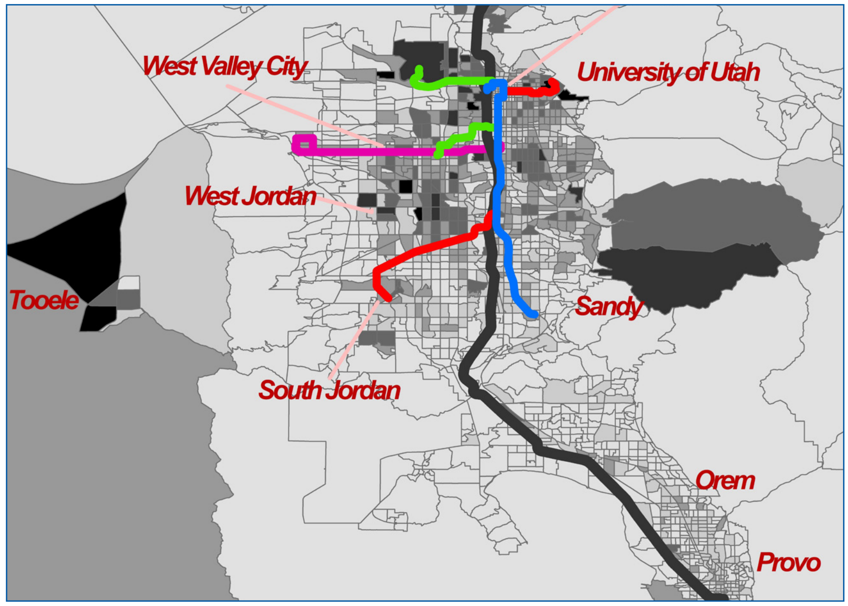
MOUNTAIN-PLAINS CONSORTIUM

MPC 18-347 | C. Liu, R. Porter, M. Zlatkovic, K. Fayyaz, and J. Taylor

First and Last Mile Assessment for Transit Systems



A University Transportation Center sponsored by the U.S. Department of Transportation serving the Mountain-Plains Region. Consortium members:

Colorado State University
North Dakota State University
South Dakota State University
University of Colorado Denver
University of Denver
University of Utah
Utah State University
University of Wyoming

FIRST AND LAST MILE ASSESSMENT FOR TRANSIT SYSTEMS

Xiaoyue Cathy Liu, Ph.D., P.E.
Assistant Professor
Department of Civil and Environmental Engineering
University of Utah
Salt Lake City, Utah, 84112
Phone: (801) 587-8858
Email: cathy.liu@utah.edu

Richard J. Porter, Ph.D., P.E.
VHB, Inc.
940 Main Campus Drive, Suite 500
Raleigh, NC 27606
rporter@vhb.com

Milan Zlatkovic, Ph.D., P.E.
Assistant Professor
Department of Civil & Architectural Engineering
Laramie, WY 82071
mzlatkov@uwyo.edu

Kiavash Fayyaz, Ph.D.
RSG, Inc.
307 W 200 S, Suite 2004
Salt Lake City, UT 84101
kiavash.fayyaz@rsginc.com

Jeffrey Taylor
Department of Civil and Environmental Engineering
University of Utah
Salt Lake City, Utah, 84112
Phone: (801) 587-8858
Email: jeff.d.taylor@utah.edu

May 2018

Acknowledgements

The authors acknowledge the Mountain Plain Consortium (MPC) and the Utah Transit Authority (UTA) for funding this research, and the following individuals from UTA on the Technical Advisory Committee for helping to guide the research:

- Jennifer McGrath
- Hal Johnson
- G.J. LaBonty
- Kerry Doane

Disclaimer

The contents of this report reflect the views of the authors, who are responsible for the facts and the accuracy of the information presented. This document is disseminated under the sponsorship of the Department of Transportation, University Transportation Centers Program, in the interest of information exchange. The U.S. Government assumes no liability for the contents or use thereof.

ABSTRACT

The *First Mile Last Mile* (FMLM) challenge garners significant attention as a means to assess the accessibility of the first leg to transit and the last leg from public transit. As a critical barrier to public transit accessibility, the challenge provides many opportunities to closely analyze conditions from the level of the transit station upwards to the level of the system-wide network. Its usefulness in contributing to the body of knowledge on barriers to transit access provides planners and researchers important information with implications in increasing ridership, transit efficiency, multimodal travel options, and accessible mobility. In this project, we propose a methodological framework for analyzing the FMLM problems by determining varying causes of poor public transit accessibility and identifying areas with immediate needs for improvements. We showcase the analytical framework using a transit network in the state of Utah operated by the Utah Transit Authority. We also conducted analysis on the impacts of reduced automobile use on personal and environmental health. As a companion product, a spreadsheet-based sketch planning tool is developed to estimate health cost savings as a result of mode shifts from private automobiles to active transportation options.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

EXECUTIVE SUMMARY

The First Mile Last Mile (FMLM) challenge garners significant attention as a means to assess the accessibility of the first leg to public transit and the last leg from transit. As a critical barrier to public transit accessibility (PTA), the challenge provides many opportunities to closely analyze conditions from the level of the transit station upwards to the level of the system-wide network. Its usefulness in contributing to the body of knowledge on barriers to transit access provides planners and researchers important information with implications towards increasing ridership, transit efficiency, multimodal travel options, and mobility. The Salt Lake City area is experiencing a rapid growth in transit infrastructure. The ambitious program of transit construction spans across light rail, Bus Rapid Transit (BRT), streetcars, and commuter rail simultaneously. This transit expansion program, led by Utah Transit Authority (UTA), strives to provide a multi-modal system that can meet the daily transportation needs of residents. To evaluate the accessibility of existing transit services and identify access gaps, it is critical to accurately estimate travel times between transit stops, which change throughout the day due to transit schedule variations. Commonly used methods in PTA ignore such temporal fluctuation. Moreover, these methods are unable to elucidate the causes of poor PTA. To address these issues, we first implemented an algorithm to effectively compute travel times at multiple departure times throughout the day in order to enable spatiotemporal PTA analysis. A series of indicators that are intuitive to interpret were developed to determine the varying causes of poor PTA and identify areas with immediate needs for improvements. We showcase the analytical framework using a transit network in the State of Utah operated by the UTA. The analysis is based solely on publicly available open datasets, which makes it generally adaptable to other transit networks. Results can assist transit agencies with identifying areas in need of service improvement and prioritizing future investments. As a side product for quantifying the benefits of FMLM strategies, the project produced a sketch planning tool to estimate the health and environmental effects of physical activity associated with transit use.

1. INTRODUCTION

1.1 Background

Public transportation constitutes an integral part of many urban landscapes in the United States. The routes and lines that comprise transit networks traverse a myriad of geographies, topographies, and land types. Further deconstructed, these geographies, topographies, and land types also constitute many other layers of diverse transit landscape characteristics, including demography, social conditions, environment, and infrastructure. Consequently, public transportation networks must provide services sensitive to specific contexts through the process of planning and designing routes as well as stations serving as access/egress means to reach destinations via transit systems.

Transit stations are the primary points of access to and egress from public transportation systems. The success of public transit systems relies heavily on users' perceptions of transit station accessibility, among other things. The First Mile Last Mile (FMLM) challenge in transit has origins in the "last mile" concept related to supply chain management, where the last segment of a trip from a transport hub to a final destination in freight distribution demands tough negotiation of cost, efficiency, and logistics (Boyer, 2009). Applied to public transit, FMLM describes the challenges faced by potential users and actual users of public transit according to cost, efficiency, logistics, and comfort to decide whether to use public transit or not. While public transit frames the core of a user's trip, it cannot solve origin-to-transit hub and hub-to-destination travel needs. FMLM generally refers to the first and last leg of a user's trip, and implies conditions specifically within a mile radius of a user's origin/destination. The mile radius exists as a standard buffer area encompassing the specified radial distances used in various studies, and it serves to illustrate the challenges posed within the first/last mile of travel to/from public transit (FTA, 2011). Thus, the FMLM problem directly contributes to the accessibility of a transit system.

Public Transit Accessibility (PTA), a key indicator of transit service quality, plays an important role in users' mode choices (Moniruzzaman and Paez, 2004). PTA directly affects transit ridership and, consequently, influences active transportation mode use, public health, and other characteristics of the urban environment (Farber and Paez, 2011; Litman, 2003). The social functions of urbanized areas are highly dependent on and supported by convenient access to public transportation systems, particularly for the less privileged populations with limited auto ownership. Poor PTA can cause social exclusion for disadvantaged populations (SEU, 2003). An effective understanding and evaluation of PTA is therefore necessary to help transit agencies identify areas in most need of improvement and guide investment decisions and land use development (Coffel et al., 2012).

