FT	5FT	6FT
STATIC	Vol.	14,023,798	16,631,661	15,659,282	18,466,508	21,854,365	17,339,876	10,387,725
	VC Max	4.06	6.63	3.95	6.05	51.97	10.16	4.37
	VDT	1,228,486	1,474,049	1,338,830	1,649,712	1,917,626	1,554,675	1,031,079
	VHT	42,087	56,387	63,143	90,156	645,774,987	391,406	33,565
DTA	Vol.	10,494,896	10,366,888	10,113,534	10,202,435	11,218,671	9,515,720	6,957,205
	VDT	828,954	857,287	774,677	849,072	961,343	833,880	641,058
	VHT	39,902	45,088	44,424	47,282	52,040	43,453	25,367
	Queue	185,173	250,950	276,244	304,216	305,139	233,035	96,502
	Block	74,396	84,464	97,343	111,079	103,503	66,776	39,377

Table 30: AM Auto Assignment Summary, all values are hourly

Table 30 summarizes the main output metrics for each of the inundation levels. Static volumes are consistently higher than the DTA volumes. In static assignment, Volume-to-Capacity (VC) has an extreme value at the four-foot level, almost 52. The VC value for static assignment at the five-foot level is similarly extreme with a value of 10. The DTA, by contrast, produces far more stable and consistent values that increase until five-foot inundation. After five-foot inundation, the values begin to decrease as far fewer trips occur.

In static assignment, VC and vehicle hours traveled are typically relative in scale. When the volume on a link so greatly exceeds capacity, travel time on that link increases to highly unreasonable values. Some of the links available for use at four-foot inundation in this static assignment have a limited capacity, causing these large values. When vehicles are loaded, the links become congested. By analyzing the actual network file, I was able to determine that only a few links generate these extreme values.

The links subject to this severe congestion are those that offer principal access between certain origins and destinations. An un-inundated network would have redundancy and traffic would distribute across various links. In the inundated network, however, these links are vital, providing single connections between zones. This likely unrealistic outcome, a weakness to static assignment, nonetheless illuminates something interesting. It highlights links able to withstand inundation not having the capacity to support the use demanded in such a scenario. Given the goal of showing how this work can identify resilient links, I will return to this analysis later in the section: Example of Extreme Congestion and a Resilient Link.

Another notable difference in static assignment versus DTA is the way in which the methods handle vehicle trips. The output metrics generated by the model are AM peak hourly values. For static assignment, the method forces all trips through the network within that hour, regardless of congestion. Conversely, DTA does not allow volume to exceed capacity. As a result, DTA more accurately models congestion; fewer vehicles arrive at their destination during the hour period modeled. This also explains the lower volume values predicted under DTA.

6.2.2.3.A Volumes

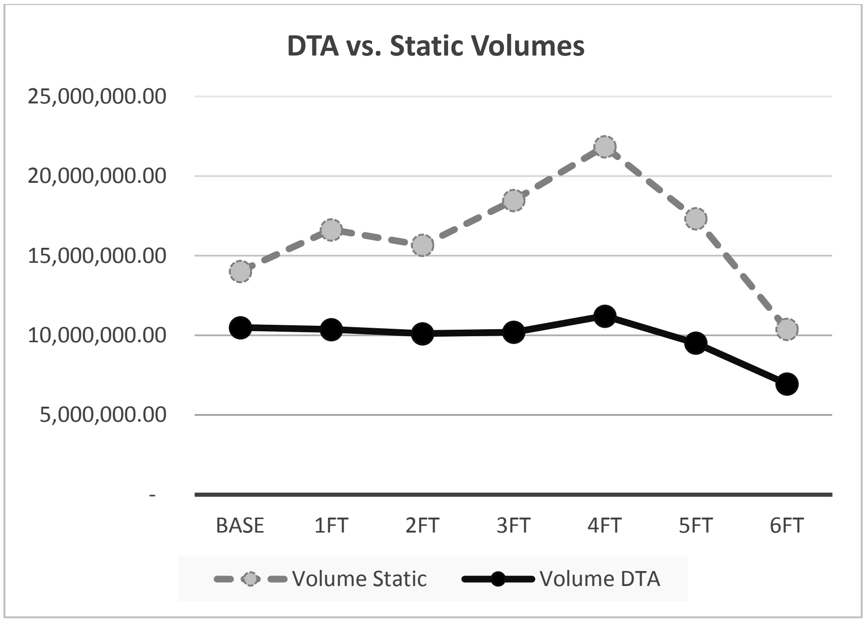

Figure 58: DTA & Static Assignment Hourly Volumes

Total network volumes measure the number of vehicles using each link in a given model run. The value can increase because shorter length routes are congested and vehicles must make use of longer routes. For this model, inundation is a key factor informing use of specific routes. Not only does inundation render links unusable, the loss of those links increases congestion on other routes.

There is a major difference in volumes between the static assignment and DTA. As previously explained, DTA does not completely load all vehicles in the given time period. The DTA volumes are, on average, about 40 percent lower. Figure 58 shows that at the four-foot mark the gap between DTA and static assignment is close to 50%. Static assignment returns a scenario where all vehicles on a network exceed even standstill packed capacity, ignoring the excess capacity with volumes continuing to increase. DTA registers “maximum capacity,” such that volume reaches a limit (i.e. when cars are no longer registered as moving) and the total sum of vehicles on the network do not increase.

6.2.2.3.B Vehicle Distance Traveled

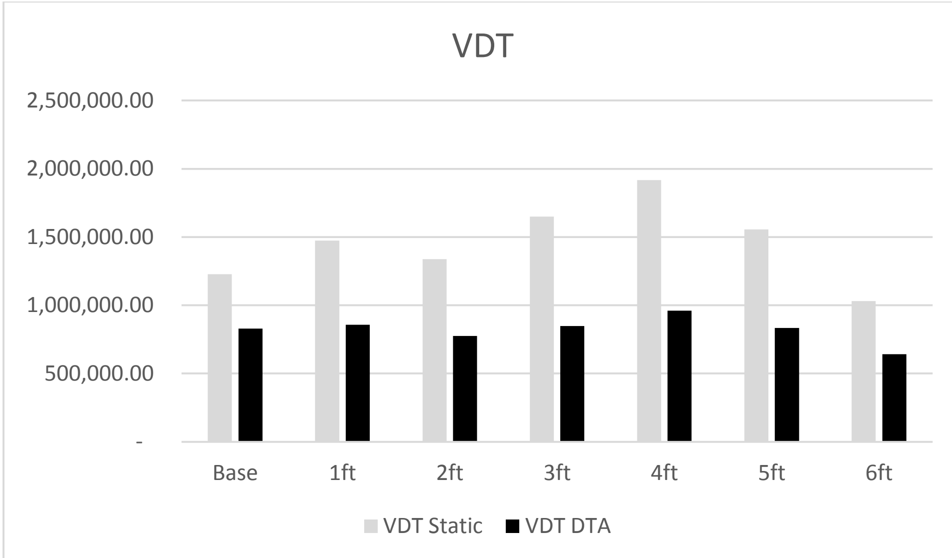

Figure 59: Vehicle Distance Traveled

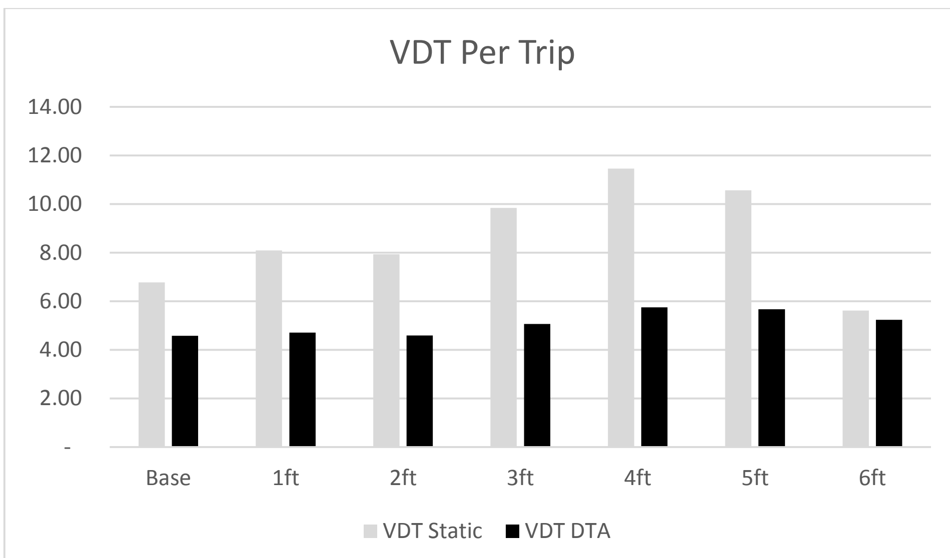

Figure 60: Average Vehicle Distance Per Trip

Vehicle distance traveled is higher in value than the baseline VDT in all scenarios except the six foot level. The DTA vehicle distance traveled stays generally constant until the three-foot mark, increasing to the five-foot mark and then decreasing from the five-foot to six-foot inundation levels.

The average vehicles distance traveled in static assignment reaches a peak of almost 12 miles at the four-foot level; the DTA vehicle distance traveled value is consistently lower. In both travel assignments cars stuck in congestion do not contribute to increased vehicle distance traveled. DTA more accurately models these scenarios. I deduce that these congestion scenarios are a likely factor contributing to these shifting levels.

6.2.2.3.C Vehicle Hours Traveled

Figure 61 displays the vehicle hours traveled (VHT) across inundation levels for both DTA and static assignment methods. The values for VHT at the three- and four-foot inundation levels exceed the limits of Figure 61.

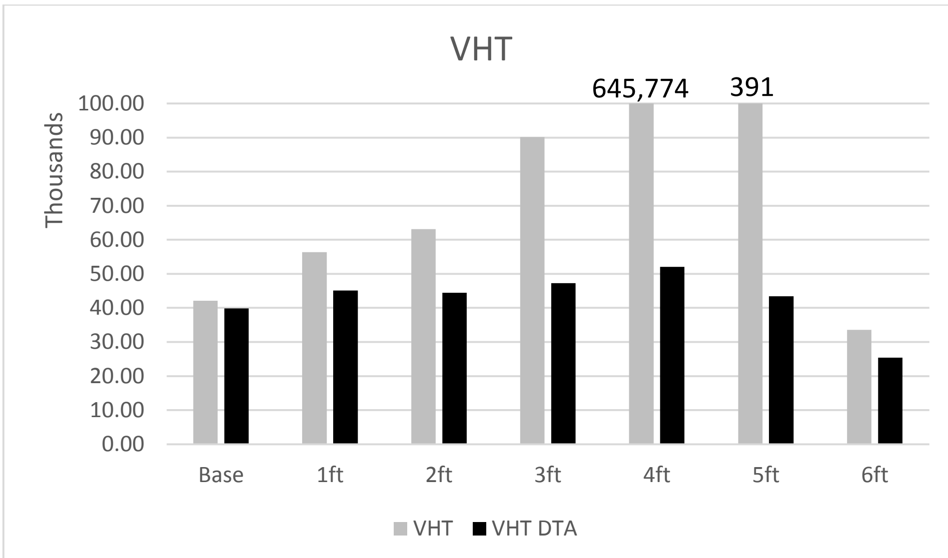

Figure 61: Vehicle Hours Traveled

VHT consistently increases under static assignment until the five-foot inundation level. The four- and five-foot levels have extreme values (645,774,000 Hours and 391,000 Hours) compared with the values found at other inundation levels. Again, the DTA values are consistently smaller and more stable. In the DTA results, the values increase from the base level to a peak at the four-foot mark. At the six-foot level we see the lowest total VHT on the chart (lower than base level), undoubtedly attributed to the loss of so many trips in the model region.

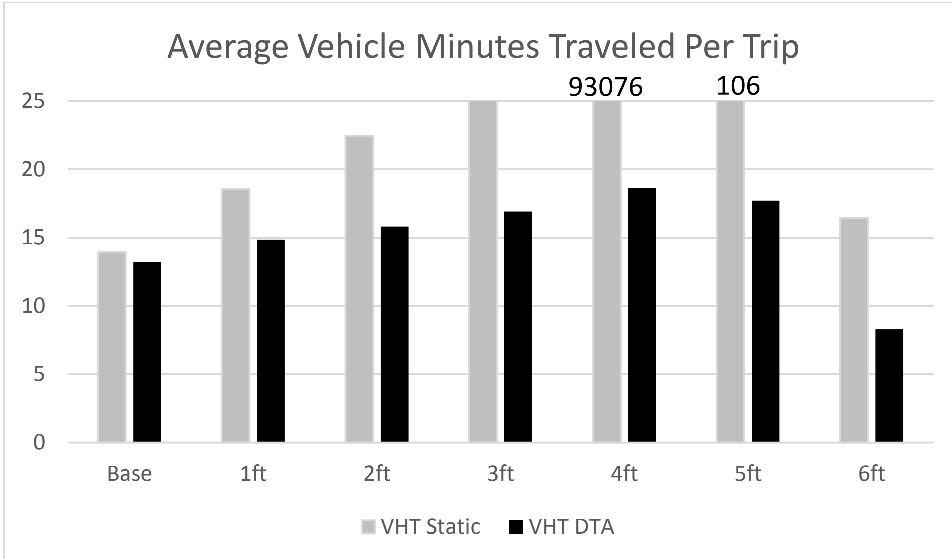

Figure 62: Average Vehicle Minutes Traveled Per Trip

Figure 62 shows the average minutes per trip across all trip purposes during the AM peak hour. The base value for static assignment is about 14 minutes while the DTA value is about 13 minutes. The values are lower than I expected, arguably because all trip purposes are included. The assignment module does not consider trip purposes separately, so I cannot present travel time for Home Based Work trips as an isolated value, which I expect to be longer. Figure 62 shows the same pattern as witnessed in Figure 61: DTA travel times are more consistent with no extreme values, with an overall increase from baseline until the six-foot inundation level when the totals decrease. At the six-foot level, static assignment and DTA values both reflect lower travel times than the baseline.

6.2.2.3.D DTA Queued and Blocked Vehicles

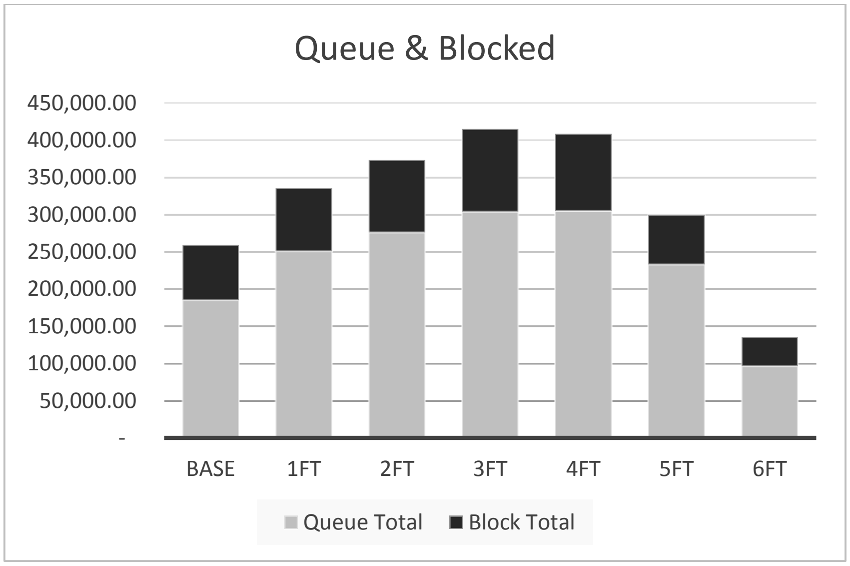

Figure 63: DTA- Queued & Blocked Vehicles

Figure 63 shows the total number of queued and blocked vehicles for the model period. To reiterate, queued and blocked vehicles are those stuck in traffic on a link during the assignment. Queued vehicles are those waiting to exit a link. Queues consistently increase, with maximum values at the three-foot level.

6.2.2.3.E Summary

FIX	TYPE	BASE	1FT	2FT	3FT	4FT	5FT	6FT
STATIC	**V_Static**	--	18.60%	11.66%	31.68%	55.84%	23.65%	-25.93%
	VC_Max	--	63.30%	-2.71%	49.01%	1180.05%	150.25%	7.64%
	VDT	--	19.99%	8.98%	34.29%	56.10%	26.55%	-16.07%
	VHT Static	--	33.98%	50.03%	114.21%	1534272.38%	829.99%	-20.25%
DTA	**Volume DTA**	--	-1.22%	-3.63%	-2.79%	6.90%	-9.33%	-33.71%
	VDT DTA	--	1.85%	-3.96%	-0.61%	12.55%	-3.91%	-27.12%
	VHT DTA	--	13.00%	11.33%	18.50%	30.42%	8.90%	-36.43%
	Queue Total	--	35.52%	49.18%	64.29%	64.79%	25.85%	-47.89%
	Block Total	--	13.53%	30.84%	49.31%	39.12%	-10.24%	-47.07%

Table 31: Percentage Change Assignment Metrics

Table 31 shows the percentage change from baseline for the different assignment metrics. The pattern shown in Table 31 reiterates previous results. DTA is much more stable than static assignment. Most of the metrics (VDT, VHT, Queue, and Block) for DTA increase or stay nearly constant until the five-foot inundation scenario where they begin to decrease.

6.2.2.4 Transit Network Performance

In this section, I examine the transit-network performance metrics.

6.2.2.4.A Travel Time & Distance

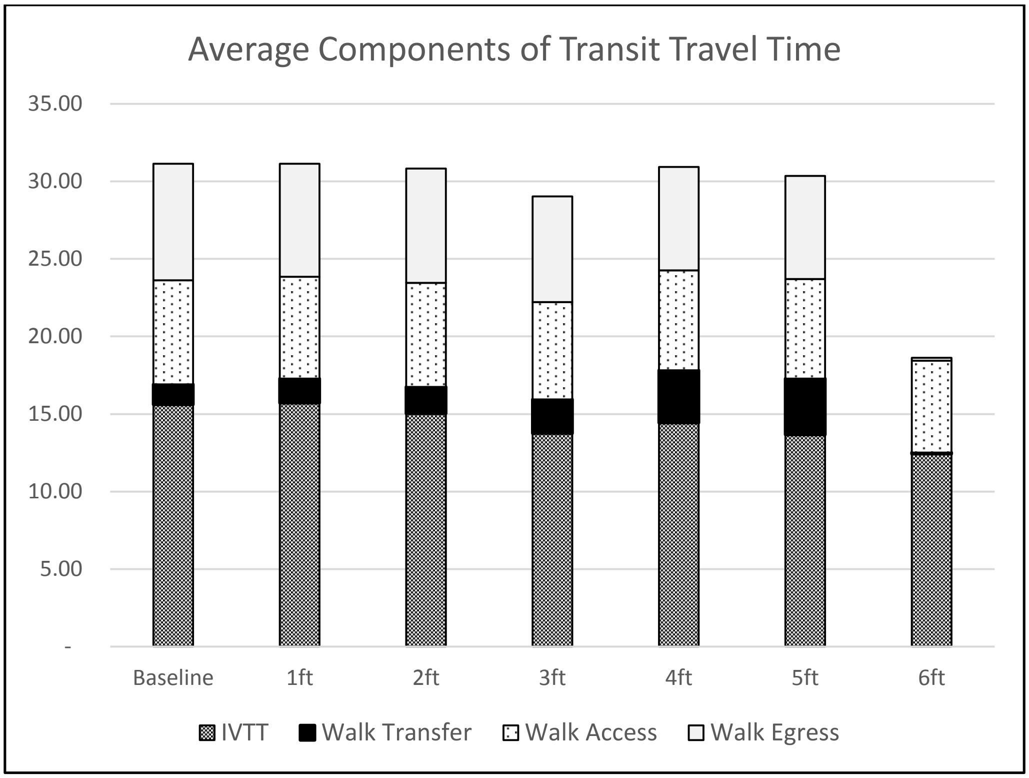

Figure 64: Average Components of Travel Time Across Inundation Levels

Total travel time in transit can be broken down into different component pieces: in-vehicle-travel-time (IVTT), walk transfer time, walk access time and walk egress time. The model for this analysis does not report individual origin destination (OD) trip times. The total system times are available for analysis as well as the number of linked trips that occurred.

The change in travel times are somewhat ambiguous. Inundation cause a reduction in the total number of longer distance trips (i.e. Commuter Rail, Heavy Rail journeys) this leads to decreased components of travel times over all. The decrease in travel time shown in Figure 64 is counterintuitive: inundation should increase travel time across modes. Because there are fewer trips overall, however, lost trips can dramatically affect averages. In fact, I suspect that the lost trips could include the passengers with the longest travel times. Figure 64 shows the changes in travel time across the different inundation levels. In general, IVTT decreases over the different inundation levels. Walk transfer travel time increases across all inundation levels. Increases in walk transfer times indicate either that people are walking farther to access transfer points or transferring more often. Despite this somewhat odd results, I have examined them extensively and no obvious anomalies appear.

Inundation affects both the transit system and the attractions that exist in inundated zones. With inundation, modeled trips lose many of these attractors and the ability to access the ones not impacted. Although walk egress and access increase as well, the values are very small. These results may be due to the lack of capacity constraints on transit modes and the lack of congestion within the transit sub models of the MIT-FSM.

Figure 65 presents the components graphed in Figure 64 in terms of distance rather than time. We see a steady reduction in overall travel distances. The pattern of change over inundation levels is noticeably different from that seen in the average travel time graph (Figure 64): specifically, the average travel distance reduces greatly at each inundation level. People spend more time going a shorter distance.

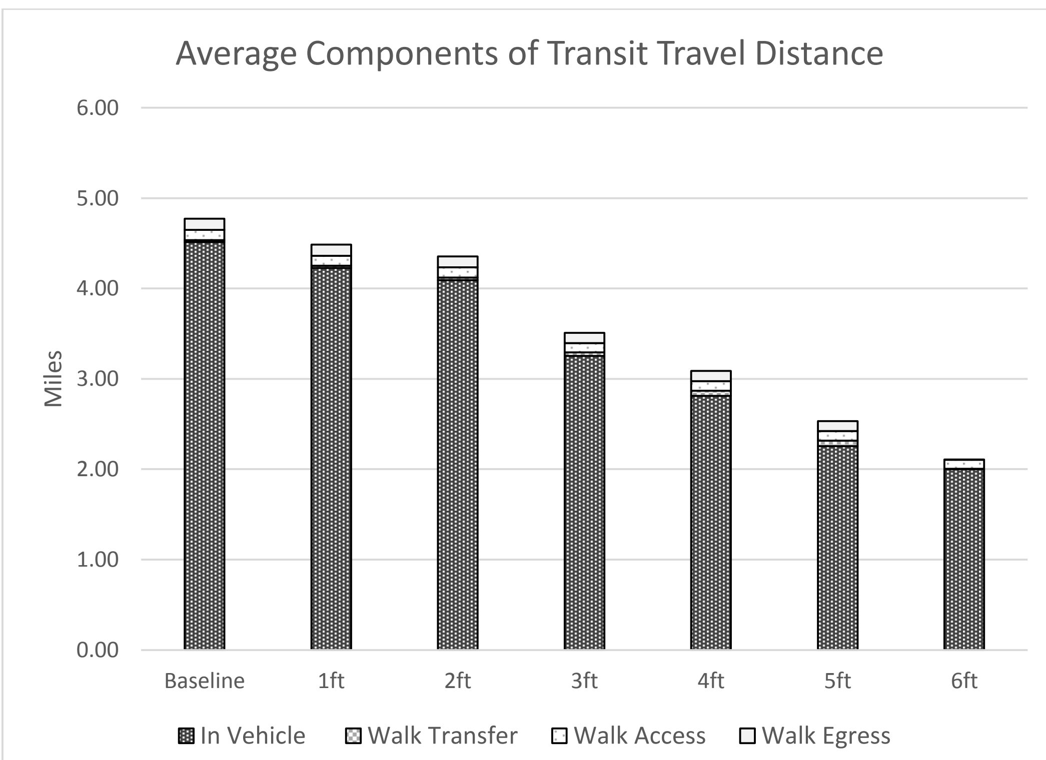

Figure 65: Average Components of Transit Travel Distance

Figure 65 shows, that of all estimated distance components, In Vehicle distance proportionally accounts for the largest amount of distance travelled. Figure 66 shows the proportion of each component of total average transit travel distance. Until the six-foot inundation level, all distance components, except In Vehicle distance, increase steadily. People are traveling farther to access both their final destination and transit itself.

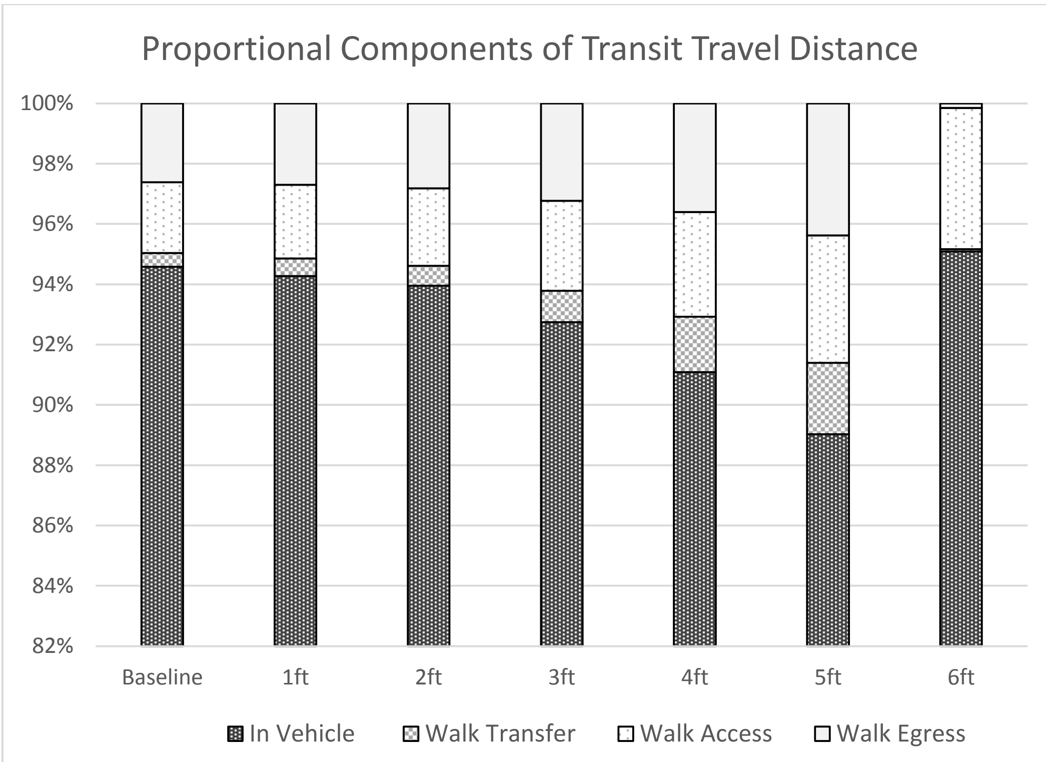

Figure 66: Proportional Components of Average Transit Travel Distance

6.2.2.4.B Transit Ridership Change by Transit Vehicle Type

Earlier in this section, I presented the total lost trips by mode, which included the categories PT_Walk and PT_Drive, or walk and drive access to transit. I do not model changed mode split, but for a transit trip, the actual type of transit used (train, bus, ferry, etc.) can change. Variations in ridership within transit modes across the different inundation scenarios offers some interesting insights. Figure 67 graphs the mode proportion across inundation levels for transit modes. The bus increases its dominance as a transit-specific mode as inundation increases. In the baseline scenario, the urban heavy rail lines carry the greatest number of passengers. However, its susceptibility to being disabled (tunnels, electric power) greatly impacts it at higher inundation levels.

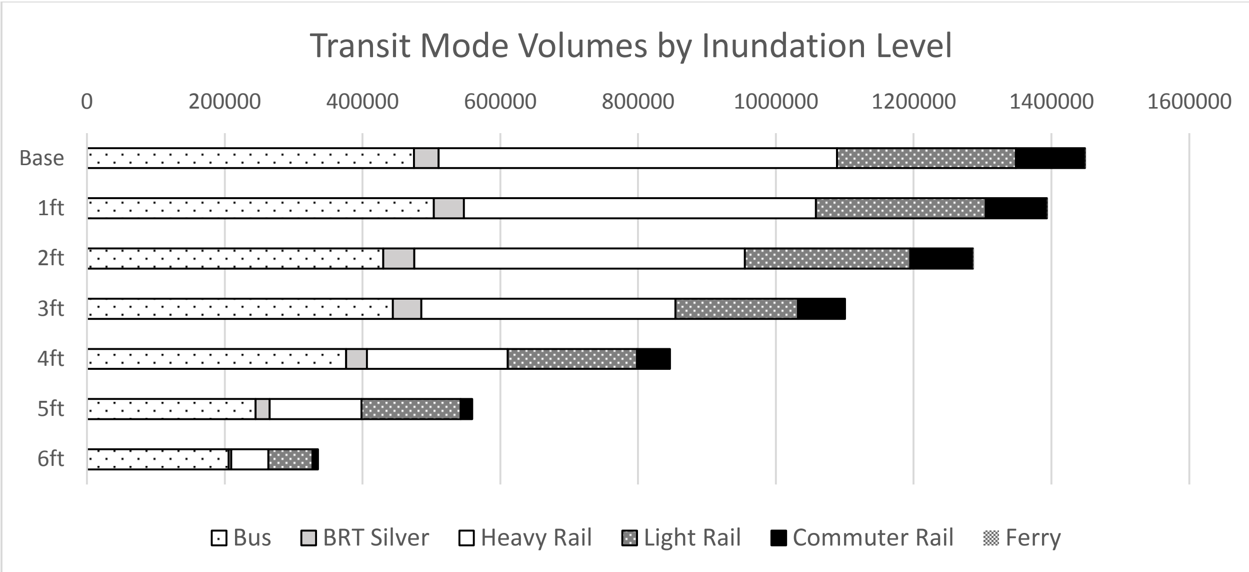

Figure 67: Transit Mode Volumes by Inundation Level

Table 32 shows miles of bus service (1594.89 miles) compared to miles of rail service (852.21 miles) in the region. The regional bus system fill in the gaps in the larger rail system. This dense system of buses offers both connections between radial rail lines and mobility resiliency to transit-dependent populations. Admittedly, the impact on the heavy rail is partially due to assumptions about the level of inundation it can withstand. These findings provide interesting insights nonetheless.

MODE	RIGHT OF WAY MILES[6]
BUS	1562.35
BRT SILVER	32.54
HEAVY RAIL	97.74
LIGHT RAIL	58.19
COMMUTER RAIL	696.28
FERRY	45.11

Table 32: Transit Miles by Mode

The Silver line bus rapid transit (BRT) sees increases in the lower inundation levels, likely in response to impacts on the Red Line heavy rail system. As the water level increases, however, the Silver Line is

[6] These are miles of service for every single line for each mode. If multiple buses or trains run along the some right of way (ROW) then they are added multiple times.

mostly inundated and ridership drops greatly. In the subsequent section, I will introduce some specific line summaries and highlight specific changes in ridership likely attributable to the loss of specific transit lines. For Light rail, specifically the Green Line, the lines maintain much of their ridership up to the six-foot inundation level. Commuter Rail has major reductions, while ferry has an initial increase in ridership. Then, as the terminals inundate, ferries suffer 100 percent loss of service.

Figure 68 provides a clearer picture of the changes in ridership for each transit mode across the different inundation levels.

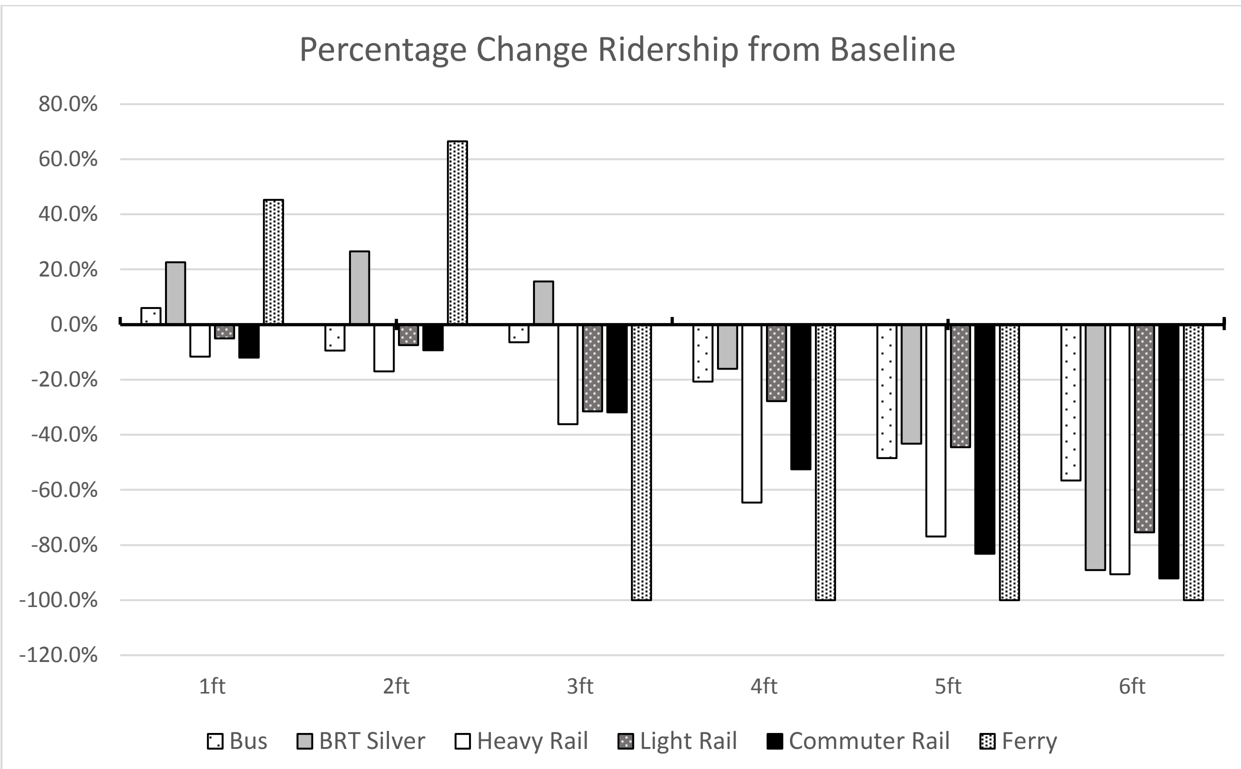

Figure 68: Percentage Change in Ridership from Baseline

By four-foot inundation all modes display losses in ridership. In fact, by six-foot inundation all modes – except buses – lose at least 50 percent of their initial ridership. At six-foot inundation, buses maintain almost half their ridership, largely for two reasons: one, many routes are not inundated at six-foot inundation; and, two, bus routes are able to pick up ridership from other inundated modes.

Ridership reduction by mode provides another way of viewing these data. Figure 69 shows major impact on riders of urban heavy rail and the loss of many bus passengers.

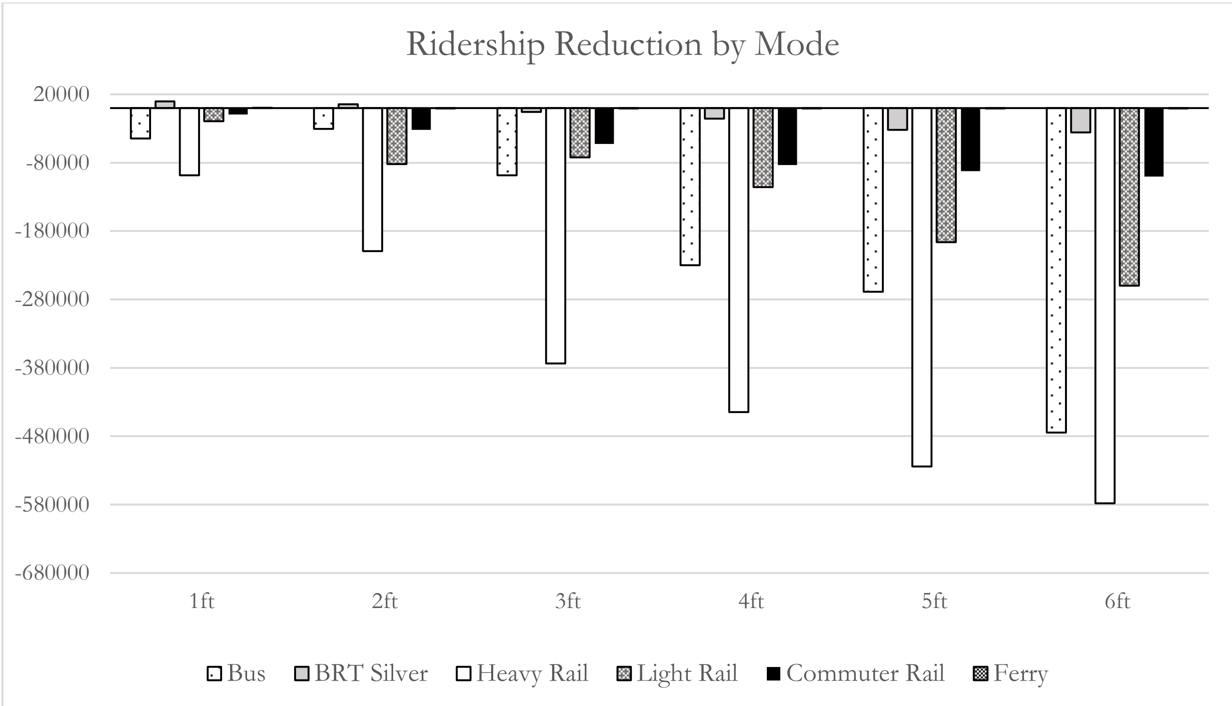

Figure 69: Ridership Reduction by Mode across Inundation Levels

The major reductions in ferry trips are trivial in terms of overall rider share. Thus, the 100 percent loss of riders at the three-foot inundation level is of minimal consequence, accounting for less than 1000 trips.

The difference between rail and bus response and usage across scenarios should be of particular interest to planners and engineers developing strategies for resilient transit systems. Bus systems are more flexible than fixed route systems. To highlight the changes in bus and rail ridership over the different scenarios, Figure 70 graphs the ratio of rail ridership to bus ridership. At the baseline (no inundation) for every 1.8 rail trips there was one bus trip (Bus includes BRT service). As the inundation level increases, this ratio decreases. At the six-foot inundation level, the ratio is slightly higher than 0.5, a complete inversion of the original relationship. At higher inundation levels, buses are the most important transit mode.

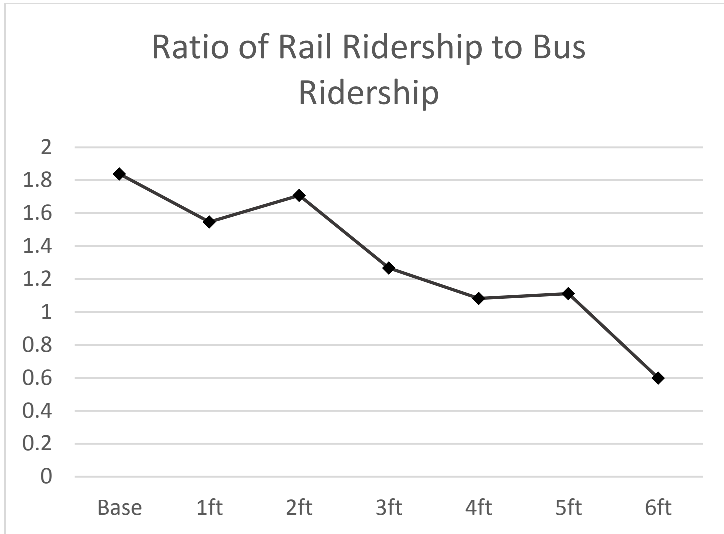

Figure 70: Ratio of Rail Ridership to Bus Ridership

6.2.2.4.C Transit Ridership Change by Route

The transit network data available provides a detailed picture of line-by-line changes in ridership, volumes and travel times on a link-by-link basis. Since the MIT-FSM model has over 100 public transit lines and my analysis includes six different inundation levels, the amount of data produced is difficult to summarize succinctly. As a result, below I examine an example of the type of data available and ways to present it. I also show results and a link to an interactive website that I created that provides an example of a way to present and communicate such data. I present example data drawn from the four-foot inundation level. At the four-foot inundation level, all of the major increases in demand occur on bus lines. The majority of decreases occur on the urban heavy rail lines – specifically the Red Line.

RANK	ROW LABELS		RIDERSHIP NO INUNDATION	RIDERSHIP 4FT	RIDERHIP DIFFERENCE
1	Red	HR	275,114	65,868	-209,246
2	Orange	HR	241,823	134,760	-107,063
3	Green	LR	259,869	187,477	-72,392
4	Blue	HR	61,199	4,043	-57,155
5	111	Bus	16,046	4,202	-11,844
6	86	Bus	20,199	8,710	-11,489
7	Framingham	CR	13,039	2,735	-10,303
8	39	Bus	24,197	15,193	-9,004
9	71	Bus	10,207	1,410	-8,797
10	7	Bus	9,662	971	-8,690
11	1	Bus	13,775	5,901	-7,874
12	Fairmount	CR	7,497	528	-6,969
13	Haverhill	CR	7,286	475	-6,810
14	77	Bus	10,113	3,934	-6,179
15	Attleboro	CR	15,674	9,913	-5,761
	Total	--	985,699	446,120	-539,578

Table 33: Top 15 Routes by Ridership Decrease

RANK	ROW LABELS		RIDERSHIP NO INUNDATION	RIDERSHIP 4FT	RIDERHIP DIFFERENCE
1	CT2	Bus	6,269	23,442	17,173
2	55.1	Bus	913	6,005	5,092
3	33.4	Bus	418	4,038	3,620
4	92	Bus	3,331	6,874	3,543
5	15	Bus	4,340	7,865	3,525
6	69	Bus	4,233	7,317	3,084
7	83	Bus	846	3,711	2,865
8	22	Bus	5,982	8,677	2,695
9	85	Bus	816	3,400	2,584
10	66	Bus	28,394	30,791	2,397
11	8	Bus	8,173	10,458	2,286
12	23	Bus	7,782	9,811	2,028
13	21	Bus	3,917	5,778	1,860
14	Needham	CR	16,756	18,410	1,653
15	90	Bus	3,261	4,890	1,629
	Total	--	95,430	151,466	56,035

Table 34: Top 15 Routes by Ridership Increase

Table 33 shows the 15 transit routes with the greatest decrease in ridership, from no inundation to the four-foot inundation level. Inundation causes a total loss of -539,758 passengers on these routes. Table 34 shows the 15 routes with greatest increase in ridership, from no inundation to the four-foot inundation level. The total decrease in the top 15 lines shown in Table 33 (-539,758) far exceeds the

the increases for the top 15 lines graphed in Table 34. Bus use in the top 15 routes increases substantially, by +54,382.

This comparison highlights that, though buses do offer resiliency, they are unable to recoup all lost ridership. In particular, the large loss of trips on the heavy rail line are not entirely redirected to buses. A more detailed version of this anlaysis that focuses on ridership loses and gains by geographical location of ridership is in the Ridership Shifts section.

I have compiled two example demonstrations of how these data may be useful for practical planning purposes. First, I demonstrate how extreme congestion provides some useful insights into resilient links. Second, I examine how a specific transit ridership route shifts due to inundation.

6.2.2.5 Example Application of Metrics

6.2.2.5.A Example of Extreme Congestion and a Resilient Link

The MIT-FSM model, and all four-step modeling platforms, report volumes and travel times for each network link. This provides detailed insights into impacts on specific roadways, which can be especially useful for climate change planning as it makes readily apparent the systemic impact on specific segments caused by inundation in other areas. This type of analysis, if conducted by a regional agency or consultancy, could target specific metrics, by, for example, creating an inventory of "critical roadways" to identify impacts under various inundation levels.

Figure 71 shows one example of the extreme congestion link described in the Auto Assignment section, highlighting with a series of thick lines marked with an A and a circle. The line indicates high levels of VC, in this case, levels over 10.