PTA refers to the ability to reach goods, services, and activities via public transit. By definition, PTA has two main components: activity and transportation (Burns, 1980; Koenig, 1980). The activity component describes the attractiveness of destinations and is usually measured by population density, job density, and/or facilities available at destinations. The transportation component measures the ability to reach destinations and is influenced by spatiotemporal coverage of services, travel cost (e.g., travel time), and the comfort of service as experienced by users. It is difficult for any single PTA analysis to consider all factors that potentially affect the ease of travel. Ignoring critical factors, however, will result in the over- or under-estimation of PTA. Travel time is one of the critical factors reflecting the feasibility of transit use. Overlooking travel time tends to overestimate the portion of population with transit access (Polzin, et al., 2002). As a result, travel time dependent PTA measures, such as cumulative and gravity-based accessibility measures, have been widely used in recent years (El-Geneidy et al., 2016; Foth et al., 2013; Lei and Church, 2010; O'Sullivan et al., 2000; Widener et al., 2015).

Most relevant studies (Benenson et al., 2010; Krizek et al., 2009; Mavoa et al., 2012; Owen and Levinson, 2012) on transit performance have focused on transit travel time for a specific time of day (e.g., peak hour). This leads to an overly optimistic evaluation, as the optimum transit services (e.g., highest frequency and largest geographic coverage) are usually provided in peak periods. PTA could be measured for several times of day to unveil the temporal fluctuation in transit services (Farber and Fu, 2016; Farber et al., 2016), but analyzing and interpreting the results can be challenging due to the complexity of the added temporal dimension. Past studies in PTA have concentrated on identifying areas with poor accessibility (Benenson et al., 2010; Krizek et al., 2009; Mavoa et al., 2012; Owen and Levinson, 2012; Owen and Levinson, 2015) or mismatches between transit services (supply) and the need for public transit services (NPTS) (demand) (Farber et al., 2016; Fransen et al., 2015). However, little has been done in regard to identifying the causes of poor PTA in order to inform transit investment decisions. There are two main causes leading to poor PTA: inefficient transit services (e.g., inadequate spatial/temporal coverage), and geographical disadvantage (e.g., long distances between the study area of interest and desired destinations). Poor PTA due to inadequate transit services can be remedied by a transit agency via transit investment. However, a remote area with good transit services may still experience poor PTA. There is not much a transit agency can do in this latter case other than play one part of much broader land development efforts. There is, therefore, a critical need for PTA analysis to reflect both causes and distinguish between the two to avoid making poor investments in the wrong sets of solutions. To address this issue, the transit gap causality analysis is required. Transit gap causality analysis measures the size of the gap between PTA and NPTS and whether the gap is fixable by transit agencies. Dynamic PTA analysis, considering spatiotemporal dimensions with finer resolution, offers greater insights into the various causes of poor accessibility. This study complements the existing literature by developing effective indicators that provide a fuller exploration of PTA variation and transit gap causes in order to guide future transit investments to address the FMLM challenges.

1.2 Objectives

The primary objective of this research project is to rank areas based on their need for transit improvement to further inform FMLM investment decisions. This is achieved by developing a concept called the public transit accessibility gap (PTAG) to identify regions with transit mismatches by comparing transit service quality to the NPTS. We showcase the analytical framework using a transit network in Utah operated by the Utah Transit Authority (UTA). The analysis is based solely on publicly available open datasets, which makes it generally adaptable to other transit networks.

A secondary objective of this research project is to develop a sketch planning to estimate the health and environmental effects of physical activity associated with transit use. Health effects are estimated using a simplified version of a health impact assessment (HIA). HIA is a generalized framework for estimating the potential health effects of a policy, program, or project, similar to environmental impact assessments applied in transportation planning and design. Environmental effects are estimated using average per-mile emission rates and estimated changes in vehicle-miles traveled (VMT).

1.3 Outline of Report

The rest of the report is structured as follows. Section 2 summarizes literature on FMLM, accessibility analysis, and assessment of the health impact of reduced automobile use. Section 3 describes data sources used for our analysis. Section 4 presents the analytical framework for measuring PTA and identifying accessibility gaps for FMLM investment prioritization. Section 5 demonstrates the results from the analytical framework applied to the UTA transit network in Utah. Section 6 presents the conclusion of this study and recommendations for future research. The Appendix provides the sketch planning tool user guide.

2. LITERATURE REVIEWS

2.1 FMLM Overview

While information on FMLM studies attempt to address a concept with wide-ranging implications in personal mobility, studies and available information tend to focus on “active transportation” improvements as means to overcome the FMLM challenge. Active transportation refers to modes of transportation that rely on user energy and power (Partnership for Active Transportation, 2014). Active transportation network is critical for solving FMLM problems as it provides transit users with safe and efficient routes to access stations. Typically, active transportation planning revolves around pedestrian and bicycling as primary means, two categories of which guide a significant amount of FMLM solutions.

Improvements to pedestrian facilities discussed in various research projects point to an increase in continuous pedestrian sidewalks, less circuitous and more direct pedestrian paths to transit stations, pedestrian streets, pedestrian amenities at transit stations, street furniture, and improved lighting to enhance pedestrian safety (SCAG, 2013). Pedestrian improvements generally look to reduce pedestrian-vehicle interaction, enhance pedestrian safety, and create a comfortable user experience.

Improvements to bicycle facilities commonly described to improve FMLM connectivity include bike lane networks, bike boulevards, secure bike storage areas, space for bikes on public transit, and bike-sharing programs (SCAG, 2013; Metro, 2010; MTI, 2014). Studies acknowledge that, while bicycle facilities commonly exist within metropolitan communities, such networks lack coherency, consistency, and measures to ensure cyclist safety in vehicle-bicycle interactions. Furthermore, some studies also note context-specific challenges and nuances to improved bike facilities as a result of local topography, space constraints, and local bike culture (MTI, 2014).

Other types of transportation alternatives to personal vehicles cited in studies have included shuttles, circulators, flex-route vehicles, car-share programs, and personal rapid transit (SCAG, 2013). Such transportation planning concepts tend to describe the use of alternative modes of transportation that do not fall completely under active transportation. However, they also provide more options (other than personal vehicle use) for people with disabilities, which make the personal journey to or from a transit hub difficult or unfeasible. Programs like car sharing reduce the need for people to own a vehicle yet serve to provide users extended reach beyond the distance comfortably traveled by bike or by foot in order to conduct trips for groceries, recreation, etc.

In 2013, the Los Angeles Metropolitan Transportation Authority released a Path planning guide, which provides a comprehensive overview of transit system improvements specifically designed to address the FMLM challenge. The report articulates system improvements in the planning guide “toolbox.” Detailed explanations of wayfinding strategies distinguish the Path report from others on FMLM studies. Wayfinding applies to most, if not all, alternative transportation networks in bringing visibility and clarity to public transit, local destinations, and alternative travel options (SCAG, 2013). Improved wayfinding presents itself as an economically attractive FMLM strategy due to relatively low costs associated with the installment of effective branding, signage, and aesthetic cues versus the procurement of more costly infrastructural or technological solutions. Furthermore, wayfinding enhances cohesion and maneuverability of active transportation networks and thus serves as an educational tool for users.

Active transportation strategies implemented in Utah have included bike lanes, a bike-share program, mid-block crossings, street furniture, secure bike parking, and improved pedestrian access to stations

(UTA, 2013). However, these strategies do not exist ubiquitously throughout areas requiring greater FMLM connectivity within Utah.

2.2 Accessibility Analysis for FMLM Analysis

An accessibility analysis links land use with transportation (Horner, 2004). The land use part of the analysis seeks to quantify the activity component of accessibility based on desired urban/rural services that are available. The transportation part of the analysis characterizes the ease of travel, and is usually described with a cost function. Several measures have been developed to date for PTA. The cost function is an important factor that distinguishes these measures (Lei and Church, 2010). Some of them, such as local index of accessibility (Rood and Sprowls, 1998), percentage of service coverage (Kittelson et al., 2003), and transit level-of-service (Ryus et al., 2000, Tumlin et al., 2005), do not consider travel time and emphasize the assessment of spatial coverage, service frequency, vehicle capacity, and comfort of service. Polzin et al. (2002) proposed a "time-of-day" PTA evaluation, and discussed the fact that ignoring travel time could induce bias in PTA results. Gradually, PTA measures that consider travel time gained popularity. Among them, cumulative and gravity-based measures are the most widely used. The former gauges the number of opportunities reachable within a fixed cost threshold (e.g., travel time window) (Bhat et al., 2000; El-Geneidy et al., 2016; Geurs and Ritsema van Eck, 2001; Vickerman, 1974; Wachs and Kumagai, 1973). Thus, the selection of the threshold for cumulative measures greatly influences the accessibility results. The gravity-based accessibility measures count the number of opportunities reachable, normalized by a weighting cost function (Bhat et al., 2000; Bhat et al., 2006; Geurs and Ritsema van Eck, Hansen, 1959). It addresses the single-threshold limitation of the cumulative methods, yet its result is dependent on the weighting function specification. Our discussion of PTA will primarily be focused on these two measures for this project.