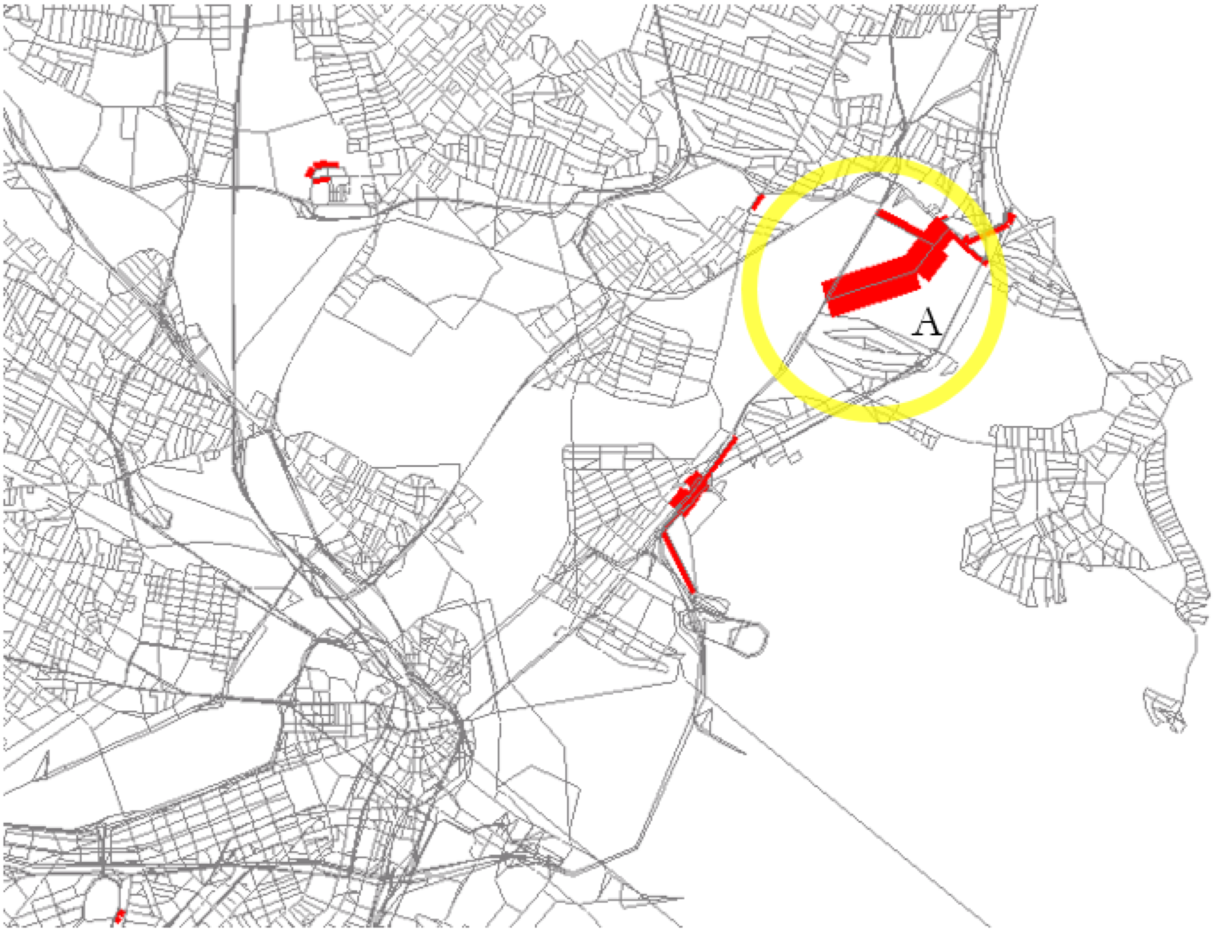

Figure 71: Extreme Congestion Link

Figure 72 shows the specific links highlighted in Circle "A" in Figure 71 (via Google Maps). Furlong Drive (diagonal roadway in upper left quadrant) initially appears to be a dead end. Once appropriately zoomed in, Google Maps shows that it is, in fact, the entrance to a "big box" shopping store. The street with the greatest VC in this highlighted area is Tomassello Way (highlighted roadway to the right of Furlong Drive). The actual VC measured on this link is not realistic, as people would not continue attempting to access this path given such congestion. What *is* of interest here: the model has highlighted the single path – into and out of this area –not compromised at the four-foot inundation level.

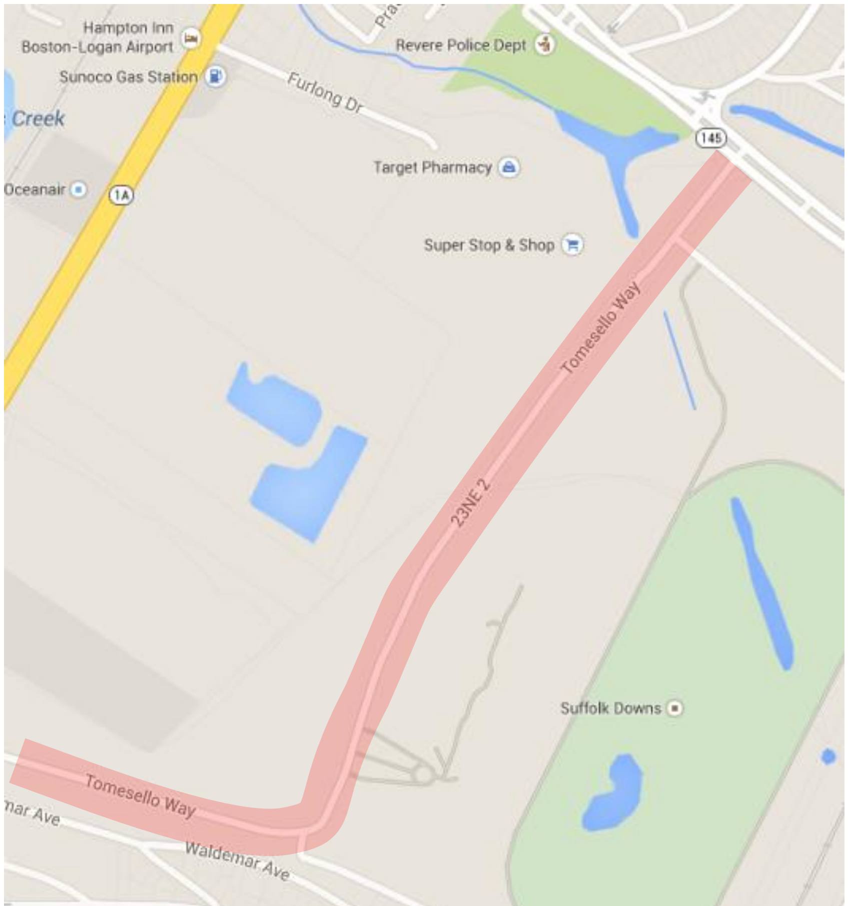

Figure 72: Close Up Extreme Inundation Link

This special case provides information that could be useful, for example, to local leaders to assist in resiliency planning, e.g.: to justify capacity improvements along this link or to reinforce other nearby links. VC ratios such as this provide valuable information on necessary interventions, including for emergency planning, identifying evacuation routes, or providing emergency service information systems with the best routes in case of flooding. Many comparable links appear in the modeling across the different inundation levels.

6.2.2.5.B Ridership Shifts

In this section I present an example of exploratory ridership shift anlaysis for a four-foot inundation level focusing on the urban heavy rail line, the Red Line.

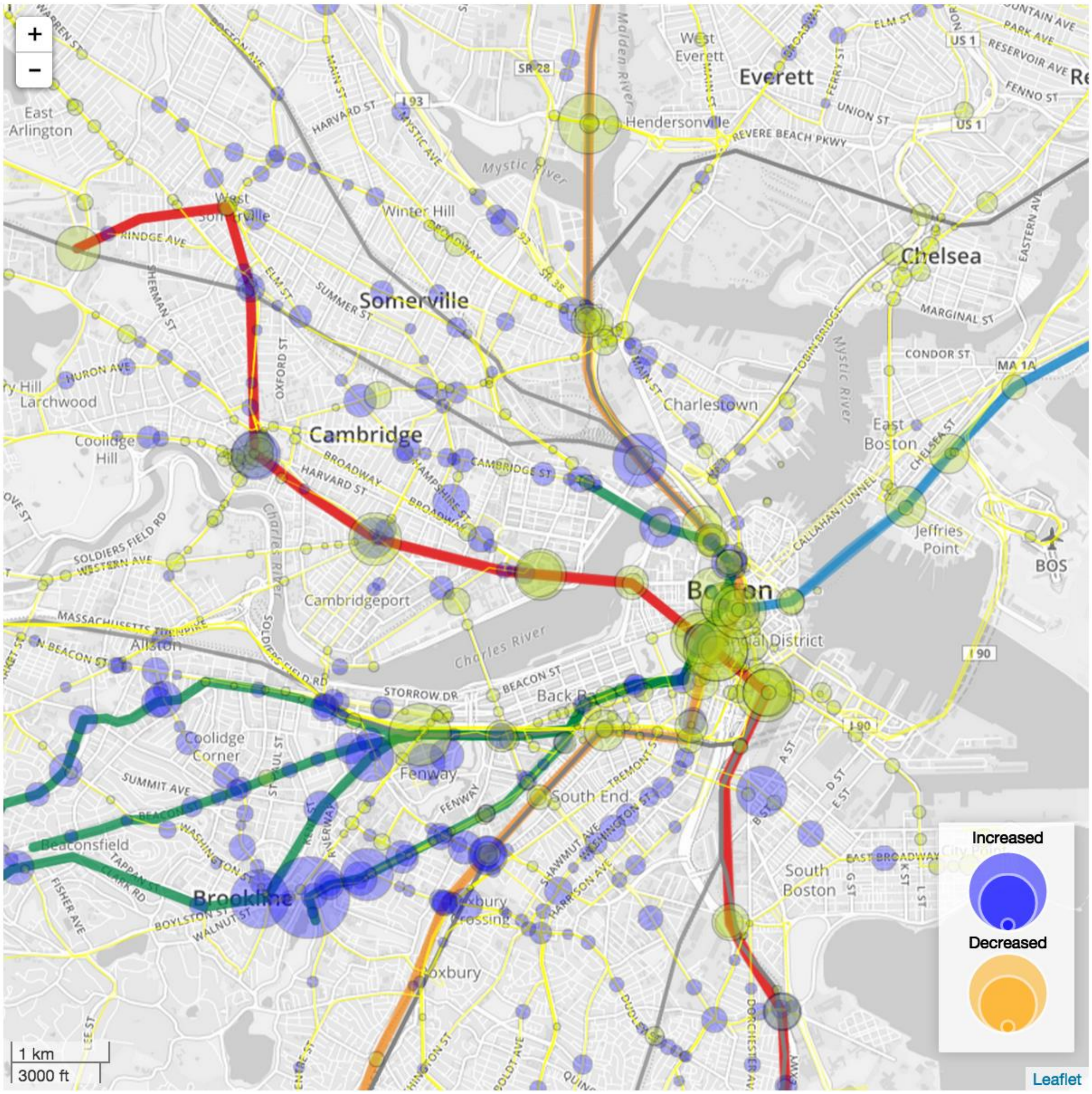

Figure 73: Ridership Change 4ft Inundation – Medium View

In Figure 73, the orange circles indicate those stops that lose ridership (Decreased Boardings), while the blue circles indicate those with growth (Increased Boardings). I scaled the circles relative to total count of riders: small = 100 – 500 riders; medium = 500-15,000 riders; large=15,000-31,000 riders.

There are major concentrations of transit stops with decreased ridership. The route that has the largest decrease in ridership is the Red Line.

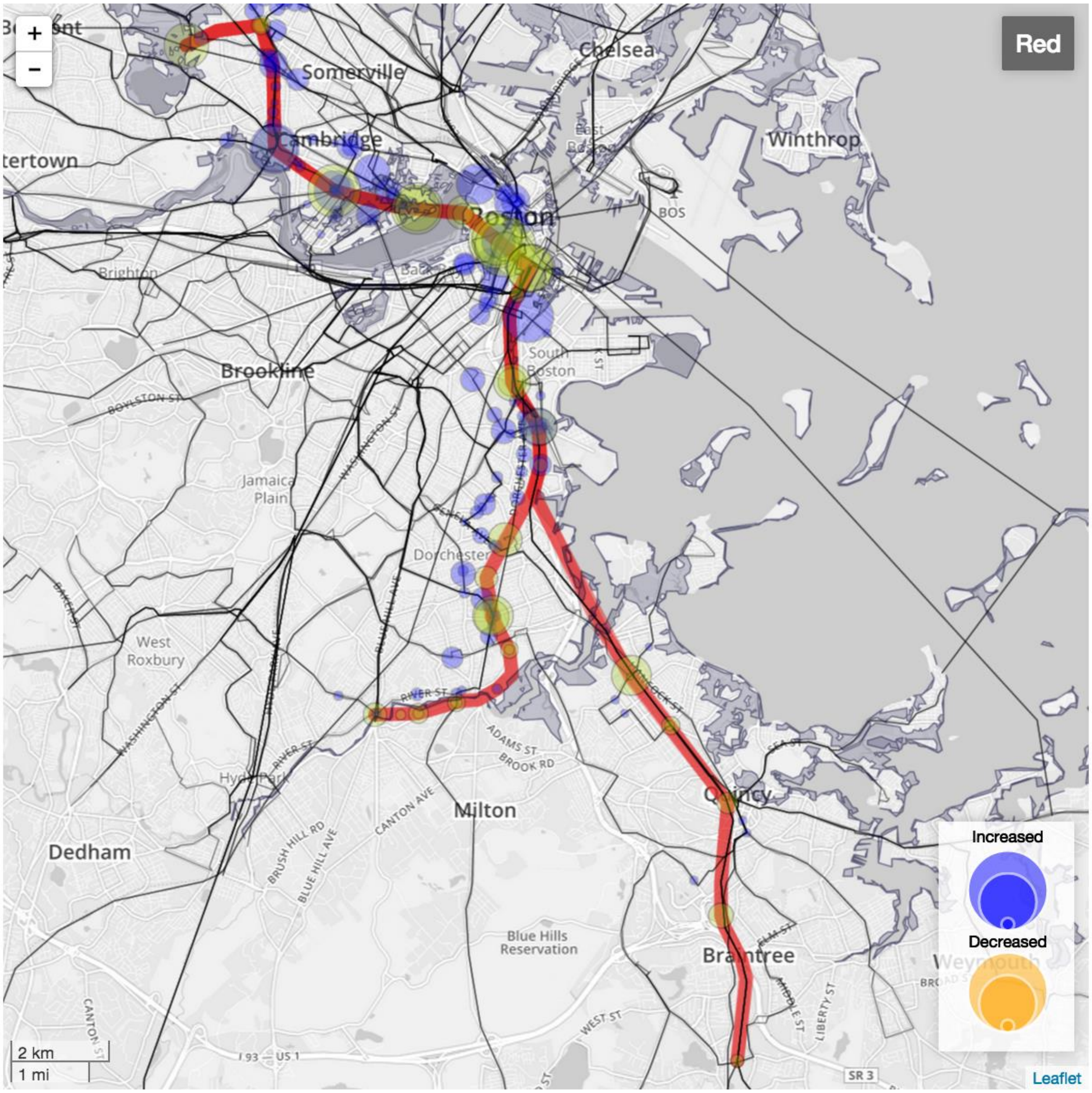

Figure 74: Red Line Decreased Ridership

Figure 74 shows the increase and decrease of ridership on just the Red Line. The orange circles indicate stops along the Red Line with decreased boardings. The blue circles, however, are all stops within a half mile of the route with increased boardings. This maps an approximation of diversion in ridership, though I do not know the specific diversion of trips to other routes. The places marked with blue circles on the map (increased boardings) may indicate alternative routes geographically corresponding to the Red Line transit stops with decreased boardings (orange circles).

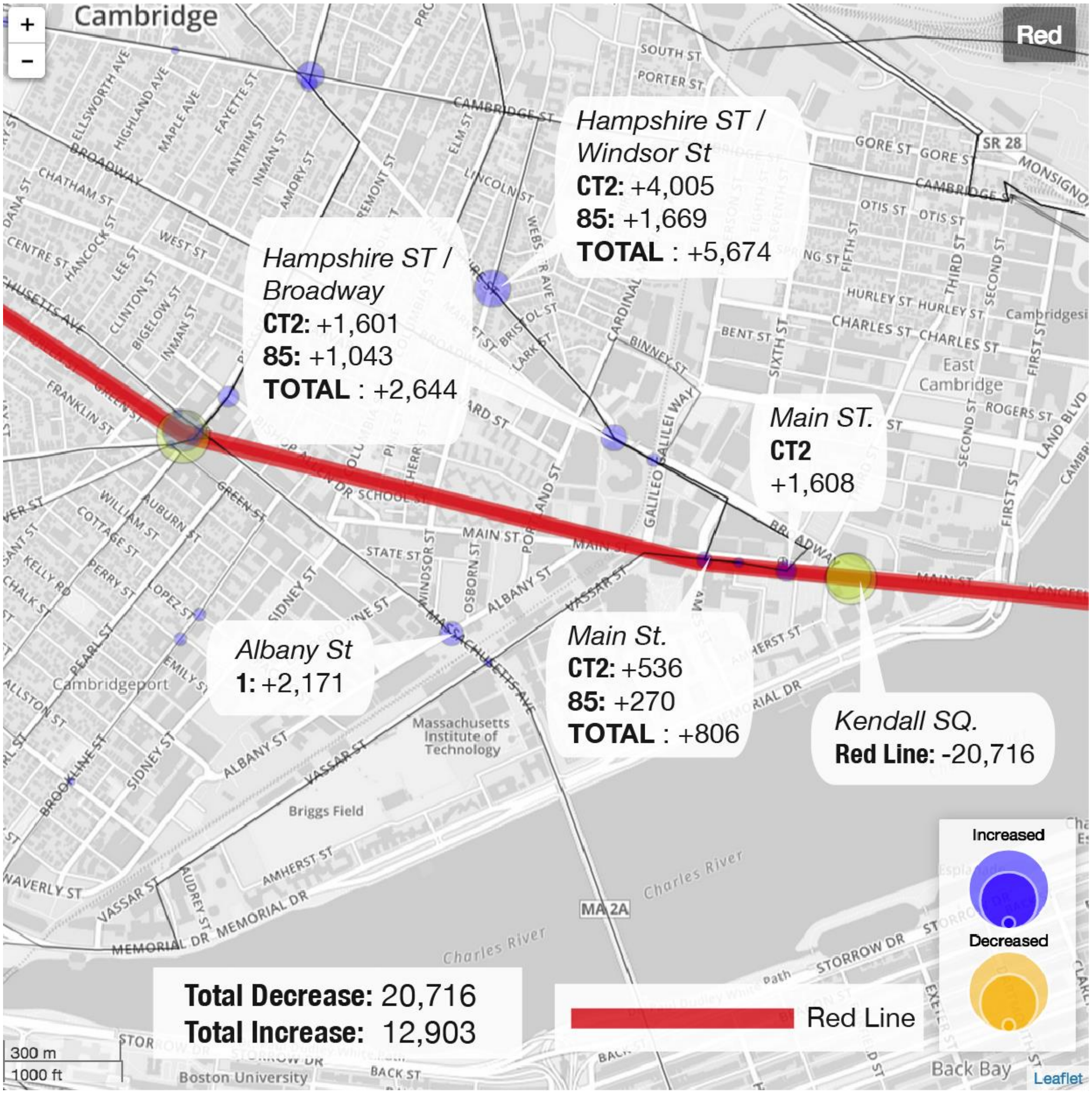

Figure 75: Red Line Ridership Shift

Figure 75 shows an enlarged section of the Red Line near MIT. The Red Line stop, marked with the orange circle, is the Kendall Square stop. This stop loses 20,715 riders due to inundation. The blue circles mark the bus stops within a half-mile of Red Line that had ridership increases in the four-foot inundation scenario. Ridership at these stops increases by 12,903 in the inundation scenario, likely representing diverted trips from the Red Line.

This exercise could be repeated for each of the different inundation levels, using different thresholds to display the relevant information. Such results could be useful for planners, policy makers, engineers, the public and, most notably, transit planners. The data provide insights into potential routes that should be bolstered in the event of inundation. If a certain amount of inundation is expected, a planner could analyze these data to identify routes that may need increased capacity.

Buses experience increased ridership in inundation scenarios. However, transit agencies have limited resources, including vehicles (required to increase capacity). The ability to prioritize this increased capacity is extremely valuable. In the example in Figure 75 capacity could be increased on the CT2 and the 85, the two routes with the greatest ridership increase in four-foot inundation event. The interested reader can visualize and explore these data at http://mdgis.github.io/.

The congestion and ridership shift example analyses suggest the value of this information, not currently available. This analysis highlights potential real world interventions. The amount of data output by these models can be daunting and it is nigh impossible to summarize all the potentially important insights available. This is not a weakness of this analysis. Rather it is a great strength. What is important is that the information is available. Given a real world application of this method within a planning agency, different output metric groupings of data (auto network, transit network, etc.) could be disseminated to relevant agencies to allow them to prioritize the questions that they would like to answer.

6.2.2.6 Accessibility to Jobs

Accessibility to jobs for each zone in the model region is another metric estimated from the outputs of the Inundation Impact Assessment Modeling. I use congested travel time skims reflecting inundated conditions to calculate these measures.

6.2.2.6.A Auto

Figure 77 is the baseline isochrone (no inundation) accessibility map. In this map, the areas with the highest access to jobs are in the inner core and downtown Boston; the corridor south of downtown

Boston along U.S. Route 1/Interstate 93; and a region along Route 128 to the west of the city (mapped in Figure 76). Figure 77 has major highways overlaid on the map. Figure 76 provides names and other contextual information for these highways.

The map highlights the level of accessibility provided by major highway infrastructure in the region. Nearly all of the highest access areas are either along the highways or adjacent to them. Outer regions of the model area have much lower accessibility to the major jobs centers in the area. The model area does not include Worcester, a central Massachusetts job center, so persons in the outer western TAZs may have higher accessibility than pictured (i.e., possible jobs fall outside model boundary); the same could be true for zones in the north and south, bordering New Hampshire and Rhode Island, respectively. The impedance/gamma measure has its highest values in the core of the city and then decreases slowly outward displaying a smoother gradient.

Figure 76: Massachusetts Major Highways, source: MassDOT

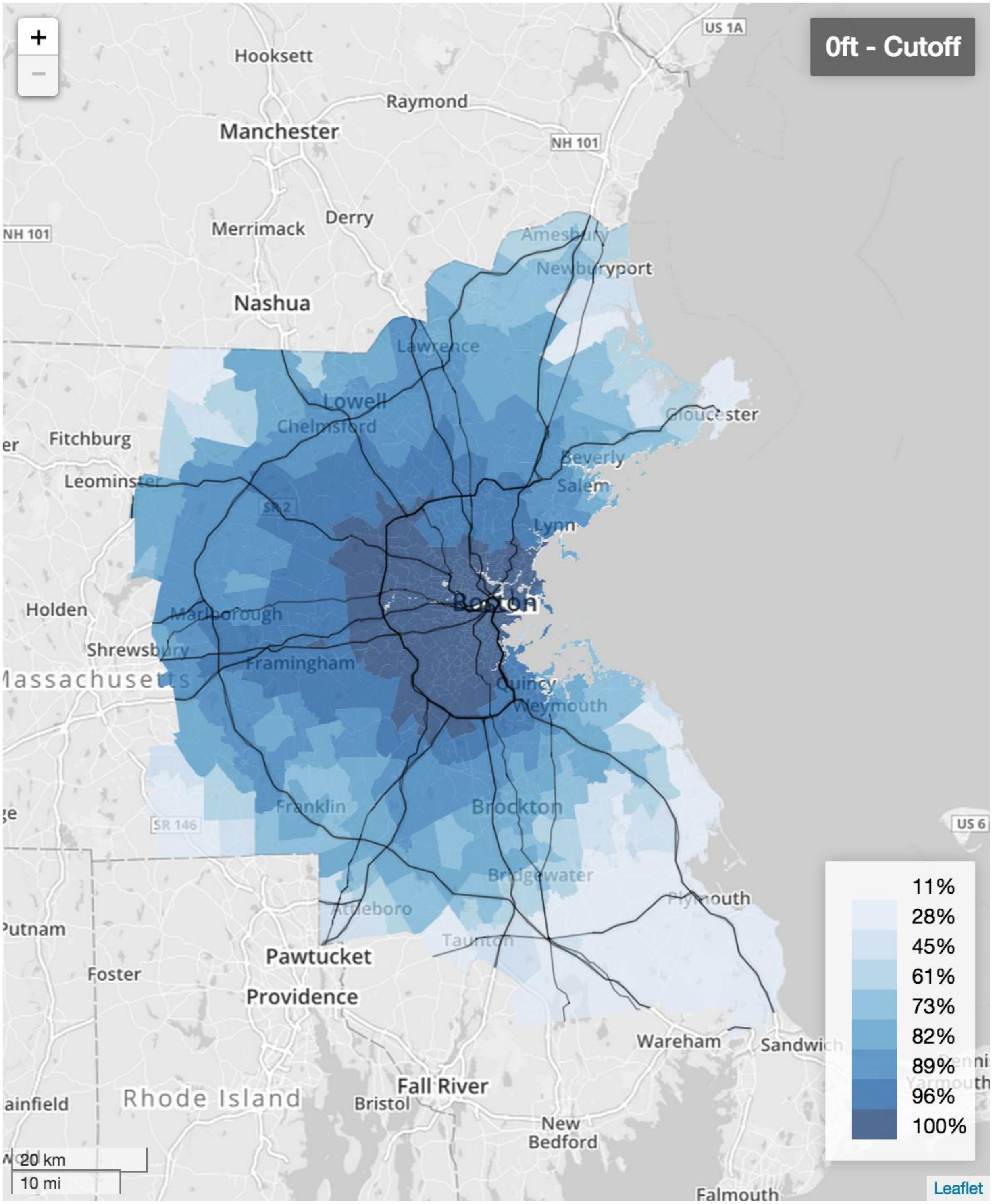

Figure 77: Baseline Auto Isochrones

The gamma measure (Figure 78) shows a similar overall pattern but with more concentrated values in the inner core. These values of accessibility outside of the inner core decrease more substantially than the values of the isochrone measures.

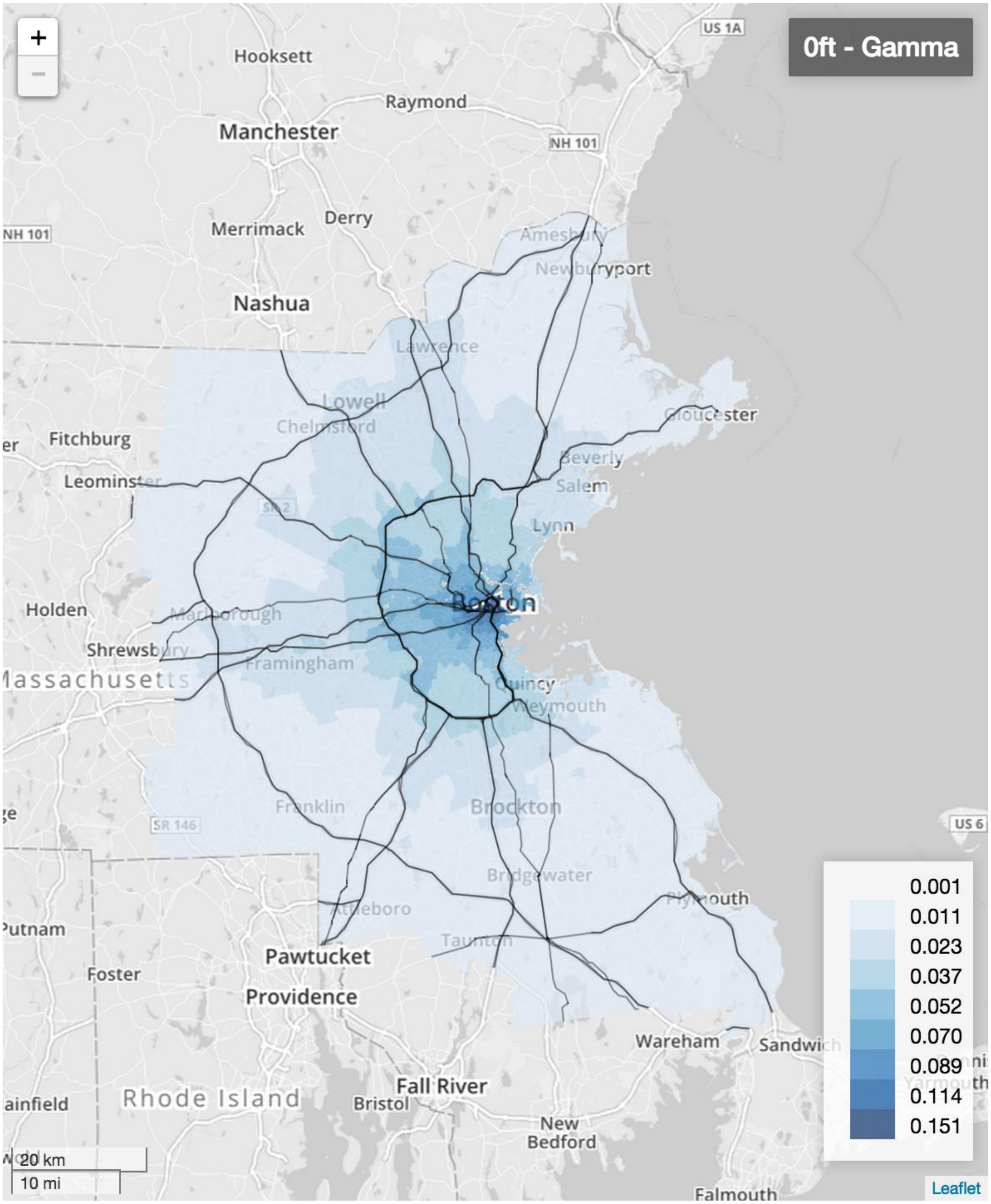

Figure 78: Gamma Impedance Baseline Accessibility

Figure 79 through Figure 94 map each inundation level from baseline (no inundation) to the six-foot level. Figure 79 through Figure 86 map isochrone (cutoff) measures by inundation level. Figure 87 through Figure 94 map impedance (gamma) measures by inundation level. All maps are presented interactively and in more detail at http://mdgis.github.io/.

Isochrone (Cutoff)

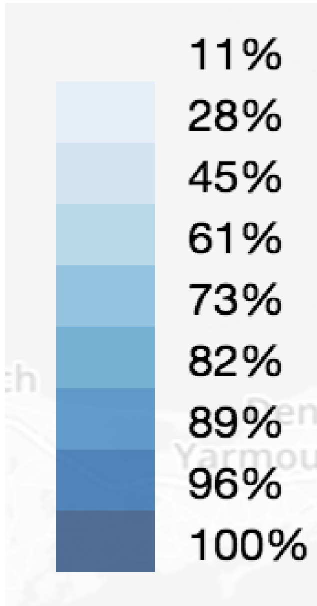

Figure 79: 60 Minute Isochrone Legend

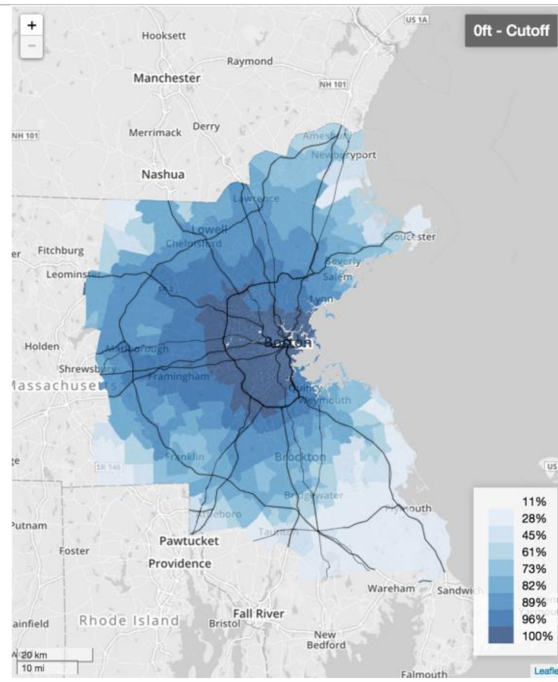

Figure 80: Auto Isochrone No Inundation

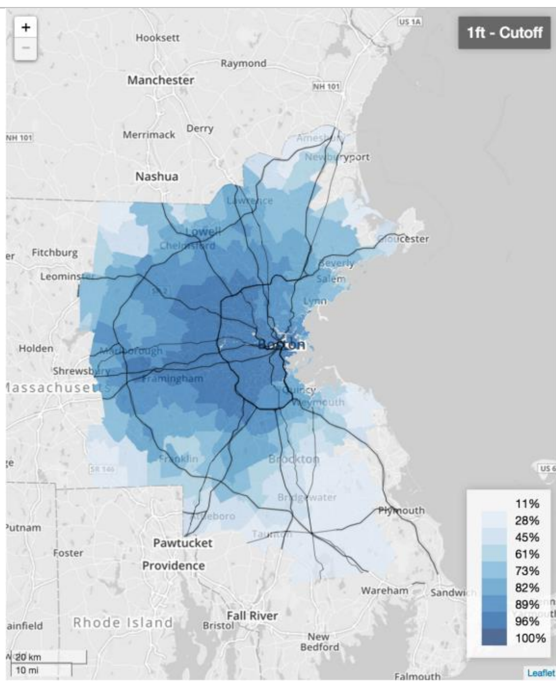

Figure 81: Auto Isochrone 1ft

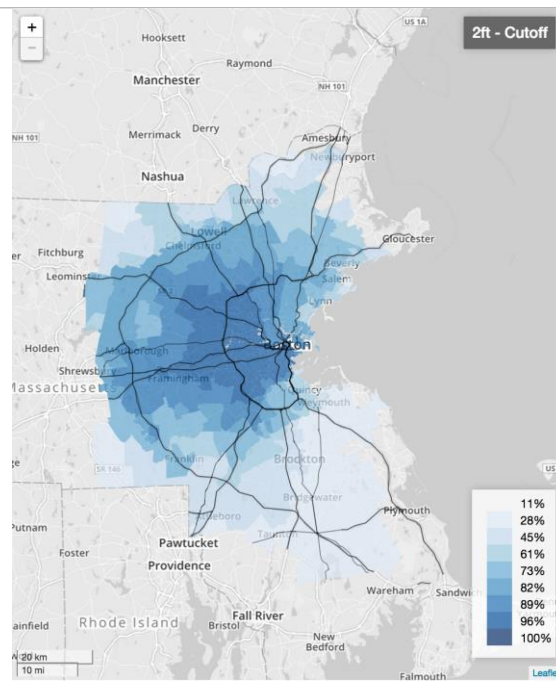

Figure 82: Auto Isochrone 2ft

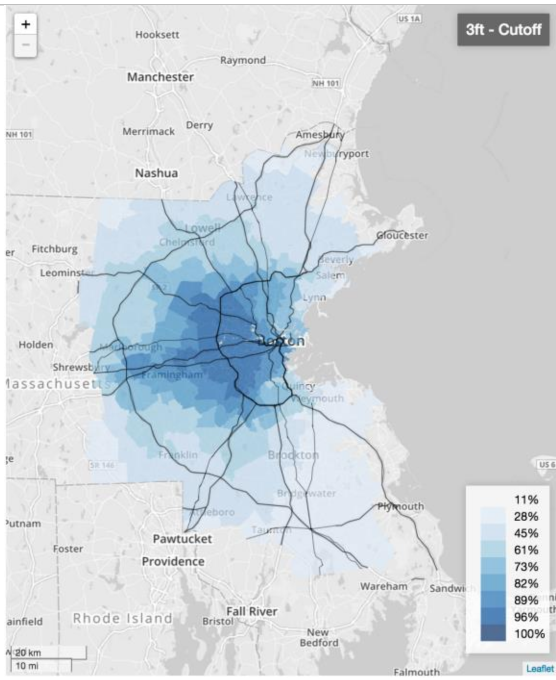

Figure 83: Auto Isochrone 3ft

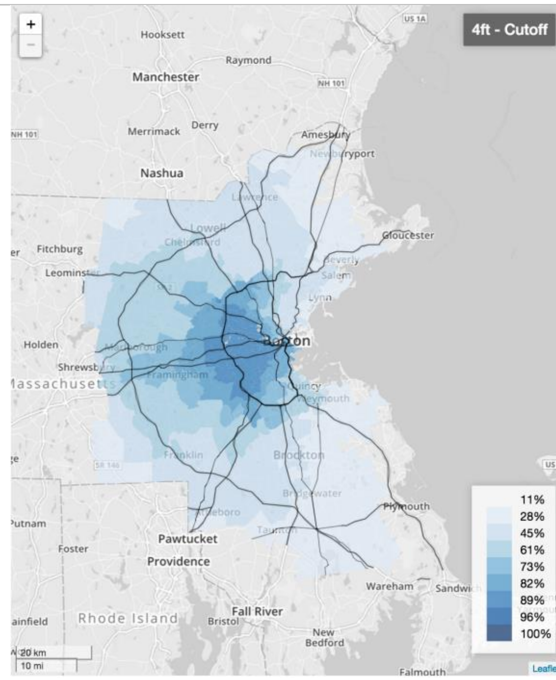

Figure 84: Auto Isochrone 4ft

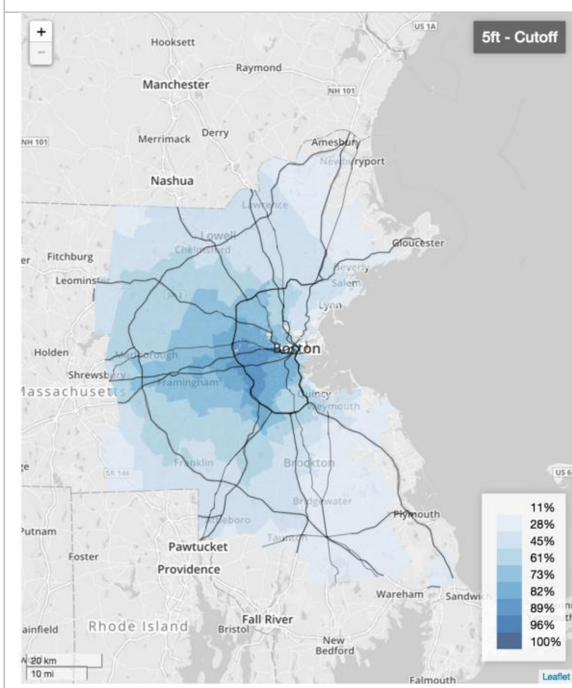

Figure 85: Auto Isochrone 5ft

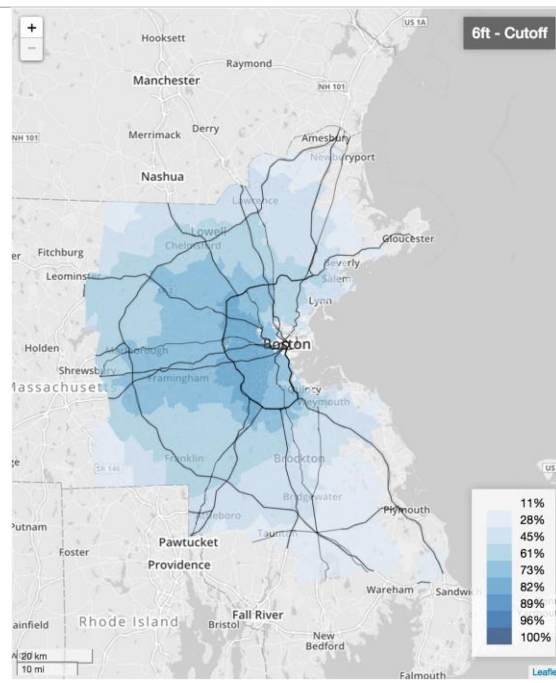

Figure 86: Auto Isochrone 6ft

Impedance (Gamma)

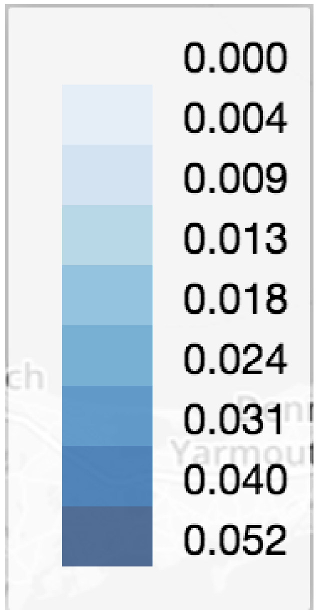

Figure 87: Auto Impedance Accessibility Legend

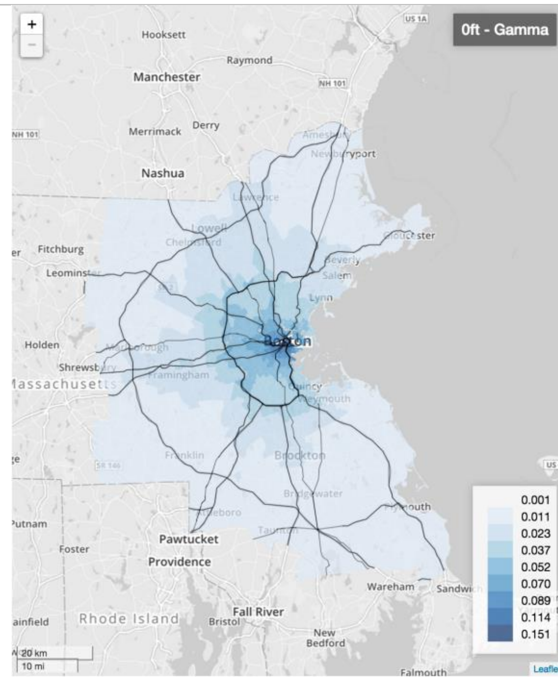

Figure 88: Auto Impedence 0ft

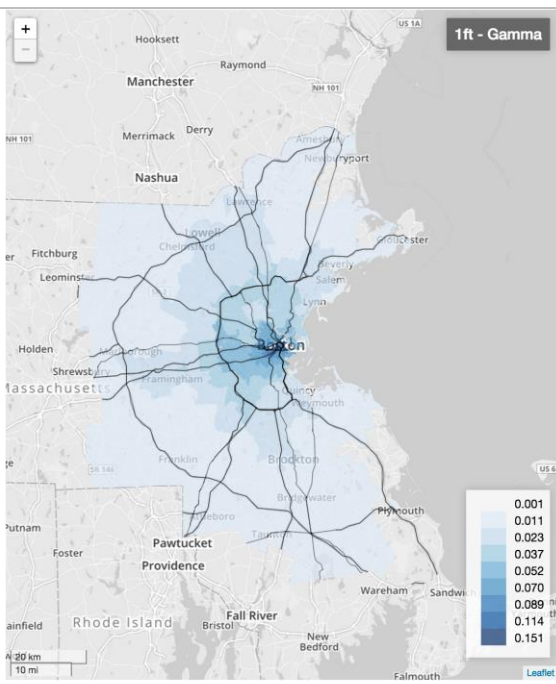

Figure 89: Auto Impedence 1ft

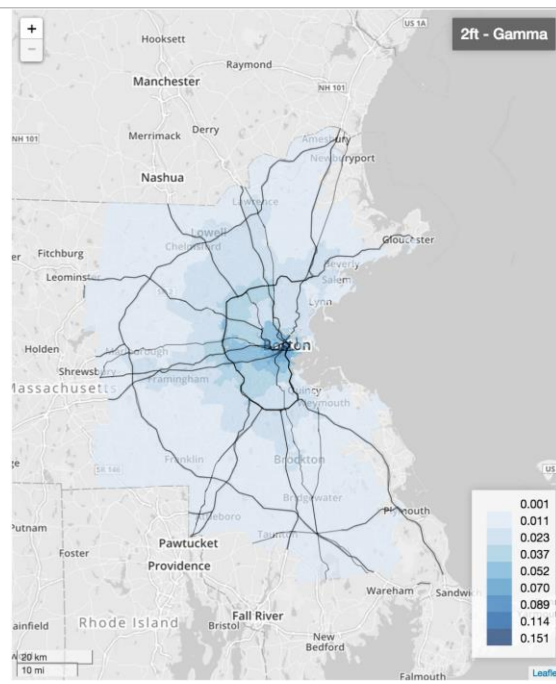

Figure 90: Auto Impedence 2ft

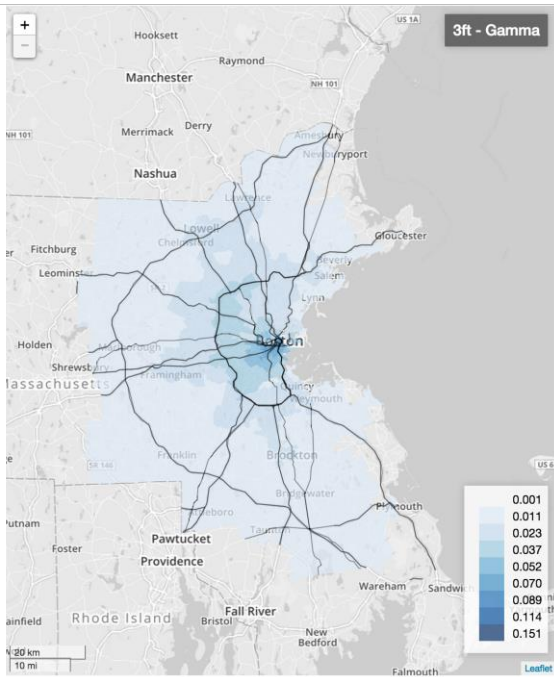

Figure 91: Auto Impedence 3ft

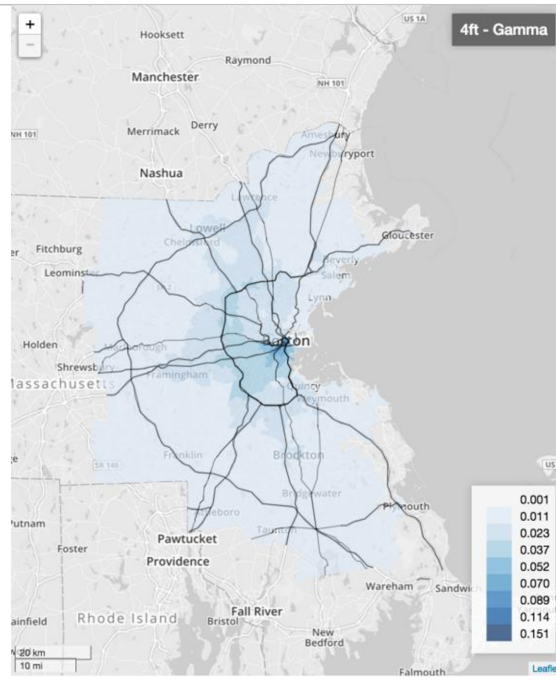

Figure 92: Auto Impedence 4ft

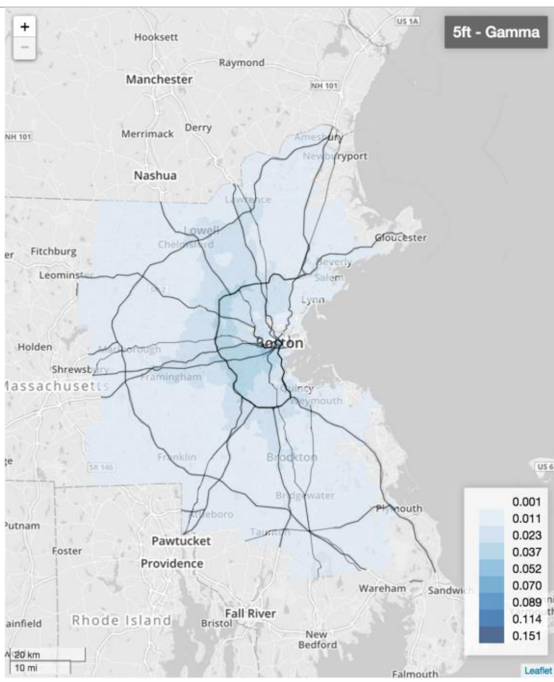

Figure 93: Auto Impedence 5ft

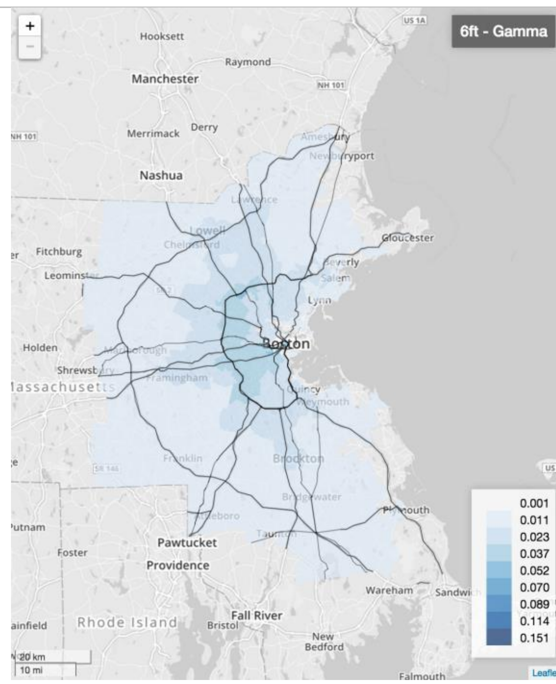

Figure 94: Auto Impedence 6ft

The largest decreases in both isochrone (cutoff) and impedance (gamma) measures are located along the coastline. These inundated areas can no longer access any jobs. Thus, they have great decreases in accessibility. Both measures show consistent decreases with increased inundation levels. The accessibility maps highlight the impacts on un-inundated regions, as well as inundated regions.

The areas that have decreased accessibility but no actual inundation are of particular interest. I expect inundated areas to lose access to jobs: the question is how impacted the areas that do not experience direct inundation will be if the necessary auto network is inundated. For example, accessibility decreases in the region to the south of downtown Boston along Highway 1/Interstate 93 in the map when the isochrone (cutoff) accessibility value is at the three-foot level (Figure 83). Inundation impacts Highway 1 and Interstate 93; however, there is a loss in accessibility that extends the boundaries of the mapped water level. As was mapped in Road and Highway Impacts, inundation greatly affects this highway.

There is a direct relationship between areas with a large number of available jobs and the areas with the highest accessibility to jobs. This includes areas downtown and along the first ring road, Route 128. The inundation of areas downtown affects those jobs within the inundated area, as well as the neighboring zones that had easy access to these zones. The loss of accessibility to the un-inundated areas is not as extreme as the inundated areas (and the areas closest to inundation).

The six-foot scenario highlights a great degree of impact across the region, with the region's commercial and economic hub essentially underwater. The less extreme three-foot scenario just as readily highlights vulnerabilities and impacts to regional job accessibility by auto.

6.2.2.6.B Transit

Transit accessibility represents accessibility to jobs by the MIT-FSM walk access transit mode. This does not include park and ride access. Transit Baseline values are concentrated around the extent of the transit system, with the highest values clustered in the inner core area where transit access is densest. These areas have diverse access to transit, with a high number of bus lines, access to light rail and heavy rail, and commuter rail. The areas of high job accessibility by auto, along Route 128, do not appear in the transit accessibility measures, reflecting the lack of transit access along that corridor. The regions with the highest transit accessibility only offer access to up to 36 percent of jobs in the 60-minute cutoff measure. Both isochrone and impedance measures are represented as quantiles (groups of 8). The values are more uniform in the impedance measure, with relatively high values concentrated in downtown Boston and Cambridge. In Figure 95 through Figure 112, clusters of TAZs that follow the black lines on the map correspond with commuter rail stops, thus reflecting commuter rail accessibility.

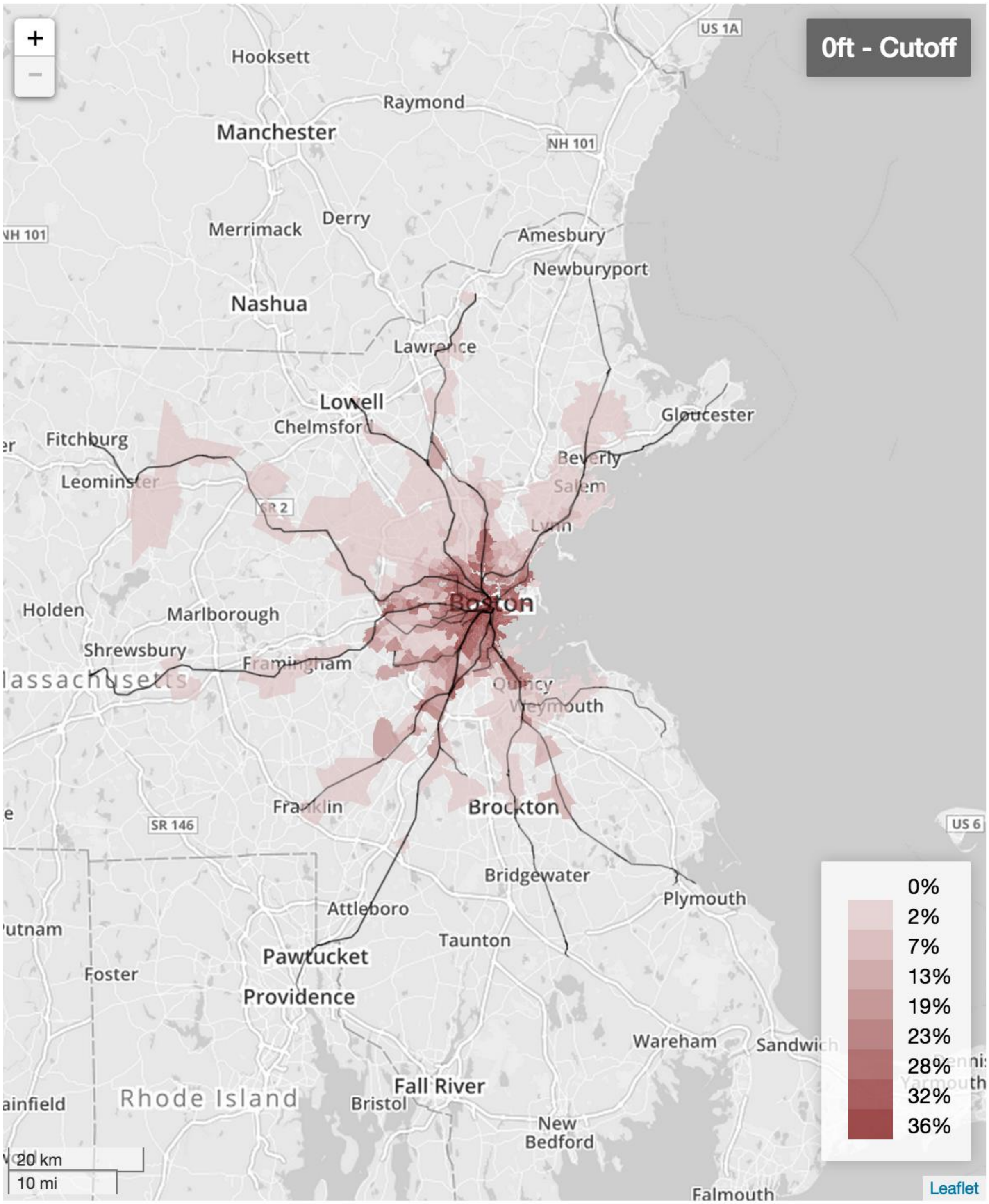

Figure 95: Transit Isochrone Baseline

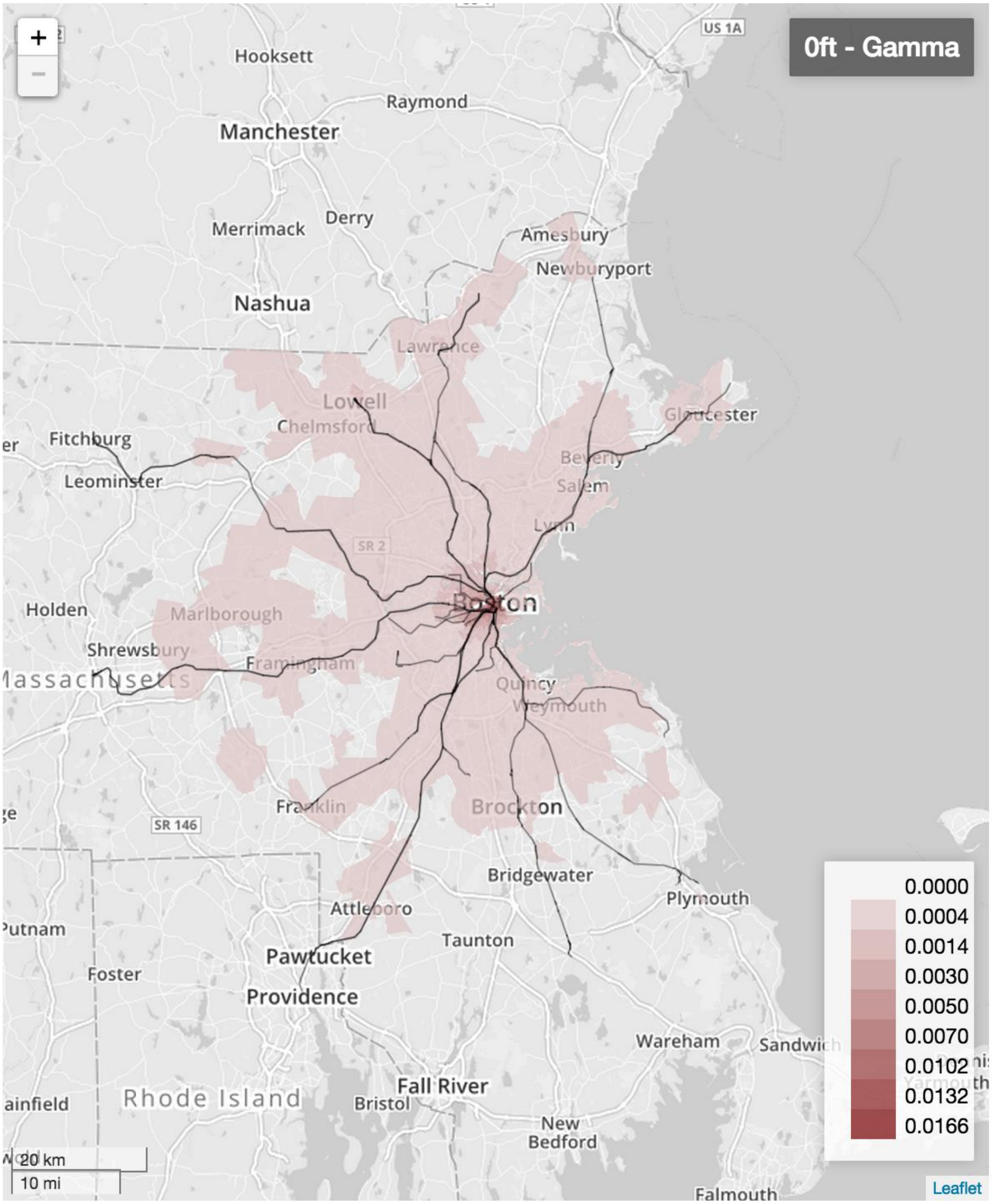

Figure 96: Transit Impedance Baseline

Isochrone (Cutoff)

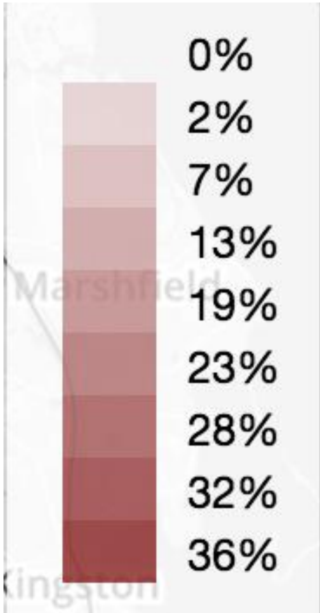

Figure 97: 60 Minuter Transit Isochrone Legend

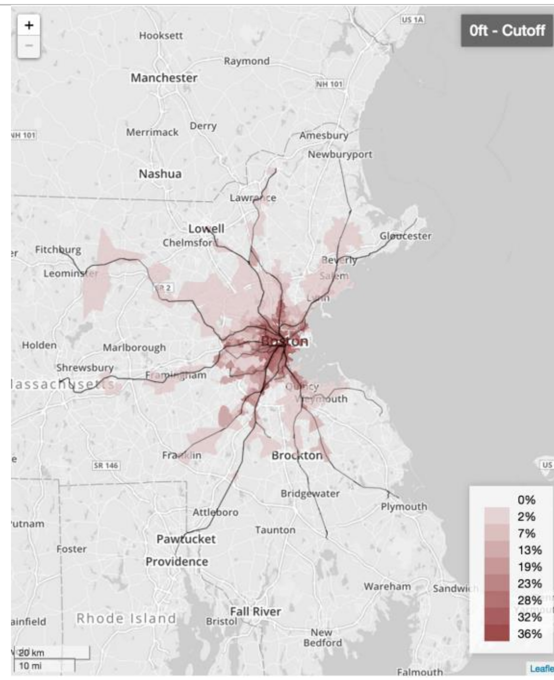

Figure 98: Transit Isochrone 0ft

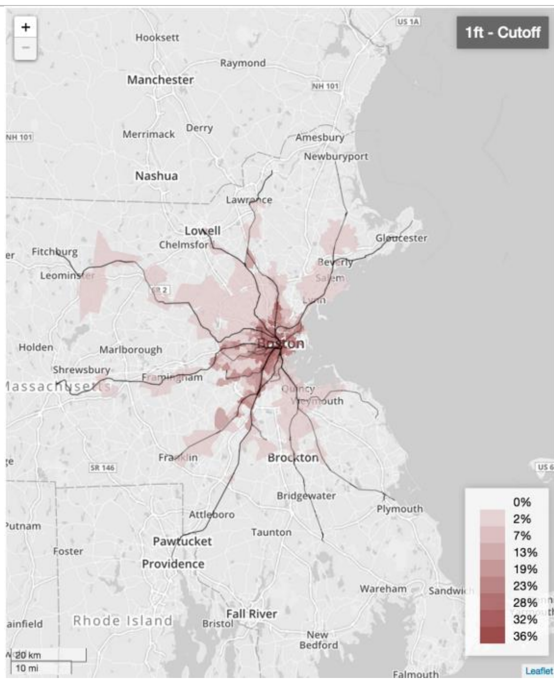

Figure 99: Transit Isochrone 1ft

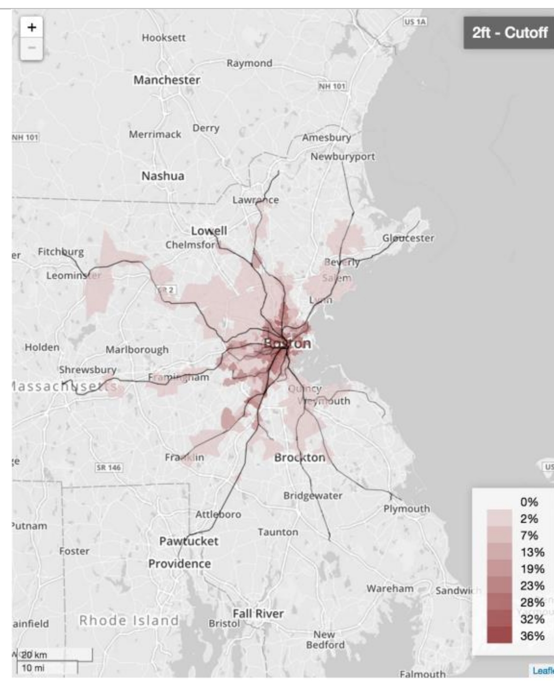

Figure 100: Transit Isochrone 2ft

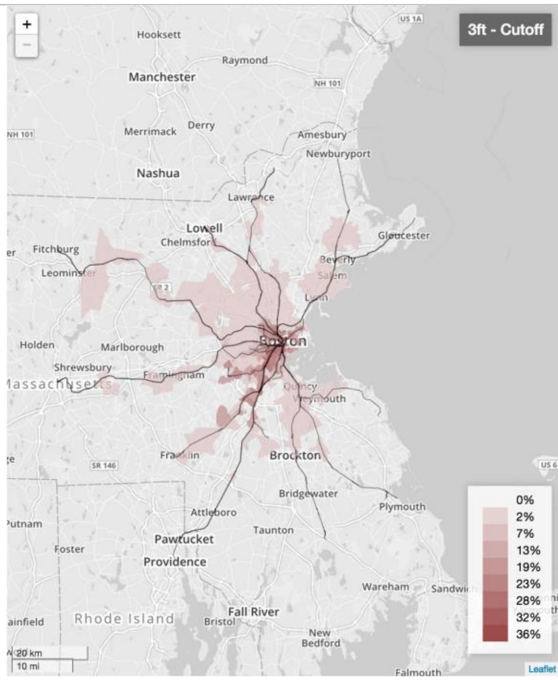

Figure 101: Transit Isochrone 3ft

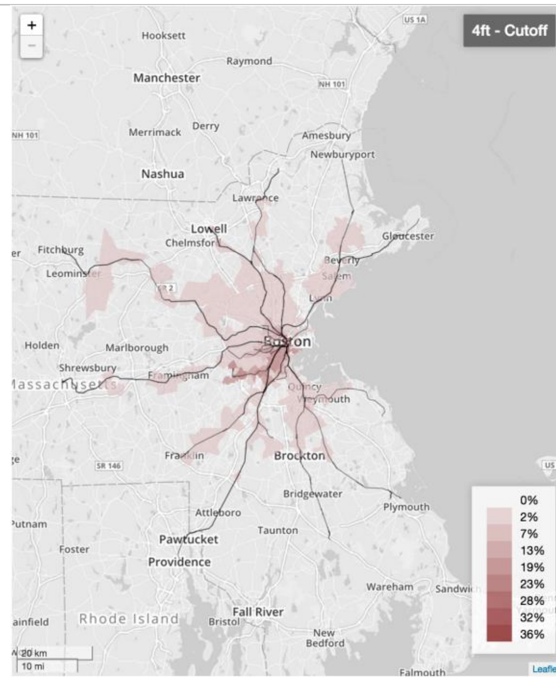

Figure 102: Transit Isochrone 4ft

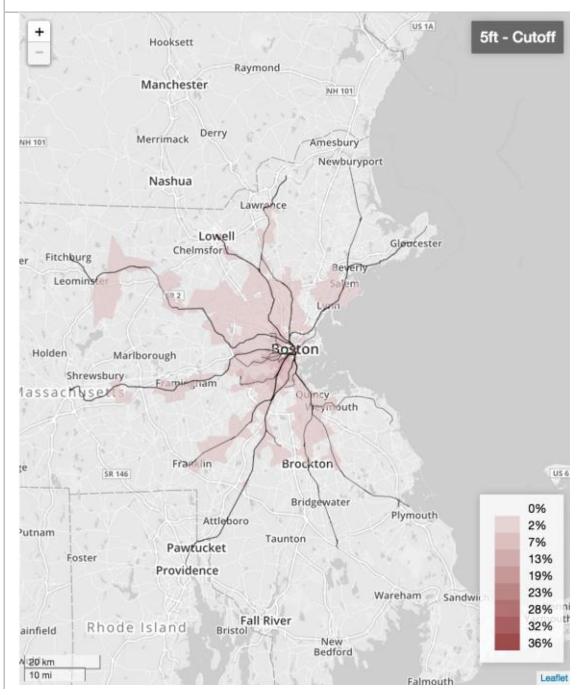

Figure 103: Transit Isochrone 5ft

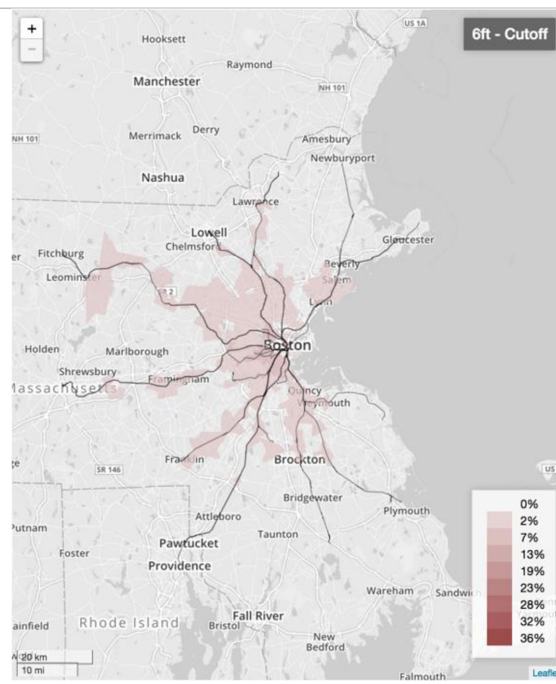

Figure 104: Transit Isochrone 6ft

Impedance (Gamma)

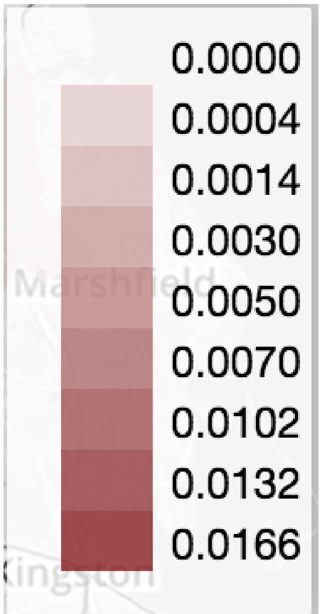

Figure 105: Impedance Transit Accessibility Legend

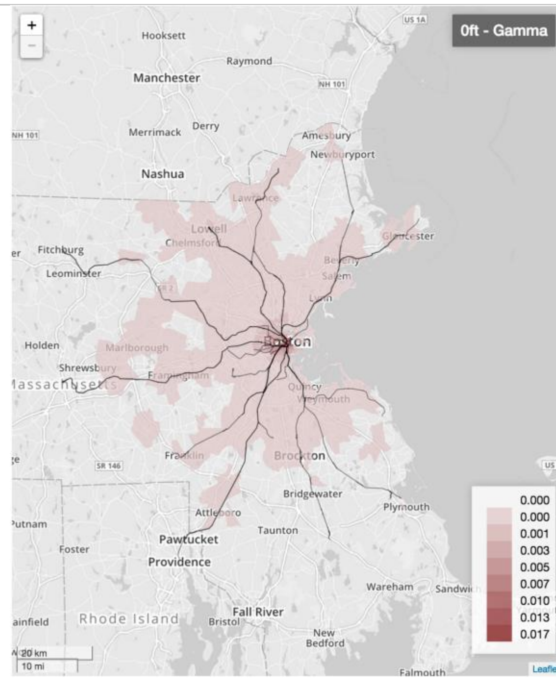

Figure 106: Transit Impedance No Inundation

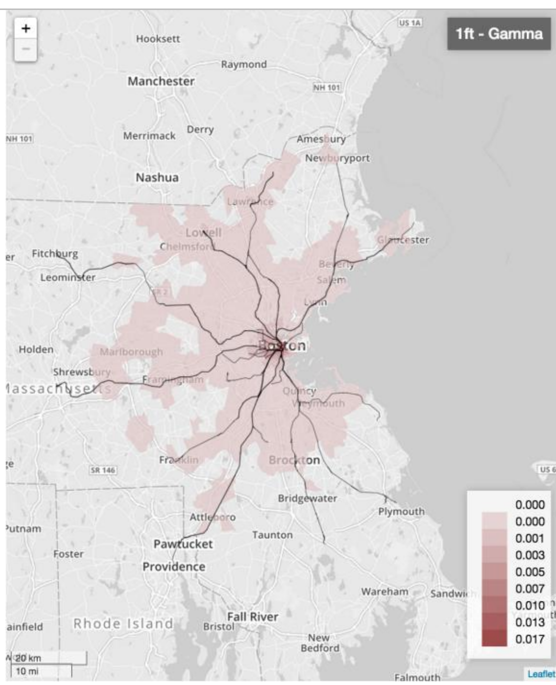

Figure 107: Transit Impedance 1ft

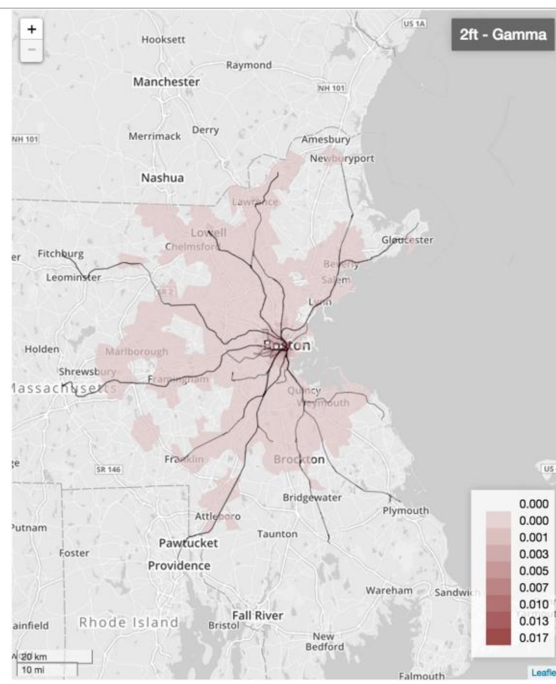

Figure 108: Transit Impedance 2ft

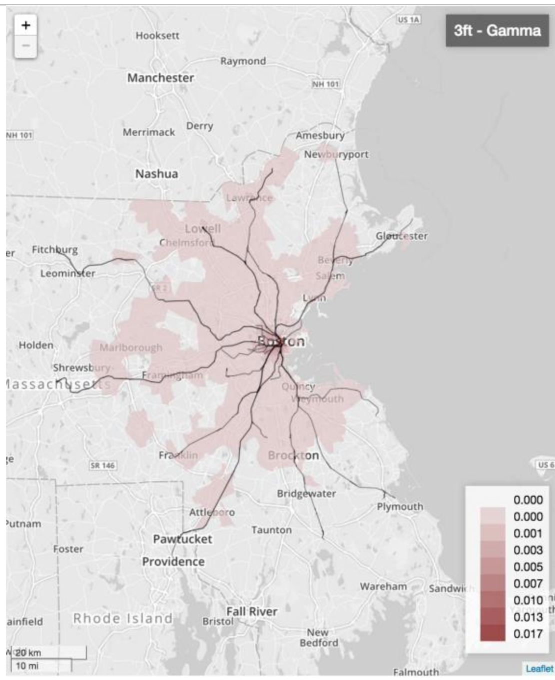

Figure 109: Transit Impedance 3ft

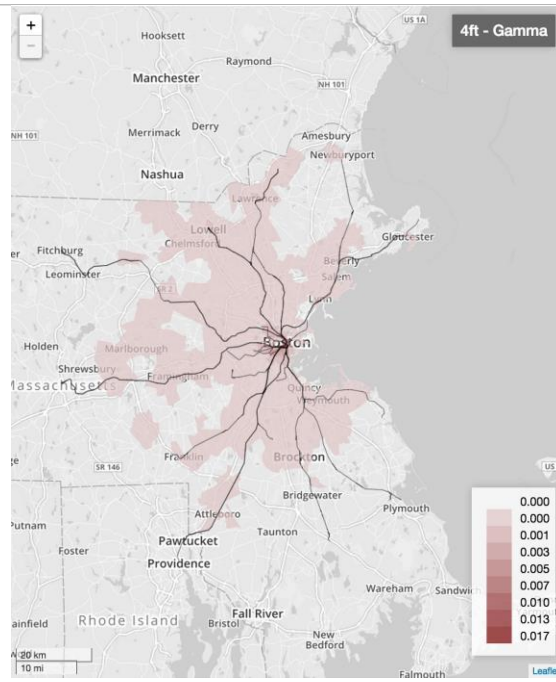

Figure 110: Transit Impedance 4ft

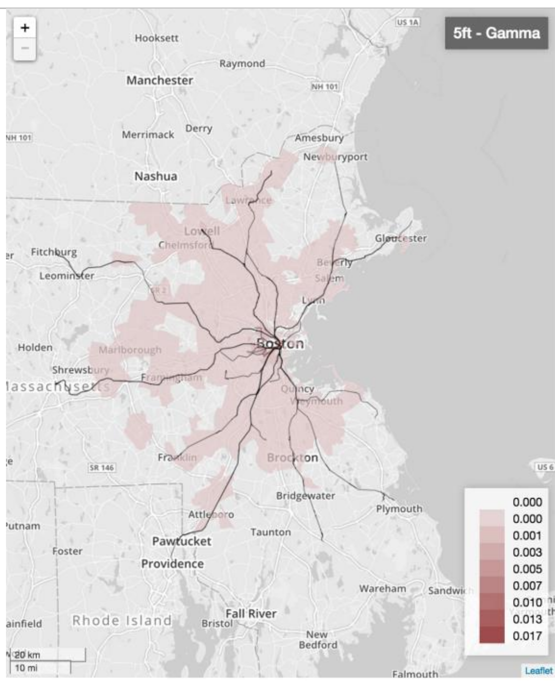

Figure 111: Transit Impedance 5ft

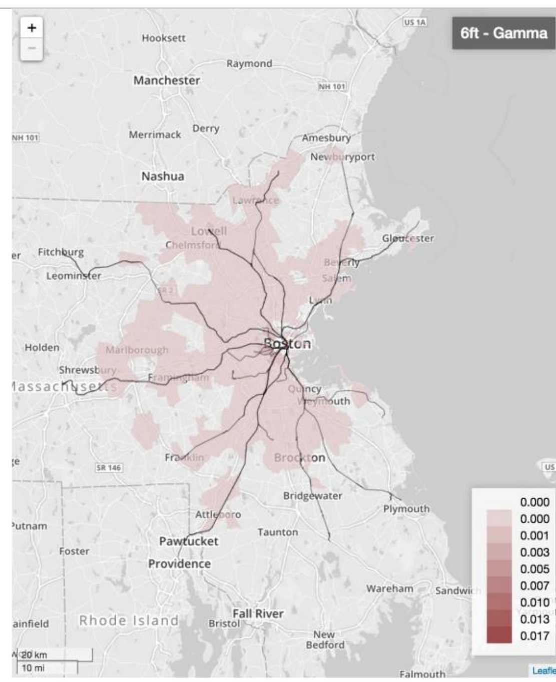

Figure 112: Transit Impedance 6ft

The isochrone and impedance transit maps look very different from the isochrone and impedance auto maps (Figure 77 through Figure 94). The isochrone maps (Figure 95; Figure 97 through Figure 104) show higher accessibility along transit lines, as expected. The impedance (gamma) maps (Figure

96; Figure 105 through Figure 112) show high values only in the inner core. The impedance measure maps show values along transit lines that decrease more quickly than the isochrone measure maps. Inundation impacts on accessibility is more evident in the isochrone maps. There is a large decrease in jobs accessibility from the baseline map (Figure 95) to the six-foot inundation map (Figure 104).

Jobs are located in the inner core. Transit is densest in this area, but it is also the area most threatened by inundation. The outer regions in the isochrones and impedance measures did not show great reductions in accessibility by inundation. This due to the fact that travel from these outer regions to Downtown Boston is greater than an hour, excluded in the isochrone measure and having a very small value in the impedance measure. In the Inundation Impact Assessment section of this work, I showed the large number of routes and the quantity of route miles affected. Now I analyze the effect of this impact on accessibility.

6.2.2.6.C Accessibility Summary Values:

Figure 113 through Figure 116 show the sum of all accessibility isochrones values (Jobs and Population) for no inundation through the six-foot inundation level. Figure 117 through Figure 120 show the average of all impedance values (jobs and population) for no inundation through the six-foot inundation level. In the isochrone measure, I sum all the values for each inundation level. For the impedance measure, I take the average value for each inundation level. Each inundation level results in a readily evaluated single number measure. I use the average impedance values rather than sums because of conceptual concerns about summing the impedance-based accessibly values.

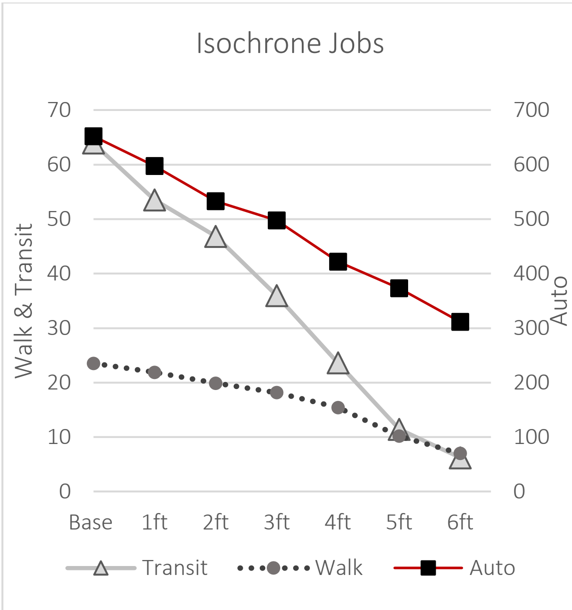

Figure 113: Accessibility Value Sums - Jobs

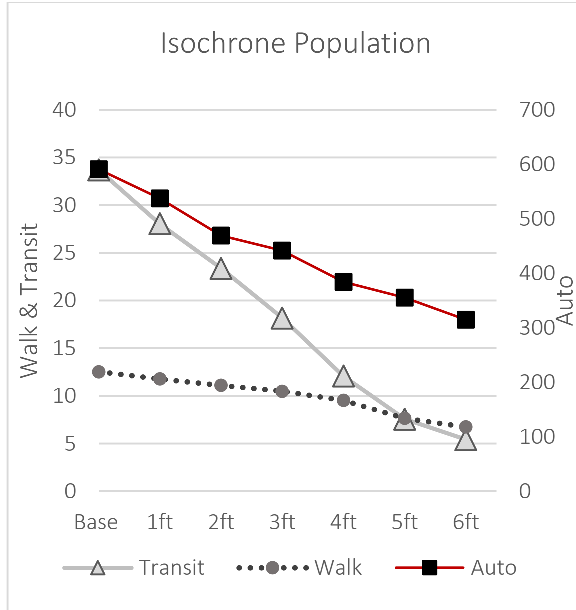

Figure 114: Accessibility Value Sums - Population

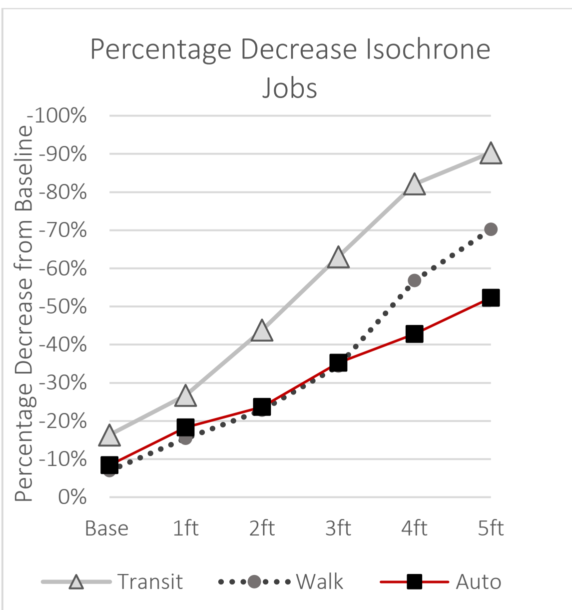

Figure 115: Accessibility Value Sums Percentage Difference from No Inundation Jobs

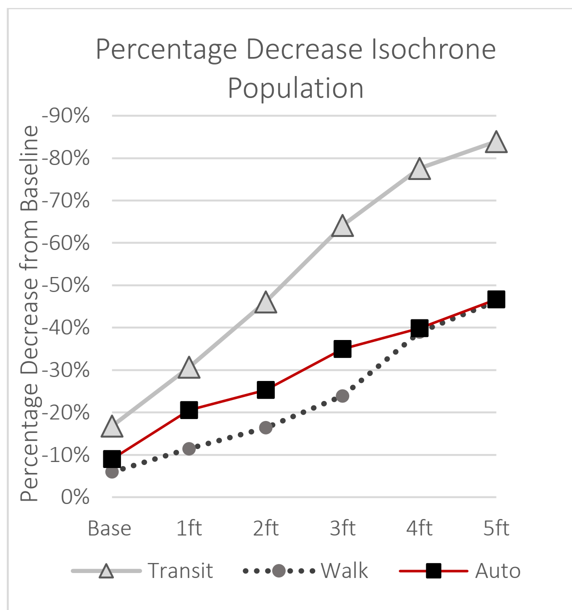

Figure 116: Accessibility Value Sums Percentage Difference from No Inundation Population

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Auto has the greatest absolute reduction in total accessibility values. It also has the highest initial values. Transit has the greatest percent reduction in total accessibility values. Though the absolute losses in walk and transit are of drastically different scale, they have similar percent reductions (Figure 115 and Figure 116).

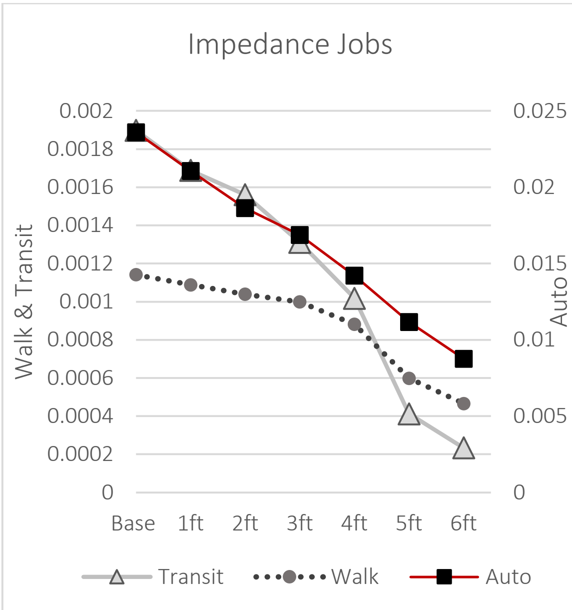

Figure 117: Accessibility Average Value - Jobs

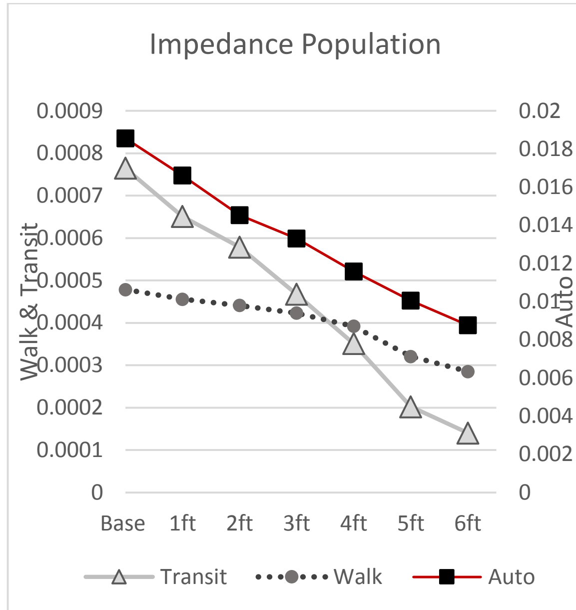

Figure 118: Accessibility Average Value - Population

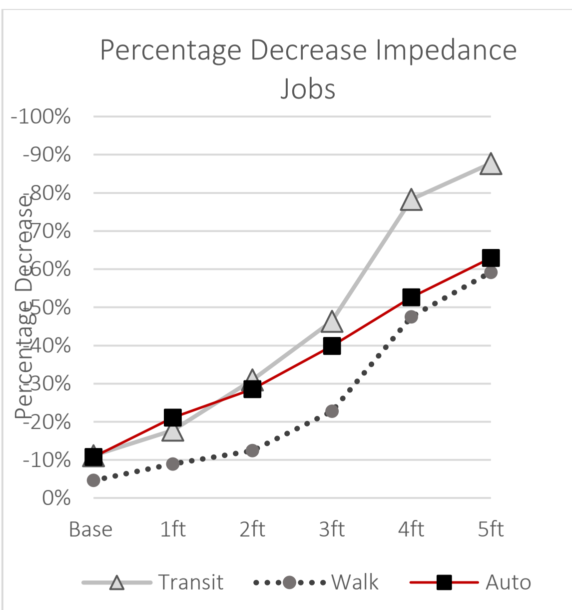

Figure 119: Accessibility Average Value - Percentage Difference from No Inundation Jobs

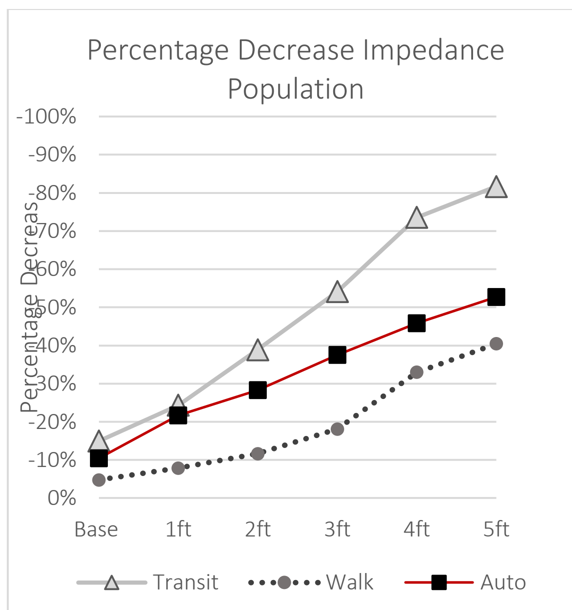

Figure 120: Accessibility Average Value - Percentage Difference from No Inundation Population

The impedance charts show a similar pattern to the isochrone charts, with one main difference: in the impedance chart, the average value of transit accessibility drops below the average value of walk accessibility in at the five-foot level (in absolute terms). In the isochrone chart, the average value of transit accessibility drops below the average value of walk accessibility at the six-foot level (again, in absolute terms).