Prior to the mid-2000s, the calculation of public transit travel time was challenging due to the unavailability or inconsistent format of transit schedule data. Simplified forms of public transit networks were used for calculating travel times (Beimborn et al., 2003; Kawabata and Shen, 2006; Kawabata, 2009; Polzin et al., 2002; Wu and Hine, 2003). Travel time was estimated based on service availability at a specific time of day, distance to and from transit stops, or a combination of both. Service frequency and reliability were used to measure the waiting time. In-vehicle travel time was estimated based on survey data or incomplete transit operation times. Yet, since travel time was estimated rather than measured with these approaches, there were estimation errors and losses of fidelity (Owen and Levinson, 2015). The recent advent in automatic data collection methods and uniformity of available data formats has enabled and facilitated the measurement of travel time in public transit (Ma and Wang, 2014).

The creation of General Transit Feed Specification (GTFS) sparked a stream of research and applications on travel-time-dependent PTA. GTFS was developed in 2005 by Google and TriMet for transit agencies to publish their schedules, trips, routes, and stops data in an open-source format that is usable for Google Transit Web-based Trip Planner (Google, Inc., 2013). GTFS provides a detailed public transit schedule in plain text format that greatly facilitates travel time measurement. Most studies in PTA have focused on using GTFS data to measure travel times between origin-destination (O-D) pairs for specific times of day (Benenson et al., 2010; Krizek et al., 2009; Mavoa et al., 2012; Owen and Levinson, 2012). Yet ignoring the temporal fluctuation due to schedule variation leads to biased results (Farber and Fu, 2016). For example, stops that are served by bus routes operating only during peak periods might have an overestimated level of accessibility.

To address such limitations, Mavoa et al. (2012) jointly considered a PTA index and transit frequency measure. They argued that transit frequency measures represent the transit level of service. However, transit frequency is not necessarily constant throughout the day and the PTA index is measured based on specific time-of-day travel times. The value of the PTA index can vary significantly, depending on the specific departure time that the index is measured. For example, when measured at the moment where a bus is approaching the transit stop, the PTA index is close to its maximum value. Similarly, when measured at the time point when the bus has just departed from a stop, the value is approximate to its minimum. Thus, a single departure time method might lead to over- or under-estimating PTA for different stops. Studies that use the minimum travel time throughout the day to measure PTA also suffer from similar issues of accessibility overestimation (Lei and Church, 2010; Owen and Levinson, 2012).

Fan et al. (2010) measured PTA for each hour of the day and averaged the values for analysis. Hourly measures can still be coarse in terms of resolution, as PTA can vary greatly from minute to minute (e.g., when the bus arrives and waiting time is minimum versus when the bus leaves and waiting time is maximum). Fransen et al. (2015) and Owen and Levinson (2015) measured PTA for each minute of specific peak periods of the day. They did not consider the service variability for other times of day in their calculation. Farber et al. (2016) addressed all the aforementioned issues by measuring travel times between all O-D pairs for each minute of the day using GTFS. They developed a travel time ratio to represent its temporal fluctuation. The ratio was calculated based on the local average travel time (e.g., within one hour of the selected trip) and global average travel time (all times of day). The proposed ratio is highly sensitive to the selection of time range (e.g., one hour) for averaging the local PTA value. In addition, the value of the proposed ratio itself varies throughout the day. Thus, interpreting and analyzing the spatiotemporal fluctuation in PTA remains challenging.

2.3 Impacts of Reduced Auto Use on Personal and Environmental Health

Recently published literature on the topic of impacts of reduced automobile use on personal and environmental health was extensive and covered a broad range of topics. A cursory review of these publications showed that the reported research generally fell into one or two of the following ten categories:

1. Establishing fundamental links between physical activity and all-cause mortality and morbidity (medical research)
2. Benefits (including health, attitude, and medical costs) of physical activity associated with transit use (including some neighborhood-specific analyses)
3. Links within the built environment (urban design), physical activity, reduced emissions, and health
4. Economic analysis of “hidden health costs” associated with infrastructure planning and policies
5. Health trade-offs associated with active travel
6. Health impacts of air pollution and reductions in air pollution
7. Health impact assessments of mode shifts
8. High-level discussions of healthy transportation policies
9. “Nuts and bolts” of emissions modeling
10. Methodological issues in health impact assessments (HIAs)

Among these categories, literature categories 2, 6, and 7 were considered most relevant to this project objectives. Basic insights to category 9 (“nuts and bolts” of emissions modeling) and category 10 (methodological issues in HIAs) are provided in an effort to give context to the methodologies and results reported in published research.

2.3.1 Physical Activity and Related Benefits Associated with Transit Presence and Use

Besser and Dannenberg (2005) analyzed transit-associated walking times for 3,312 transit users identified in the 2001 National Household Travel Survey (NHTS). Transit users were those who walked to and from transit as documented in their 24-hour travel diary. They represented 3.1% of the 105,942 people in the 2001 NHTS sample. The transit users spent a median of 19 minutes walking to and from transit daily. Approximately 32% of them achieved the Surgeon General's recommended 30 minutes of daily physical activity just from walking to and from transit. Figure 2.1 illustrates the distribution of total 24-hour walking trip times for the 3,312 transit users in the NHTS sample.

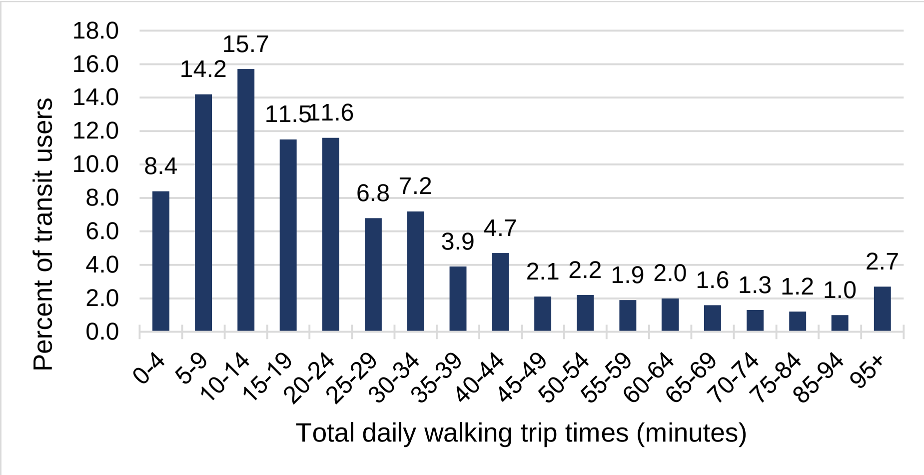


Figure 2.1 Total Daily Walking Trip Times to and from Transit (n = 3,312 transit users from 2001 NHTS) (from Besser and Dannenberg, 2005)

The type of transit (rail versus bus) did not impact the mean total walking times during the 24-hour period, but it did influence the likelihood of whether the Surgeon General's recommended 30 minutes was reached. People who walked at least 20 minutes were 1.67 times more likely to have used rail. Approximately 72% of single-segment walking trips to and from transit were reported as being less than 10 minutes in duration, which is less than the Surgeon General's recommendation that people obtain physical activity in periods of 10 minutes or more. Conflicting evidence made it difficult to decisively conclude whether these short walking trips qualify as beneficial physical activity.

Edwards (2008) used the same 2001 NHTS data to project differences between transit and non-transit users in terms of medical costs and welfare costs of obesity-related disabilities based on differences in daily walking activity. He first estimated several alternative specifications of ordinary least squares and Tobit regression models, converging on an estimate that transit users walk 8.3 more minutes per day than non-transit users. His models showed that train users walked an estimated 10.5 minutes more per day than non-transit users. Bus users walked an estimated six minutes more per day than non-transit users. These relative comparisons between transit types were consistent with those found by Besser and Dannenberg (2005).

Using this 8.3-minute walking difference, Edwards (2008) then estimated differences in kilocalories of energy expended, followed by differences in obesity prevalence, and, finally, differences in medical costs and quality of life between transit and non-transit users. He found the present value of medical savings to be $5,500 per transit user and the value of reduced obesity-related disability costs to be an additional $10,000 per user. These values had a range that depended on assumptions made for walking pace and total number of steps. Edwards (2008) did note that transit users were less likely than non-transit users to make trips to the gym, to exercise, or to play sports according to the travel diary data in the 2001 NHTS. This difference appeared to be small and was not incorporated into the health impacts analysis.

Brown and Werner (2008) surveyed 51 residents within one-half mile of a new light rail stop at 900 South in Salt Lake City, both before and after the light rail stop was opened. The participants were classified as continuing riders, new riders, or non-riders based on their light rail use before and after the new stop was operational. Heights and weights were measured using portable stadiometers and scales; activity was measured through belt-mounted accelerometers, worn for an average of 7-8 days during both before and after periods; and attitudes were measured using questions related to place attachment, neighborhood satisfaction, pro-suburb attitudes, and favorable transit-oriented development attitudes. Adjusted for income and employment, obesity (determined through measured BMI > 30) was much higher among non-rail riders (65%) than new riders (26%) and continuing riders (15%). Continuing riders had the highest number of accelerometer-measured activity bouts (moderate-intensity activity lasting at least eight minutes), strongest place attachment, highest level of neighborhood satisfaction, most favorable attitudes towards TOD, fewest car rides, and the weakest pro-suburb attitudes. Non-riders were on the opposite end of these categories. New riders always fell between the extremes of non-riders and continuing riders.

MacDonald et al. (2010) collected data on 498 adult household members living within one mile of the South Corridor Light Rail (LRT) line in Charlotte, North Carolina, both before and after the LRT became operational. The objective was to determine the effect of the LRT line and its use on BMI, obesity, and on meeting the American College of Sports Medicine and the American Heart Association recommended weekly physical activity (RPA) levels through vigorous or moderate physical activity. Vigorous activity includes exercise that results in breathing much heavier than normal (e.g., aerobics, fast bicycling). Moderate exercise includes walking. Respondent data, including self-reported height and weight, physical activity, perceptions of their neighborhood environment, and public transit use, were collected through telephone surveys. After the line was opened, LRT users were matched with non-LRT users based on pre-LRT variables in an effort to remove or minimize hidden study biases, and then outcomes of the new LRT line were quantified. LRT users in the "after" period reduced their BMI by an average of 1.18 kg/m2 compared with similar non-LRT users, corresponding to a weight loss of approximately 6.5 pounds for a person 5'5" tall. This result appeared plausible given the proximity of LRT users to transit stops, which would require about 1.2 miles of walking per day. LRT users were also 81% less likely to have become obese over time and more likely to meet RPA levels of vigorous and moderate exercise requirements (the results related to exercise requirements were not statistically significant).

Stokes et al. (2008) estimated the health cost savings that would be realized by this same LRT line in Charlotte. Results indicated a nine-year cumulative public health cost savings of $12.6 million resulting from health benefits to transit riders who were obese at the start of the analysis period. Potential benefits associated with preventing obesity in those who might otherwise become obese were not considered.

Morency et al. (2011) estimated the walking distance and total number of steps associated with trips involving transit in Montreal. Relevant data were collected using the 2003 Montreal Region household survey database, which included data on 75,000 households reporting a total of 360,000 trips. A "total disaggregate approach" was employed to attain a high level of resolution for each reported trip involving transit, including origin and destination, sequence of specific routes, boarding and alighting stations, and geographic coordinates corresponding to each of these locations. Approximately 15% of daily trips involved transit and 20% of traveling people used the transit system at least once during a typical weekday. Four conversion rates corresponding to four different age groups (5-9, 10-14, 15-64, and ≥ 65) were used to convert walking distances to steps. Results showed that one-directional trips involving transit averaged 1,250 steps (563 to access transit, 111 between routes or mode, and 576 to egress). A round trip resulted in 2,500 steps on average, 25% of the 10,000 daily steps needed for an adult to be considered active. Variables influencing the expected number of steps included age, gender, transit mode used (i.e., bus, train, subway, or various combinations) trip purpose, and trip destination. Findings were then used to demonstrate what would happen if 1) every car trip on Montreal Island less than one mile was converted to a "walk only" trip, and 2) 5% of car trips where there is transit service between origin and destination were converted to “walk to transit” trips. A total of 51,472 car trips would be affected on a typical day. This shift would translate into 56.8 million additional steps due to “walk to transit” and 246.6 million additional steps due to “walk only” trips.

2.3.2 Health Effects of Replacing Car Trips with Alternative Modes

Dhondt et al. (2013) conducted an integrated health impact assessment of changes in travel behavior resulting from a 20% increase in car fuel prices. While the change in fuel price was not a directly relevant treatment to the FMLM study, the resulting mode shift analysis in this study provides insights into the health and environmental effects of reduced automobile use. Travel behavior changes were predicted using the activity-based model FEATHERS (Forecasting Evolutionary Activity-Travel of Households and their Environmental Repercussions), a microscopic agent-based simulation model of Flanders and Brussels in Belgium. Health effects were quantified using disability adjusted life years (DALYs), which represent the sum of years of life lost (YLL) and years of life lived with disability (YLD). Health effects of air quality were estimated by combining emissions and dispersion models (to estimate on-road and background elemental carbon concentration), the activity-based travel model (to estimate exposure), mortality rates, and rates of cardiovascular hospital admissions. The health effects of active travel were estimated by converting walking and cycling trip distances, speeds, and times into age- and gender-specific metabolic equivalents (METs) and using published relationships between different levels of METs and mortality rates (it was noted that evidence on morbidity rates is still not as strong as mortality rates). The health effects of road safety were estimated using victim rates by travel mode, fatality rates, hospitalizations, and injury distributions.

Lindsay et al. (2011) estimated the health effects of using bicycles instead of light personal vehicles for varying proportions of short trips (≤ 7km) in New Zealand urban areas. The following databases and tools were used:

- New Zealand Household Travel Survey (NZHTS) to obtain information on trip purpose, distance, and average speeds for motor vehicle trips in urban areas that were 7 km or less
- Vehicle Emissions Prediction Model (VEPM) version plus some additional emission factors to calculate light vehicle emissions and total greenhouse gas load
- Health and Pollution in New Zealand (HAPiNZ) study for mortality and morbidity rates as a function of vehicle kilometers traveled
- WHO HEAT for Cycling to estimate reductions in mortality and resulting economic savings resulting from increases in cycling
- National Injury query system to estimate cyclist fatality and injury rates resulting from traffic crashes, plus an additional “safety in the numbers” rate reduction based on (Jacobsen, 2003).

Results showed that shifting 5% of “short trip” vehicle kilometers to cycling would reduce vehicle travel by approximately 223 kilometers each year. This would reduce greenhouse gas emissions by 0.4%. Each year, approximately 116 deaths would be avoided as a result of the physical activity associated with cycling. There would also be six fewer deaths due to local air pollution, but an additional five cyclist fatalities due to traffic crashes. Using the NZ Ministry of Transport Value of a Statistical Life, the changes reflect a net savings of $200 million per year. This number increased to $291 million annually if 10% of the short trip vehicle kilometers were shifted to cycling and $1.3 billion annually if 30% were shifted.

Two different extensive analyses dealing with the effects of decreasing automobile use and increasing cycling and transit use in Barcelona were reported in the literature (Rojas-Rueda et al., 2012; Rojas-Rueda et al., 2013). Combined, they represent what seems to be the most comprehensive health impact assessment of mode shifts in terms of air pollution dispersion and inhalation rate models, mortality, and morbidity considerations. The primary outcome explored in the 2012 analysis was all-cause mortality and change in life expectancy because of the following:

- The exposure of travelers to physical activity, air pollution, and traffic crashes
- The exposure of the general population to air pollution

Carbon dioxide emissions were also considered as a secondary outcome. Results showed that the greatest reduction in annual deaths was attributable to the increased physical activity associated with cycling and walking to transit. Numbers ranged from 19 to 98 fewer deaths per year due to the increased physical activity in Barcelona. Results also showed very minor increases in annual deaths due to the increase in PM2.5 for active travelers, which offsets the decrease in PM2.5 exposure to the general population. Numbers range from an additional 0.15 to 1.28 deaths per year attributable to pollution. There were also very small increases in traffic fatalities for the scenarios where all of the replaced car trips became cyclist trips (approximately one additional death every 10 years). For other scenarios where some of the replaced car trips became transit trips, traffic fatalities decreased, again by a small amount.