6.2.3 Fixed Vs. Semi-variable

Here I analyze the differences between the fixed and semi-variable results (see appendix for Semi-Variable Inundation Impact Assessment Modeling Charts). In general, I expect fewer lost trips in the semi-variable model results. In all tables and charts in this section, I refer to semi-variable as simply "variable." Figure 121 shows lost trips across all inundation levels. There are fewer lost trips in the variable results than in the fixed results. As predicted, allowing alterations to trip distribution and mode results in fewer lost trips.

6.2.3.1 Lost Trips

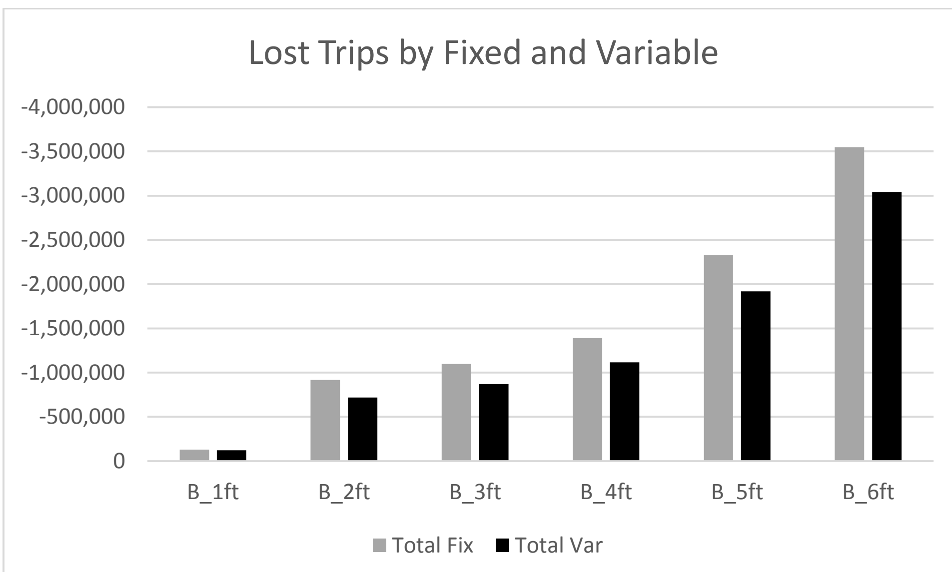

Figure 121: Lost Trips by Fixed and Variable

The fixed model has nearly 500,000 more lost trips at the six-foot inundation level than the variable model.

Table 35 shows the percent difference between the variable and fixed results of lost trips by trip purpose. Overall, there are fewer trips lost for all trips purposes. There are some minor variations, including fewer trips to the Airport at the four-foot inundation level. The total increases are quite small.

BASELINE	BASE	B_1FT	B_2FT	B_3FT	B_4FT	B_5FT	B_6FT
HBW	3276380	0.34%	0.66%	1.27%	2.60%	3.04%	0.94%
HBS	1243061	0.15%	0.30%	0.48%	1.26%	0.78%	0.49%
HBSHOP	2259043	-0.05%	1.56%	1.72%	1.91%	2.99%	4.03%
HBO	4259490	-0.04%	1.36%	1.46%	1.56%	2.94%	5.42%
NHBW	2522716	-0.02%	1.52%	1.57%	1.70%	2.80%	4.40%
NHBO	2763319	-0.02%	1.89%	1.98%	2.12%	3.73%	5.88%
AIRPORT	82997.97	-0.15%	-0.03%	-0.13%	-11.09%	-0.88%	-0.09%
TOTAL	16407006	0.05%	1.28%	1.48%	1.83%	2.91%	3.93%

Table 35: Percentage Difference in Lost Trips Between Fixed and Variable Results

Table 36 shows the percentge change in mode from fixed to variable results. A cursory analysis of the table shows more auto trips with some shifts in walking trips. I was surprised that the variable results showed increases in walking trips compared to the fixed model results. This may be a result of the trip distribution sub-model distributing trips to nearer zones (in a walkable distance) – lkely a response to inundation-related travel time increases. There are major decreases in the PT_Drive in the variable results; these are probably redistributed into the auto mode.

BASETOTALS		B_1FT	B_2FT	B_3FT	B_4FT	B_5FT	B_6FT
10265427	Auto	-0.4%	0.4%	0.7%	0.8%	1.8%	2.0%
1049129	AutoPax	0.0%	0.6%	0.8%	1.3%	2.4%	4.2%
4259798	Walk	1.3%	3.5%	3.8%	4.4%	5.8%	8.1%
760167	PT_Walk	-0.2%	0.4%	-0.4%	1.5%	0.1%	0.8%
72485.58	PT_Drive	-3.0%	7.0%	-17.4%	-25.6%	-28.4%	-18.2%
16407006	Total	0.1%	1.3%	1.5%	1.8%	2.9%	3.9%

Table 36: Percentage Difference Variable to Fixed

FIXED	BASETOTALS	B_1FT	B_2FT	B_3FT	B_4FT	B_5FT	B_6FT
Auto Lost	9853280	-2,322	-655,800	-702,828	-728,788	-1,208,836	-1,988,917
AutoPax Lost	1461274	-6	-51,766	-59,087	-73,659	-221,638	-398,016
Walk	4259797	-83,318	-104,005	-146,132	-222,593	-375,506	-528,496
PT_Walk	760167	-36,187	-77,291	-146,251	-302,766	-455,241	-561,626
PT_Drive	72485	-8,080	-27,822	-44,298	-63,926	-68,394	-70,872
Total Lost	**16407005**	**-129,913**	**-916,685**	**-1,098,596**	**-1,391,732**	**-2,329,616**	**-3,547,928**
VARIABLE	**BASETOTALS**	**B_1FT**	**B_2FT**	**B_3FT**	**B_4FT**	**B_5FT**	**B_6FT**
Auto Lost	9853280	-46,195	-618,640	-635,150	-653,279	-1,051,741	-1,832,650
AutoPax Lost	1461274	230	-43,281	-47,343	-55,863	-192,436	-353,278
Walk	4259797	-27,347	42,687	8,172	-45,333	-150,951	-225,752
PT_Walk	760167	-37,739	-74,685	-148,452	-295,883	-455,016	-559,974
PT_Drive	72485	-10,003	-24,717	-49,191	-66,120	-69,557	-71,166
Total Lost	**16407005**	**-121,053**	**-718,636**	**-871,966**	**-1,116,478**	**-1,919,701**	**-3,042,819**

Table 37: Fixed vs. Variable Lost Trips by Mode

Table 37 shows a large decrease in auto use (-45,298) in the variable model run at the one-foot inundation level, probably due to the shift from auto to walk. As is shown in the table, there is a much larger decrease in walk mode in the fixed results (-83,318) versus the variable results (-27,346), most likely the changed trip distribution and mode split is causing an increase in walk trips. This appears in the table as a decrease in auto trips at the one-foot inundation level. This shift highlights a challenge in interpreting these data: the decrease or increase of trips in one mode may actually be a result of mode shift, as I have interpreted.

At higher inundations levels, the trends are clearer and, in general, the fixed results have more lost trips for each mode compared to the variable results. The fixed results always have more lost trips.

6.2.3.2 Transit Network

Transit-specific mode totals can alter in both fixed and variable model runs. In fixed model runs, the more general (or "parent") mode cannot change (i.e. Auto, Transit, PT_Drive, etc.), but types of transit can change based on travel time (the user will select whichever transit mode – i.e. bus, ferry, commuter rail – has the best travel time). In variable model runs, both general and specific modes can change. Trips can shift into transit mode from some other mode, or out of transit to some other mode. Variation can also occur because of different trip destinations (Trip Distribution).

Table 38 shows the percent difference of total ridership by transit-specific modes between fixed and variable results. At the one-foot level, Table 38 charts a decrease in buses (-15 percent) and in urban heavy rail (-6 percent) and very minor increases in ferry and commuter rail. Table 39 provides the total absolute difference in ridership between fixed and variable results.

MODE	1FT	2FT	3FT	4FT	5FT	6FT
BUS	-15.1%	1.1%	0.0%	0.5%	3.6%	0.1%
BRT SILVER	1.3%	-1.8%	-1.7%	2.7%	-18.6%	-12.4%
HEAVY RAIL	-6.2%	0.3%	-0.7%	1.0%	0.7%	1.6%
LIGHT RAIL	-2.9%	-0.2%	-3.6%	-2.5%	-6.2%	0.3%
COMMUTER RAIL	2.7%	-0.1%	2.7%	1.2%	-7.7%	-9.0%
FERRY	3.1%	-11.0%	0.0%	0.0%	0.0%	0.0%
TOTAL VOLUME	-7.7%	0.4%	-0.7%	0.1%	-0.5%	0.0%

Table 38: Percentage Difference in Ridership by Mode from Variable to Fixed

MODE	1FT	2FT	3FT	4FT	5FT	6FT
BUS	-65879.6	4868.23	-162.29	2053.15	9246.29	121.64
BRT SILVER	593.99	-819.96	-694.56	845.32	-3170.3	-429.87
HEAVY RAIL	-29660.6	1553.76	-2615.54	2074.7	997.81	850.41
LIGHT RAIL	-7035.43	-595.67	-6228.53	-4636.41	-8450.85	175.3
COMMUTER RAIL	2457.73	-129.87	1930.76	602.99	-1203.3	-650.41
FERRY	23.51	-83.98	0	0	0	0
TOTAL	-99500.4	4792.51	-7770.16	939.75	-2580.35	67.07

Table 39: Difference in Ridership by Mode (Variable - Fixed)

Table 39 reveals 65,000 fewer bus trips and 30,000 fewer heavy rail trips in the one-foot inundation scenario. This likely results from people shifting modes, perhaps from transit to a walk. Overall, other differences are minor, including changes in other modes or changes at later inundation levels.

Differences in Transit Ridership at 4ft of Inundation

Table 40 shows the top 15 routes with the greatest increase in riders in the four-foot inundation scenario for both fixed and variable results. The routes present in the fixed and variable halves of the chart are similar overall. Routes 8, 90 and the Silver line only appear in the fixed results; route 65 only appears in the variable results.

	FIXED		VARIABLE	
RANK	Route	Increase	Route	Increase
1	CT2	17173.22	CT2	10772.29
2	55	5092.1	66	8525.09
3	33.4	3619.82	55	4325.79
4	92	3543.05	Needham	4088.98
5	15	3525.26	15	3491.87
6	69	3083.91	92	3434.9
7	83	2865.37	69	3106.95
8	22	2695.15	22	2848.66
9	85	2584.25	33.4	2839.39
10	66	2396.8	85	2436.27
11	8	2285.74	23	2054.05
12	23	2028.26	83	2003.64
13	21	1860.29	21	1971.7
14	Needham	1653.12	SIIVERS	1920.89
15	90	1629.14	65	1768.39
TOTAL	--	56035.48	--	55588.86

Table 40: Top 15 Routes by Ridership Increase Given 4ft of Inundation by Fixed and Variable

There are also differences in terms of the route rank between fixed and variable results. Notably, the 66 bus has an increase in ridership of 2,300 passengers in the fixed results, with a rank of 10, and an increase in ridership of 8,525 with a rank of 15, in the variable results. The total increase on any one line is larger in the fixed results (17,713 vs. 10,772).

	FIXED		VARIABLE	
RANK	Route	Decrease	Route	Decrease
1	Red	-209,246	Red	-211,198
2	Orange	-107,063	Orange	-103,674
3	Green	-72,392	Green	-77,029
4	Blue	-57,155	Blue	-56,518
5	111	-11,844	111	-12,011
6	86	-11,489	Framingham	-10,420
7	Framingham	-10,303	86	-10,144
8	39	-9,004	39	-9,174
9	71	-8,797	7	-8,579
10	7	-8,690	71	-8,533
11	1	-7,874	1	-7,449
12	Fairmount	-6,969	Fairmount	-6,980
13	Haverhill	-6,810	Haverhill	-6,861
14	77	-6,179	Attleboro	-6,657
15	Attleboro	-5,761	77	-5,996
TOTAL	--	-539578	--	-541221

Table 41: Top 15 Routes by Ridership Decrease Given 4ft of Inundation by Fixed and Variable

Table 41 shows the shows the top 15 routes with greatest decrease in riders in the four-foot inundation scenario, for both fixed and variable results. These results are much more consistent than the results in Table 40. In fact, identical routes appear in both lists at a similar rank with relatively similar decreases in ridership.

Admittedly, this is a superficial analysis of visible changes on Table 40 and Table 41. A transit agency can analyze this kind of data for operations planning, such as in the event of inundation, to better describe the influence of behavioral response on these results. These tables illuminate many questions about how people might vary their destination and mode and resulting influences on demand. Such deep, geographical and behavioral analysis is outside the purview of this thesis.

6.2.3.3 Auto Network:

The fixed and variable model run Auto network metrics reveal notable differences. In general, the Auto network metrics in the variable model runs are lower than those from the fixed model runs, as seen in Table 42. A few exceptions appear where the variable model run metrics are higher than the fixed, likely due to an overall increase in auto trips.

COMPARE	TYPE	1FT	2FT	3FT	4FT	5FT	6FT
STATIC	V_Static	-7%	6%	-4%	-3%	-8%	-3%
	VC_Max	-38%	51%	31%	-9%	7%	11%
	VDT	-10%	10%	-4%	-1%	-5%	-2%
	VHT Static	25%	-11%	-2%	58%	-34%	-8%
DTA	V_DTA	-2%	1%	-5%	-6%	-9%	-3%
	VDT_DTA	-2%	1%	-1%	-3%	-4%	-2%
	VHT DTA	-9%	9%	0%	-3%	-3%	0%
	Queue Total	8%	-9%	-9%	-8%	-20%	-7%
	Block Total	13%	-13%	0%	-1%	-23%	-5%

Table 42: Fixed vs. Variable Auto Metrics Percentage Difference ((Variable-Fixed)/Variable)

Figure 122 and Figure 123 show the average and total values for Vehicle Distance Traveled (VDT) for fixed and variable static and dynamic assignment model runs. Figure 124 and Figure 125 show the average and total values for Vehicle Hours Traveled (VHT) for fixed and variable static and dynamic assignment model runs. Generally, the average total values for VDT and VHT are lower for the variable model results.

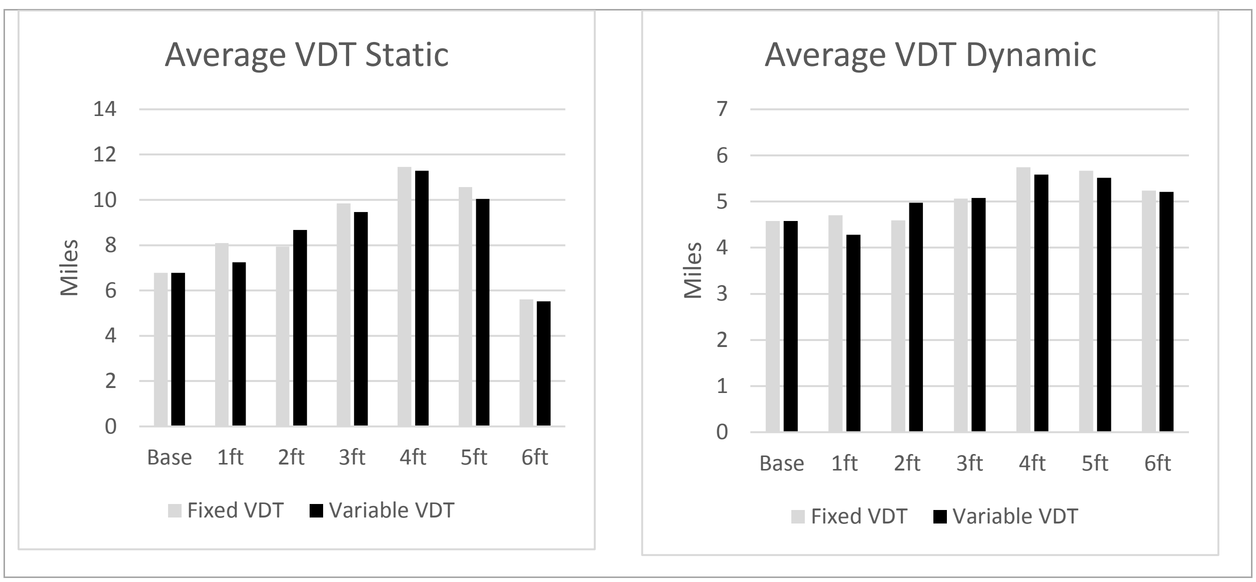

Figure 122: Average VDT for Static and Dynamic Traffic Assignment by Fixed and Variable

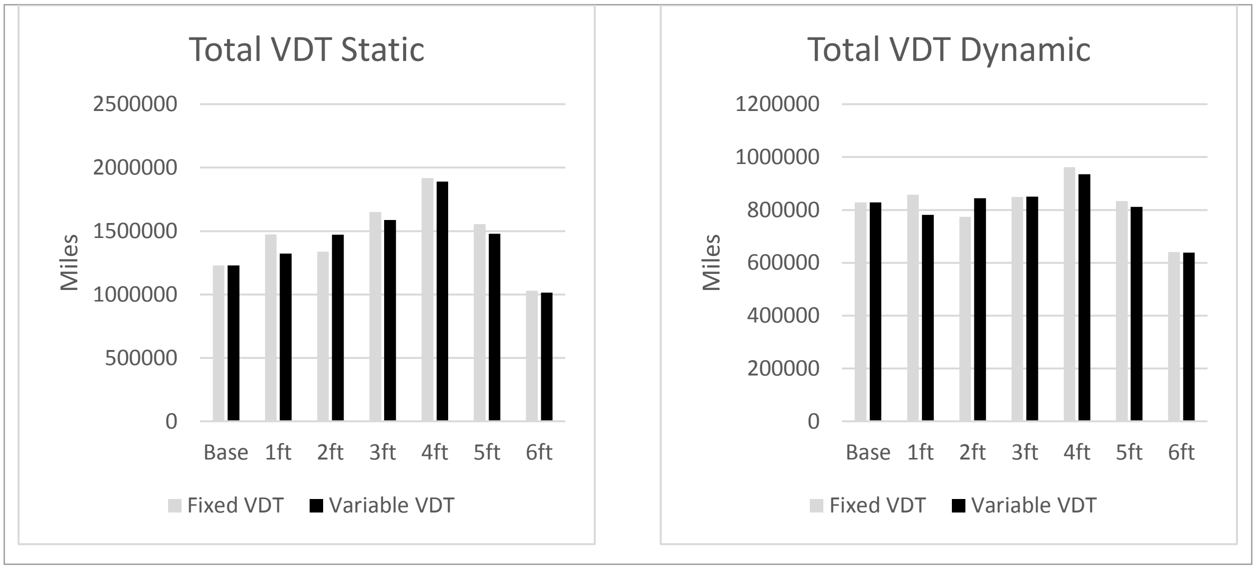

Figure 123 Total VDT for Static and Dynamic Traffic Assignment by Fixed and Variable

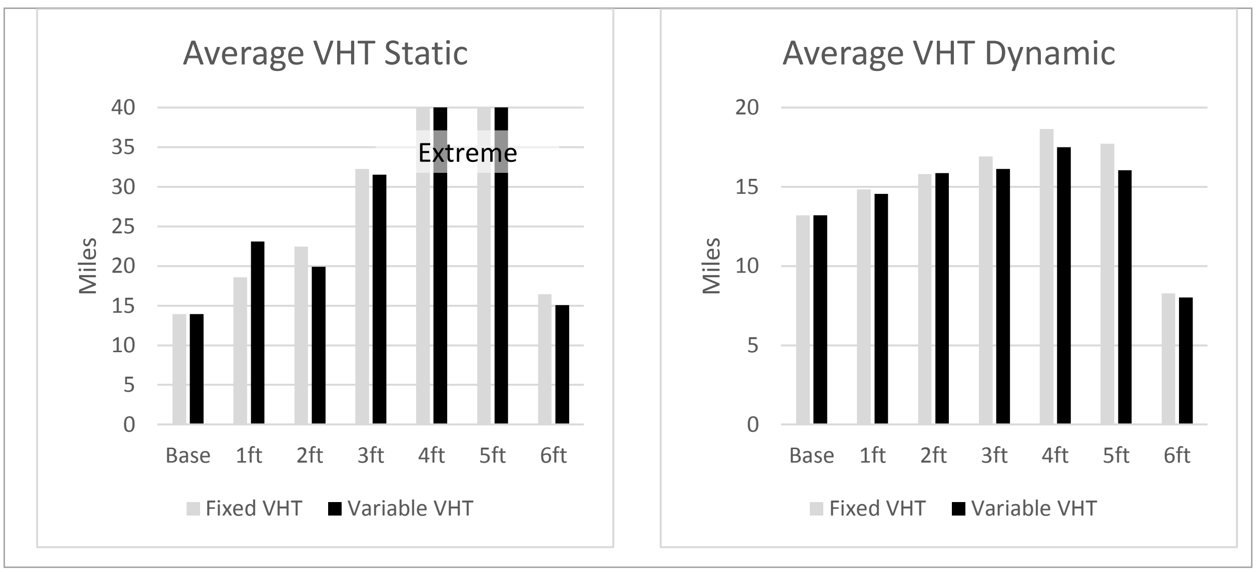

Figure 124: Average VHT for Static and Dynamic Traffic Assignment by Fixed and Variable

Figure 124, the average VHT graph, shows extreme congestion values in the variable static assignment model run results, likely a result of the continued presence of a large majority of the original fixed 2010 baseline trips in the network.

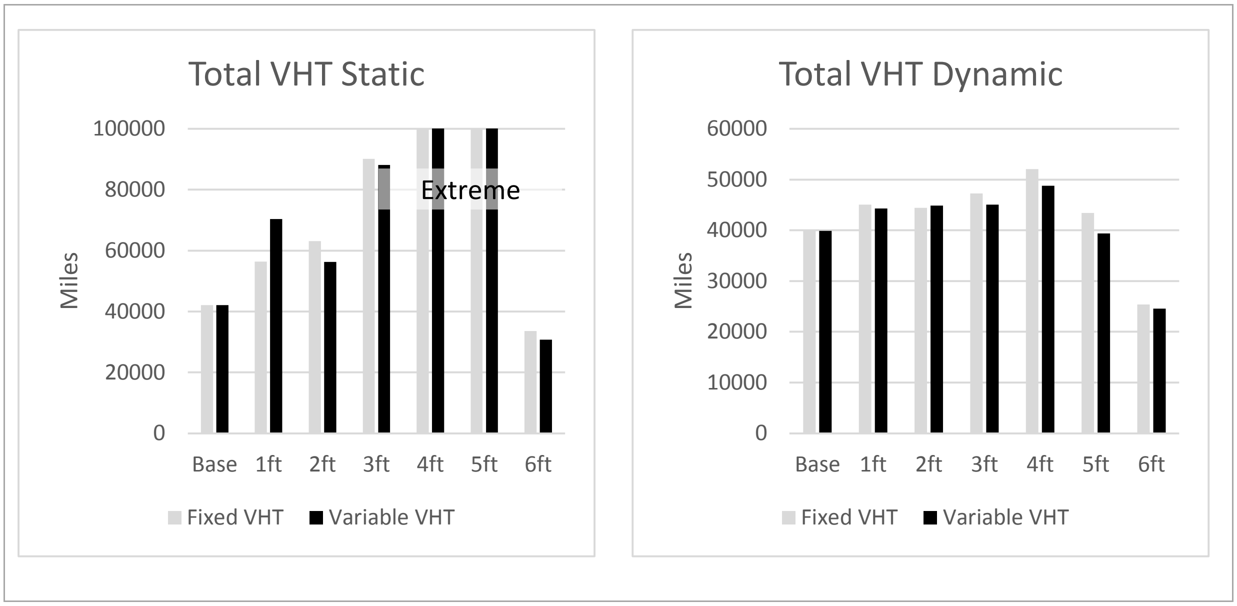

Figure 125: Total VHT for Static and Dynamic Traffic Assignment by Fixed and Variable

In general, the semi-variable static and dynamic assignment results have fewer lost trips, increased auto trips, increased walk trips, overall fewer transit trips, and general decreases in VDT and VHT. The metrics derived for Auto and Transit networks show minimal differences across the fixed and variable approaches. I only allowed semi-variable trip distribution and mode split, which could account for this result. With a fully variable trip distribution and mode split, the results would likely differ. My intent is to model an inundation event and not a new equilibrium; without a better understanding of behavioral response to inundation events, I believe that constraining trip distribution and mode split is logically sound. The results of these model runs highlight the flexibility of the method and illuminate deeper questions regarding the behavioral response of travelers. This demonstrates the value of the method as a viable means for more in-depth analysis by other agents and agencies with more appropriate resources.

Given the minimal variation witnessed in these results, I will not present fixed and semi-variable results in - 7 Scenario Modeling.

6.2.4 Inundation Impact Assessment Conclusion

In this chapter, I have demonstrated the use of inundation performance metrics using the Boston regional transportation system, and show potentially major impacts of inundation on transportation performance (especially at the four-foot level and higher). The mode most impacted by inundation is transit, which has greatest reduction in mode shares and accessibility. Overall, most of the metrics generated had reasonable values. The VC values and the VHT values, though clearly unreasonable, served to highlight some interesting insights on network resiliency. I have also demonstrated how transit ridership shift can be explored with this approach and how the results of this exploration can inform operational interventions by transit planners. In the following section, I will apply the same methodology to future 2030 scenarios.

7 Scenario Modeling

7.1 Methodology Summary: Scenario Modeling

7.1.1 Purpose

The Scenario Modeling portion of this work combines the insights and methods of the previous analyses to demonstrate how transportation models can assist in examining the future impacts of inundation events. Given that experts anticipate such events to increase in frequency in the future, the Impact Assessment Modeling exercise, while useful, does not directly provide insights into the future state of the system and the possible impacts from inundation events. The scenario modeling approach develops an understanding of network performance in the future and/or provides an additional step in project evaluation processes. Project evaluation processes incorporate cost-benefit analyses, which should include environmental impacts, as well as social benefit analysis. Scenario Modeling, however, allows a means of assessing such factors as network resiliency gains relative to inundation levels. This could be specifically useful for projects that may not achieve a positive net present value due to the omission of such a metric. Currently, the FTA and many regional planning and transportation groups are actively examining how to increase the resiliency of infrastructure to the impacts of climate change, indicating that a recognized need for this type of analysis already exists (Eilperin, 2015). Citizens and policy makers must decide if such matters are relevant in a region – and, if the potential value of resilience is something they are comfortable adding to a balance sheet.

7.1.2 Method Summary

Functionally, the Scenario Modeling analysis combines a traditional transportation forecasting process with the inundation Impact Assessment Modeling procedure presented in the previous Chapter. The traditional aspects of this process include developing forecasts of demographic growth and spatial concentrations for a future year, in this case the year 2030. These scenarios are modeled along with different infrastructure projects to examine the performance of the infrastructure projects relative to different demographic scenarios, with and without inundation. The traditional analysis is run to equilibrium and provides baseline (i.e. no inundation) totals for various network performance metrics. These baseline models, and their respective networks, are then modified to approximate an inundation event. Once modified, the models are run once more, following the Inundation Impact Methodology outlined in Methodology Summary: Scenario Modeling. Performance. Metrics are calculated, examined, and compared. I then evaluate the infrastructure projects to see which is most effective in increasing inundation resiliency. I assess the value of these infrastructure projects primarily in terms of recouped trips.

7.1.2.1 Demographic Scenarios:

The two chosen demographic scenarios reflect different concentrations of people and jobs in the future.

Scenario One: "*Stronger Region*" anticipates highly concentrated growth in the region's inner core that surpasses current observed trends in population and job growth rates. This scenario is derived from the regional Metropolitan Planning Organization's (MPO) *preferred* scenario for the region's future.

Scenario Two: *"Inundation Awareness"* incorporates current observed regional growth rates and an assumption that persons and firms in the region are sensitive to inundation threats when making siting decisions in areas inundated at the three-foot level or below. Current observed growth rates over the past ten years are used to estimate regional growth in persons and jobs. This growth is then allocated to those zones that are never (or only) inundated at water levels higher than the three-foot level. Persons and firms already located in such areas are not relocated; instead, no growth occurs in these areas over the 20-year forecast period (2010 – 2030).

7.1.3 Method

7.1.3.1 Demographic Scenario Estimations

The Metropolitan Area Planning Council (MAPC) and its sister organization, the Central Transportation Planning Staff (CTPS), carry out a greater part of the analysis tasks required by the Boston Region MPO. One of the major analysis tasks undertaken by these organizations is the creation of regional demographic projections intended to help cities and towns in the region plan for the future. The 2030 forecasts produced by MAPC/CTPS were the primary source for creating the 2030 demographic scenarios used in this section of this thesis.

The basis for my previously defined *"Stronger Region"* scenario derives from the base MAPC data available for the MAPC Stronger Region. MAPC's data present a vision of the future where urban growth in the region's inner core exceeds current observed growth rates: there are more younger households in the region and more persons are in the labor force. The MAPC Status Quo scenario assumes growth rates consistent with what the region has experienced over the past decade.

Scenario Comparison			
	2010	Status Quo, 2010 – 2040	Stronger Region, 2010 - 2040
Population	4,458,000	+ 6.6%	+12.6%
Households	1,719,000	+ 17%	+23%
Housing Units	1,827,600	+ 17%	+24%
Percent Multifamily	51%	48% of new units	62% of new units
Labor Force Population	2,516,000	+0.4%	+6.9%

Figure 126: Source MAPC Scenario Comparison

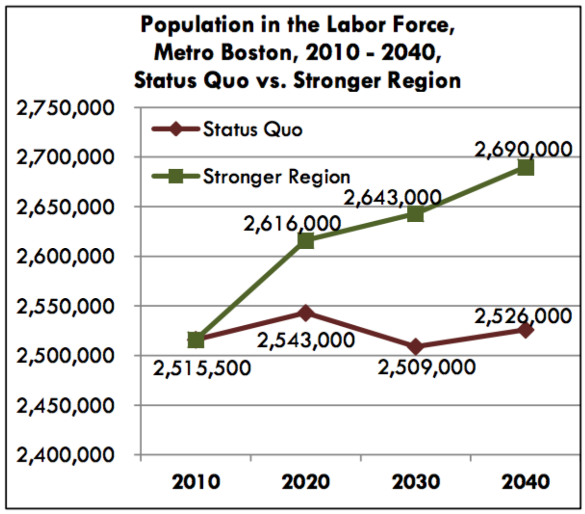

Figure 127: Figure 74: Source MAPC Scenario Comparison | Population in the Labor Force (Link: http://www.mapc.org/projections)

Overall, the Stronger Region scenario forecasts more people, households and jobs by the year 2030 compared with the Status Quo scenario. Both scenarios assume growth in the region overall.

The MAPC data come in two different formats. The Stronger Region data come from the MAPC's Cube Land model: a 2,727-zone model calibrated to produce specific municipal totals. The status quo scenario data were only available by municipality.

In order to model 2030, I extracted key components of the MAPC data and combined these with MIT-FSM demographics. These two data sets differ in several ways, not excluding format and geography. For instance, MAPC uses slightly different census data to estimate regional demographics. Therefore, I chose to estimate growth rates using the MAPC data and apply these growth rates to MIT-FSM demographics. The following sections discuss the methods and assumptions used to create these two scenarios.

7.1.3.1.A Scenario 1 - Stronger Region (SR)

The Stronger Region scenario data were available in the 2,727 traffic analysis zonal structure. The MIT-FSM and MAPC models cover the same geographic extent but their internal zonal structures differ. Furthermore, the household composition used by MAPC differs from that used in the MIT-FSM model, producing slight variations in population and job totals for 2010 between the two models. These differences are likely because MAPC uses the most recent ACS estimates, while the MIT-FSM model's 2010 demographics are derived from the 2010 Census Transportation-Planning Products. Though the differences are minor (MAPC Data is ~1.82 percent greater), I chose to estimate growth rates from the data and apply them to the MIT-FSM model's base 2010 demographics.

I converted the MAPC data into the MIT-FSM zones using a basic proportional split procedure in ArcMap. A proportional split determines the percentage of shared area between overlapping zones and then applies this percentage to the demographic data. This method assumes a uniform distribution of people across space. The MAPC model has about three times more zones (2,727) than the MIT-FSM model (986) and their boundaries are not consistent. Figure 128 shows the zonal structure around MIT and Boston's Back Bay. Blue lines indicate the boundaries of the MAPC model while yellow lines indicate the boundaries of the MIT-FSM model.

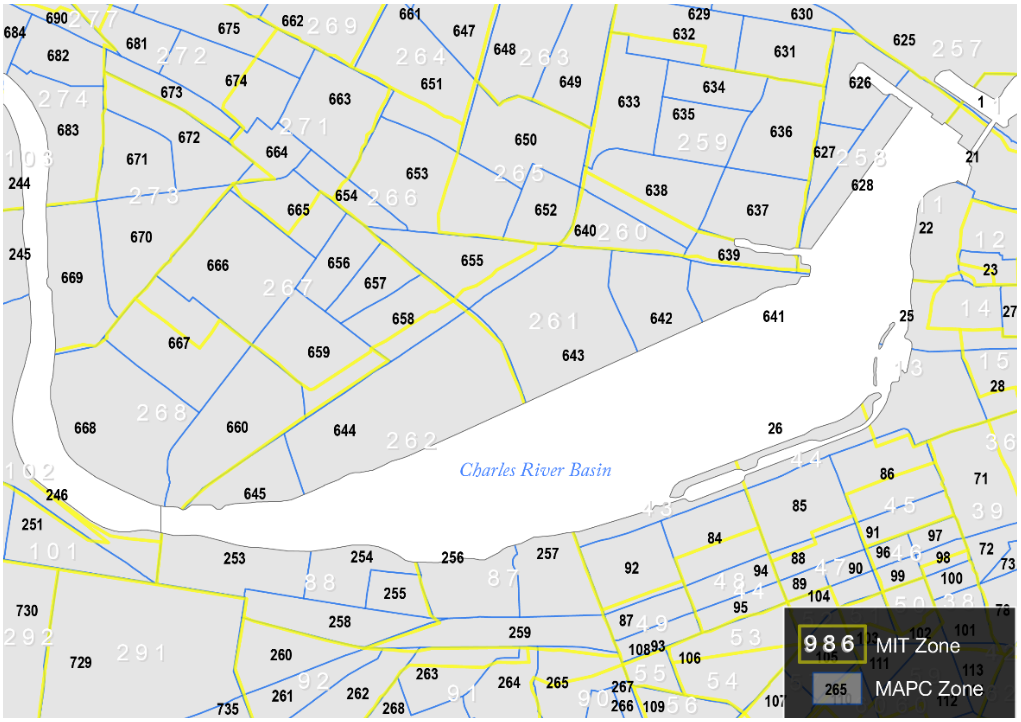

Figure 128: Example of MIT & MAPC Zones

With these data in the correct model structure, I calculated the growth rates by MIT-FSM model zone for the various households, population and employment categories from the modified MAPC data. I then applied these growth rates to the MIT 2010 demographic totals to find the 2030 demographic totals. Table 43 shows an excerpt of the growth rate table.

TAZ	TOTAL JOBS	POPULATION	HOUSEHOLDS	SERVICE	BASIC	RETAIL
1	14.4%	40.1%	18.3%	15.7%	-9.9%	8.1%
2	8.0%	37.2%	16.1%	14.8%	-11.6%	-1.7%
3	4.4%	31.0%	19.0%	11.0%	-9.9%	-2.5%
4	1.4%	30.4%	18.4%	7.0%	-10.4%	-2.1%
5	1.7%	33.5%	18.3%	4.6%	-6.6%	-3.1%

Table 43: Excerpt of Growth Rate Table (Zones 1-5, of 986)

Overall, there is growth across all demographics, though basic and retail employment decrease in some zones. In general, the MAPC data assume that basic and retail jobs will reduce in the future while service jobs will increase.

Figure 129 shows the baseline population density for the MIT-2010 model. Figure 130 shows the 2030 Stronger Region scenario population density; these maps are symbolized in the 2010 quantile buckets used in the initial map to facilitate comparison. Figure 131 indicates percentage changes in population density in the Stronger Region scenario, providing a better view of the areas of growth. This map shows that the majority of growth is in the inner core urban area of Boston, although growth also occurs in some of the outer urban areas. A handful of small areas have some population decrease, indicated in gray [see Figure 131 detail insert].

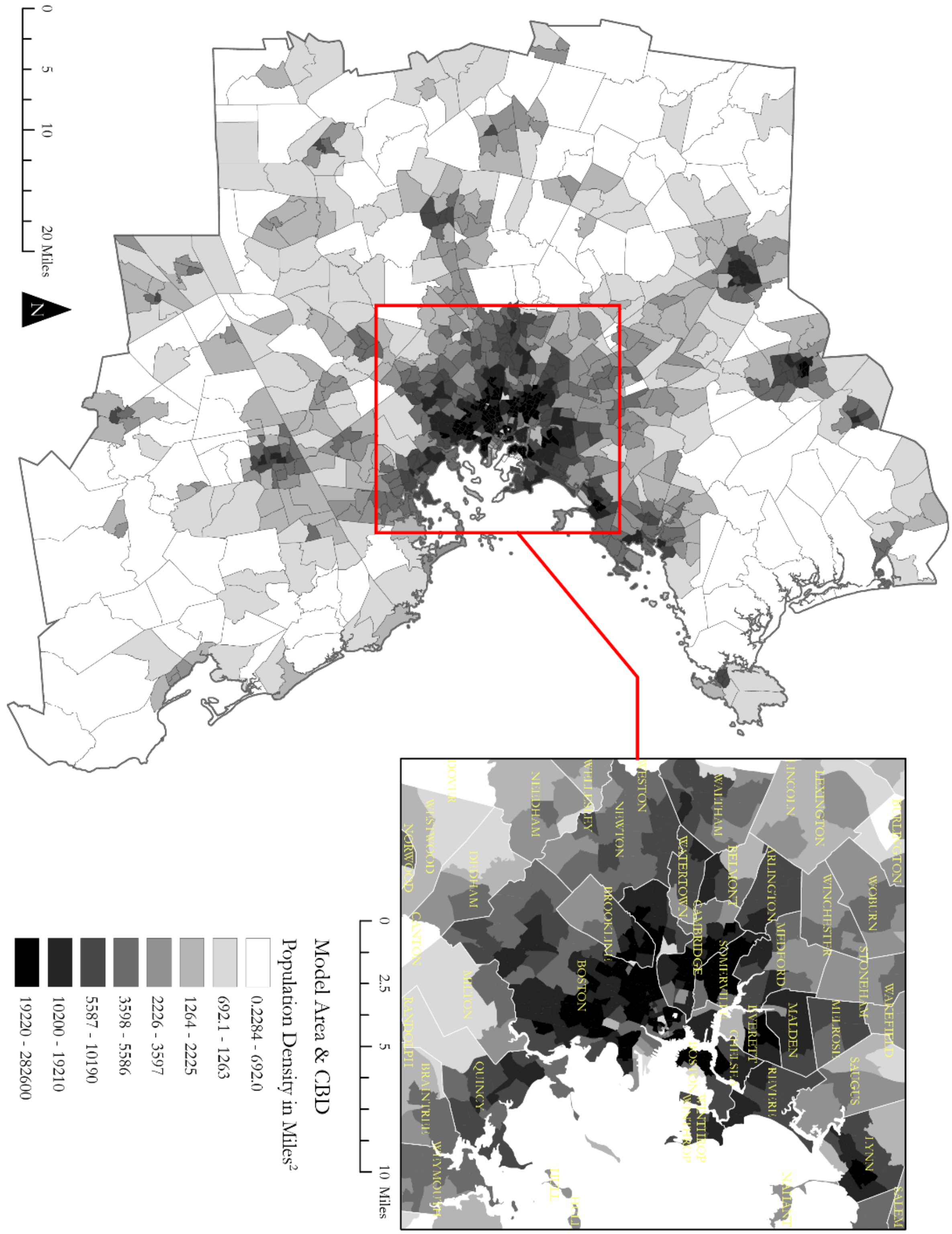

Figure 129: Baseline 2010 - Population Density

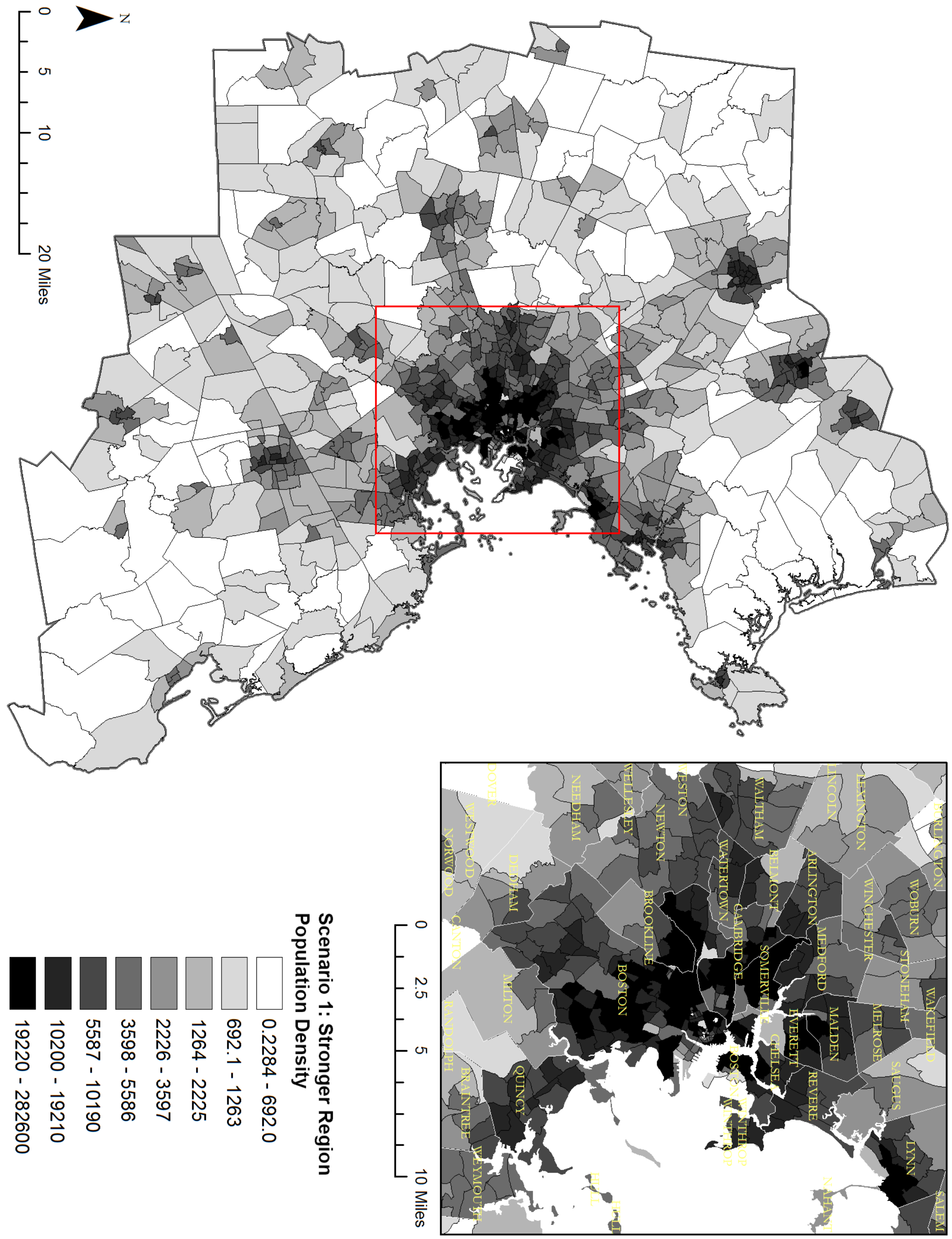

Figure 130: Scenario 1: Stronger Region 2030 - Population Density

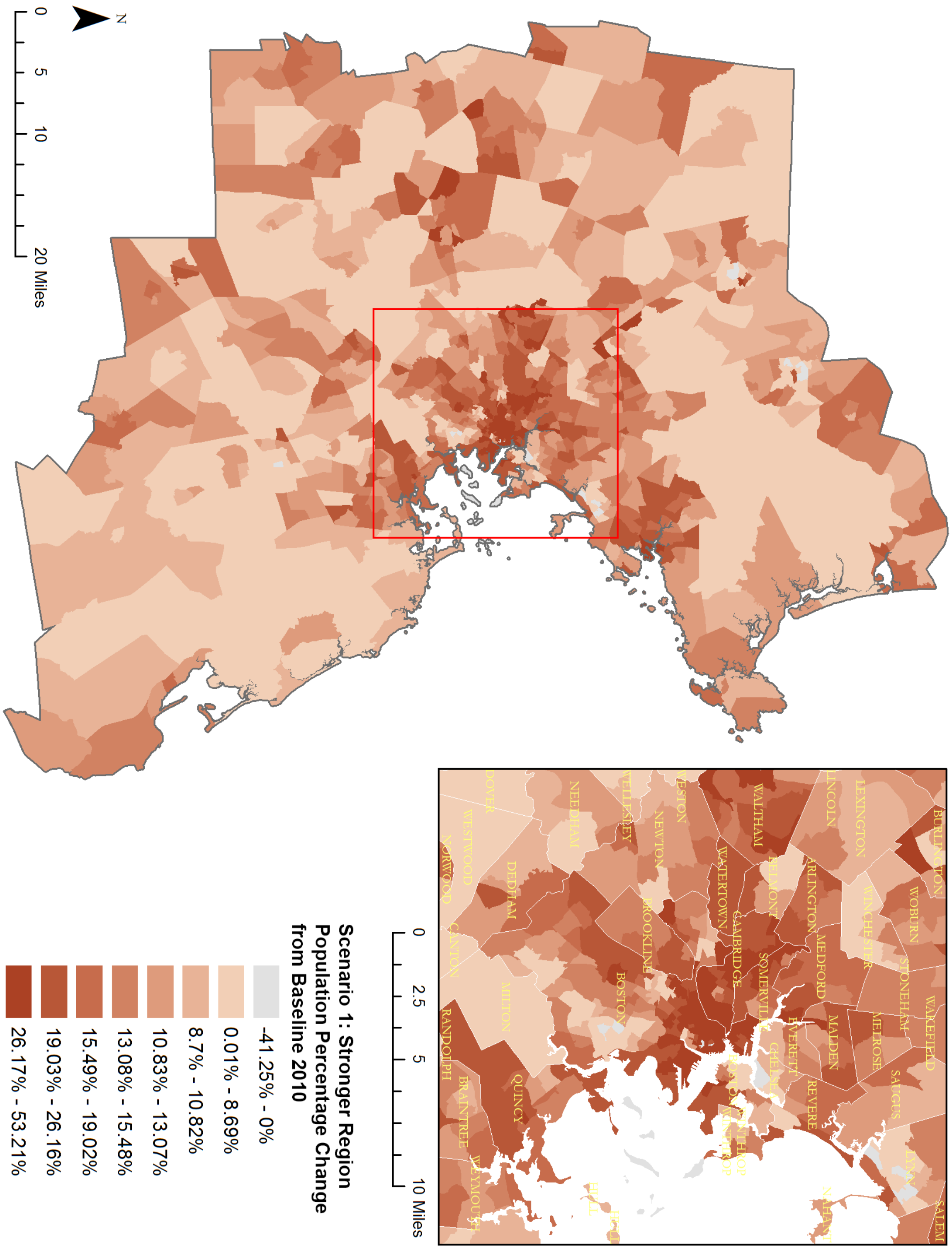

Figure 131: Scenario 1: Stronger Region - Population Percentage Change from Baseline 2010

7.1.3.1.B Scenario 2 - Inundation Awareness (IA)

I created the Inundation Awareness model using growth rates from the MAPC Status Quo data coupled with adjustments to reflect assumed "awareness" of inundation threats by regional residents. The MAPC Status Quo data were only available at the town level. To develop a baseline Status Quo scenario similar to the baseline Stronger Region scenario, I determined town growth rates and applied those town-level growth rates to the respective MIT-Model TAZs.