2.3.3 Effects of Reduced Automobile Use on Air Quality

Air quality can be related to automobile use through emission rates – the rate at which exhaust gases and particulate matter are expelled from a vehicle during operation. Vehicle emission rates can be measured using on-board equipment, such as a portable emissions measurement system (PEMS). Alternatively, rates can be measured in-place using a chassis dynamometer in combination with additional emissions measurement equipment (e.g., particulate sampling systems, gas analyzers, etc.). Vehicle emissions rates are measured as part of an effort to quantify vehicle contributions to air pollution and produce emissions inventories, which describe emissions rates for different types of automobiles in the national fleet under varying operating conditions. The types of emissions measured typically include volatile organic compounds (VOCs), hydrocarbons (HCs), carbon monoxide (CO), and nitrogen oxides (NOx), in addition to PM10 and PM2.5 (particulate matter with diameters smaller than 10 μm and 2.5 μm, respectively).

The EPA reports (EPA 2008a, 2008b, 2008c) that the following factors may affect emission rates:

- Vehicle type/size (passenger cars, light-duty trucks, heavy-duty trucks, urban and school buses, motorcycles), including gross vehicle weight
- Vehicle age and accumulated mileage
- Fuel used (gasoline, diesel, others)
- Ambient weather conditions (temperature, precipitation, wind)
- Maintenance condition of the vehicle (well-maintained or in need of maintenance, and presence and condition of pollution control equipment)
- Type of driving (e.g., idling, long cruising at highway speeds, stop-and-go urban congestion, typical urban mixed driving)

Rather than using average emissions rates, an alternative methodology uses vehicle operating conditions to describe more specific emissions rates over short time periods. One of the more commonly used methods, applied by the EPA in MOVES to estimate vehicle emissions, uses the concept of vehicle-specific power (VSP). VSP is a metric used to describe the estimated power required to move a vehicle (under varying acceleration and speed conditions) per unit mass, and is often reported in terms of kilowatts per metric ton. It is commonly calculated as a function of acceleration and speed, as well as roadway grade, rolling resistance, and aerodynamic losses.

3. STUDY NETWORK AND DATA PREPARATION

UTA is the primary transit provider in the Wasatch Front Region of Utah. UTA's services cover six counties, including Salt Lake, Utah, Davis, Weber, Box Elder, and Tooele. The transit network consists of 6,265 transit stops for 125 transit routes encompassing bus, light rail, and commuter rail. Figure 3.1 shows UTA's service network, including transit stops, Bus Rapid Transit (BRT), light rail (TRAX), and commuter rail (Frontrunner). In this study, we used UTA's network to implement the analytical framework. Transit stops were treated as transit service origins and destinations. The GTFS dataset for UTA's network is publicly accessible from the GTFS-data-exchange website (Google, 2016). It consists of six required and seven optional plain text files that have been formatted as comma-separated values (CSV). The required CSV files include agency, stops, routes, trips, stop-times, and calendar and provide detailed public transit schedules and associated geographic information. GTFS's stop file was used to extract the location of transit stops as the access points to transit services. The GTFS schedule data were used to measure the travel time between all O-D pairs at 10-minute intervals.

The number of opportunities was represented using job density and salary/income at the destination stops/locations in the PTA analysis. This socioeconomic dataset was obtained from the Census Transportation Planning Product (CTPP) website (AASHTO, CTPP, 2016). The CTPP was developed based on a partnership between AASHTO and all states to provide census transportation data packages. These packages contain detailed information on demographic characteristics, home/work locations, and commuting trips. The number of jobs, number of workers, and salary/income at the traffic analysis zone (TAZ) level were extracted from a CTPP-5-year-dataset from 2006-2010. The TAZ level provided the highest resolution of the required data compared with other geographic levels.

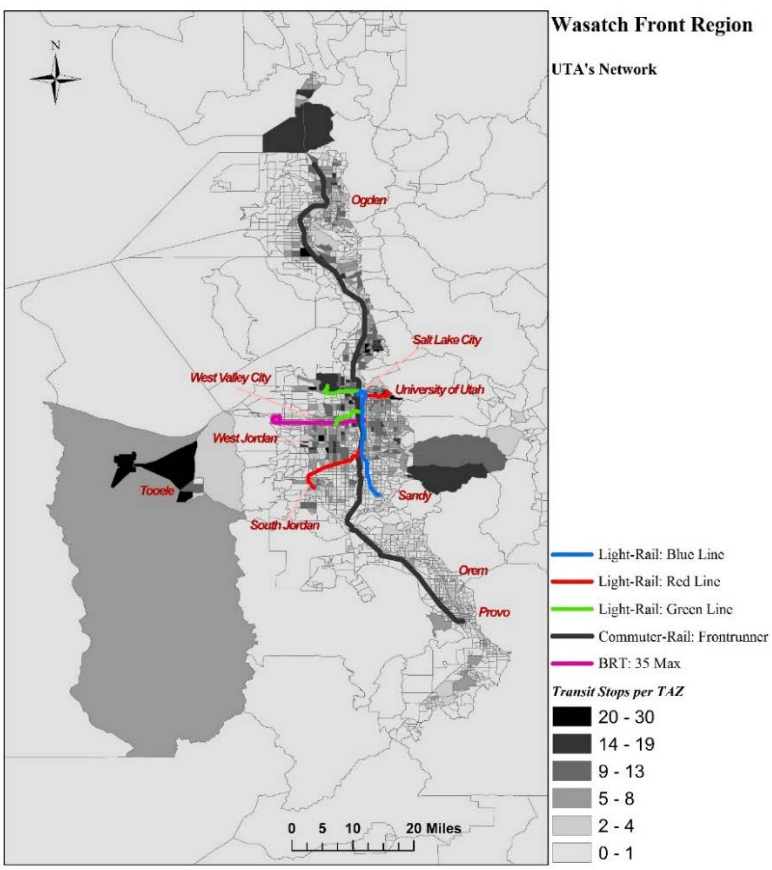


Figure 3.1 Wasatch Front TAZs and UTA's Transit Stops

4. RESEARCH METHODOLOGY

This study aims to address the challenges in dynamic PTA analysis and transit gap causality. To that end, we used WATT as a PTA measure and elucidated the time interval selection to fully capture PTA in spatiotemporal dimensions. Average to median WATT ratio (AMWR) is developed as a unified ratio that captures the spatiotemporal variation of transit service provisions. The computational procedure for determining potential opportunities and travel time, considering both transit service quality and geographic location, is described in detail in this section. The methods for providing the fuller picture of dynamic PTA and transit gap causality are also presented. As a summary, Table 4.1 presents the details of all the indicators developed in our study.

Table 4.1 Summary of Indicators Developed

Indicator	Description	Formula	Explanation	Resolution
WATT	Weighted Average Travel Time	$\frac{\sum_{j=1}^{J} O_j * tt_{ij,t}}{\sum_{j=1}^{J} O_j}$	Higher WATT = Lower PTA	Stop level, convertible to TAZ level
NPTS	Need for Public Transit Service	$WD_{TAZ_i} * NI_{TAZ_i}$	Higher NPTS = Higher dependency and demand for transit	TAZ level
PTAG	Public Transit Accessibility Gap	$WATT_{TAZ_i} * Norm(NPTS_{TAZ_i})$	Higher PTAG = Larger difference between demand and accessibility	TAZ level
AMWR	Average to Median WATT Ratio	$\frac{Average\ WATT_{TAZ_i}}{Median\ WATT_{TAZ_i}}$	AMWR > 1 = Lower temporal fluctuation in transit services	Stop level, convertible to TAZ level
NPTI	Need for Public Transit Improvement	$\frac{PTAG_{TAZ_i}}{(AMWR_{TAZ_i})^n}$	Higher NPTI = Higher PTAG caused by poor transit service	TAZ level

4.1 WATT

WATT is a gravity-based accessibility measure, mostly used in large scale networks (Cao et al., 2013; Gutierrez et al., 1996; Gutierrez, 2001). It is also referred to as a location indicator (Gutierrez et al., 1996). According to Fayyaz et al. (2017), WATT can be represented as:

$$WATT_{i,t} = \frac{\sum_{j=1}^{J} O_j * tt_{ij,t}}{\sum_{j=1}^{J} O_j}, \qquad j = 1,2, \dots, J, \qquad i \in J \tag{1}$$

where $WATT_{i,t}$ is the weighted average travel time of stop *i* at departure time *t*; O_j is the number of opportunities available at stop *j*; $tt_{ij,t}$ is the travel time from stop *i* to stop *j* at departure time *t*; and *J* is the total number of stops.

As mentioned in Section 2.2, the gravity-based accessibility measure's result is dependent on the weighting function specification. The gravity-based accessibility measure weighs opportunities based on a function of travel time (e.g., linear or nonlinear). On the other hand, WATT weighs travel time based on opportunities. Gravity-based accessibility measure is of opportunity nature and WATT is of travel time nature. Thus, super-linearity of distance-decay function will have no effect on WATT results.