While the Stronger Region scenario is a direct application of derived growth rates from the MAPC data, the Inundation Awareness scenario is not a direct translation of the Status Quo rates. To represent some regional residents' response to the threat of inundation, zones threatened by inundation at lower levels do not experience growth over the 20-year model period. I examined each of the model zones and checked for inundation at the three-foot level or less. I specifically chose to designate the three-foot level or less as the key inundation level that would inform or affect the behaviors of residents within the model due to expert claims that this level of sea level rise is expected by 2050 (Douglas, 2010). Other critical claims include the potential for increased frequency of extreme storms. Three feet of inundation could become something that occurs on a yearly basis in the future. Higher - or lower - levels of inundation are possible but this highly probably inundation level would inevitably lead persons and firms in the region to grow wary of siting in these locations. I assume that sea level rise "awareness" is based on actual patterns of inundation, highlighting the areas where the inundation awareness will be most acute.

These assumptions essentially prevent growth from occurring in any zone inundated at three feet or less, though these zones will not experience the loss of persons or jobs. I assume that 80 percent of the growth from 2010-2030 that would have occurred in these zones will still choose to locate in the region, while 20 percent of this growth is lost to other regions. The growth no longer locating in these inundated zones is reallocated to other zones in the region in a non-uniform way: some areas experience greater growth, including established communities and areas that have more jobs and amenities. Furthermore, considering that the reallocated people, jobs, and households mostly come from the region's inner core, I assume reallocation will go to other dense urban areas

In the Inundation Awareness scenario, I assume the areas of high growth would mirror the same areas in the MAPC Stronger Region scenario. I examined the Stronger Region scenario to identify those TAZs that experienced growth. If a zone in the MAPC Stronger Region scenario experienced growth, and is not inundated at three feet or less, it is included as a possible reallocation zone.

In the following analysis I define: "Assets" as persons, households, and jobs and "Reallocation Zones" as those zones previously mentioned that demonstrate both projected growth and little or no discernible inundation.

I follow four steps:

1. Identify Reallocation Zones
2. Determine Zonal Weights for Each Reallocation Zone:
    a. All else equal, a zone that attracts more persons in the MAPC Stronger Region scenario will similarly attract persons in the Inundation Awareness scenario. Thus, these zones have a higher weighting when reallocating assets.
        i. Using this criterion, 728 zones have growth.
    b. Weighting is organized by quantile groupings based on rank. The 728 zones are equally divided into eight quantiles. These quantiles represent ratings based on expected growth with each zone ranked one through eight according to its growth rate and grouped into correlated quantiles. A rank of eight indicates that a zone is in the highest growth quantile and a one indicates a zone is in the lowest growth quantile.

QUANTILE	NUMBER OF REALLOCATION ZONES	RATIO PER QUANTILE	RATIO PER ZONE IN GROUP
1	91	2.8%	0.03%
2	91	5.6%	0.06%
3	91	8.3%	0.09%
4	91	11.1%	0.12%
5	91	13.9%	0.15%
6	91	16.7%	0.18%
7	91	19.4%	0.21%
8	91	22.2%	0.24%
TOTAL REALLOCATION ZONES	728	100.0%	--

Table 44: Quantile Groups, Weights, and Ratios

The weighting is based on 36 units, the sum of each quantile rank (8+7+6+5+4+3+2+1). Therefore, those zones in quantile eight will, as a group, receive 22.2 percent of the total redistributed assets, while those zones in quantile seven will receives 19.4 percent of the assets. The Ratio Per Quantile Column indicates the totals for each quantile group and sums to 100%. The Ratio Per Zone In Group column indicates the percentage of total assets each zone in a given group will receive. If each row of this column were multiplied by 91, it would sum to 100%.

3. Determine Total Number of Households, Persons and Jobs to Reallocate:
    a. I calculate the growth that would have occurred in these zones by multiplying the growth rates from the previous step by 80 percent of the baseline 2010 values. I then sum these data to find the total number of households, persons, and jobs to reallocate.

ASSET	ALLOCATION TOTAL
HOUSEHOLDS	354,797.41
POPULATION	714,816.13
WORKERS	351,978.53
TOTAL JOBS	411,131.35
RETAIL JOBS	88,452.90
SERVICE JOBS	213,698.10
REST OF JOBS	108,980.35

Table 45: Reallocation Totals

4. Allocate:

    a. Each reallocation zone's quantile rank is used to determine the ratio per zone for each TAZ.

	ZONES		**REALLOCATED ASSETS**			
TAZ	Town	Quantile Group	Ratio Per Zone	Households	Population	Total Jobs
227	Malden	7	0.21%	758.11	1,527.38	878.49
267	Cambridge	4	0.12%	433.21	872.79	501.99
119	Boston	7	0.21%	758.11	1,527.38	878.49
109	Boston	8	0.24%	866.42	1,745.58	1,003.98
270	Cambridge	8	0.24%	866.42	1,745.58	1,003.98
172	Boston	0	--	-	-	-
913	Plainville	2	0.06%	216.60	436.40	251.00
620	Medfield	2	0.06%	216.60	436.40	251.00
614	Norwood	1	0.03%	108.30	218.20	125.50
510	Andover	2	0.06%	216.60	436.40	251.00

Table 46: Excerpt of Allocated Output Table

Example Calculation:

$$TAZ_{227}\ Allocated\ Households = 0.0021 * 354{,}797.41 => 758.11$$

The patterns of how persons, jobs, or households reallocate will follow pre-existing growth trends. For example, if an area is already predicted to have more growth, it can be reasonably assumed that the Inundation Awareness scenario would follow this pattern, if not to a greater extent. In the face of fear of inundation, people will presumably seek out safer areas, especially those with established or increasing resources. Though a simplification, this provides a reasonable and defensible assumption about true demographic growth.

Figure 132 is a population density map that follows the same pattern as the baseline map and the Stronger Region maps. Comparing Figure 132 to Figure 129 and Figure 130, Figure 132 shows lower density in most zones throughout the model. Though there is an objective similarity of these two maps because of the inner core's high relative density, the overall difference in population is measurable. The percentage difference [from the baseline] map, Figure 133 , communicates the differences more easily. In Figure 133, gray represents the areas of zero or negative growth. The map indicates that areas of growth are away from the coastal core and generally follow the major inland highway system.

The increases in other factors, such as jobs, households, etc., follow a similar pattern. The general trend of greater growth in the Stronger Region scenario is more concentrated in the urban areas. The Inundation Awareness scenario shows lower levels of growth, including negative growth rates in some areas. Areas threatened by inundation of the three-foot level or less show no growth and some reduction compared to 2010.

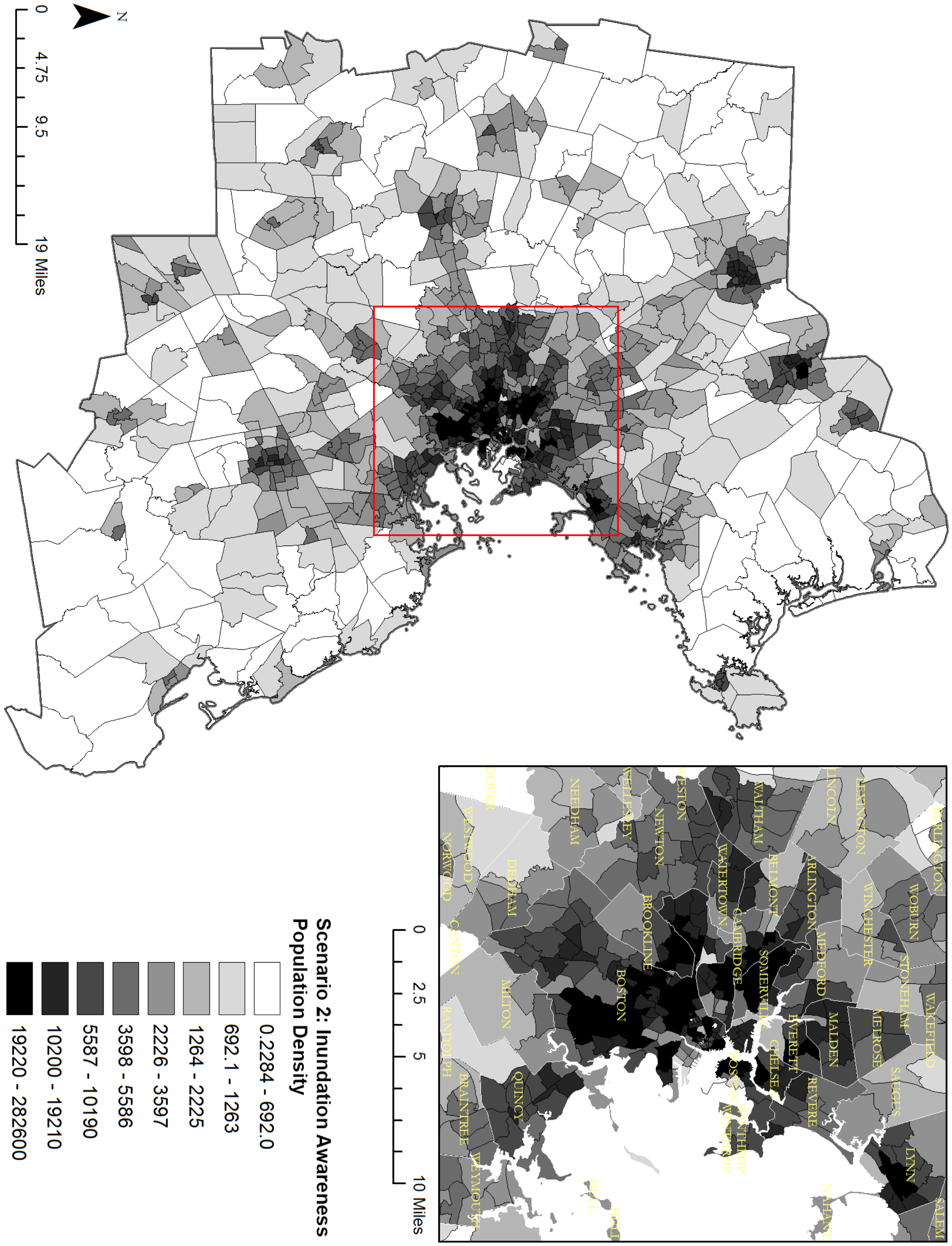

Figure 132: Scenario 2: Inundation Awareness - Population Density

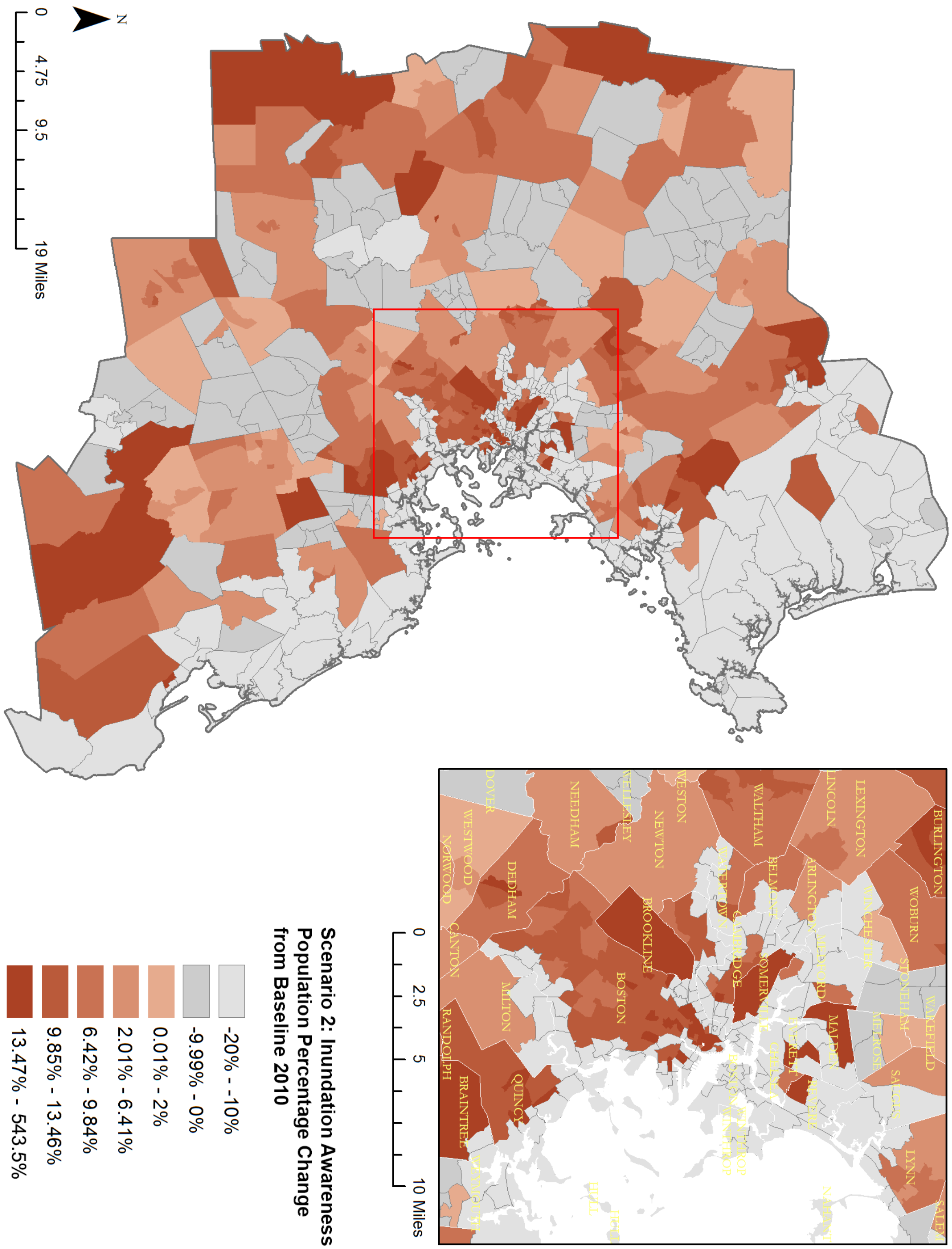

Figure 133: Scenario 2: Inundation Awareness - Population Percentage Change from Baseline 2010

7.1.3.2 Special Trip Generator: Logan Airport

Finally, Logan airport is the main "special generator" in the model. Research released by MassPort (MassPort, 2013) (the operator and owner of the airport) predicts a growth rate of 37 percent for the airport in the year 2030. I assume a more conservative estimate of 30 percent growth for the Stronger Region scenario and half of that growth for the Inundation Awareness Scenario (15%). Since the links required to easily access the airport are located in areas highly vulnerable to inundation (Inundation Assessment Results) halving the expected growth is reasonable.

7.1.3.3 Demographic Summary Comparison:

SCENARIO	2010	STRONGER REGION	INUNDATION AWARENESS
NUMBER OF TAZS	986	986	986
MODEL HOUSEHOLDS	1,688,704	1,999,042	1,827,588
POPULATION	4,457,779.01	5,044,916.54	4,746,114.56
WORKERS	2,211,883.00	2,513,288.39	2,226,096.44
VEHICLES	2,653,793.00	3,141,339.64	2,893,931.66
TOTAL JOBS	2,378,383.91	2,542,227.11	2,382,529.91
RETAIL JOBS	517,303.99	535,300.07	504,052.66
SERVICE JOBS	1,222,445.94	1,405,535.46	1,309,216.46
REST OF JOBS	638,633.99	601,391.57	569,260.79

Table 47: Model Totals

Table 47 summarizes the 2030 growth assumptions for the two scenarios.

7.1.4 BRT Alignments

I model each scenario to equilibrium with a base case and with two different versions of a hypothetical Bus Rapid Transit (BRT) route. This requires six full model runs. Modeling this many versions of the future, with and without the BRT system, allows for comparisons across scenarios and provides information on the performance of a given project in an uncertain future. To demonstrate the applicability of the techniques developed in this thesis, each of these subsequent scenarios will also be modeled with a critical inundation level: a four-foot inundation level. That is, I run the model for each inundated demographic scenario, for the no-project case and for each BRT alignment. I use the four-foot inundation level because, as seen in the previous Chapters that level represents an inflection point of major change (even though much of the region remains free of inundation). This allows critical examination of the potential positive impacts the two different BRT routes offer. For example, I specifically focus on the number of trips that are lost relative to each BRT alignment, as well as without a BRT route.

7.1.4.1 Bus Alignments and descriptions

The BRT routes modeled in this work are inspired by the Urban Ring Bus Rapid Transit project which has been discussed and studied for the Boston Metro region since the 1970s (MASSDOT, n.d.). The route was intended to offer a presumed much-needed continuous circumferential transit route in the inner core. One version of such an alignment was examined in a workshop I participated in at MIT in the Fall of 2013 (http://brtod.net/region/boston/). Given my familiarity with the project, its major scope, and the lack of other major infrastructure projects on the drawing board for the Boston Metro region, I chose the Urban Ring Bus Rapid Transit project as a suitable example to demonstrate how the techniques can be applied to provide useful information for project evaluation.

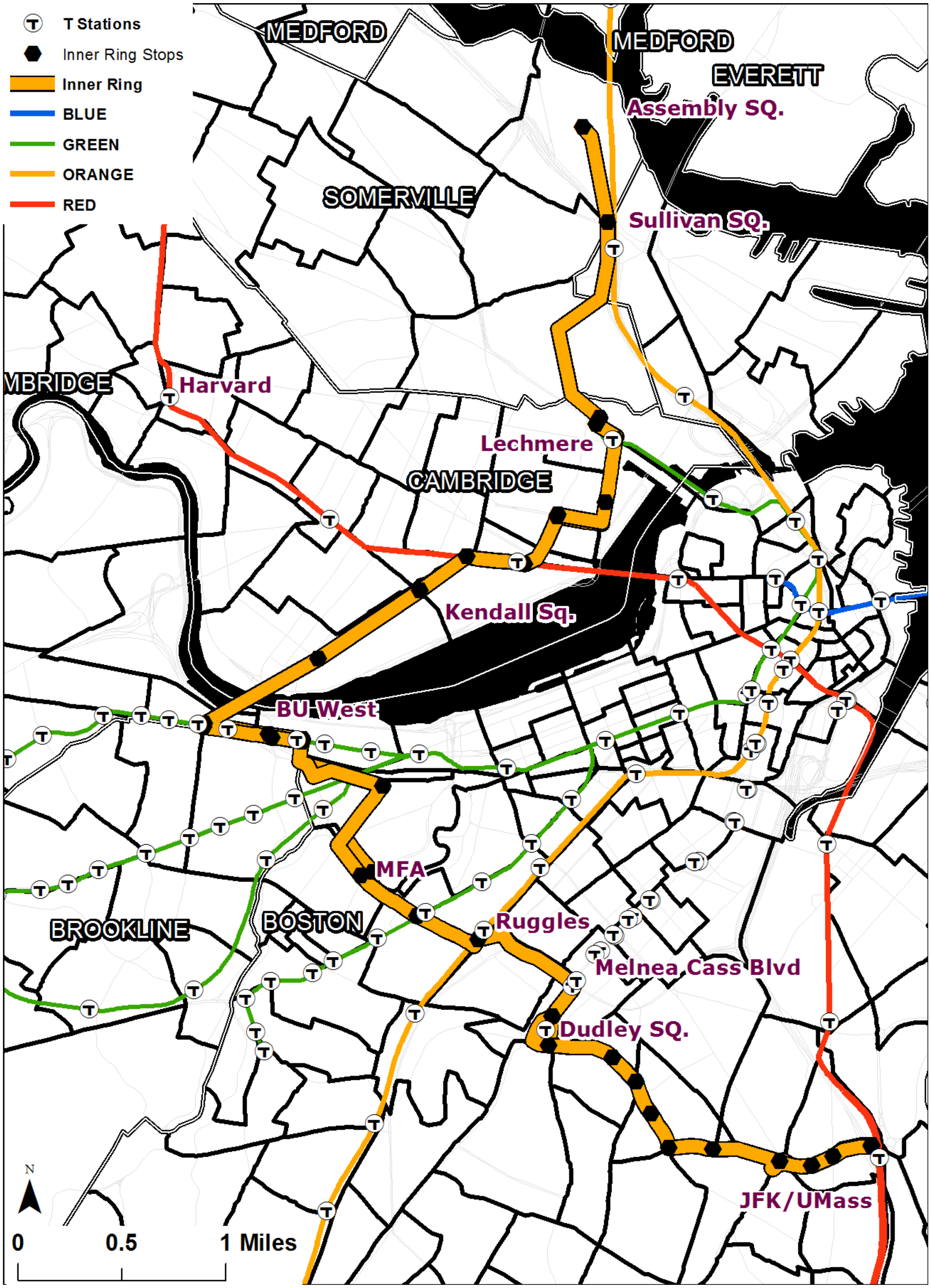

Figure 134: Inner Bus Alignment

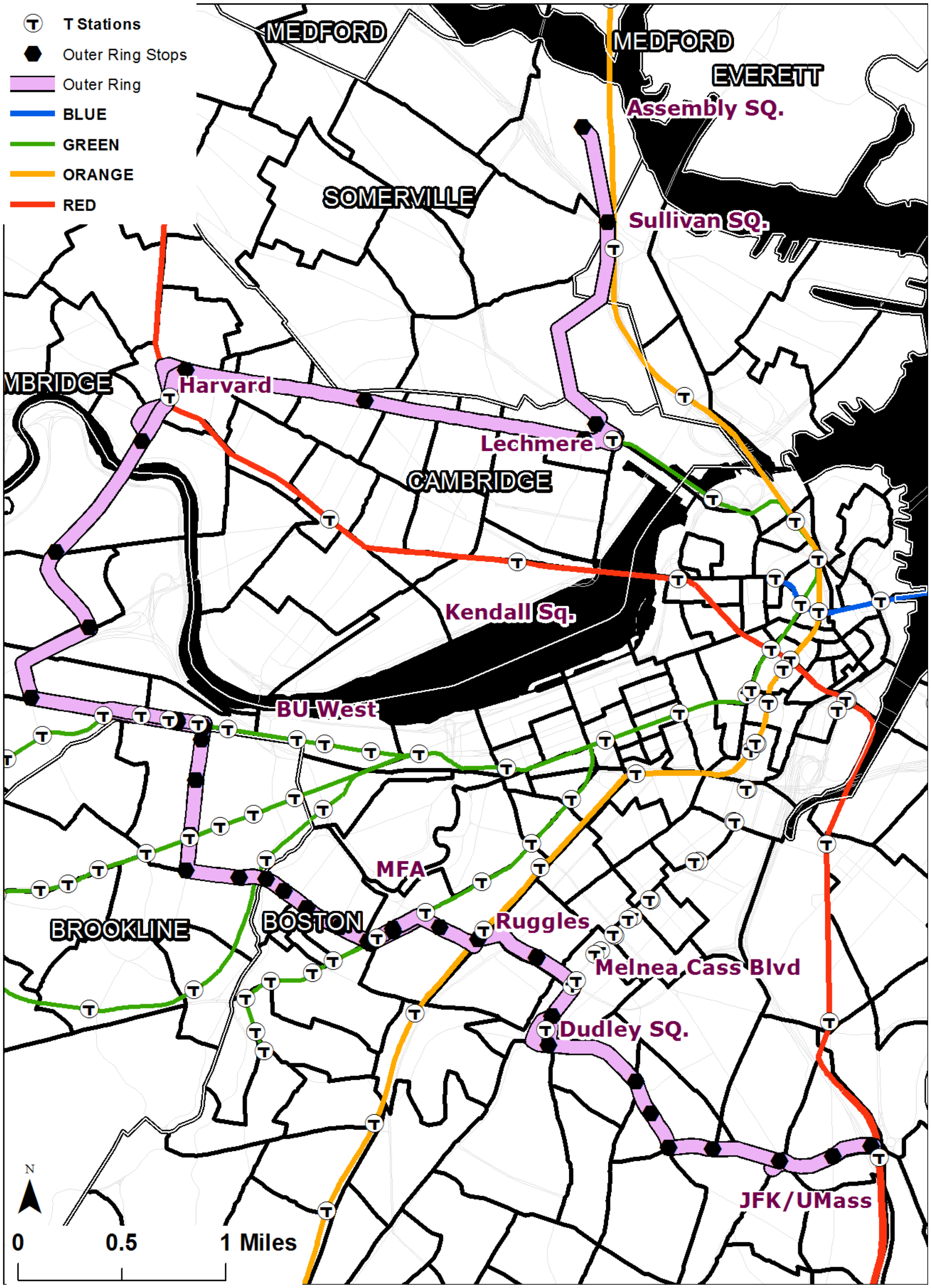

Figure 135: Outer Bus Alignment

The Inner alignment (Inner Bus; Figure 134) follows the general path decided upon in the MIT workshop, with an addition to the south connecting to the Red Line JFK/UMass Station. Both alignments begin and end in the same location and overall follow a very similar route, originating in Somerville near Assembly square and passing through the new Lechmere station. Both routes also pass through Brookline, the Longwood Medical District (Station: MFA), Dudley and finally terminate at JFK/Umass. The main difference lies in the path used through Cambridge. The inner alignment runs through Kendall Square & MIT, both major attractions and work hubs. Initial analysis of the different inundation levels indicates that the Kendall/MIT area will be heavily inundated, even at lower levels of water. Therefore, I developed the outer alignment (Figure 135), in part, to provide a route that avoids an area heavily threatened by inundation. The Outer alignment (Outer Bus) represents an alignment that attempts to avoid the impacts of potential inundation. Further, this alignment connects to Harvard Square, a jobs center and tourist attraction. The alignments cross the Charles River at different locations but converge near the Boston University West Green Line light rail station.

The Inner Bus has 28 stops and travels a distance of about 10 miles in a little over half an hour. The longer Outer Bus has 36 stops and covers 12 miles in about 43 minutes in free flow (non-congested network) conditions.

Bus and Direction	Stops	Distance	Running Time
Inner Bus NS	28	10.05	31.75
Inner Bus SN	28	9.76	31.18
Outer Bus NS	36	12.53	44.39
Outer Bus SN	36	12.23	43

Table 48: Bus Alignments

Both alignments have sections inundated at the four-foot inundation level. The Inner Bus has more areas inundated, including some areas that exceed one foot of inundation. Four-foot inundation does not mean that there is four feet of water throughout the extent of the inundation. Some parts will register as inundated at the four-foot level that do not register as inundated at the three-foot mark. To explain further, the areas throughout the Inner Bus route expected to be inundated at the four-foot inundation level could see water levels within a measured range of two to four feet. The Outer Bus route has one inundated segment, but with an expected inundation of only one foot. As described in the Method, I consider one-foot inundation areas as degraded, but not disabled. I assume that water crossings and dedicated right of ways are inundation-proof to allow unimpeded travel. The Inner Bus has a dedicated right of way along the Grand Junction railroad and on the railroad bridge it uses to cross the Charles River. The Outer Bus crosses a bridge further west, the JFK Bridge, also used by automobiles (protected area in Figure 137). Figure 136 and Figure 137 show the protected and inundated areas for Inner and Outer Bus routes, respectively.

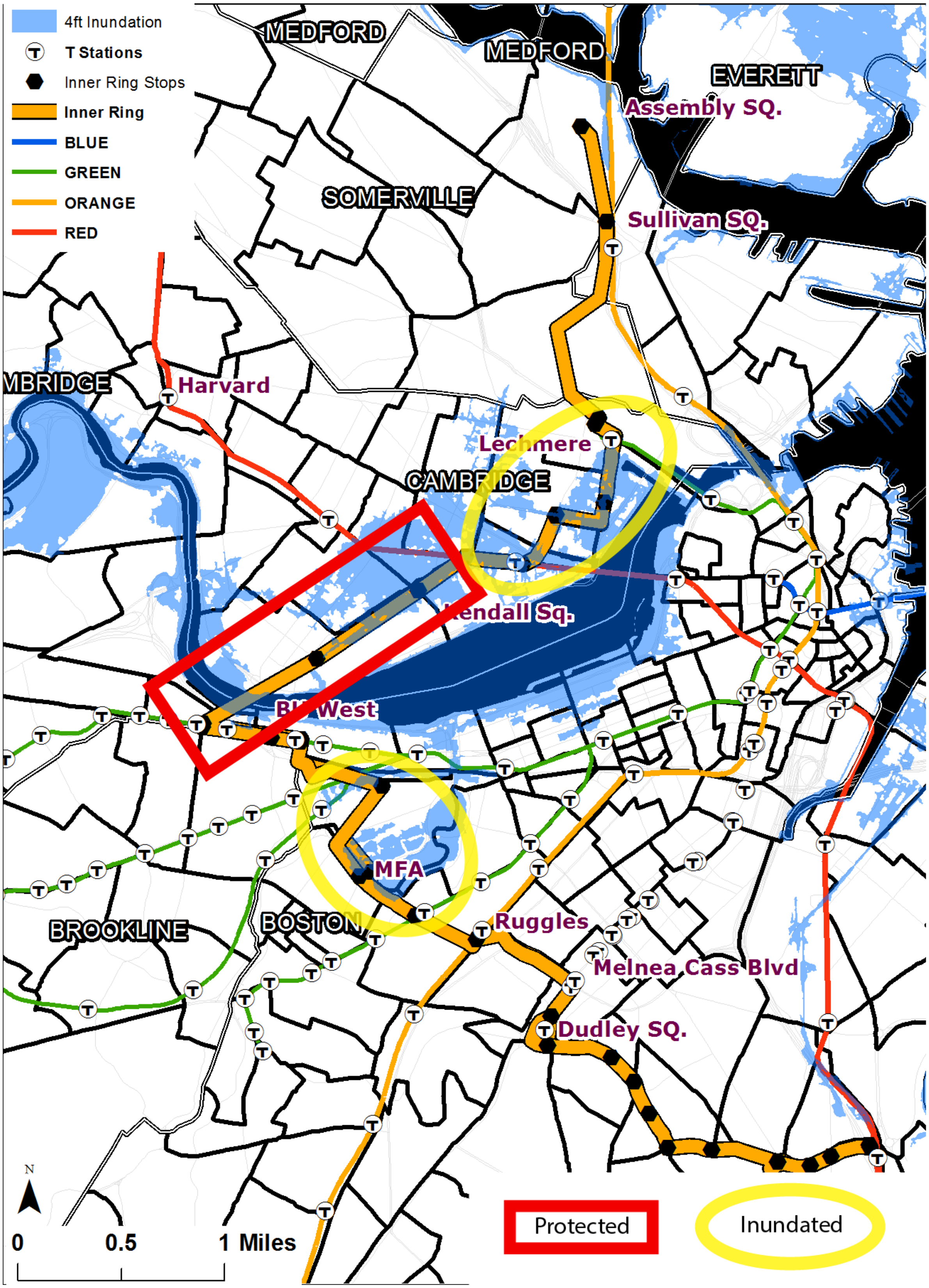

Figure 136: Inner Bus and 4ft of Inundation – Protected Area is Grand Junction Railroad

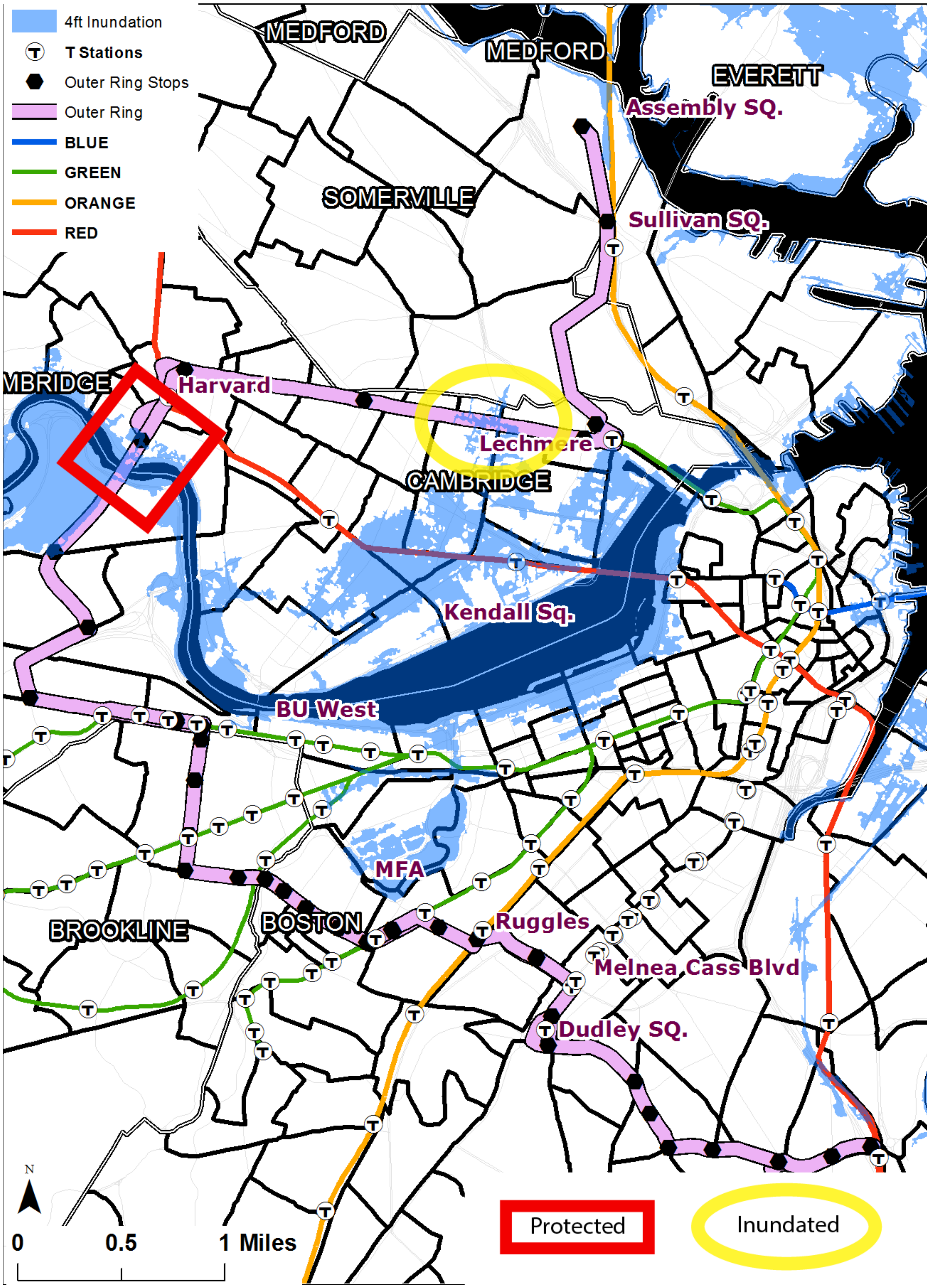

Figure 137: Outer Bus and 4ft of Inundation : Protected area is JFK Bridge

These two alignments should provide interesting comparisons of ridership demand under no inundation versus under inundation. For example, the Kendall/MIT route may have higher demand prior to inundation, but even with portions protected against inundation, the surrounding area will be impacted. The Harvard route will be able to connect areas that are not as inundated and still have people making trips and accessing transport.

7.1.5 Modeling Approach

Inundation modeling of the different demographic scenarios and the bus alignments follows the method outline in Method. The metrics presented will be limited to outputs related to the number of lost trips and to certain specific transit metrics like ridership, focusing primarily on the BRT alignments and differences in the relevant metrics. I provide only a sample of auto network metrics.[7]

7.1.6 Research Summary

I examine how two different demographic scenarios for the year 2030 will perform in inundation events:

- One scenario focuses on increased density near the Boston inner core (Stronger Region).
- The second scenario focuses on growth near the periphery of the inner core with much smaller absolute growth, without growth in areas threatened by inundation from the one- to three-foot levels (Inundation Awareness).

I then model TWO partial circumferential transit routes.

1. One route that follows previously identified alignment (MIT BRT Workshop) (Inner Bus)
2. One route that avoids areas of major inundation but attempts to connect similar zones (Outer Bus)

I assume that future evaluation criteria for transportation climate change resiliency measure the contribution of a project to protecting the ability of persons to: one, complete their trips; and, two, complete their trips in a reasonable amount of time.

[7] I have explored the results and the auto network is not affected by the addition of the BRT lines; limited time prevents an in-depth presentation of these materials.

7.2 Baseline Results

I fist examine growth under the two different demographic scenarios, with and without the circumferential transit. The Stronger Region Scenario produces about 3,000,000 more trips, while the Inundation Awareness Scenario produces about 1,400,000 more trips.

Scenario	Total Trips
Stronger Region (SR)	19,366,319.75
Inundation Awareness (IA)	17,797,553.84
2010	16,407,005.99

Table 49: Total Trips by Scenario

7.2.1 Trips by Mode and Purpose

MODE	2010	SR NO BUS	SR INNER BUS	SR OUTER BUS	IA NO BUS	IA INNER BUS	IA OUTER BUS
AUTO	10,265,427	17.1%	17.1%	17.1%	8.2%	8.2%	8.1%
AUTO PAX	1,049,129	19.6%	19.2%	19.2%	8.1%	7.8%	7.6%
WALK	4,259,798	18.9%	18.7%	18.5%	9.4%	9.2%	9.2%
PT WALK	760,167	20.8%	22.3%	22.7%	5.5%	6.4%	7.7%
PT DRIVE	72,486	54.0%	55.1%	63.6%	28.8%	29.4%	38.6%
TOTAL	**16,407,006**	**19,367,048**	**19,366,553**	**19,365,358**	**17,798,351**	**17,797,398**	**17,796,912**

Table 50: Percentage change by Mode from Baseline 2010 by Model Scenario and BRT Alignment

The largest percentage increase in trips is in the PT_Drive (Park and Ride) mode, irrespective of the addition of either BRT corridor. This increase is likely due to two factors: the increased population and density in Park and Ride regions and the degradation of service on the roadways, which makes Park and Ride more attractive. Although this increase is relatively high, Park and Ride still will not account for a large number of users relative to other modes. Expectedly, auto has the greatest increase in trips across all scenarios and BRT alternatives in absolute terms, followed by walk (Table 51)

MODE	2010	SR NO BUS	SR INNER BUS	SR OUTER BUS	IA NOBUS	IA INNER BUS	IA OUTER BUS
AUTO	10,265,427	1,753,227	1,751,337	1,751,227	843,859	844,703	831,495
AUTOPAX	1,049,129	206,023	201,351	201,781	85,436	82,013	79,968
WALK	4,259,798	803,282	797,593	786,475	399,283	393,842	391,846
PT WALK	760,167	158,353	169,359	172,780	41,917	48,557	58,609
PT DRIVE	72,486	39,157	39,907	46,090	20,850	21,277	27,988
TOTAL	**16,407,006**	**19,367,048**	**19,366,553**	**19,365,358**	**17,798,351**	**17,797,398**	**17,796,912**

Table 51: Difference In Total Trips by Scenario and Mode from 2010

Table 52 shows the mode split for every scenario. Vis-à-vis the 2030 scenarios, Table 52 suggests that the addition of the BRT lines has nominal impact on the regional mode split as a whole. PT_Walk shows modest increases in both the Stronger Region and Inundation Awareness scenarios with the introduction of the BRT (<1 percent). These increases likely result from shifts from the auto and/or walk modes to PT_Walk.

MODE	2010	SR NO BUS	SR INNER BUS	SR OUTER BUS	IA NOBUS	IA INNER BUS	IA OUTER BUS
AUTO	62.57%	62.06%	62.05%	62.05%	62.42%	62.43%	62.35%
AUTOPAX	6.39%	6.48%	6.46%	6.46%	6.37%	6.36%	6.34%
WALK	25.96%	26.14%	26.11%	26.06%	26.18%	26.15%	26.14%
PT_WALK	4.63%	4.74%	4.80%	4.82%	4.51%	4.54%	4.60%
PT_DRIVE	0.44%	0.58%	0.58%	0.61%	0.52%	0.53%	0.56%

Table 52 Mode Split Across Scenarios

7.2.2 Ridership

MODE	SR 2030 INNER BUS	SR 2030 OUTER BUS	IA 2030 INNER BUS	IA 2030 OUTER BUS
PT WALK	11,005	14,426	6,640	16,691
PT DRIVE	750	6,933	427	7,138
TOTAL	**11,756**	**21,360**	**7,068**	**23,830**

Table 53: Transit Ridership Difference with Addition of BRT Routes

Table 53 shows the total transit trip differences with the addition of the BRT lines versus the respective "No Bus" scenarios. In both scenarios, the Outer Bus has from twice to three times as many riders. The Outer Bus has a substantially (over ten times) higher proportion of Park and Ride trips compared to the Inner Bus.

MODE	2010	SR NO BUS	SR INNER BUS	SR OUTER BUS	IA NOBUS	IA INNER BUS	IA OUTER BUS
BUS	**510,421**	613,535	673,897	684,504	536,420	581,527	602,867
LIGHT RAIL	**259,869**	327,533	295,105	286,721	280,917	256,208	245,538
HEAVY RAIL	**578,136**	728,342	698,899	698,298	615,125	591,856	593,400
COMMUT. RAIL	**100,466**	133,763	132,037	135,410	118,895	116,599	121,060
FERRY	**507**	636	618	662	394	398	390
TOTAL	**1,449,399**	**1,803,808**	**1,800,557**	**1,805,595**	**1,551,752**	**1,546,587**	**1,563,255**

Table 54: No Inundation BRT Ridership

The addition of the BRT line increases the bus mode share in both demographic scenarios and both route alignments by about 55,000 riders. In both scenarios, the Outer Bus attracts more riders, about 10,000 for the Stronger Region scenario and about 20,000 for Inundation Awareness scenario. There are major decreases in other modes.