In this project, WATT was measured for all transit stops within UTA's network at 10-minute time intervals on a typical weekday (Tuesday) from 4 a.m. to 10 p.m. (transit in-service). Ten-minute intervals were chosen here as the desirable resolution since the minimum headway in the study network was 15 minutes. Such resolution ensured that every trip was considered during the travel time measurement. It is important to note that since WATT was measured every 10 minutes (e.g., 4:00 a.m., 4:10 a.m., 4:20 a.m.), the shift between the measuring moment and vehicle departure time (e.g. 4:00 a.m., 4:15 a.m., 4:30 a.m.) varies. This directly led to different waiting times throughout the day (e.g. 0, 5, and 10 minutes), which result in a full range of possible travel times, as well as PTA values.

4.1.1 Available Opportunities

Potential opportunities at each TAZ was measured as:

$$O_{TAZ_i} = D_{TAZ_i} * I_{TAZ_i} \tag{2}$$

where O_{TAZ_i} is the potential opportunities available at TAZ_i; D_{TAZ_i} is the job density (number of jobs available divided by the area) of TAZ_i; and I_{TAZ_i} is the salary adjustment factor at TAZ_i. I_{TAZ_i} was calculated as:

$$I_{TAZ_i} = \frac{\sum_{k=1}^{K} WAS_{TAZ_k}}{K * WAS_{TAZ_i}} \tag{3}$$

where WAS_{TAZ_k} is the weighted average salary at TAZ_k; K is the total number of TAZs; and WAS_{TAZ_i} is the weighted average salary at TAZ_i. The weighted average salary at each TAZ was calculated by weighting the specific salary range with the number of jobs within that range. Equation (3) shows that an increase (decrease) in weighted average salary of a TAZ will decrease (increase) the salary adjustment factor, and consequently decrease (increase) the potential opportunities available. I_{TAZ_i} effectively adjusts the attractiveness of the destination TAZs to the transit users. The relationship expressed between weighted average salary and potential opportunities by I_{TAZ_i} at first might seem counterintuitive. Note that high-salary job holders are less dependent on public transit since traveling by private vehicle is a feasible option. On the other hand, low-salary job holders are rather more dependent on public transit due to limited car ownership and the cost associated with it (Giuliano, 2005). By introducing I_{TAZ_i}, if a TAZ has a large number of high-paying jobs, then the attractiveness (a.k.a. potential opportunities) of that TAZ decreases for low-income transit users.

Potential opportunities available at each transit stop was then computed based on the potential opportunities of the TAZs intersecting within a 400-meter buffer around the transit stop. The 400-meter buffer was selected based on the distance that a transit user is willing to walk (Kittelson et al., 2003). One issue with this method is the possibility of duplicated inclusion of potential opportunities if transit stops are adjacent to each other such that buffer areas might intersect. To remedy this, an adjustment factor was used to prevent the duplicate assignment of potential opportunity (e.g., job density or jobs) to stops. The adjustment factor for each stop was calculated as:

$$AAF = \frac{A_0 + \frac{A_1}{2} + \frac{A_2}{3} + \frac{A_3}{4} + \cdots + \frac{A_n}{n+1}}{A} \tag{4}$$

where AAF is the adjustment factor for each stop, $A_0, A_1, \ldots, A_n$ are the shared area of stop buffer area with 0,1, …, n other stops buffer area, and A is the buffer area of the stop ($A = \pi * 400^2$). The potential opportunities available at stops was then adjusted as:

$$O'_{Stop_i} = O_{Stop_i} * AAF_{stop_i} \tag{5}$$

where O'_{Stop_i} is the adjusted potential opportunities of $Stop_i$, O_{Stop_i} is the weighted average potential opportunities of $Stop_i$ calculated based on the intersecting area with different TAZs, and AAF_{stop_i} is the adjustment factor of $Stop_i$.

4.1.2 Public Transit Travel Time

Public transit travel times between all stop-pairs were measured for each 10-minute interval from 4 a.m. to 10 p.m. on a typical Tuesday using GTFS data. The total number of stop-pairs for the UTA network was 39,250,225 (6,265×6,265). Such a large network required extensive computation power for the PTA analysis (Farber and Fu, 2016; Farber et al., 2016; Owen and Levinson, 2015). To address this issue, an open source toolbox was developed in this study to compute travel times. The algorithm starts at each stop at a specific departure time and traces the next available trips serving this stop and other stops within walking distance. If the stops met on these trips are transfer stops (connected to new routes), then the next available trips serving the transfer stops are traced as well. This process continues until all the transit stops are met or the maximum allowable number of transfers is taken. Interested readers can refer to Fayyaz and Liu (2016) for further details on the algorithm. The algorithm enables PTA analysts to customize the constraint on walking distance to/from origin/destination stops, walking distance between transfer stops, and the number of transfers. The WATTs computations for each specific departure time took approximately 1.5 hours, and the computation for all times-of-day took less than six days to complete on a normal desktop computer (Core™ i7-4790 3.6 GHz computer processor and 16 GB of RAM). The same process using Esri's ArcMap Network Analyst would take up to 165 days.

The measured travel time includes initial access time, waiting time, transfer access time, in-vehicle time, and destination time. Initial access time and destination time were computed on the basis of a 300-meter walking time with a walking speed of 1.4 meters per second (O'Sullivan and Morrall, 1996), assuming most jobs are located within a 200- to 400-meter radius of a stop. The maximum number of transfers on each trip was set to three because the majority of transit trips (over 90%) involve one or two transfers (Owen and Levinson, 2015). When a destination was not reachable within three transfers, the walking time between O-D was selected as the travel time. This prevented the WATT value from becoming extremely small or large considering the numerator in Equation (1). Specifically, the impact of travel time to reachable destinations will be undermined if a large travel time value is selected for non-accessible destinations. The walking time is selected as travel time between an O-D in cases where transit travel time is longer than walking time and walking distance is less than 700 meters.

$WATT_i$ for the time periods when no transit service was available was also calculated using the algorithm described above (i.e., treating all travel times as walking times). This $WATT_i$, similar to closeness centrality (Newman, 2001; Newman, 2004; Opsahl et al., 2010), indicates how close stop *i* is to all other stops in the transit network with distances weighted based on the number of opportunities available at destinations. When transit service is available, $WATT_i$ is still representative of a weighted closeness centrality since travel time to stops that are not accessible within three transfers is walking time. In our study, the difference between $WATT_{i,t}$ and $WATT_{i,10:00\ PM}$ (when no service is available for most stops) reflects the quality of transit service. The closer the local maximum $WATT_i$ is to $WATT_{i,10:00\ PM}$ (see Figure 4.1), the worse the transit service is at the stop *i*. This directly impacts the average and median WATTs, and such effect is captured in the AMWR.

Although the aforementioned PTA analysis was carried out at a stop level, when trying to identify the transit service gap, the analysis needed to be mapped to the TAZ level to be comparable with NPTS in that TAZ. Thus, once the WATT was measured for each stop, the average WATT of stops within each TAZ was used as the surrogate for the TAZ's WATT for transit service gap identification.

4.1.3 Temporal Fluctuation of Transit Service and AMWR

The AMWR was used to demonstrate temporal fluctuation of service. Each stop's AMWR was determined as the ratio between its average WATT and median WATT throughout the day. As shown in Figure 4.1(c) and (d), when AMWR<1 (i.e., WATT distribution negatively skewed), temporal fluctuation in service was large (compared against the WATT range). A majority of the WATTs during the day were closer to the maximum. On the other hand, in Figure 4.1(a) and (b), when AMWR>1 (i.e., WATT distribution positively skewed), the temporal fluctuation in service was small (compared against the WATT range). In the latter case, the transit service appeared to be frequent and consistent.

High variation of PTA leads to unexpected delays and reduces the quality of service. In order to determine the quality of transit services at each stop, the probability of WATT for each random departure being closer to minimum (or local minimum) WATT is compared with maximum (or local maximum) WATT. In other words, for a random departure time, if the expected WATT is closer to the minimum WATT than maximum WATT, then the quality of service is better. It is noted that, by comparing WATT graphs across these four stations, Stop No. 5492 has the best transit service, followed by Stops No. 11, No. 13123, and No. 22208. Table 4.2 shows the comparison of AMWRs, standard deviations, frequency, coefficients of variation, and Fourier transform frequency (w) for these four stops on quantifying the temporal variation of accessibility (WATT).

Standard deviation cannot logically distinguish level of service as shown in Table 4.2 (i.e., No. 13123 has the smallest standard deviation). The coefficient of variation can discern the service quality when the standard deviation of WATT is relatively large, yet fails when standard deviation of WATT for that station is small since it is very sensitive to standard deviation values. The Fourier's fundamental frequency value was calculated from fitting the following specification to a WATT graph throughout the day:

$$F(t) = \beta_0 + \sum_{i=1}^{8} \beta_i * cos(w * t) + \alpha_i * sin(w * t) \qquad (6)$$

where $\beta_0, \beta_i, \alpha_i, and\ w$ are parameters that must be estimated and t is the time interval counter. Lower values of W indicate better transit service. Although it provides correct ranking for these four stops, the values do not scale. For example, the quality of service for Stop No. 5492 is estimated six times better than Stop No. 11, which is apparently incorrect. Finally, the frequency measure neither produces correct ranking nor scales properly. Based on the frequency measure, service provided in Stop No. 5492 is 2.5 times better than Stop No. 11, which appears not to be aligned with the WATT patterns shown in Figure 2, where only marginal differences between the two are detected in early morning and late afternoon hours. This is because frequency measure does not consider the waiting time for transfers (coordination between routes), connected stop headway, and headway fluctuations throughout the day.

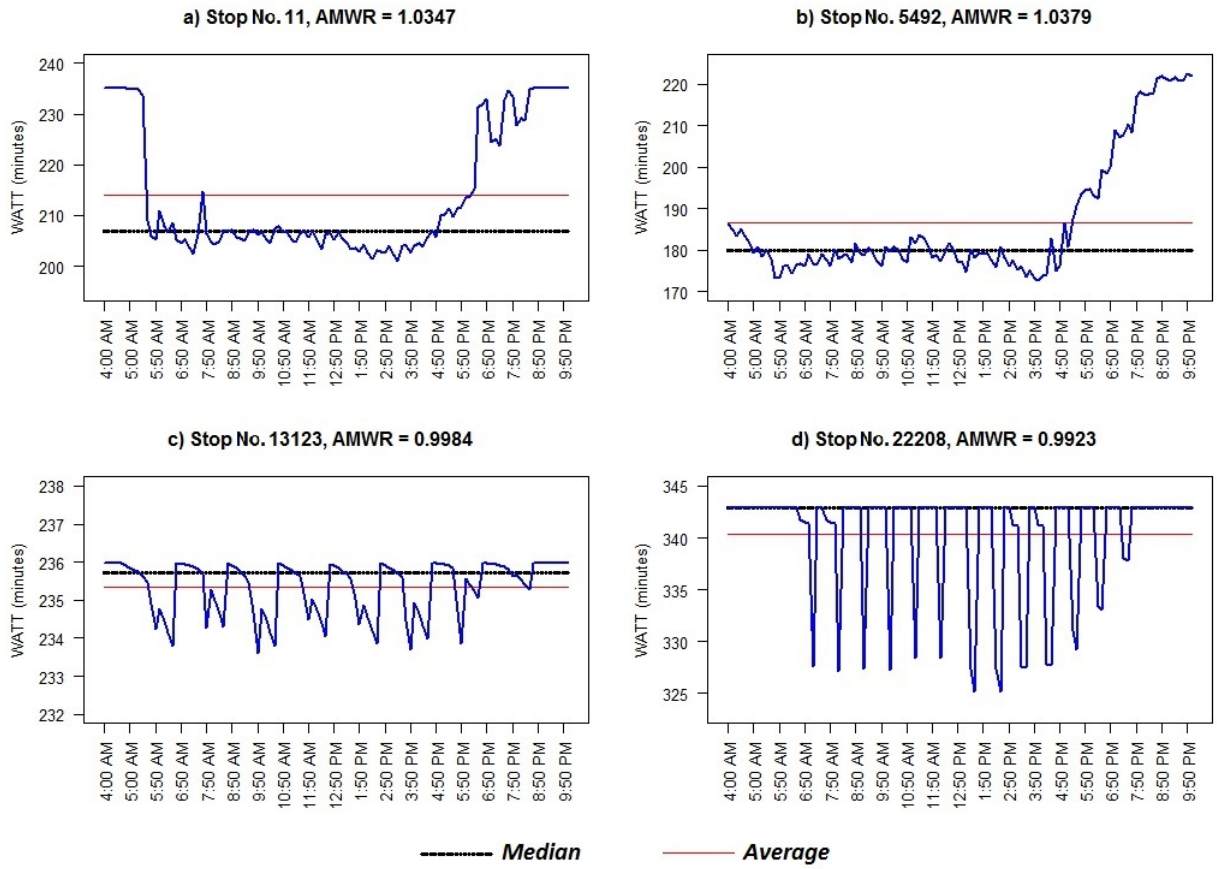


Figure 4.1 Temporal Fluctuation, Average, and Median Value of WATT Throughout the Day for a) Stop No. 11, b) Stop No. 5492, c) Stop No. 13123, and d) Stop No. 22208

Table 4.2 Comparing Different Measures Used to Quantify Temporal Variability of PTA

Stop No.	AMWR	Standard Deviation	Coefficient of Variation	W (Fourier's Fundamental Frequency)	Transit Frequency
11	1.0348	12.59	0.06	0.31	10.40
5492	1.0379	15.05	0.08	0.05	25.00
13123	0.9985	0.71	0.00	0.52	0.50
22208	0.9923	5.46	0.02	1.04	1.00

4.2 Public Transit Service Gap

In order to detect public transit service gaps in the analysis network, public transport needs (NPTS) and provisions (WATT) must be compared. NPTS in this project was measured using number of workers and average income at each TAZ:

$$NPTS_{TAZ_i} = WD_{TAZ_i} * NI_{TAZ_i} \tag{7}$$

where $NPTS_{TAZ_i}$ is the NPTS at TAZ_i; WD_{TAZ_i} is the number of workers living in TAZ_i divided by the area of TAZ_i; and NI_{TAZ_i} is the income adjustment factor at TAZ_i. NI_{TAZ_i} was calculated as:

$$NI_{TAZ_i} = \frac{\sum_{k=1}^{K} WAI_{TAZ_k}}{K * WAI_{TAZ_i}} \tag{8}$$

where WAI_{TAZ_k} is the weighted average income at TAZ_k; K is the total number of TAZs; and WAI_{TAZ_i} is the weighted average income at TAZ_i.

To find areas with high NPTS and poor PTA, an indicator named public transit accessibility gap (PTAG) was defined as:

$$PTAG_{TAZ_i} = WATT_{TAZ_i} * Norm(NPTS_{TAZ_i}) \tag{9}$$

where $PTAG_{TAZ_i}$ is the PTAG for TAZ_i; $WATT_{TAZ_i}$ is the average WATT of stops in TAZ_i; and $Norm(NPTS_{TAZ_i})$ is the normalized (in the range of 0 to 1) value of NPTS for TAZ_i. The NPTS is normalized to make the indice commensurable in Equation (9). The resulting PTAG allowed comparison between different TAZs to identify areas that need attention. A high PTAG value indicates poor PTA and high NPTS.

Finally, the AMWR was used to determine the underlying reason for high PTAG – poor transit service or geographical disadvantage. The need for public transit improvement (NPTI) was developed by combining PTAG and AMWR as follows:

$$NPTI_{TAZ_i} = PTAG_{TAZ_i} / (AMWR_{TAZ_i})^n \tag{10}$$

where $NPTI_{TAZ_i}$ is the NPTI for TAZ_i; $PTAG_{TAZ_i}$ is the PTAG of TAZ_i; $AMWR_{TAZ_i}$ is the average AMWR of stops in TAZ_i; and *n* is the scaling parameter. Note that WATT and AMWR in Equations (9) and (10) were geographically standardized (converted from stop level to TAZ level) for joint usage. In UTA's network, AMWR is in the range of 0.090 to 1.107. Yet small changes (e.g., 0.01 in magnitude) in AMWR can result in significant variations in quality of service (Figure 4.1). The current form of AMWR is unable to effectively express the NPTI pattern since its range is relatively small (around 1). Thus, AMWR needs to be scaled or normalized. As mentioned earlier, AMWR > 1 indicates relatively good transit service and vice versa. Normalization methods such as feature scaling are based on the position of value on its distribution with augmented or shrunken range. Normalization methods cannot provide sufficiently large (or small) values for AMWR to enable the shift in NPTI distribution as described above. Such issue can be remedied by power scaling. Power scaling will penalize the AMWR < 1, and reward the AMWR > 1. The scaling parameter is selected in a way to enable the shift with the following formula:

$$\frac{Mean_{PTAG} + St.Dev._{PTAG}}{Mean_{PTAG} - St.Dev._{PTAG}} = \frac{Mean_{AMWR^n} + St.Dev._{AMWR^n}}{Mean_{AMWR^n} - St.Dev._{AMWR^n}} \tag{11}$$

where $Mean_{PTAG}$ and $Mean_{AMWR^n}$ represent average values in PTAG and scaled AMWR distributions, respectively, and $St.Dev._{PTAG}$ and $St.Dev._{AMWR^n}$ represents the standard deviation values in PTAG and scaled AMWR distributions, respectively. This formula will ensure that scaled AMWR can move a TAZ over almost all NPTI distribution. Note that, range of [Mean - St.Dev., Mean + St.Dev.] covers almost 80% of TAZs in both PTAG and scaled AMWR distribution.