MODE	2010	SR NO BUS	SR INNER BUS	SR OUTER BUS	IA NOBUS	IA INNER BUS	IA OUTER BUS
BUS	35.2%	34.0%	37.4%	37.9%	34.6%	37.6%	38.6%
LIGHT RAIL	17.9%	18.2%	16.4%	15.9%	18.1%	16.6%	15.7%
HEAVY RAIL	39.9%	40.4%	38.8%	38.7%	39.6%	38.3%	38.0%
COMMUTER RAIL	6.9%	7.4%	7.3%	7.5%	7.7%	7.5%	7.7%
FERRY	0.0%	0.0%	0.03%	0.03%	0.0%	0.0%	0.0%
TOTAL	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**

Table 55: No Inundation BRT Ridership Percentages

Ridership on urban light and heavy rail decreases compared to the "No Bus" scenario, suggesting that the BRT diverts riders from those modes. In general, total volume of riders, in fact, decreases with the BRT, which suggests that fewer people are transferring to other modes and, thereby, reducing the total volumes. When comparing the demographic scenarios, I would expect Stronger Region to have higher riders overall given the greater regional density and greater number of trips produced. This is, in fact, what happens, though the bus mode share is greater in the Inundation Awareness scenario.

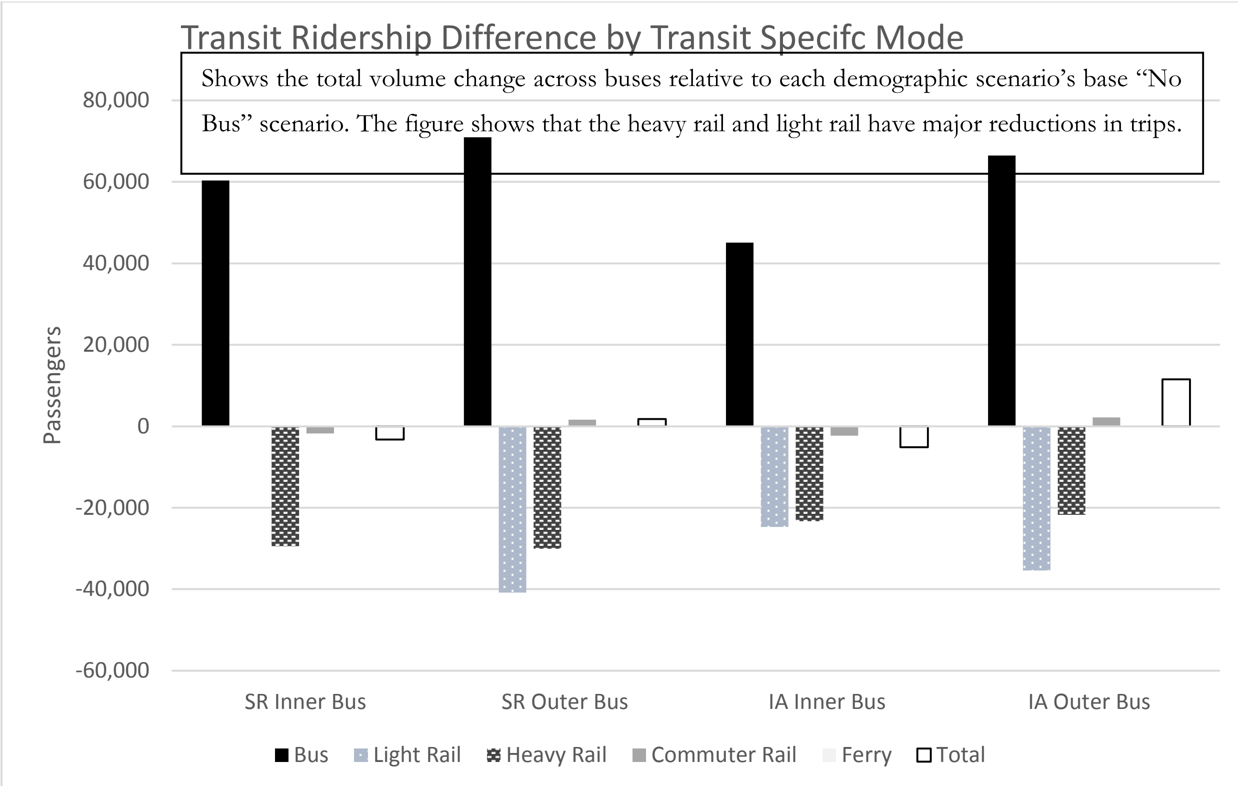

Figure 138 : Transit Ridership Difference from "No Bus" by Transit Specific Mode

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These results suggest that the BRT lines in both scenarios and both alignments attract substantial numbers of riders and are actually able to decrease the total number of multi-mode transit trips (Trips with transfers utilizing multiple transit modes). I infer that the BRT is attracting riders from other transit types, regardless of inundation. I will now present BRT-specific data to show the actual line ridership in the different scenarios, both by direction and stops.

LINE & DIRECTION	SR NO BUS	SR INNER BUS	SR OUTER BUS	IA NOBUS	IA INNER BUS	IA OUTER BUS
UR_INNER_SN	-	38,227	-	-	31,100	-
UR_INNER_NS	-	44,474	-	-	36,523	-
OUTER_IND_NS	-	-	63,385	-	-	57,166
OUTER_IND_SN	-	-	60,609	-	-	55,042
TOTAL		**82,702**	**123,995**	**-**	**67,623**	**112,208**

Table 56: BRT Ridership by Urban Ring Alignment and Scenario

Table 56 shows the actual ridership on the lines across the scenarios. The Outer Bus alignment in the "Inundation Awareness" scenario has the highest ridership in any direction with a 24-hour load of over 112,207 passenger trips.

Figure 139 and Figure 140 show the station loading profiles of the Inner Bus alignment in the Stronger Region scenario. There are consistent boardings of 1000 riders or more along most of the route. The major alighting location is the Ruggles stop. Figure 140, which charts the loading profile of the route of the Inner Bus alignment from North to South, shows only about 1,700 daily boardings until the Lechmere area. From the Lechmere stop boardings and volumes increase. There are many alightings in the area between St. Paul Street and Ruggles, the area generally called Longwood. The alightings continue somewhat consistently through the final stop, JFK (which is also the final stop for the JFK UMass Red Line).

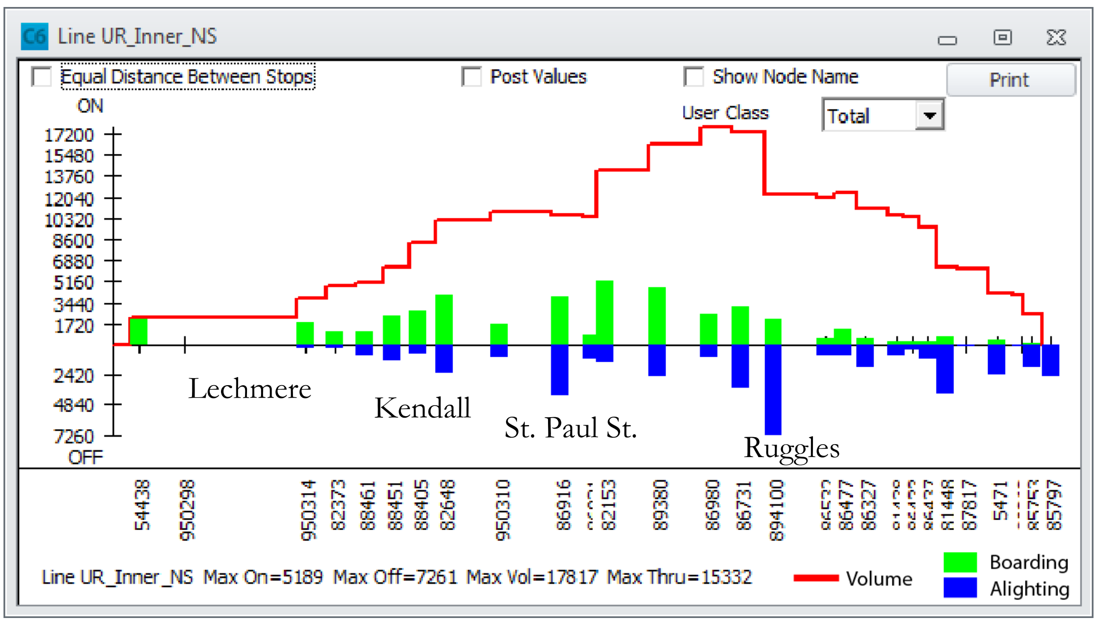


Figure 139: Stronger Region Inner Bus NS Load Profile

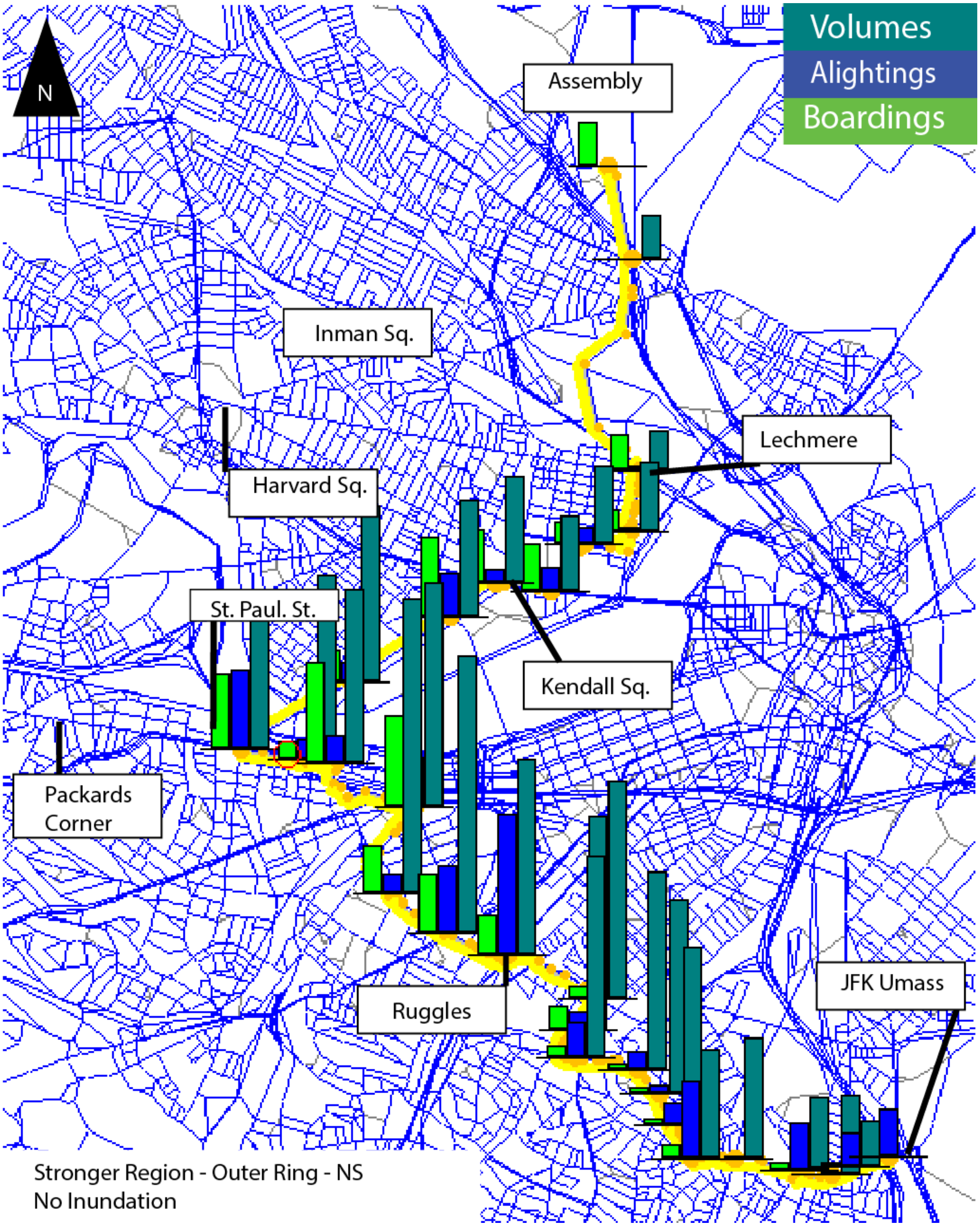


Figure 140: Scenario 1: Inner Bus Load Profile

The demand on the Inner Bus has a more consistent profile than that on the Outer Bus. The Outer Bus shows similar boarding levels in the Lechmere to Harvard areas (about 3,000 people boarding at these specific stops in a 24-hour period), but distinct differences appear at key stops along the route.

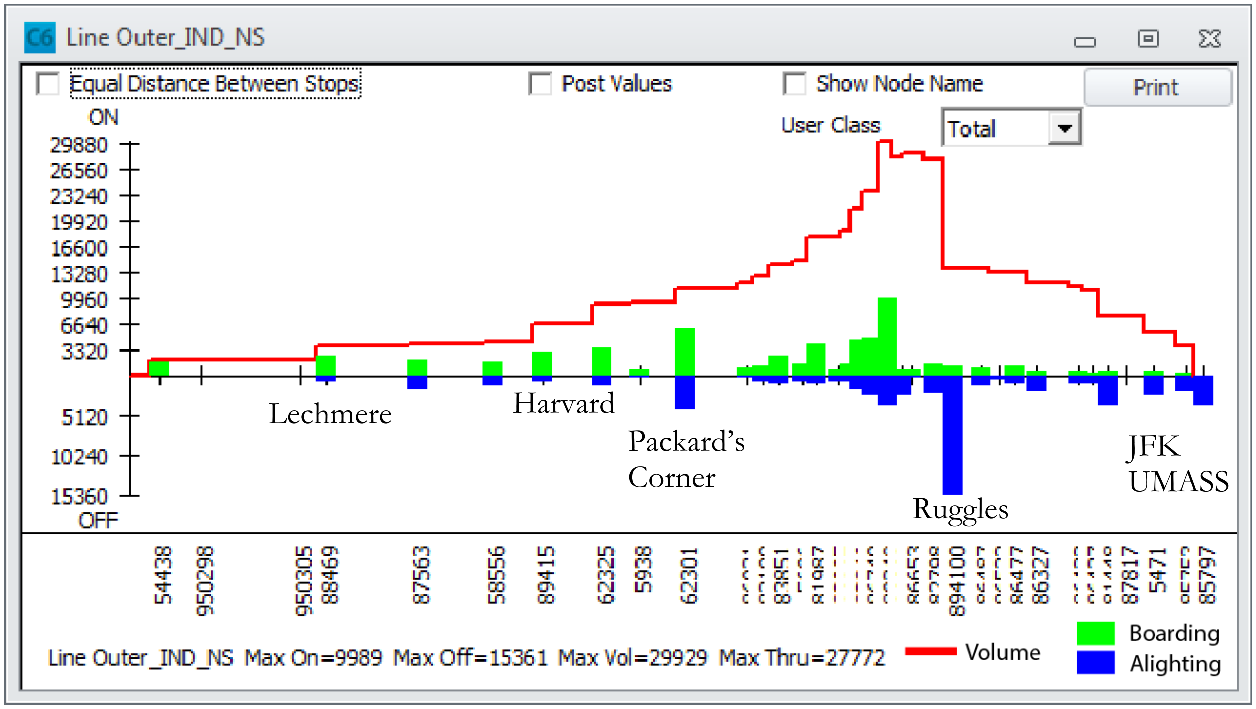


Figure 141: Stronger Region: Outer Bus Load Profile

The Outer Bus has several points along its route where total volume exceeds the Inner Bus. Figure 141 shows high boardings and alightings in the Longwood area between the Packard's Corner and Ruggles stops. Figure 141 shows that the Ruggles stop is a primary destination for the Outer Bus riders as the bar charted in the load profile accounts for the alighting of a majority of total riders. Similarly, a large number of alightings are predicted at Packard's Corner, the many Longwood area stops, and JFK UMass.

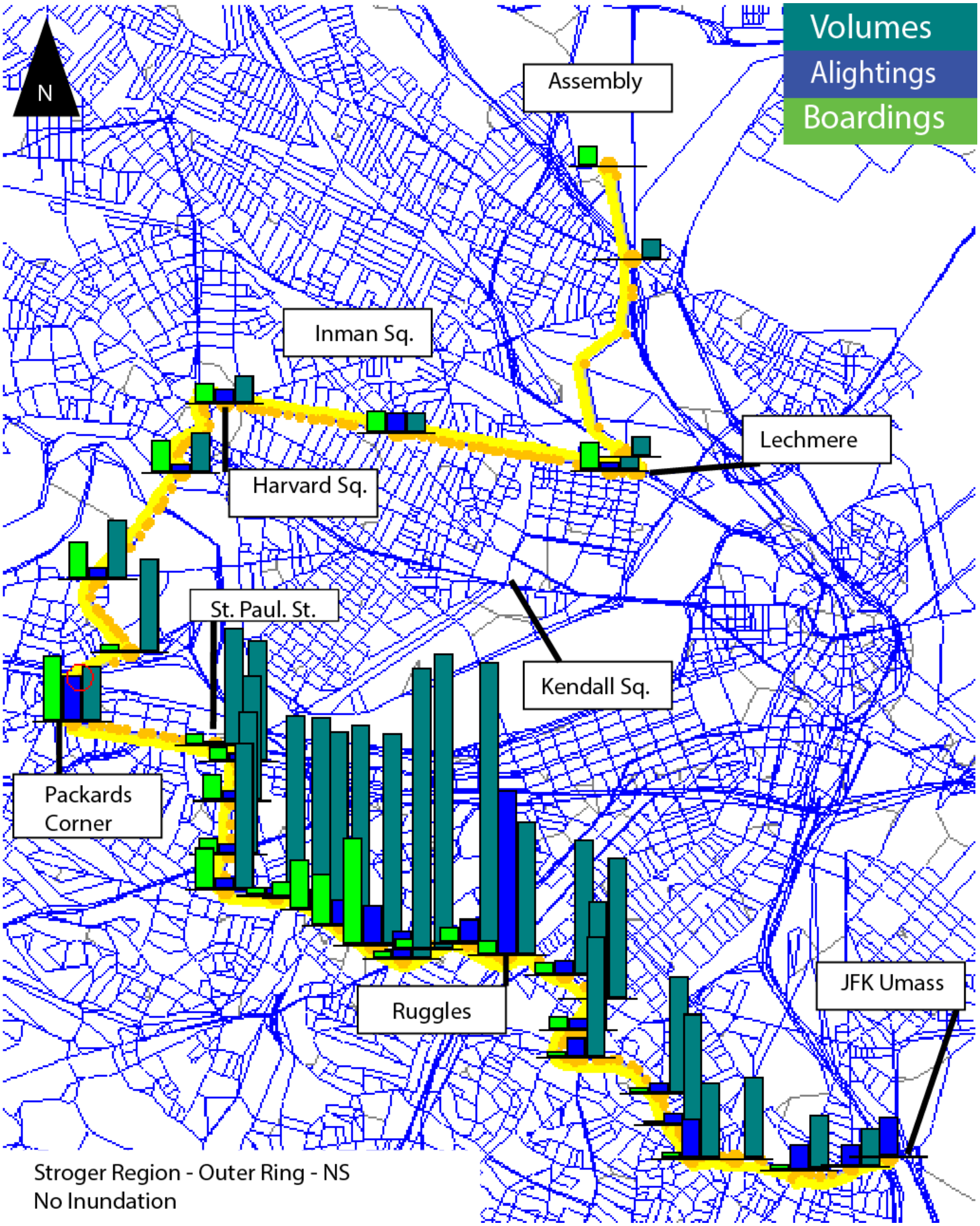


Figure 142: Stronger Region Outer Bus Load Profile Map

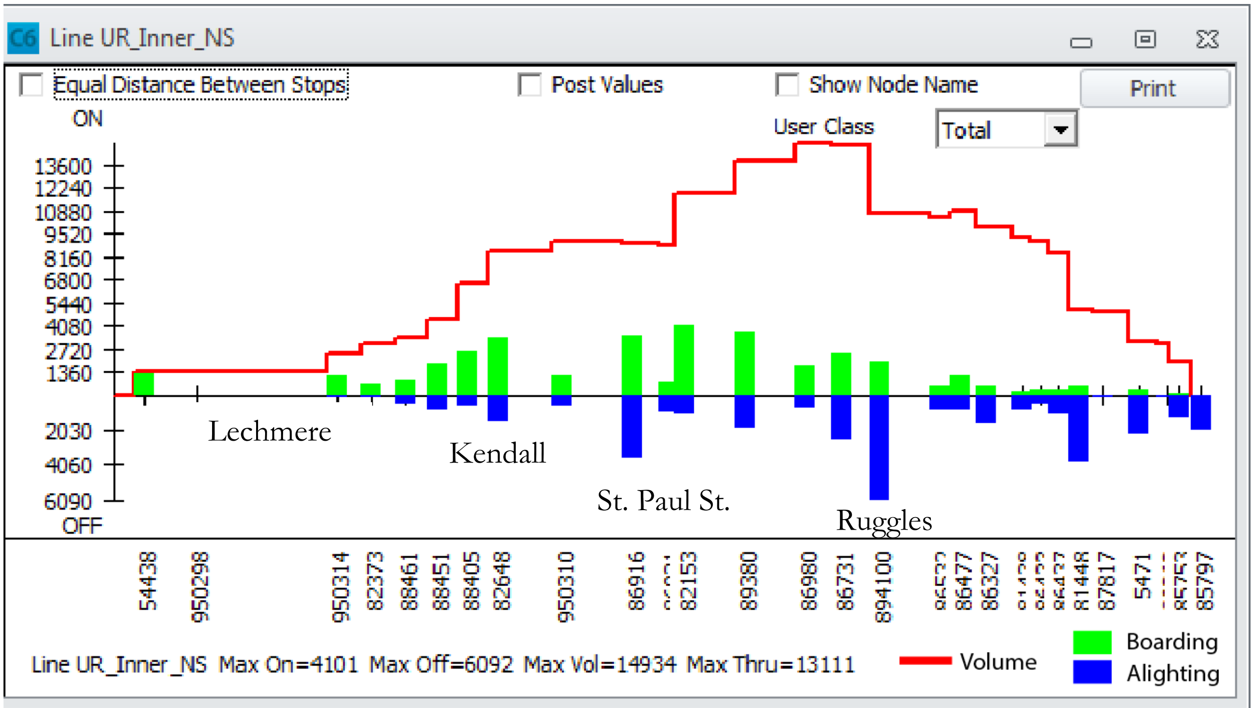


Figure 143: Inundation Awareness Inner Bus Load Profile

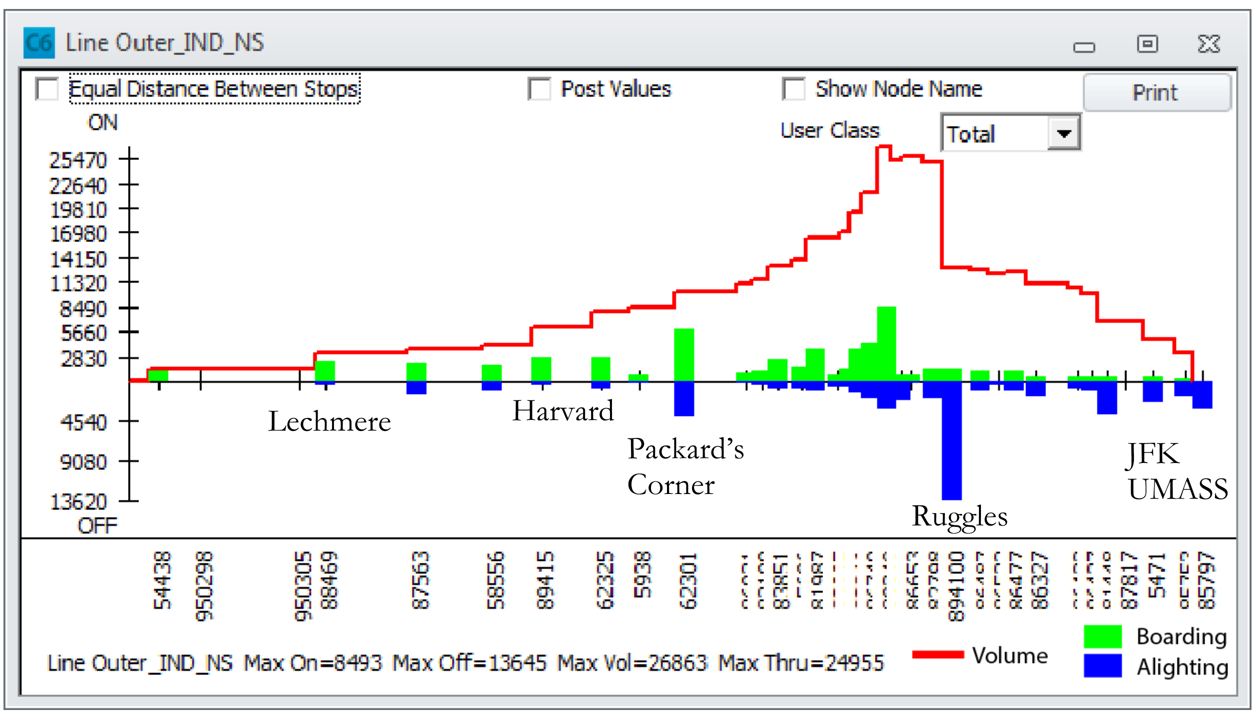
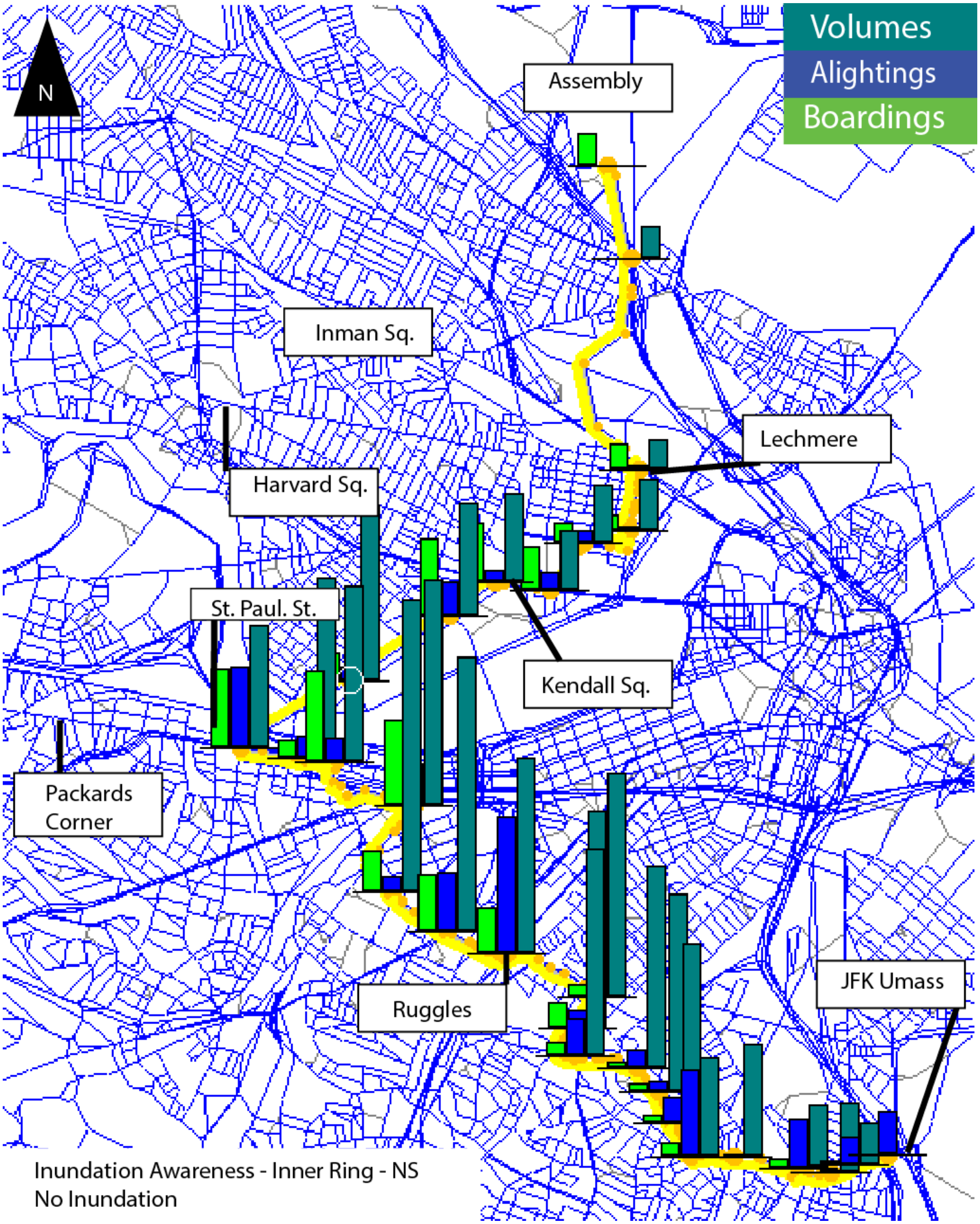
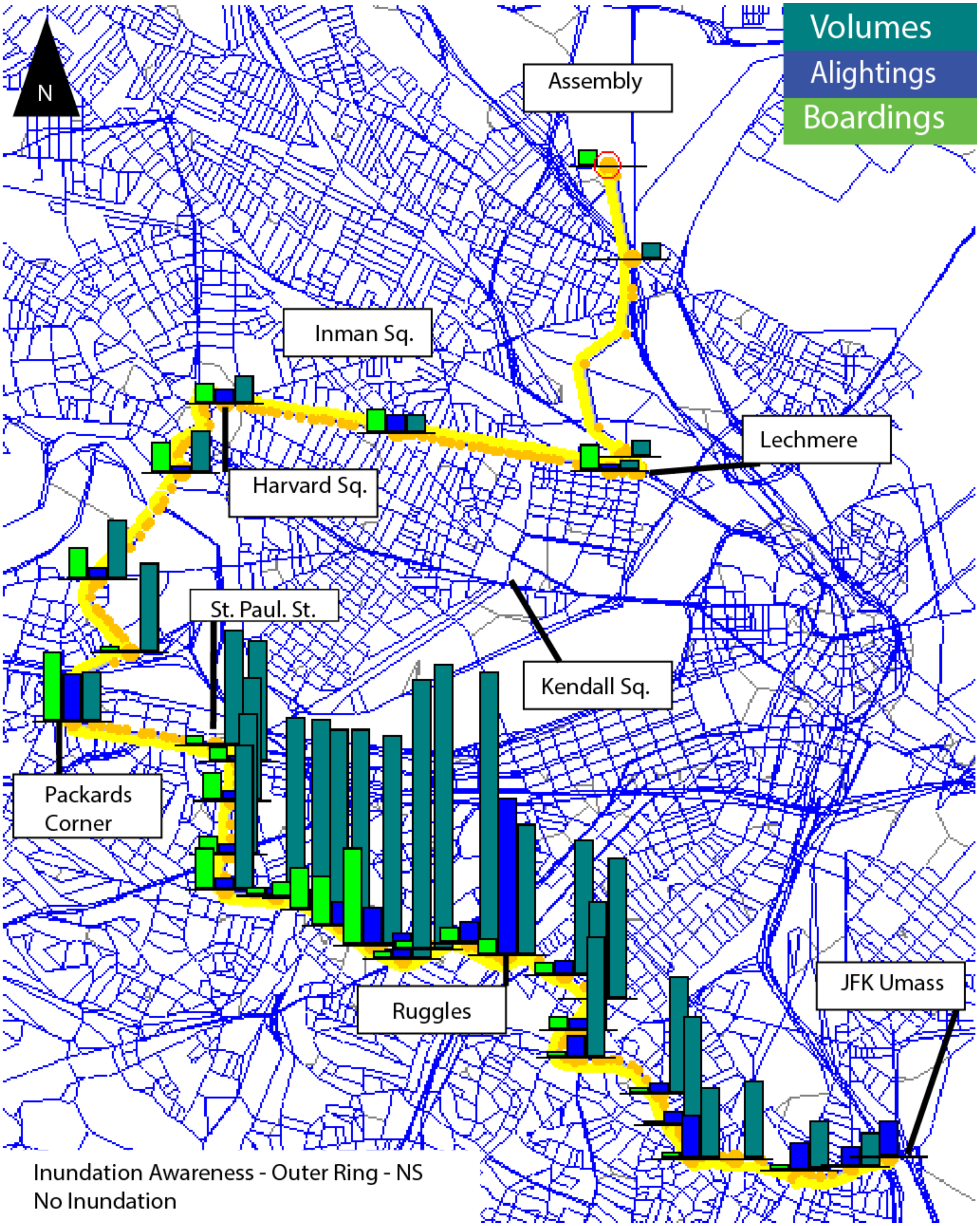


Figure 144: Inundation Awareness Outer Bus Load Profile



Inundation Awareness - Inner Ring - NS
No Inundation



Inundation Awareness - Outer Ring - NS
No Inundation

Although the total volumes are different, the shape of the load profiles for each scenario are similar. The volumes are higher in the Stronger Region scenario versus the Inundation Awareness scenario.

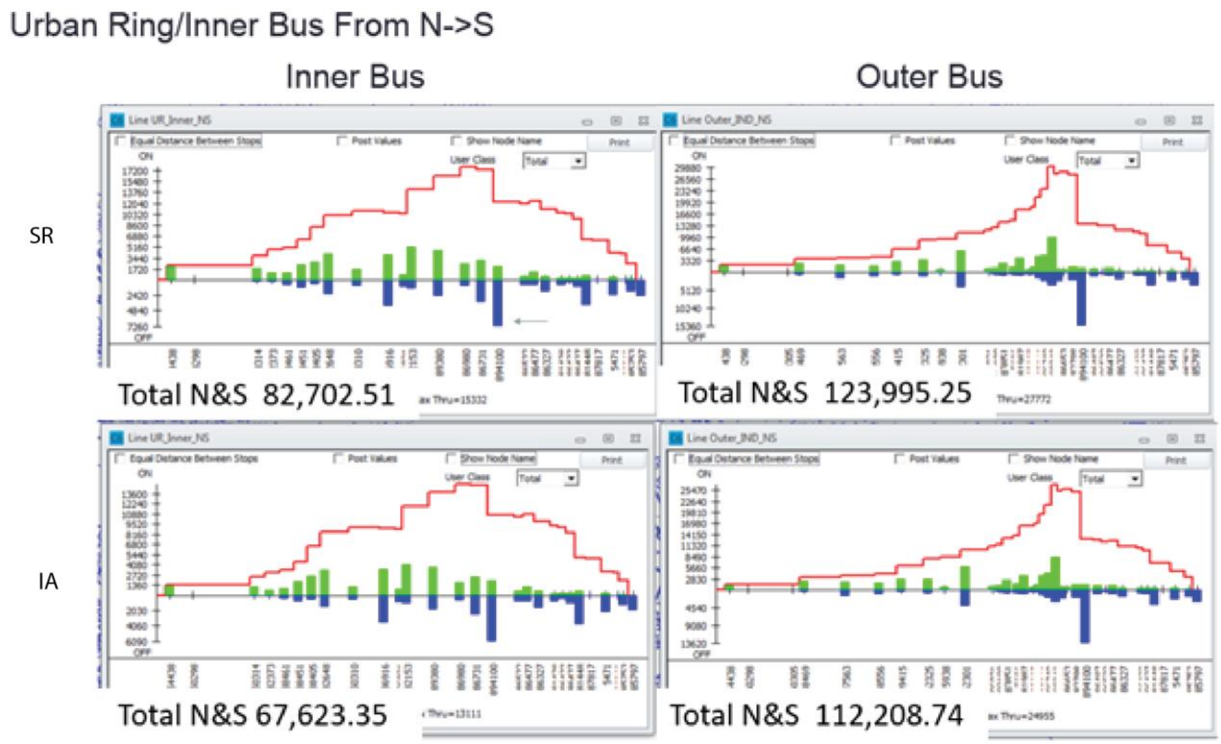


Figure 145: Loading Pattern Comparison

Given the lower density in the Inundation Awareness scenario, it is interesting to see that the bus still attracts many riders and follows the same loading profile as the Stronger Region Scenario.

	Base No Bus		Base Inner Bus		Base Outer Bus	
Rank	Line	Ridership	Line	Ridership	Line	Ridership
1	Orange Line NB	156,047	Orange Line NB	150,236	Orange Line NB	151,960
2	Orange Line SB	148,832	Orange Line SB	143,935	Orange Line SB	145,739
3	Red Line BrAl	87,754	Red Line BrAl	83,893	Red Line BrAl	83,915
4	Red Line AlBr	82,574	Red Line AlBr	77,755	Red Line AlBr	77,383
5	Red Line AlAs	80,888	Red Line AlAs	75,899	Red Line AlAs	74,776
6	Red Line AsAl	77,328	Red Line AsAl	73,170	Red Line AsAl	71,324
7	Green E EW	57,510	Green E EW	53,736	**Outer Bus NS**	63,385
8	Green E WE	52,606	Green E WE	49,347	**Outer Bus SN**	60,610
9	Green B EW	41,545	**Inner Bus NS**	44,475	Green E EW	50,858
10	Green D WE	40,487	Blue Line NS	38,359	Green E WE	46,586
~11	---	---	Inner Bus SN	38,228		

Stronger Region

Figure 146: Top Ten Transit Routes Stronger Region Scenario

KEY:

BrAL: Braintree to Alewife	AlBr: Alewife to Braintree
AsAl: Ashmont to Alewife	AlAs: Alewife to Ashmont
WE: West-East	EW: East-West
NS: North-South	SN: South-North

Figure 146 shows the top ten transit routes under the Stronger Region scenario, showing how the new BRT routes rank in terms of total ridership (by route direction) relative to preexisting transit lines. The list shows that preexisting lines – Red, Orange, and Green – maintain high ranks. The Inner Bus NS ranks number nine in total ridership. Inner Bus SN ranks at number 11, just outside the top ten. The Outer Bus in each direction ranks at seven and eight.

		Base No Bus		Base Inner Bus		Base Outer Bus	
Inundation Awareness	Rank	Line	Ridership	Line	Ridership	Line	Ridership
	1	Orange Line NB	136,210	Orange Line NB	132,198	Orange Line NB	134,958
	2	Orange Line SB	132,031	Orange Line SB	128,317	Orange Line SB	130,253
	3	Red Line BrAl	75,073	Red Line BrAl	71,577	Red Line BrAl	71,113
	4	Red Line AlBr	70,911	Red Line AlBr	66,875	Red Line AlBr	66,118
	5	Red Line AlAs	68,460	Red Line AlAs	64,259	Red Line AlAs	63,400
	6	Red Line AsAl	65,176	Red Line AsAl	61,606	Red Line AsAl	60,304
	7	Green E EW	47,199	Green E EW	44,493	**Outer Bus NS**	57,166
	8	Green E WE	43,898	Green E WE	41,466	**Outer Bus SN**	55,043
	9	Green B EW	36,140	**Inner Bus NS**	36,523	Green E EW	41,675
	10	Green D WE	35,001	Green D WE	32,370	Green E WE	38,973

Table 57: Top Ten Routes Inundation Awareness Scenario

Table 57 shows the top ten list for the Inundation Awareness scenario. The Inner Bus NS ranks ninth, while the Inner Bus SN ranks 13^{th} (thus it is not included in the chart). The Outer Bus NS and Outer Bus SN rank seventh and eighth, respectively, in this scenario.

The urban ring alignments attract large numbers of riders that are likely diverting from other transit modes, specifically heavy rail. Diverting trips from heavy rail could be beneficial to the transport system as the capacity increases on heavy rail are more expensive and difficult to implement. These capacity alleviation benefits may, therefore, support its introduction regardless of potential inundation.

7.2.3 Auto Metrics

I do not expect to see major changes in the auto network performance metrics with the introduction of the BRT alignments. Recall, that we saw that auto trips remain essentially unaffected by both BRT alignments. This may partly result from the fact that the model is not very sensitive to the addition of a transit line because buses do not contribute to vehicular congestion. Overall, demand shifts little between modes, i.e. shift from walk to transit, transit to car, walk to car, etc. Most shifts occur within different transit modes (e.g., heavy rail to BRT), so impacts on the auto network are imperceptible in the model. .

NON INUN -DATED	2010	SR NO BUS	SR INNER BUS	SR OUTER BUS	IA NO BUS	IA INNER BUS	IA OUTER BUS
VOLUME (STATIC)	14,023,798	16,553,638	16,530,709	16,238,850	14,589,326	14,573,233	14,601,160
VOLUME (DTA)	10,494,896	12,294,886	11,974,320	11,611,094	10,618,044	10,705,046	10,691,105
MAX VC	4.06	4	4.32	4.01	4.12	4.03	3.91
QUEUE	185,173	237,304	255,215	257,234	203,445	197,047	200,594
VDT (STATIC)	1,228,486	1,446,302	1,446,344	1,423,835	1,293,155	1,292,215	1,293,379
VDT (DTA)	828,954	967,641	939,276	910,594	847,940	856,315	855,237
VHT (STATIC)	42,087	50,617	50,992	47,905	43,300	42,953	43,848
VHT(DTA)	39,902	50,182	50,410	49,257	42,087	41,699	41,818

Table 58: Scenario Auto Network Performance Metrics - No Inundation

Table 58 contains information on a subset of the auto performance metrics. Unsurprisingly, the general trends indicate increases across the auto metrics is that the values in both 2030 scenarios (SR & IA) are higher than baseline 2010 values, and the values of the Strong Region scenario are highest of all. Note, despite the demographic growth by 2030, my model runs include no improvements to auto infrastructure, beyond those mutually included in the BRT alignments. Interestingly, the model predicts that the Stronger Region scenario would result in worsening of certain auto performance metrics: higher auto volumes and greater total travel distances and times.

In the Stronger Region scenario, certain metrics decrease with the addition of the BRT lines. Most notable is the reduction of VDT (dynamic traffic assignment), VHT (static traffic assignment) and Volume (static and dynamic traffic assignment) with the Outer Bus alignment, which all have reductions greater than 5 percent (Table 59). I was surprised to see these reductions as the mode shift shows very little reduction in auto mode share. Five percent is a large decrease if empirically observed. That said, within the model system 5 percent may be noise. There are 7-8 percent increases in the DTA queues (for both alignments) suggesting that the increase in Park and Ride trips are contributing to more congestion on the network. There are, however, reductions in the static assignment metrics.

	PERCENTAGE DIFFERENCE FROM SR NO BUS		PERCENTAGE DIFFERENCE FROM IA NO BUS	
NON INUN-DATED	**SR Inner Bus**	**SR Outer Bus**	**IA Inner Bus**	**IS Outer Bus**
VOLUME (STATIC)	-0.14%	-1.9%	-0.1%	0.1%
VOLUME (DTA)	-2.61%	-5.6%	0.8%	0.7%
MAX VC	1.17%	-6.1%	-2.2%	-5.1%
QUEUE	7.55%	8.4%	-3.1%	-1.4%
VDT (STATIC)	0.00%	-1.6%	-0.1%	0.0%
VDT (DTA)	-2.93%	-5.9%	1.0%	0.9%
VHT (STATIC)	0.74%	-5.4%	-0.8%	1.3%
VHT(DTA)	0.45%	-1.8%	-0.9%	-0.6%

Table 59: Percentage Change of Metrics from No Bus For Each Scenario

The differences in the Inundation Awareness scenario are minor.

I believe that the differences are due to the slight increase in Park and Ride but I do not have a strong idea as to why there is a 5 percent reduction in the static volumes.

7.2.4 Scenario Summary: Without inundation

From the above analysis, we can draw several key conclusions:

- Overall, in both 2030 scenarios we see increases in general auto network metrics
- The addition of BRT does little to alter overall trends in auto assignment and auto network performance
- Mode split is stable across scenarios
- Both BRT routes seem to attract a relatively large amounts of riders
    - Both directions of the Outer Bus appear in the top ten routes ranked by ridership
    - Both directions of the Inner Bus appar in the top 11 routes ranked by ridership
    - Both buses have ridership concentrated on the Boston-side of the river

Assuming no inundation and without considering cost, I would recommend implementing the BRT route with the highest number of riders. The analysis shows that the BRT routes likely will cannibalize riders from other transit modes, principally the urban heavy rail. This has benefit both within and without inundation scenarios. First, given that the heavy rail routes are threatened by inundation (as seen in Transit System Impacts and Inundation Impact Assessment Modeling Results), alternative capacity for heavy rail may offer some resiliency (this will be covered in detail in Scenario Impact Assessment Modeling Results:). Moreover, heavy rail in the Boston area – regardless of inundation - could benefit from increased or alternative capacity. Keep in mind that the MIT-FSM does not reflect transit capacity constraints, thus cannot reflect demand reactions to potential long-term benefits of freeing up capacity on other parts of the transit system.

Based on the above, the Outer Bus alignment appears more attractive: in all scenarios, it has a higher ridership. In the Stronger Region scenario, the Outer Bus alignment spurs slightly less transit-specific mode shift than the inner alignment, but only minimally. It spurs greater mode shift in the Inundation Awareness scenario.

7.3 Scenario Impact Assessment Modeling Results:

As shown in the Impact Assessment Modeling work presented in earlier sections, four-foot inundation is a critical inundation level with major impacts on network operations. Therefore, I modeled each of the different demographic scenarios and the two BRT alignments with four-foot inundation. The assumptions made about network operations are identical to previous exercises, meaning that vehicles operating on the roadway (autos, Bus, BRT) can travel in up to six inches of water but with degraded operating conditions. I made two key assumptions in the BRT Impact Assessment Modeling exercise: that the Inner Bus route has dedicated right of way (Inner Bus Grand Junction); and, that bridges are fortified against inundation. These bridges are also available to automobile traffic.

The decision criteria used in the inundation assessment of these routes focuses on the difference between the number of trips lost when no bus is present and the number of trips lost when the buses are present. Accessibility change was not a metric by which I assessed the benefit of the implemented BRT lines (partly because of time constraints). The focus of this exercise is to appreciate the total quantity of recouped trips due to the implementation of these BRT lines.

7.3.1 Lost Trips

After running the model, I obtain results showing the difference in the total number of lost trips across the scenarios with the addition of the BRT lines.

	STRONGER REGION TOTAL TRIPS			INUNDATION AWARENESS TOTAL TRIPS		
ALIGNMENT	***No IND***	***4ft Inundation***	***Lost***	***No Inundation***	***4ft Inundation***	***Lost***
NO BUS	19,366,320	17,712,062	-1,654,258	17,797,554	16,565,179	-1,232,375
INNER BUS	19,366,320	17,761,366	-1,604,953	17,797,554	16,608,614	-1,188,940
OUTER BUS	19,366,320	17,767,776	-1,598,544	17,797,554	16,621,028	-1,176,525

Table 60: Change in Total Trips from No Inundation to 4ft Inundation by Scenario and Alignment

Table 60 shows the difference in total number of trips completed and trips lost in the model, for each scenario and bus alignment, at both no inundation and four-foot inundation levels. Both the Stronger Region and Inundation Awareness scenarios show fewer trips are lost with either the Inner Bus or the Outer, compared to the “No Bus” situation. The addition of the BRT, regardless of alignment, allows more trips to be completed.

Table 61 shows the difference for each scenario and alignment compared to the “No Bus” situation. The last row shows the difference between the Inner bus and the Outer Bus.

	Stronger Region	Inundation Awareness
Inner Bus Difference from No Bus	49,304	43,434
Outer Bus Difference from No Bus	55,713	55,849
Inner Bus Minus Outer Bus	(6,409)	(12,414)

Table 61: Total Difference in Recouped Trips by Alignment (Compared to "No Bus")

For the Stronger Region scenario, the difference between the two bus routes is trivial. In the Inundation Awareness scenario, however, both BRT alignments allow for the completion of many more trips compared to Stronger Region. The Outer Bus alignment has the greatest number of recouped (i.e. not lost) trips. However, the difference between each ring alignment is modest – only 6,409 more trips are recouped by the Outer Bus than by the Inner Bus.

7.3.2 Ridership

Table 62 shows large predicted increases on the Inner Bus alignment across both demographic scenarios (in terms of actual bus line ridership). The Inner Bus alignment recoups three times more riders in the Stronger Region scenario than the Inundation Awareness scenario. The Outer Bus alignment, by contrast, has decreases in the Inundation Awareness scenario and nominal increases in the Stronger Region scenario. There are more recouped trips than there are increases in ridership with the BRT present: this means that a portion of the people would have chosen the bus, regardless of inundation.

SCENARIO	LINE & DIRECTION	NO INUNDATION	4FT INUNDATION	DIFFERENCE
STRONGER REGION	**Inner Bus**	**82,702**	**119,152**	**+36,450.46**
	Outer Bus	**123,995**	**126,331**	**+2,336.08**
INUNDATION AWARENESS	**Inner Bus**	**67,623.35**	**79,213**	**+11,590**
	Outer Bus	**112,208.7**	**100,948**	**-11260**

Table 62: Total Ridership Change by Scenario

The results in Table 62 – showing high increases in Inner Bus demand under Inundation – are somewhat surprising, considering that the four-foot inundation level has major impacts on the MIT/Kendall area. Major inundation in the area reduces the area's total number of jobs and attractions. To shed light on this, Table 63 details the ridership data by bus direction.

RIDERSHIP	**LINE & DIRECTION**	**SR 2030**	**SR 2030 OUTER BUS**	**IA 2030**	**IA 2030 OUTER BUS**
DIFFERENCE	Inner Bus NS	37,610.37	--	9,685.92	--
	Inner Bus SN	-1,159.91	--	1,904.42	--
	Outer Bus NS	--	16,002.83	--	-7,541.95
	Outer Bus SN	--	-13,666.75	--	-3,718.59
	Total	36,450.46	2,336.08	11,590.34	-11,260.54

Table 63: Differences in Ridership by Scenarios

The ridership increase on the Inner Bus is completely concentrated on the NS direction, while the SN direction sees minor decreases. The Outer Bus in the Stronger Region shows a similar pattern. We see a greater predicted reduction in ridership in the Outer Bus SN direction relative to the Inner Bus SN direction. The difference in directional flow is somewhat confusing but may represent reduced demand because of inundation elsewhere, such as inundation farther south affecting the Red Line. This would prevent users from transferring to the Inner Bus from the JFK UMass station (its southern terminus). The shape of the NS and SN flows is almost identical, simply reversing direction. Because of time constraints, I was not able to determine the actual cause of the difference in flows.

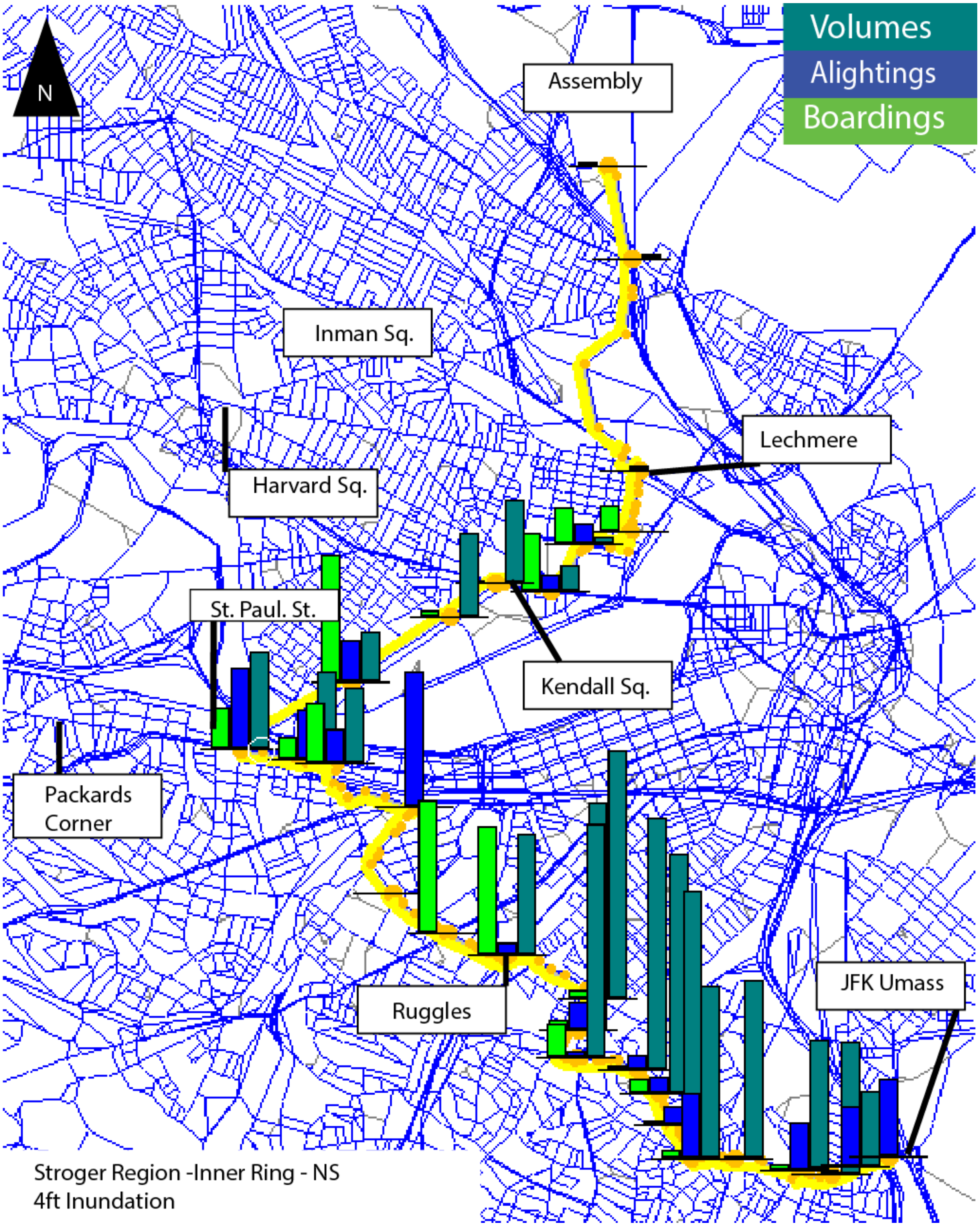


Figure 147: Stronger Region – Inner Bus NS 4ft

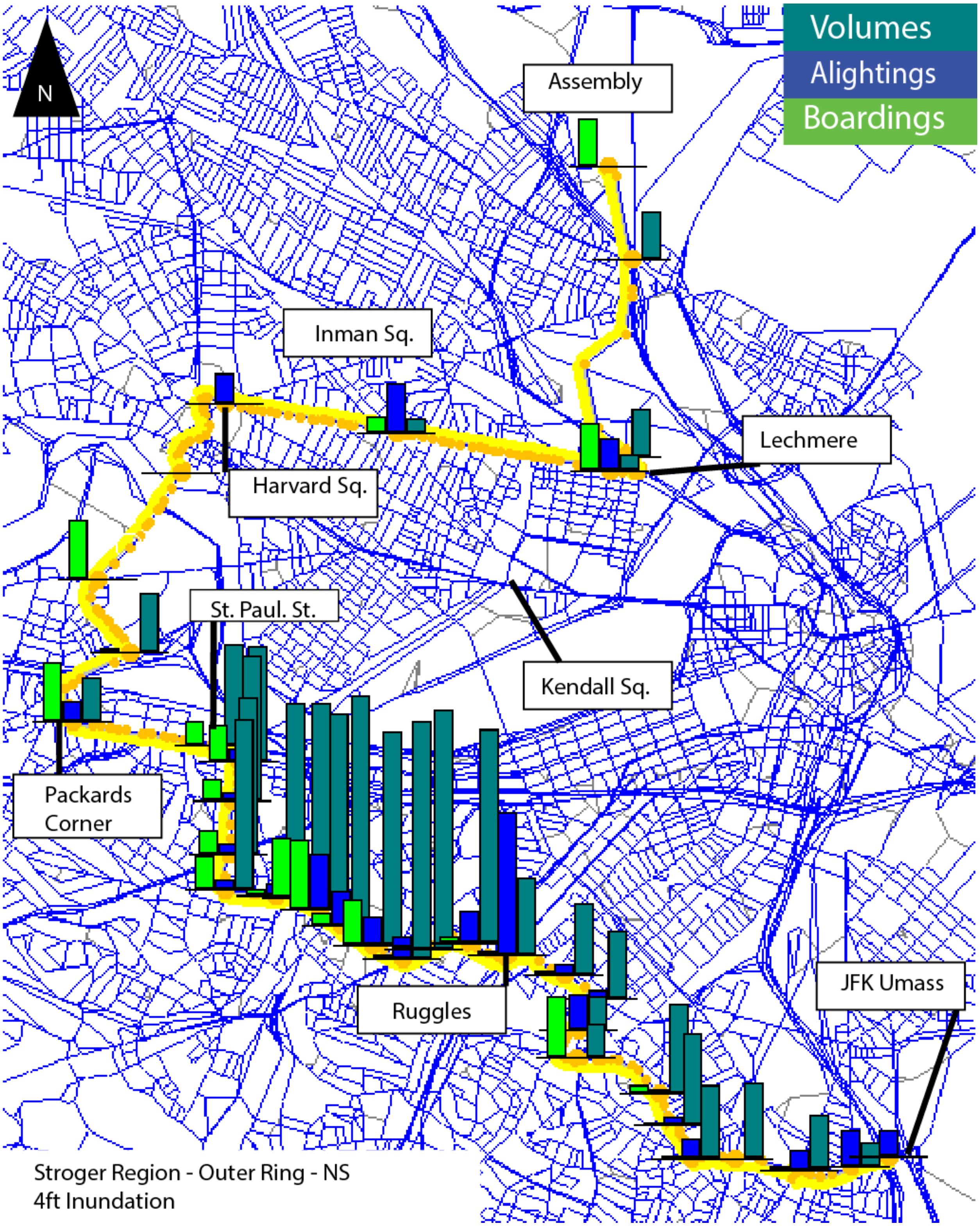


Figure 148: Stronger Region – Outer Bus NS 4ft

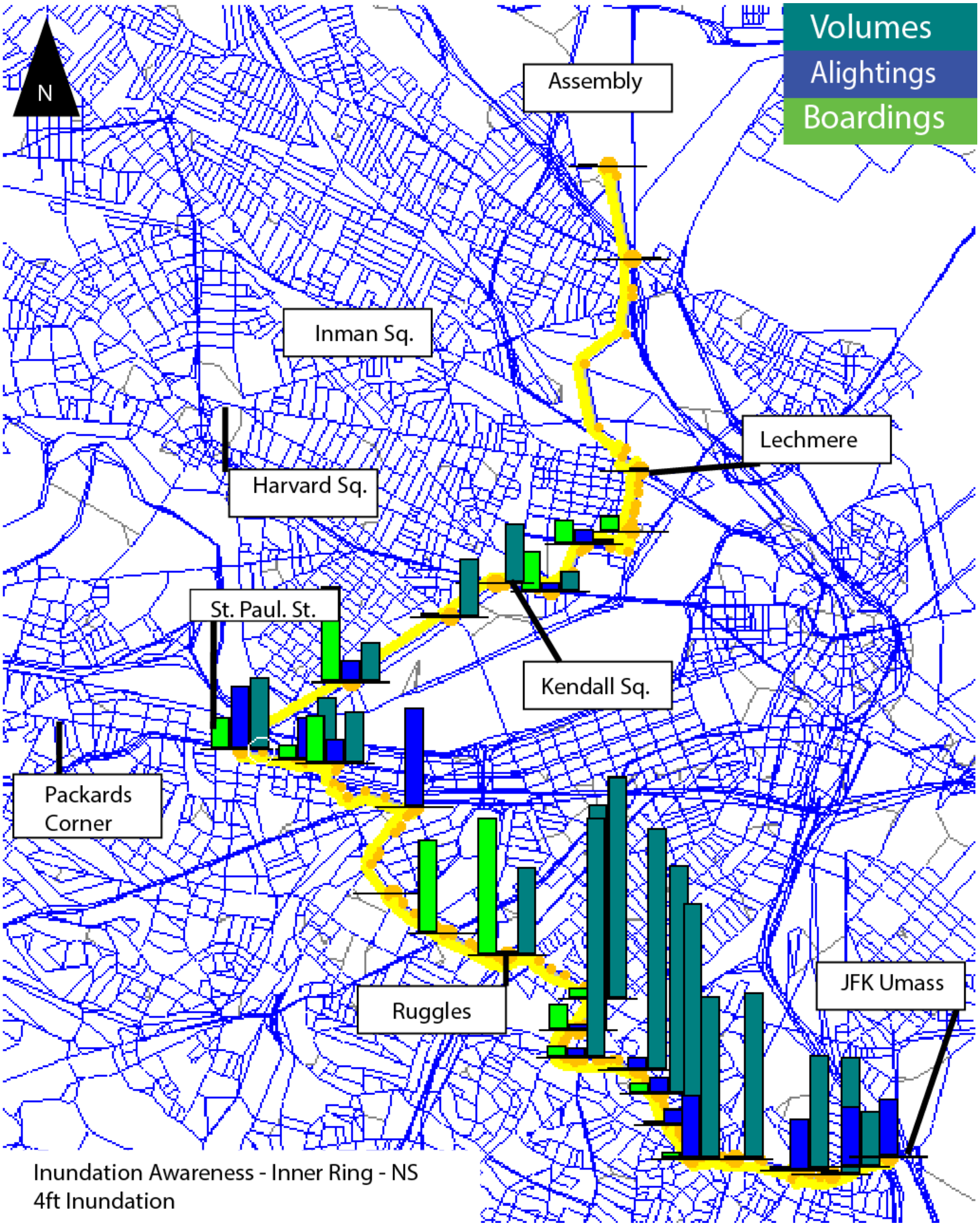


Figure 149: Inundation Awareness – Inner Bus NS 4ft

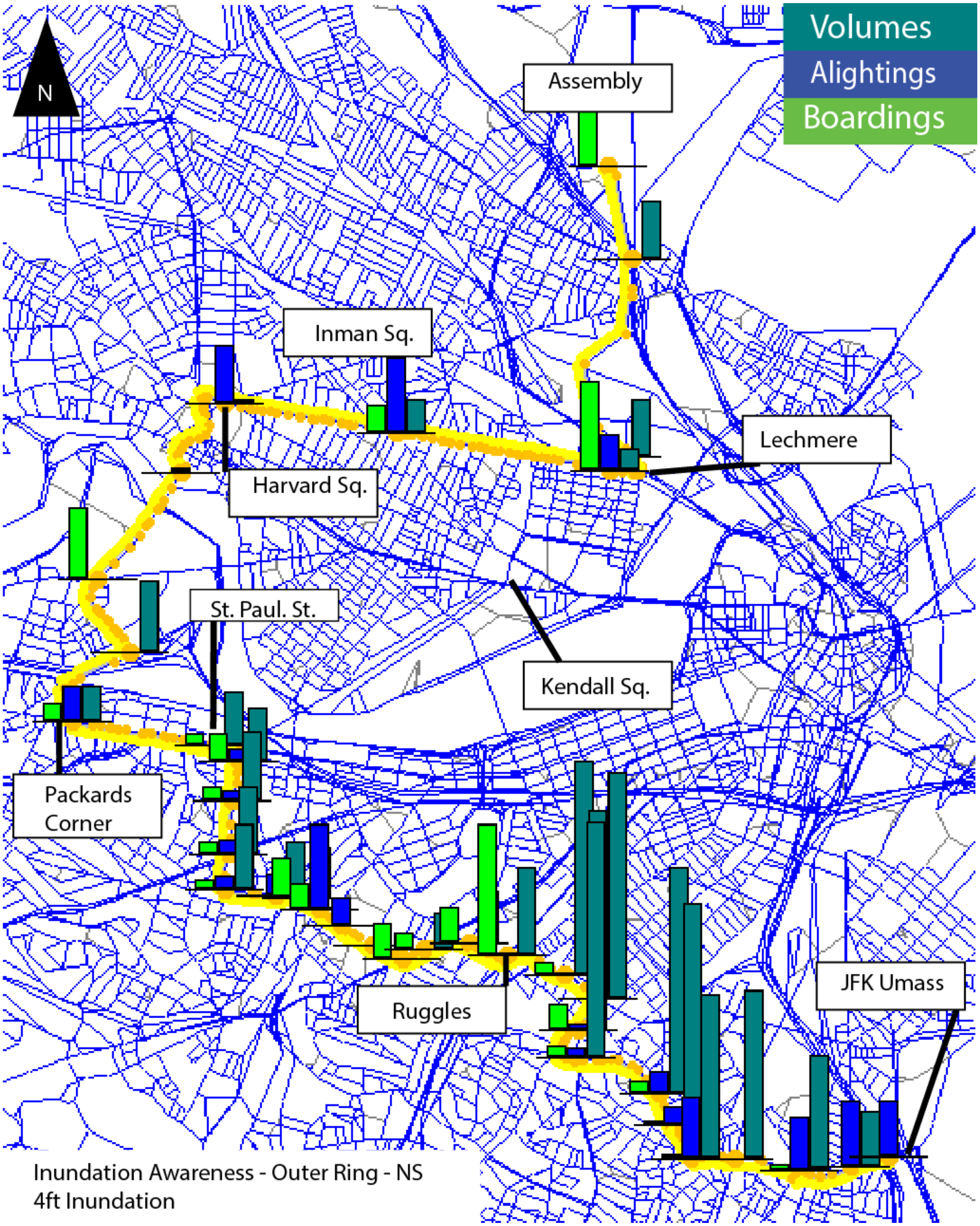


Figure 150: Inundation Awareness – Outer Bus NS 4ft

The pattern of ridership on the Inner Bus alignment follows a distinct pattern: first, there is an influx of riders at the Kendall stop. Then, the bus appears to completely empty a few stops past St. Paul Street. The Inner Bus route is inundated at this area (Figure 136). The bus then takes on a new group of riders just before Ruggles, the majority travelling to JFK UMass.

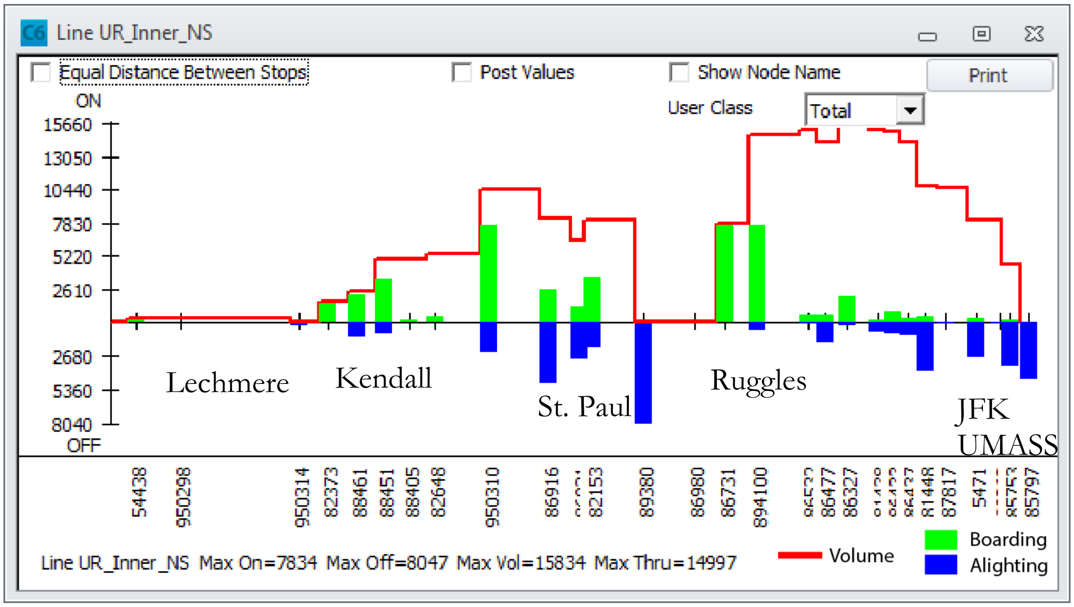


Figure 151: Stronger Region Inner Bus NS 4ft Inundation

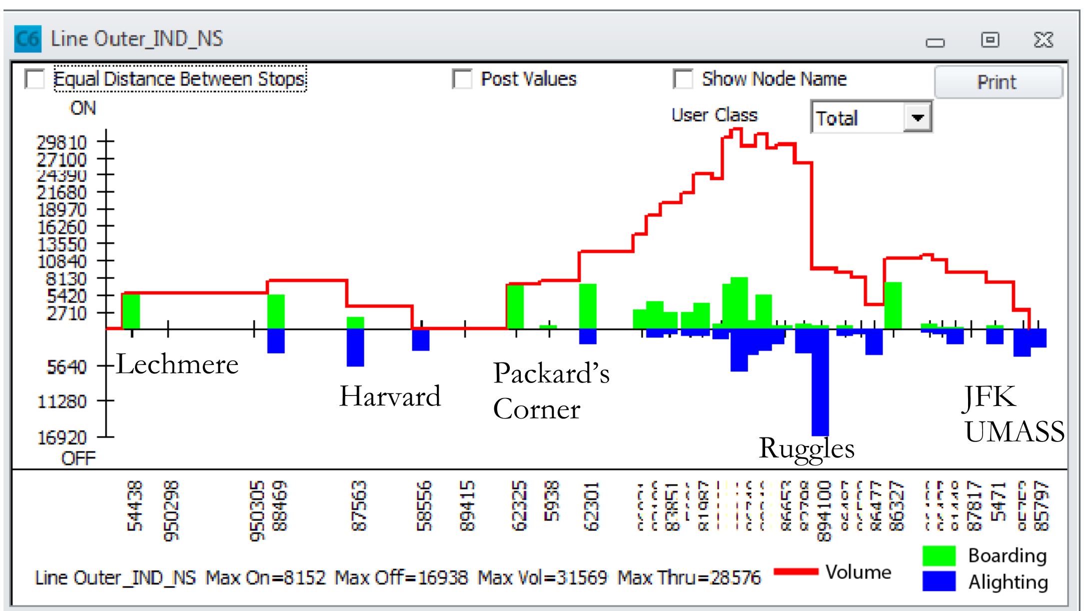


Figure 152: Stronger Region Outer Bus NS 4ft Inundation

The Outer Bus alignment has a similar pattern. Riders utilize the Outer Bus alignment primarily from Lechmere to Harvard. The bus empties and regains riders at Packard's Corner. The two major destination hubs are Ruggles and JFK UMass. Unlike the Inner Bus Alignment, the Outer Bus is not inundated in the area between Harvard and Packard's Corner. The minimal ridership in that area is likely due to bus stop inundation in surrounding areas. This is true for the areas on either side of the Charles River. Although the route, itself, is not inundated, the areas from which it might draw users may be. Still, this very low ridership is unexpected and I checked all relevant network files to ensure no inundation had occurred and that there was not extreme congestion on the links that was preventing the bus from crossing the links in a reasonable amount of time.

The pattern of boardings for the Inundation Awareness scenario is nearly identical to Stronger Region at the same inundation level. As described in Table 60, the Inundation Awareness scenario had lower volumes of riders.

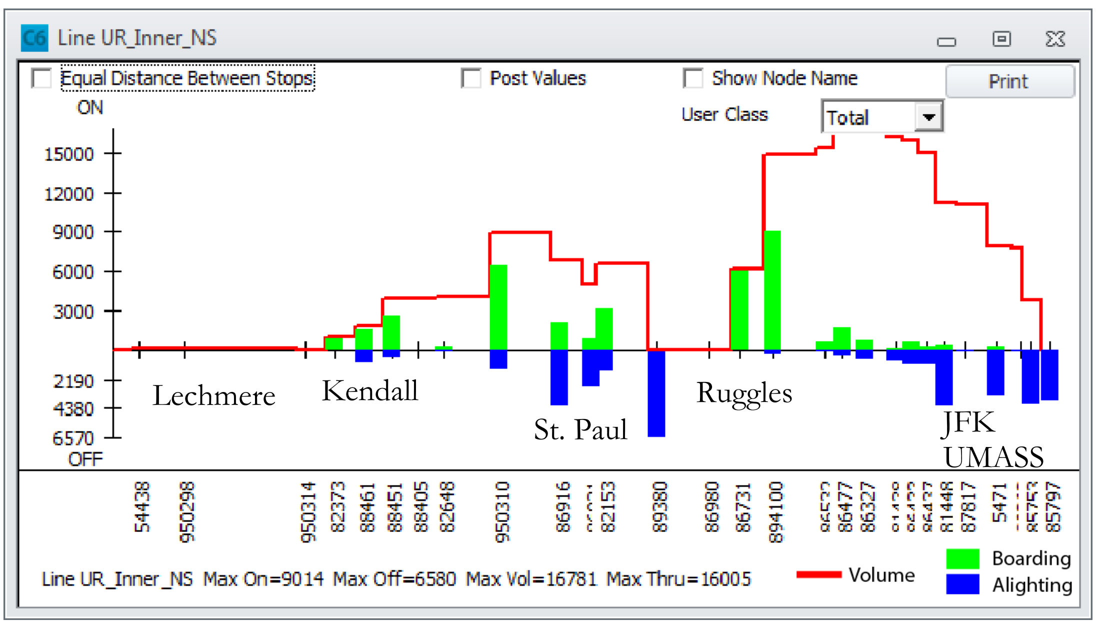


Figure 153: Inundation Awareness Inner Bus NS 4ft Inundation

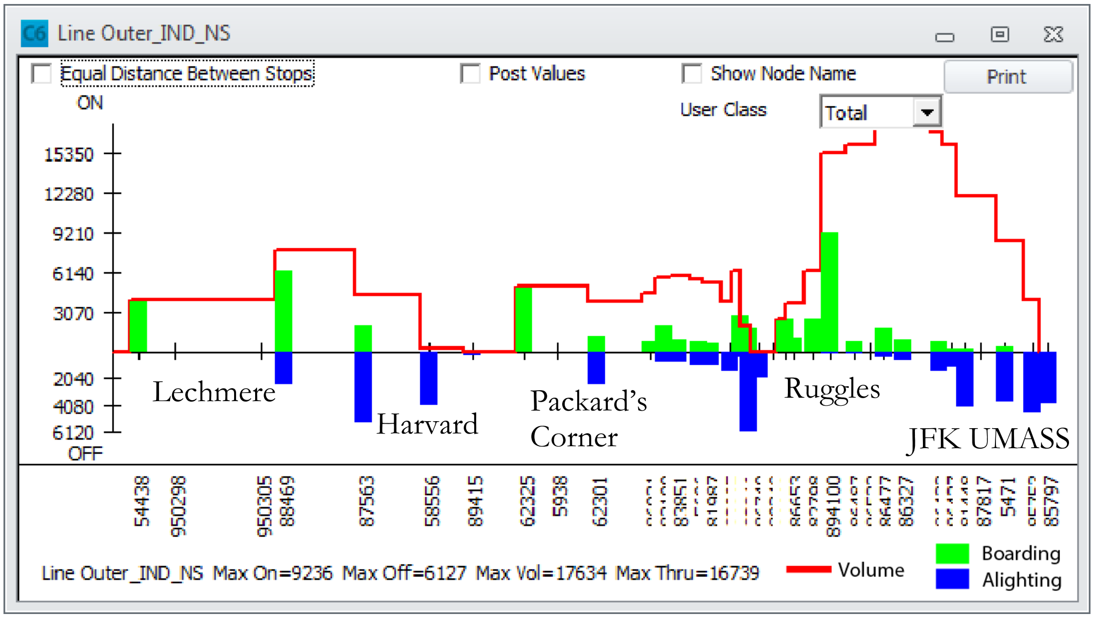


Figure 154: Inundation Awareness Outer Bus NS 4ft Inundation

7.3.3 Auto Metrics

Four-foot inundation causes major impacts on the auto networks.

	SR NO BUS 4FT	SR INNER BUS 4FT	SR OUTER BUS 4FT	IA NO BUS 4FT	IA INNER BUS 4FT	IA OUTER BUS 4FT
VOLUME (STATIC)	25,638,700	25,613,617	25,124,367	22,094,048	22,164,973	22,068,485
VOLUME (DTA)	11,902,474	12,084,120	11,962,209	11,397,558	11,252,211	11,094,119
MAX VC	65	65	65	56	56	56
QUEUE	372,800	366,023	353,683	287,317	295,350	290,704
VDT (STATIC)	2,220,509	2,215,181	2,181,875	1,965,579	1,971,130	1,964,356
VDT (DTA)	1,028,758	1,035,640	1,023,476	991,174	987,326	969,286
VHT (STATIC)	3,204,165,962	3,182,976,315	3,122,456,969	1,401,813,028	1,409,003,366	1,425,094,030
VHT(DTA)	57,801	58,712	57,780	50,729	51,125	49,631

Table 64: Scenario Auto Metrics 4ft Inundation

Table 64 shows the auto metrics for the four-foot inundation level. This table demonstrates areas with extreme levels of predicted congestion: maximum VC values of 65 and 56 for the Stronger Region and Inundation Awareness scenarios, respectively, and high levels of vehicle hours traveled (for static assignment). Again, as discussed in previous section, the model will not predict much effect of the BRT alignments highway network performance. Table 65 shows the difference in auto network output metrics by scenario for each bus alignment relative to "No Bus."

	PERCENTAGE DIFFERENCE FROM SR NO BUS		PERCENTAGE DIFFERENCE FROM IA NO BUS	
NON INUNDATED	SR Inner Bus	SR Outer Bus	IA Inner Bus	IA Outer Bus
VOLUME (STATIC)	-0.10%	-2.01%	0.3%	0%
VOLUME (DTA)	1.53%	0.50%	-1.3%	-1%
MAX VC	-0.31%	-0.89%	0.1%	0%
QUEUE	-0.24%	-1.74%	0.3%	0%
VDT (STATIC)	0.67%	-0.51%	-0.4%	-2%
VDT (DTA)	-0.66%	-2.55%	0.5%	1%
VHT (STATIC)	1.58%	-0.04%	0.8%	-3%

Table 65: Percentage Difference from Scenario No Bus and other Bus Alignments

Table 65 shows that the metrics remain relatively constant across both scenarios. The auto network performance measure would be of extreme interest if modeling a new highway or some other road improvement that has major benefits for vehicles. The addition of the protected bridge in the outer bus scenario is the only direct contribution to improving network performance offered by these transit lines. Thus, it is not surprising that values are essentially the same as the "No Bus" situation.

7.3.4 Evaluation

	Stronger Region	Inundation Awareness
Inner Bus Difference from No Bus	49,304.09	43,434.85
Outer Bus Difference from No Bus	55,713.76	55,849.61
Inner Bus Difference from Outer Bus	(6,409.67)	(12,414.76)

Table 66: Difference in Recouped Trips by Scenario and Alignment

Table 66 shows the difference in recouped (i.e., not lost) trips for the two bus lines, the "No Bus" scenario, for both the Stronger Region and Inundation Awareness scenarios. The Outer Bus recoups more trips, but the difference is minor. These values – 6,400 in the Stronger Region scenario and 12,400 in the Inundation Awareness scenario – are not considerable enough to suggest a superior infrastructure intervention for inundation. It is only a fraction of total trips lost due to inundation.

Neither **alignment is decidedly superior**. The Outer Bus included improvements to bridges also accessible to autos, a general benefit. Interestingly, the system-wide auto metrics barely pick up the these benefits. The buses have higher ridership across all scenarios when inundated. The model predicts 1.65 million lost trips in the Stronger Region scenario and 1.2 million lost trips in the Inundation Awareness scenario. Approximately 50,000 trips would be recouped with the BRT alignments examined. This means that the addition of a BRT line recoups approximately 3 percent of trips in the Stronger Region scenario and approximately 4 percent of trips in the Inundation Awareness scenario. Understanding the relative value of this benefit would require knowing the investment and operational costs.

One theory for the lack of clear performance difference between the routes is their relative similarity, serving many of the same stops. Even in the Inundation Awareness scenario, the inner core remains the area of highest demand.

Nonetheless, in terms of ridership, regardless of inundation, both alignments are predicted to have relatively high demand for BRT service, especially the Outer Bus alignment. Immediately, the routes in both directions compete with the major preexisting rail lines.

Finally, there may be corollary benefits of the Outer Bus additional to recouping lost trips. For example, the Outer Bus could provide an area more security from inundation and spur development in the region. Such potential benefits warrant further research.

8 Limitations & Further Research:

This Chapter highlights some of the limitations of the work and identifies some areas for further research.

In this thesis, I aimed to demonstrate how four step models can be used to estimate the impacts of inundation on transportation network performance. The analysis required many simplifications due to time and personal expertise. The impacts of climate change, even on this limited sector (i.e. Transportation network performance) are broad and undeniably complicated. Carrying out such an for actual policy-making purposes would require many improvements.

8.1 Flood Extent & Likelihood

One of the major simplifications made in my analysis was the use of the NOAA sea level rise layers as inundation layers. In a "real world" application of this analysis, I would recommend developing location-specific sea level rise and flood zone scenarios. The estimated extent of long-term sea level rise will differ from the estimated extent of hurricane flood surge, or other types of naturally occurring inundation. This distinction is important, but requires the expertise of engineers, hydrologists and climatologists to accurately estimate and gauge such differences. Ideally, different types of flood extents would be generated for the different types of inundation causing events. Furthermore, a range of estimates coupled with probabilities could be developed for each of the different scenarios. Probabilities of occurrence would assist in gauging the benefits of intervention in the face of uncertainty.

8.2 Infrastructure Impacts

Another major simplification was in classifying a link as disabled or degraded link. Actual inundation impacts on transportation infrastructure are very complicated. It is unclear to me what infrastructure can and cannot withstand inundation. For example, in my analysis I allowed portions of transit lines to operate, even if other sections were inundated. An entire transit line could become inoperable due to impacts on one part causing cascading failures along the line. Finally, given that all vehicles require some form of energy to operate, if electric power is lost in the region, then all rail lines will be inoperable.

I recommend that relevant teams of experts examine: the most likely impacts on the transportation network; its supporting needs (energy, maintenance, operators); and vehicles. These impacts are broad and complex but a thorough understanding will enrich this analysis and can be integrated into model assumptions.

Because transportation networks are large, analysis of each portion is not realistic. Data files that allow grouped analysis, such as GIS data layers, should be used. One of the simplest ways to improve the quality of the GIS inundation Assessment conducted in this thesis would be to use GIS files that had data tagged with actual elevation. For the benefit of this kind of analysis, cities, towns, transport operators, etc. should begin to incorporate elevation data into their data files.

8.3 Economic Impacts

Though not estimated in this work, the actual end goal of such an analysis is to estimate the financial and economic impacts, so that policy makers can gauge the relative impact costs to the costs of potential interventions. This work contributes to a large canon of analysis focusing on the economic impacts of climate change. The performance metrics generated can be monetized. Such an analysis would be an additional thesis, in itself. I believe a thorough economic impact analysis of just the transportation network impacts of the inundation would greatly contribute to the larger understanding of climate change impacts on urban regions.

8.4 Behavioral Response

Besides the question of when, if at all, inundation events will occur, the question with perhaps the most uncertain answer is "How will people respond to repeated inundation and/or permanent sea level rise?" I have made major assumptions in this analysis, simplifying the behavioral response of users of the system. Further research could benefit our understanding of impacts.

In terms of the modeling exercise, I used a limited set of semi-variable trip distribution and mode split results, limiting the amount of allowable changes to travel modes and destinations under inundation. An interesting extension would be to examine how varying these constraints would change the model outputs. This could be conducted for single inundation levels and demographic scenarios and would require an additional ten to twenty model runs depending on how the factors were altered. What remains highly uncertain, however, is how people will actually react in such events. Better theory might help; but perhaps we could learn from studying behavior in similar situations (e.g., Hurricane Sandy). More behavioral research could shed light on the likelihood of people still attempting trips; the variability of destinations (trip distribution); the change in mode choice; and the actual threshold for travel time in such situations.

In addition, if the goal of the model is to approximate long-term responses to permanent inundation, the likelihood and effect of intentional retreat from areas threatened by inundation must somehow be modeled. Long-term responses to inundation threats will impact the locations of persons, firms and jobs. Such changes could potentially drastically reshape our urban environments, requiring deeper understanding about how people and institutions will react. If insurance companies and governments refuse to protect these areas and offer necessary services, it will become harder and harder for persons or firms in such areas to remain. Land use models integrated with some theory of long-term behavior response may offer valuable insights. This would be a valuable extension of this work.

8.5 Local Input

The application of this analysis should incorporate the current knowledge and understanding of key local stakeholders. This would guide what projects and actions might be analyzed, and how. Recently, a report compiled by the Urban Land Institute recommending that the streets of Boston's Back Bay neighborhood be converted into canals gathered a lot of attention. Ultimately, experts like the city's Chief of Environment, Energy & Open Space dismissed the recommendation. Planners and others engaging in climate resiliency research should include local expert knowledge from the outset to ensure that plausible scenarios are being assessed. The gathering of empirical data should not be limited to just leaders or public officials.

8.6 Uncertain Future

New transportation technologies could also have unforeseen impacts on resiliency strategies and their performance. For example, autonomous vehicles might change current desires to own a personal car (and its attendant stresses like parking). Public transit may be re-invented as autonomous mobility on demand, consisting of automated micro-buses with crowd-sourced based methods for optimizing allocation to origins and destinations. Some studies argue that congestion will be worse with these vehicles, but when policy and technology eventually come together on the topic, many more people may well travel together in "on demand" vehicles. In this scenario, does classic transit even have a place for consideration? If any part of the transit system remains viable, it will likely be the heavy rail systems with dedicated right of way, but these are arguably the most vulnerable to the impacts of flooding and inundation.

8.7 Operations

The results of this work highlight that bus networks are more resilient to inundation events because they are larger, denser and can conceivably travel through low levels of water. A further contribution to understanding buses' resiliency would be to model the effect of buses with alterable routes that can adapt to new conditions. Designing a system with detailed routes for standard and inundated scenarios is feasible. The assumption that buses could still operate in slightly inundated scenarios is a method of approximating this possibility. The speeds would be lower, but the buses could still provide connections. This assumption would require a great deal of programming and the implementation of an optimization algorithm that would find the most efficient new path while attempting to maintain the original route (or, serve the new demand patterns produced by the inundation). This type of work may require the use of toy networks or a specific subsets of routes, but it would an interesting and potentially valuable contribution. Such a tool (and resulting analysis) could provide transit agencies with operational intervention options that could lead to improved transit performance during an inundation event.

9 Conclusion

"We were **trying to make those balancing decisions in real time under real pressure**… That's not the optimum way to do that. Now we have the advantage of learning from what [we] did and didn't do right, so that we can go into next winter, and we already have the plans and we don't need to make these really tough calls."

- Stephanie Pollack, Massachusetts Secretary of Transportation (Boston Globe)

Planning for climate change impacts is necessary and strategic – we need to understand potential impacts before they occur. In the quote above, Stephanie Pollack (Massachusetts Secretary of Transportation) is referring to the massive impacts on transit in the Boston region in the winter of 2014. She highlights that decisions were made in *real time* under *real pressure* – "not the optimum way to do that." This underscores the potentially powerful insights provided by pre-event strategizing, as demonstrated in this thesis. Having advance conception of the impacts of inundation allows for better infrastructure, better responses by transport operations and better plans overall. Cities should be planning for these events before they occur. This thesis provides the foundational framework for this type of planning. My interest is in a future scenario where storms and other events that historically have incapacitated cities and deleteriously affected businesses have been effectively planned for, ensuring that cities and their inhabitants can still operate.

Supporting preconceived expectations, the Inundation Assessment analysis highlights, simply, that Inundation affects a large number of persons, jobs, transport infrastructure and land use. I expected major impacts on the major highways and tunnels, especially coastal roadways that travel to downtown Boston. The extent of the impact is particularly acute in the Boston metro region – the main hub of jobs and commerce is one of the first regions that experiences extensive flooding. Transit throughout the region is heavily impacted, especially the urban heavy rail Lines- the Blue Line and the Red Line.

The Inundation Impact Assessment analysis, implemented in a four step model, enables the exploration of the performance impacts of inundation on the transport network. I presented metrics related to the potential to complete trips as a useful distillation of overall impacts to the city: the goal in planning for inundation is to ensure maintained mobility. Outputs like lost trips provide clarity in devising augmentation or reinforcement opportunities by highlighting transport modes or specific links that are particularly vulnerable (i.e. show a large number of lost trips).

With the Impact Assessment Modeling, I demonstrated the use of these metrics for the Boston regional transportation system and assess the major impacts of inundation on transportation performance (especially at the four-foot level and higher). The analysis estimates the number of trips lost due to inundation at six inundation levels. Up to almost 25% of trips are lost at the six-foot level. The mode most impacted by inundation is transit, which has the greatest reduction in mode share and accessibility. I also demonstrated how transit ridership shift can be explored and how the results of this exploration can inform operational interventions by transit planners.

I derived and demonstrated various performance metrics for the transit and automobile systems. When these metrics return unreasonable values (such as excessive VC and VHT), they serve to highlight interesting insights on network resiliency. Calculating accessibility impacts to jobs by autos and transit, revealed major impacts on people's ability to access opportunities.

Finally, I applied the method to future scenarios to highlight how it might be used as a tool to judge project effectiveness, using hypothetical transportation alternatives: two partially circumferential BRT lines. I examined the alternatives against two different demographic scenarios: Stronger Region and Inundation Awareness. The analysis suggests that neither proposed BRT route recouped significantly more lost trips when compared to each other; this may be because the two alignments are too similar and service much of the same demand. Even in the Inundation Awareness scenario, the inner core remains the area of highest demand.

Significantly, the results do suggest that a BRT line is a worthwhile consideration, *regardless of inundation*. The Inundation Impact Modeling Method can provide information about future conditions and contribute to sundry different infrastructure projects. This supports the legitimacy of the method.

The method is highly flexible, relatively easily deployable and produces insightful metrics that can assist in mitigating the impact of inundation events on transportation networks in the future. These metrics can likely be integrated into economic models and into cost-benefit assessments, so that the economic costs of inundation can be balanced against the mitigation costs (be it infrastructure, relocation or inaction).

The greatest contribution of this work to climate change planning is the development and application of the Inundation Assessment Impact Modeling method. The specific findings presented here should be viewed as preliminary, warranting further investigation by larger teams of experts from various fields. My thesis provides the necessary framework, showing how four step transportation models can be reasonably and effectively applied to the increasingly critical task of climate change planning.

References

Antunes, a, Seco, a, & Pinto, N. (2003). An accessibility–maximization approach to road network planning. *Computer-Aided Civil and Infrastructure Engineering*, *18*, 224–240. http://doi.org/10.1111/1467-8667.00312

Bloetscher, F., Ph, D., Asce, M., Berry, L., Ph, D., Rodriguez-seda, J., … Cahill, M. A. (2014). Identifying FDOT 's Physical Transportation Infrastructure Vulnerable to Sea Level Rise. *Journal of Infrastructure Systems*, *20*(2), 1–9. http://doi.org/10.1061/(ASCE)IS.1943-555X.0000174.

Brown, C. (2012). Cube Land in the Twin Cities.

Cambridge Systematics. (2012). Climate Change Vulnerability and Risk Assessment of New Jersey's Transportation Infrastructure.

Cats, O., & Jenelius, E. (2015). Planning for the unexpected: The value of reserve capacity for public transport network robustness. *Transportation Research Part A: Policy and Practice*. http://doi.org/10.1016/j.tra.2015.02.013

Chang, H., Lafrenz, M., Jung, I.-W., Figliozzi, M., Platman, D., & Pederson, C. (2010). Potential Impacts of Climate Change on Flood-Induced Travel Disruptions: A Case Study of Portland, Oregon, USA. *Annals of the Association of American Geographers*, *100*(4), 938–952. http://doi.org/10.1080/00045608.2010.497110

De Groot, R. S. va. I., & E.C. (n.d.). Climate adaptation in the Netherlands, (May 2006).

Douglas, E., Kirshen, P., Li, V., Watson, C., & Wormser, J. (2010). *Preparing For the Rising Tide*. Boston, MA.

Eilperin, J. (2015, January 30). In major shift , Obama administration will plan for rising seas in all federal projects. *Washington Post*, p. 4. Washington, DC.

Han, Y. (2015). *Temporal Transferability Assessment of Vehicle Ownership Models and Trip Generation Models for Boston Metropolitan Area*. MIT.

He, M. G., Jia, Y. H., & Li, H. N. (2014). Evaluation Model of Road Network Vulnerability and its Genetic Algorithm Solution. *Applied Mechanics and Materials*, *587-589*, 1749–1752. http://doi.org/10.4028/www.scientific.net/AMM.587-589.1749

Hodges, T. (2011). *Flooded Bus Barns and Bucked Rails: Public Transportation and Climate Change Adaptation*. *Transit*.

Horton, R., Bader, D., Kushnir, Y., Little, C., Blake, R., & Rosenzweig, C. (2015). New York City Panel on Climate Change 2015 ReportChapter 1: Climate Observations and Projections. *Annals of the New York Academy of Sciences*, *1336*(1), 18–35. http://doi.org/10.1111/nyas.12586

IPCC. (2014). FINAL DRAFT IPCC WGII AR5 Chapter 8. *Ar5*, (October 2013).

Kaufman, S., Qing, C., Levenson, N., & Hanson, M. (2012). Transportation During and After Hurricane Sandy. *Rudin Center for Transportation NYU Wagner Graduate School of Public Service*, (November), 1–36.

Koetse, M. J., & Rietveld, P. (2012). Adaptation to Climate Change in the Transport Sector. *Transport Reviews*, *32*(3), 267–286. http://doi.org/10.1080/01441647.2012.657716

Lin, N., Emanuel, K., Oppenheimer, M., & Vanmarcke, E. (2012). Physically based assessment of hurricane surge threat under climate change. *Nature Climate Change*, *2*(6), 462–467. http://doi.org/10.1038/nclimate1389

Lindgren, J., Jonsson, D. K., & Carlsson-Kanyama, A. (2009). Climate adaptation of railways: Lessons from Sweden. *European Journal of Transport and Infrastructure Research*, *9*, 164–181.

Lu, Q.-C., & Peng, Z.-R. (2011). Vulnerability Analysis of Transportation Network Under Scenarios of Sea Level Rise. *Transportation Research Record: Journal of the Transportation Research Board*, *2263*(-1), 174–181. http://doi.org/10.3141/2263-19

MAPC. (n.d.). Inner Core Committee (ICC) Summary. Retrieved November 6, 2014, from http://www.mapc.org/icc

Martin, W., & McGuckin, N. (1998). NCHRP Report 365: Travel Estimation Techniques for Urban Planning. Washington, DC: Transportation Research Board.

Martínez, F. (1996). MUSSA: Land Use Model for Santiago City. *Transportation Research Record*. http://doi.org/10.3141/1552-18

MASSDOT. (n.d.). The Urban Ring. Retrieved January 6, 2015, from http://www.massdot.state.ma.us/theurbanring/

MassPort. (2013). *Environmental Status & Planning Report*. Boston, MA. Retrieved from http://www.massport.com/media/2891/Logan_ESPR_2011.pdf

Matsuo, M. (2011). US Metropolitan Spatial Structure and Labour Accessibility. *Urban Studies*, *48*(11), 2283–2302. http://doi.org/10.1177/0042098010380954

MBTA. (2014). 2014 BLUEBOOK 14th Edition.pdf. Retrieved November 15, 2014, from http://www.mbta.com/uploadedfiles/documents/2014 BLUEBOOK 14th Edition.pdf

Mitsakis, E., Papanikolaou, A., Ayfadopoulou, G., Salanova, J., Doll, C., Giannopoulos, G., & Zerefos, C. (2014). An integrated framework for linking climate change impacts to emergency adaptation strategies for transport networks. *European Transport Research Review*, *6*(2), 103–111. http://doi.org/10.1007/s12544-013-0114-0

Mitsakis, E., Stamos, I., S., G., & Aifadopoulou, G. (2014). Optimal allocation of emergency response services for managing disasters. *Disaster Prevention & Management*, *23(4)*, 329–342. http://doi.org/10.1108/DPM-10-2013-0182

National Research Council (U.S.). Committee on Climate Change and U.S. Transportation. (2008). *Potential Impacts of CLIMATE CHANGE on U.S. Transportation*. Transportation Research Board and Division on Earth and Life Studies, National Research Council of the National Academies.

Oswald, M., & Treat, C. (n.d.). Assessing Public Transportation Vulnerability to Sea Level Rise : A Case Study Application, (Fta 2011), 59–77.

Peterson, T. C., Hoerling, M. P., Stott, P. A., & S. Herring, E. (2013). Explaining Extreme Events of 2012 from a Climate Perspecitve, 49.

Reggiani, A., Nijkamp, P., & Lanzi, D. (2015). Transport resilience and vulnerability: The role of connectivity. *Transportation Research Part A: Policy and Practice*. http://doi.org/10.1016/j.tra.2014.12.012

Schintler, L. a., Kulkarni, R., Gorman, S., & Stough, R. (2007). Using raster-based GIS and graph theory to analyze complex networks. *Networks and Spatial Economics*, *7*(4), 301–313. http://doi.org/10.1007/s11067-007-9029-4

Stamos, I., Mitsakis, E., Salanova, J. M., & Aifadopoulou, G. (2015). Impact assessment of extreme weather events on transport networks: A data-driven approach. *Transportation Research Part D: Transport and Environment*, *34*, 168–178. http://doi.org/10.1016/j.trd.2014.11.002

Suarez, P., Anderson, W., Mahal, V., & Lakshmanan, T. R. (2005). Impacts of flooding and climate change on urban transportation: A systemwide performance assessment of the Boston Metro Area. *Transportation Research Part D: Transport and Environment*, *10*(3), 231–244. http://doi.org/10.1016/j.trd.2005.04.007

Taylor, M. a P. (2008). Critical transport infrastructure in urban areas: Impacts of traffic incidents assessed using accessibility-based network vulnerability analysis. *Growth and Change*, *39*(4), 593–616.

Trb. (2008). *Potential Impacts of Climate Change on U.S. Transportation*. *TRB* (Vol. Special Re). National Rsearch Council of the National Academies.

Van Exel, N. J., & Rietveld, P. (2001). Public transport strikes and traveller behaviour. *Transport Policy*, *8*(4), 237–246. http://doi.org/10.1016/S0967-070X(01)00022-1

Vovsha, P., Freedman, J., Livshits, V., & Sun, W. (2012). Design Features of Activity-Based Models in Practice. *Transportation Research Record: Journal of the Transportation Research Board*, *2254*(-1), 19–27. http://doi.org/10.3141/2254-03

Zhu, S., & Levinson, D. M. (2012). Disruptions to Transportation Networks: AReview. In D. Eustace, E. Russell, & L. E. Dean (Eds.), *Network Reliability in Practice* (pp. 97–114). http://doi.org/10.1007/978-1-4614-0947-2

Appendix:

Inundation Impact Analysis Data

N	Type	Assets	Source
1	Other	Airports	MassGIS
2	Demographics	TAZ Population	CTPP
3	Demographics	TAZ CTPP Jobs	CTPP
4	Demographics	Business Listings	InfoUSA Licensed to MIT
5	Demographics	Proportion Population	CTPP
6	Demographics	Proportion Jobs	CTPP
7	Roads	Model Network Links(FT)	MIT
8	Roads	Model Network Nodes(FT)	MIT
9	Roads	Roads	MassGIS
10	Roads	Highway Exits	MassGIS
11	Land / Land Use	TAZ Area	MIT
12	Land / Land Use	Massachusetts Parcels	MAPC
13	SLR	Sea Level Rise 1-6ft	NOAA
14	Transit	MBTA Bus Routes	MassGIS
15	Transit	MBTA Bus Stops	MassGIS
16	Transit	MBTA T Stations	MassGIS
17	Transit	MBTA T Lines	MassGIS
18	Transit	MBTA Commuter Rail	MassGIS
19	Other	Trains / Railways	MassGIS

Table 67: GIS Data Sources

Semi-Variable Inundation Impact Assessment Modeling Charts

Lost Trips by Purpose

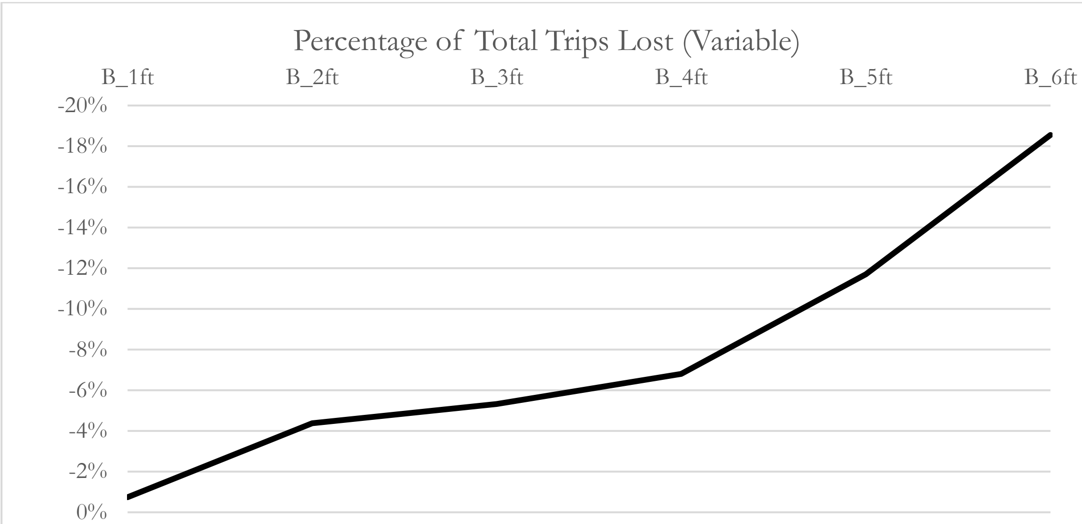


Figure 155: Percentage of Total Trips Lost Semi-Variable Model Run

Base line	Base	B_1ft	B_2ft	B_3ft	B_4ft	B_5ft	B_6ft
HBW	3,276,380	3,255,488	3,016,412	2,959,420	2,879,325	2,640,467	2,314,645
HBS	1,243,061	1,230,223	1,191,787	1,179,010	1,153,446	1,114,085	1,063,883
HBSH OP	2,259,043	2,240,755	2,194,840	2,178,756	2,153,441	2,083,546	2,008,650
HBO	4,259,490	4,225,130	4,118,183	4,087,625	4,042,112	3,865,431	3,545,429
NHBW	2,522,716	2,510,646	2,410,190	2,392,843	2,362,800	2,254,680	2,067,367
NHBO	2,763,319	2,740,842	2,677,447	2,658,159	2,629,249	2,529,057	2,364,175
AIRPO RT	82,998	82,869	79,511	79,227	70,155	39	39
Total	16,407,006	16,285,953	15,688,370	15,535,040	15,290,528	14,487,305	13,364,187

Figure 156: Total Trips Completed by Trip Purpse – Semi Variable Model Run

Desc	Baseline	B_1ft	B_2ft	B_3ft	B_4ft	B_5ft	B_6ft
HBW	3,276,380	-0.64%	-7.93%	-9.67%	-12.12%	-19.41%	-29.35%
HBS	1,243,061	-1.03%	-4.12%	-5.15%	-7.21%	-10.38%	-14.41%
HBSHOP	2,259,043	-0.81%	-2.84%	-3.55%	-4.67%	-7.77%	-11.08%
HBO	4,259,490	-0.81%	-3.32%	-4.03%	-5.10%	-9.25%	-16.76%
NHBW	2,522,716	-0.48%	-4.46%	-5.15%	-6.34%	-10.62%	-18.05%
NHBO	2,763,319	-0.81%	-3.11%	-3.81%	-4.85%	-8.48%	-14.44%
AIRPORT	82,998	-0.16%	-4.20%	-4.54%	-15.47%	-99.95%	-99.95%
Total	16,407,006	-0.74%	-4.38%	-5.31%	-6.80%	-11.70%	-18.55%

Figure 157: Percentage Lost Trips Compared to Baseline by Trip Purpse – Semi Variable Model Run

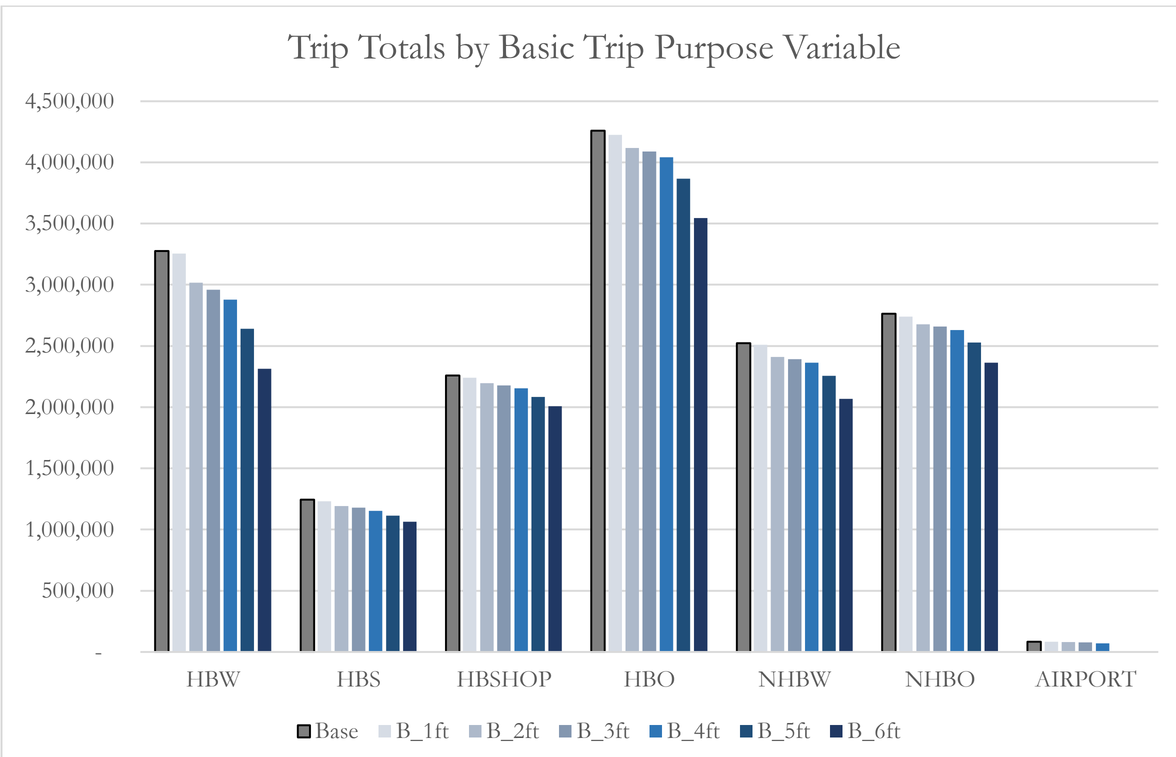


Figure 158: Total Trips by Trip Purpose and Inundation Level – Seme Variable Model Run

	DESC	BASE	B_1FT	B_2FT	B_3FT	B_4FT	B_5FT	B_6FT
CHOICE	HBW	2,906,193	2,890,213	2,672,189	2,623,938	2,562,755	2,360,109	2,074,886
	HBSHOP	1,318,086	1,310,936	1,273,090	1,263,337	1,251,044	1,221,745	1,187,180
	HBO	3,249,977	3,229,189	3,132,458	3,110,715	3,085,230	2,975,226	2,742,306
	NHBW	2,238,038	2,232,122	2,136,634	2,123,291	2,108,442	2,021,253	1,853,814
	NHBO	2,105,631	2,093,631	2,034,089	2,020,665	2,004,365	1,941,739	1,812,047
	Subtotal	11,817,925	11,756,091	11,248,459	11,141,946	11,011,836	10,520,072	9,670,233
CAPTIVE	HBW	370187	365275	344223	335483	316571	280357	239759
	HBSHOP	940957	929819	921751	915419	902397	861801	821469
	HBO	1009513	995942	985725	976910	956882	890205	803122
	NHBW	284678	278524	273557	269551	254358	233427	213553
	NHBO	657688	647211	643358	637495	624884	587318	552128
	SUB TOTAL	**3,263,023**	**3,216,770**	**3,168,613**	**3,134,858**	**3,055,091**	**2,853,108**	**2,630,032**

Table 68: Total Trips By Trip Purpose for Choice & Captive – Semi Variable Model Run

	DESC	B_1FT	B_2FT	B_3FT	B_4FT	B_5FT	B_6FT
CHOICE	HBW	-0.55%	-8.05%	-9.71%	-11.82%	-18.79%	-28.60%
	HBSHOP	-0.54%	-3.41%	-4.15%	-5.09%	-7.31%	-9.93%
	HBO	-0.64%	-3.62%	-4.29%	-5.07%	-8.45%	-15.62%
	NHBW	-0.26%	-4.53%	-5.13%	-5.79%	-9.69%	-17.17%
	NHBO	-0.57%	-3.40%	-4.04%	-4.81%	-7.78%	-13.94%
	Subtotal	6.76%	2.15%	1.18%	0.00%	-4.47%	-12.18%
CAPTIVE	HBW	-1.33%	-7.01%	-9.37%	-14.48%	-24.27%	-35.23%
	HBSHOP	-1.18%	-2.04%	-2.71%	-4.10%	-8.41%	-12.70%
	HBO	-1.34%	-2.36%	-3.23%	-5.21%	-11.82%	-20.44%
	NHBW	-2.16%	-3.91%	-5.31%	-10.65%	-18.00%	-24.98%
	NHBO	-1.59%	-2.18%	-3.07%	-4.99%	-10.70%	-16.05%
	Sub Total	5%	4%	3%	0%	-7%	-13.91%

Table 69: Percentage Decrease from Baseline for Total Trips By Trip Purpose for Choice & Captive – Semi Variable Model Run

Lost Trips by Mode

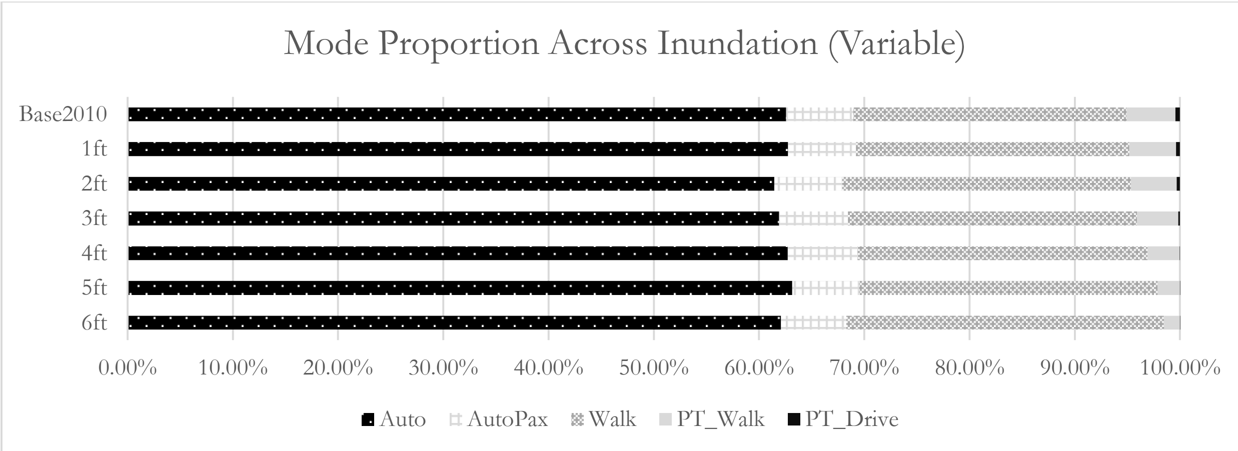


Figure 159: Mode Proportion by Inundation Level – Semi Vairable Model Run

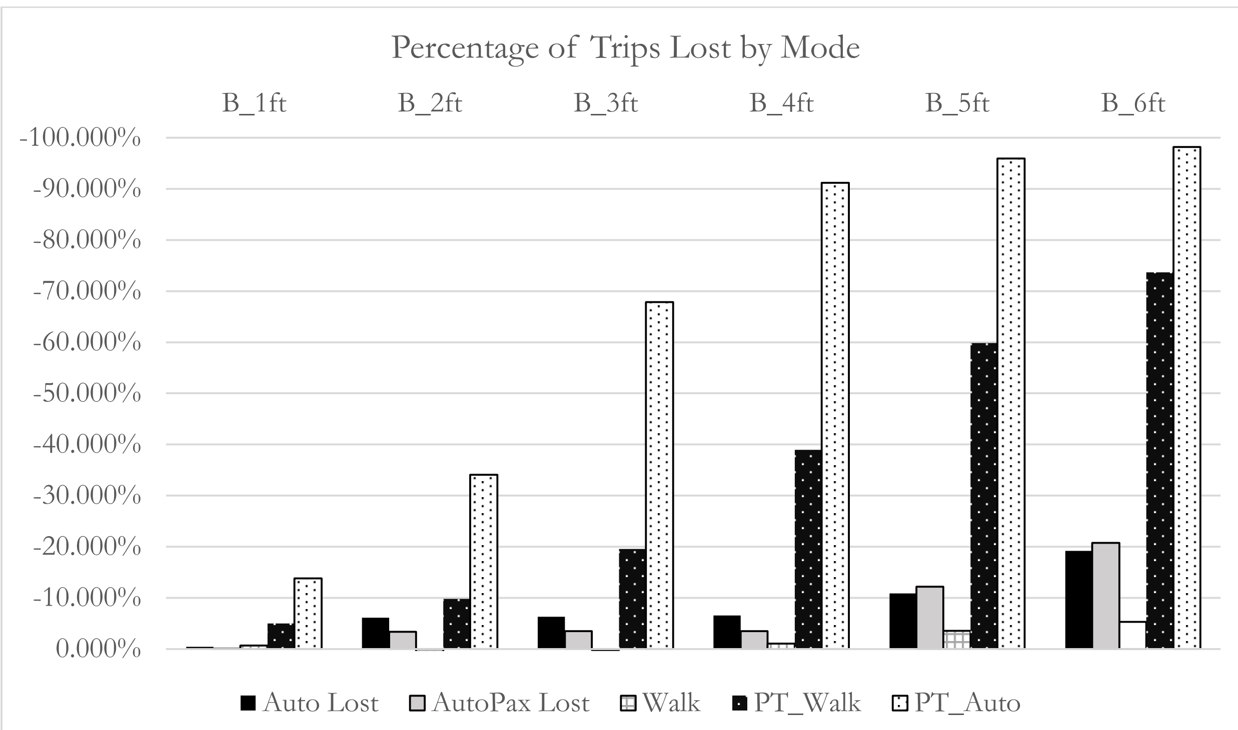


Figure 160: Percentage Tips Lost by Mode – Semi Variable Model Run

Auto

Var	Type	Base	1ft	2ft	3ft	4ft	5ft	6ft
Static	V Static	14,023,798	15,515,368	16,635,916	17,671,585	21,302,543	15,942,660	10,080,688
	VC Max	4.06	4.12	5.95	7.91	47.33	10.84	4.84
	VDT	1,228,486	1,322,745	1,471,392	1,586,556	1,889,954	1,478,111	1,014,193
	VHT Static	42,087	70,362	56,269	88,153	1,018,534,144	259,395	30,748
Dynamic	V Dynamic	10,494,896	10,148,886	10,164,705	10,147,903	10,876,884	9,172,306	6,832,207
	VDT Dynamic	828,954	781,040	843,884	850,767	935,101	811,497	638,318
	VHT DTA	39,902	44,309	44,853	45,049	48,806	39,369	24,572
	Queue Total	185,173	271,264	252,156	276,915	280,101	186,011	89,644
	Block Total	74,396	95,529	85,000	111,399	102,659	51,529	37,316

Table 70: Auto Metrics Summary - Semi Variable Model Run

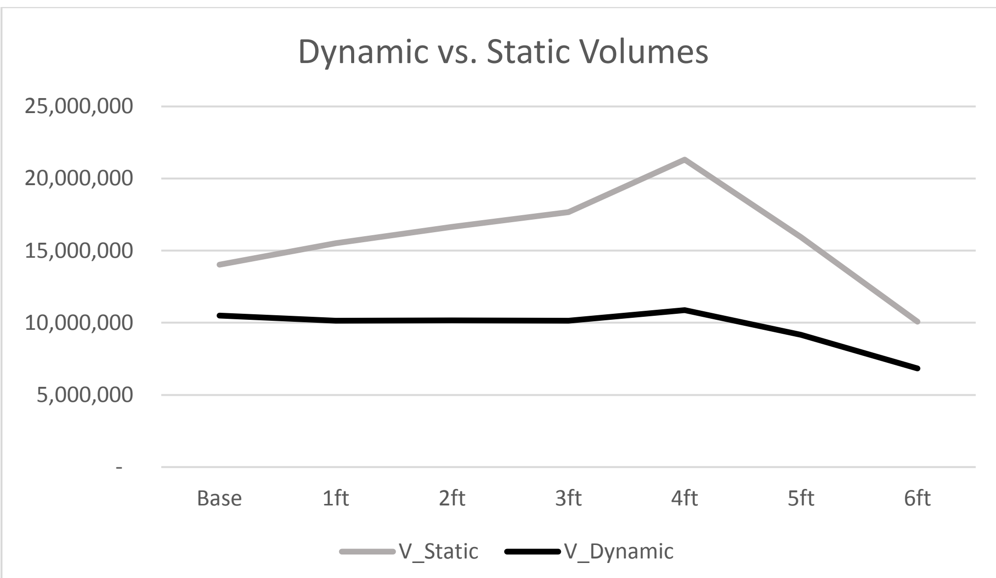


Figure 161: Dynamic vs. Static Volumes – Semi Variable Model Run

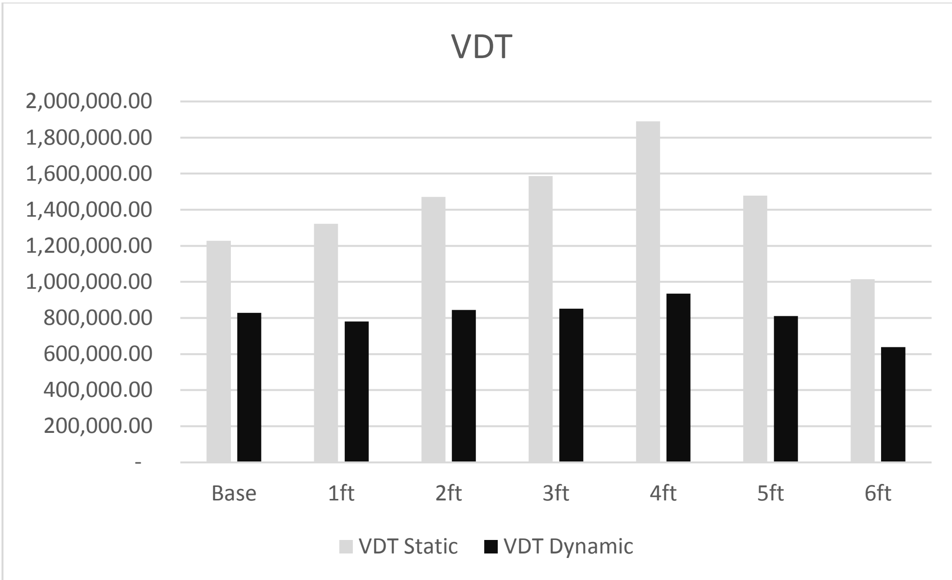


Figure 162: VDT Static & Dynamic – Semi Variable Model Run

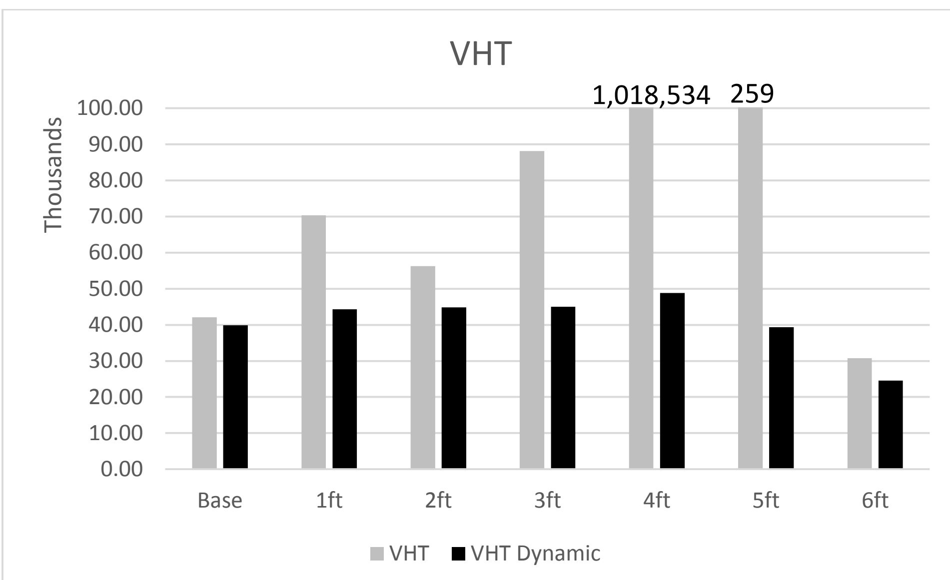


Figure 163: VHT Static & Dynamic –Semi Variable Model Run

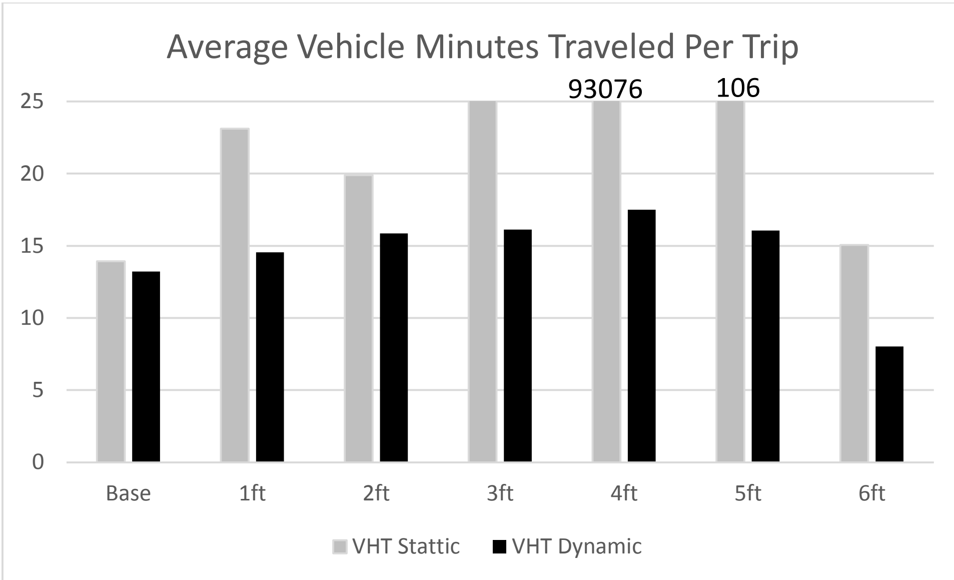


Figure 164: Avreage Vehicle Minutes Traveled – Semi Variable Model Run

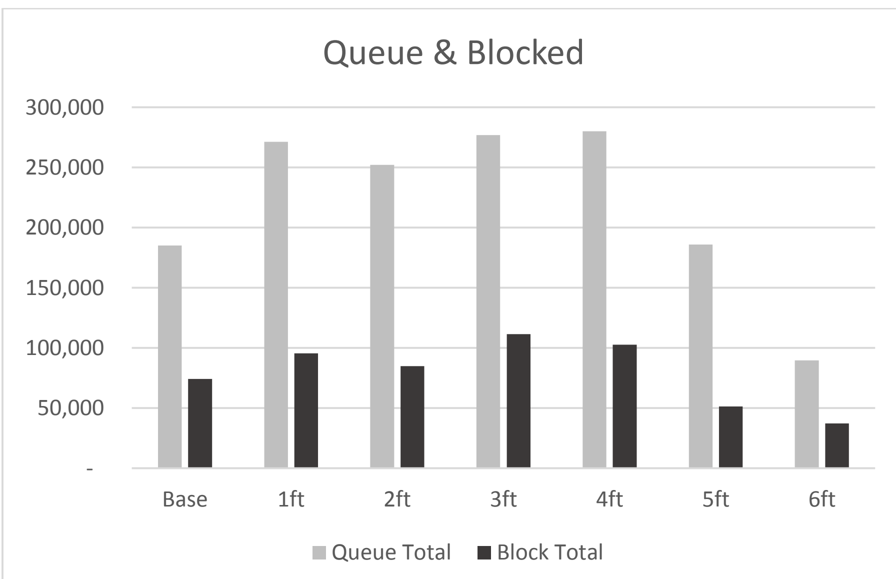


Figure 165: Queued & Blocked Vehicles – Semi Variable Model Run

Transit

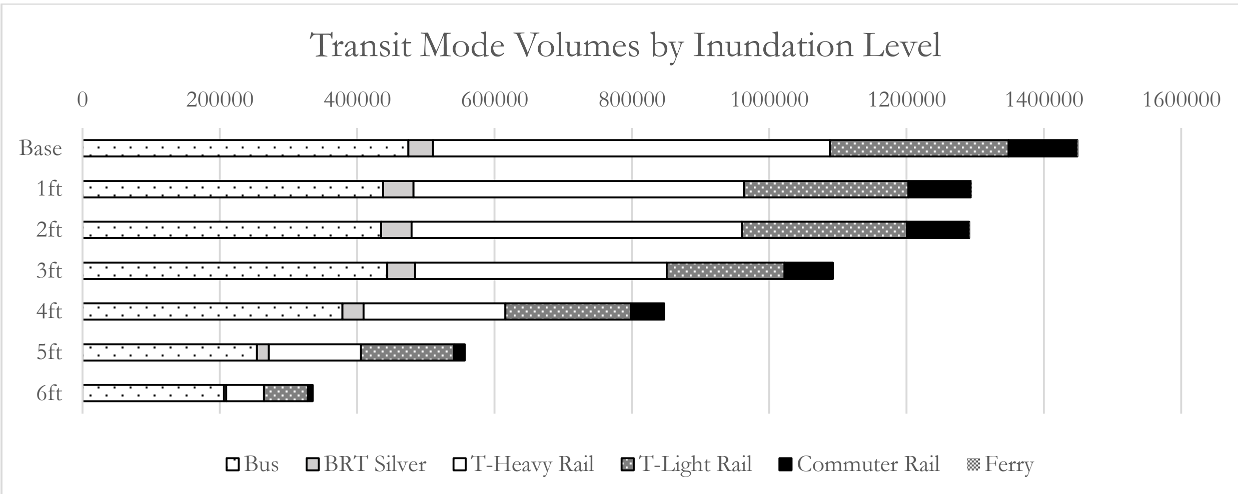


Figure 166: Transit Mode Volumes – Semi Variable Model Run

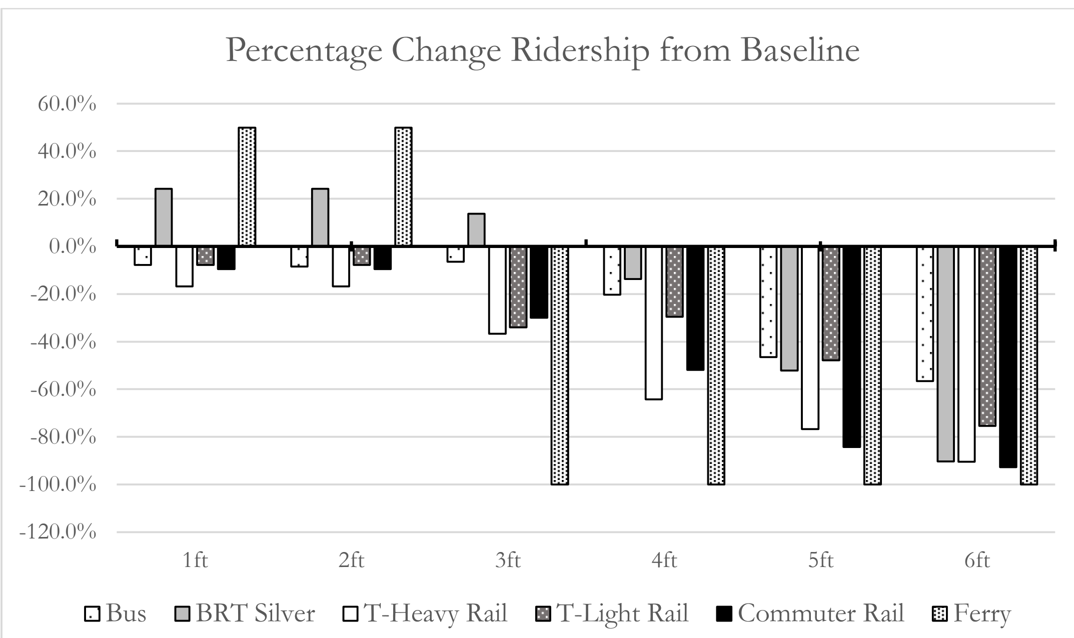


Figure 167: Percentage Change in Ridership – Semi Variable Model Run

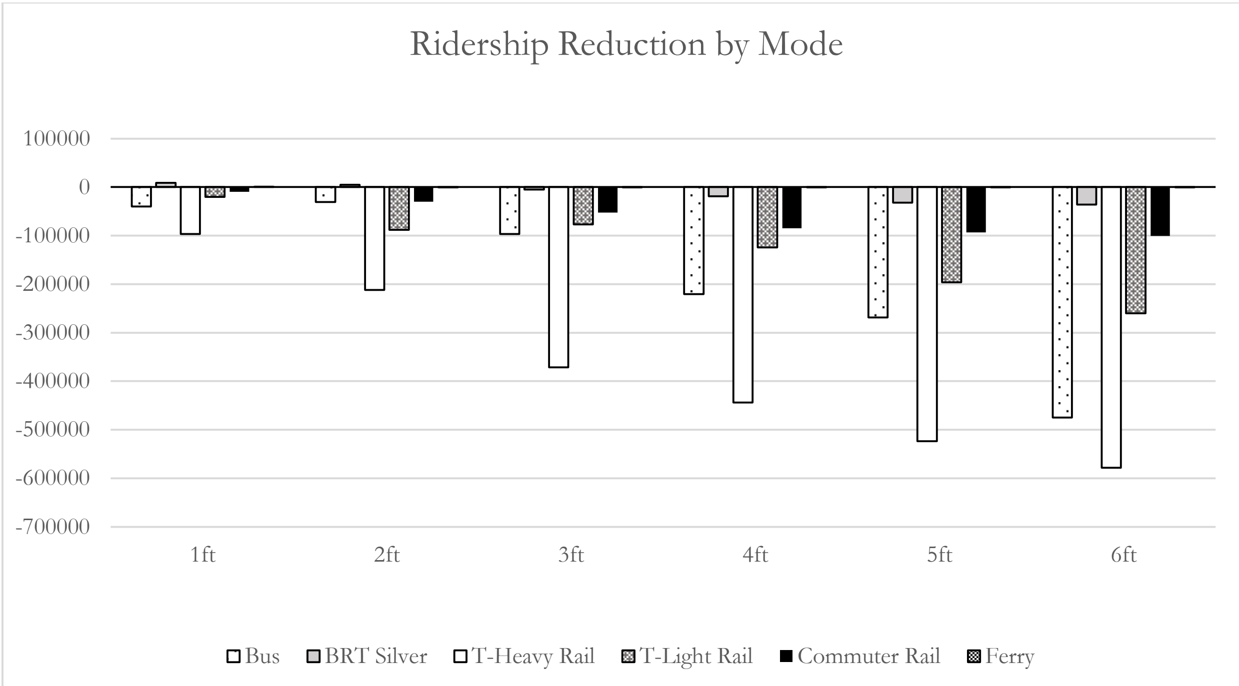


Figure 168: Ridership Reduction by Transit Mode – Semi Variable Model Run

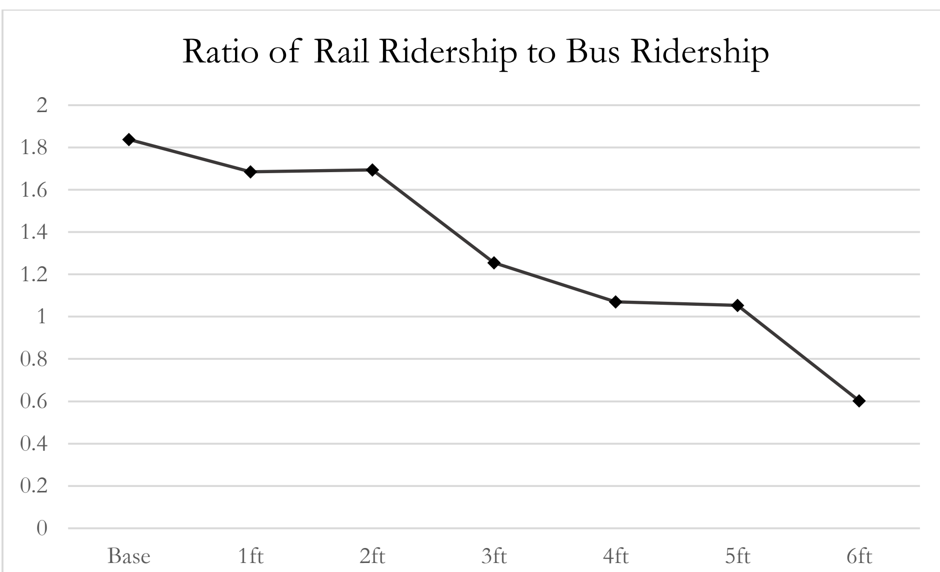


Figure 169: Ratio of Rail to Bus Ridership – Semi Variable Model Run