Higher values of NPTI are thus associated with poor PTA, high NPTS, and poor available transit service. High NPTI values indicate the need for transit service improvements. Planners and public transit agencies can use this indicator to prioritize future projects and investments.

5. DATA ANALYSIS AND RESULTS

The indicators developed in Section 4 were implemented using UTA's transit network. The value classes for all maps (i.e., Figures 5.1 through 5.6) in this section are determined using Jenks Natural Breaks algorithm (De Smith et al., 2007). The boundaries are set to minimize the within class variance and maximize between class variance. As a result, this data classification method is used to show the differences across TAZs in terms of values, scales, and clusters.

Figure 5.1 shows the potential opportunities available at each TAZ. Note that potential opportunities were measured based on job density weighted by the salary range at each TAZ. The majority of potential opportunities are concentrated in the downtown Salt Lake City area. The number decreases while gradually moving toward the west (West Valley City). The University of Utah, Provo, Orem, and Ogden also have relatively high concentrations of opportunities. West Jordan, South Jordan, and Tooele have relatively low concentrations of opportunities. Generally, the number of available opportunities is higher in urban areas compared with rural areas. Figure 5.1 indicates, everything else being equal (i.e., same transit service at all TAZs), areas farther away from the high number of potential opportunities have lower PTA.

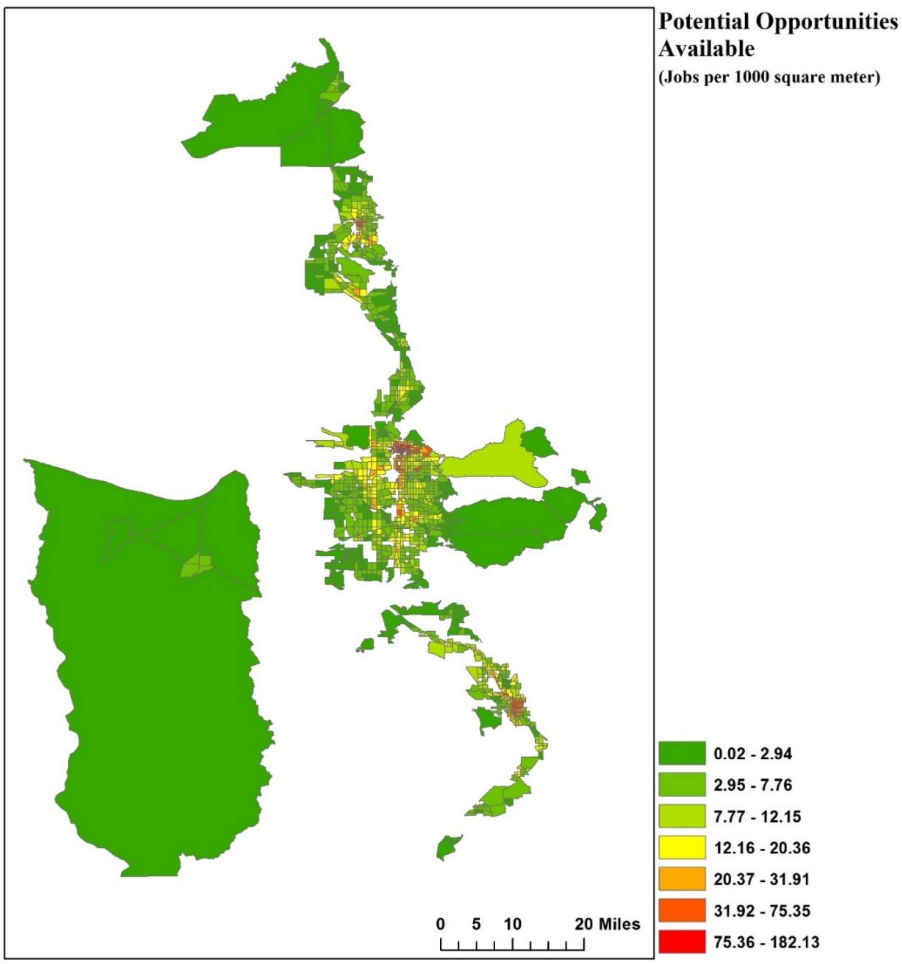


Figure 5.1 Potential Opportunities Available at Each TAZ Served by Public Transit

The measured WATT of TAZs is shown in Figure 5.2. Essentially, poor PTA is associated with high WATT. Figure 5.2 shows that downtown Salt Lake City has good PTA, and it is trending downward as one moves toward the city's outskirts. In other words, people living closer to downtown Salt Lake City can access more jobs within shorter periods of time than people living in other areas such as West Valley City. This is consistent with the findings presented in previous studies (Owen and Levinson, 2015) and demonstrates the importance of geographical location on PTA.

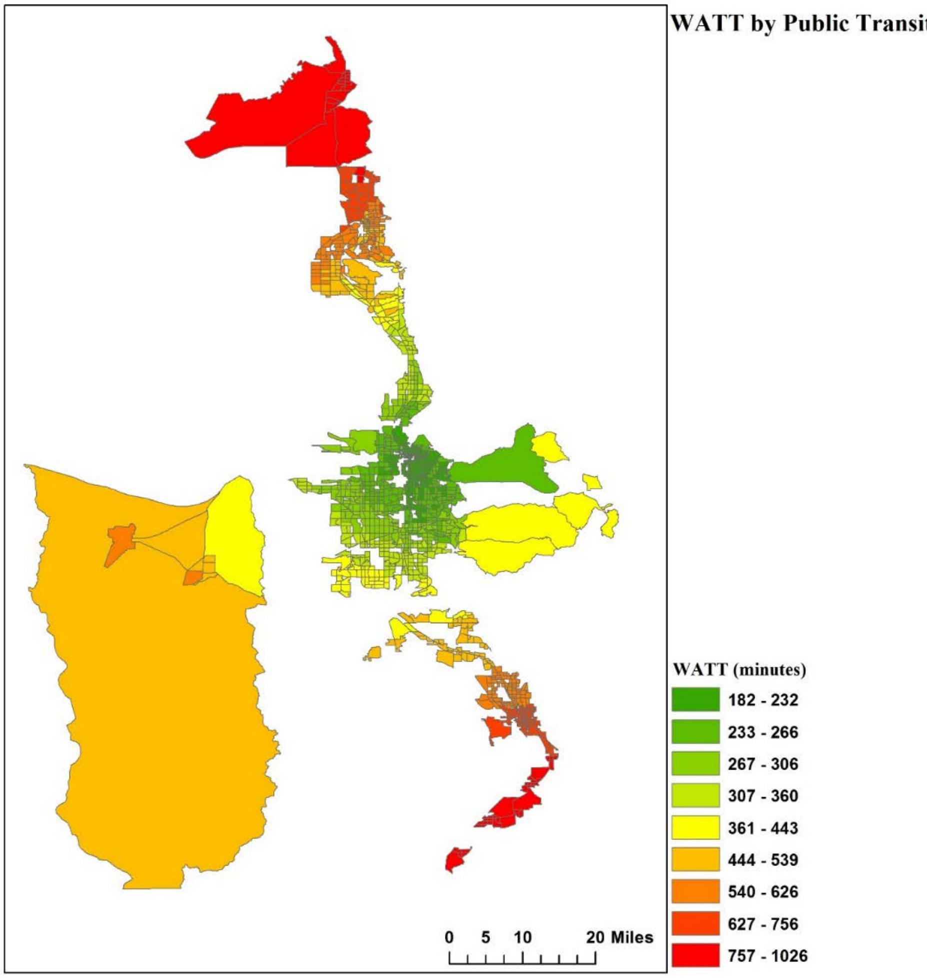


Figure 5.2 WATT for each TAZ served by public transits (minutes)

NPTS was then computed and shown in Figure 5.3. Note that high NPTS appears in Salt Lake City, West Valley City, south Downtown Salt Lake City (toward Sandy), Tooele, Ogden, and Provo. Even though NPTS is widely dispersed over the region, UTA's service covers all the TAZs with high demand (NPTS greater than 4.56) with several stops per TAZ, indicating good public transit service coverage.

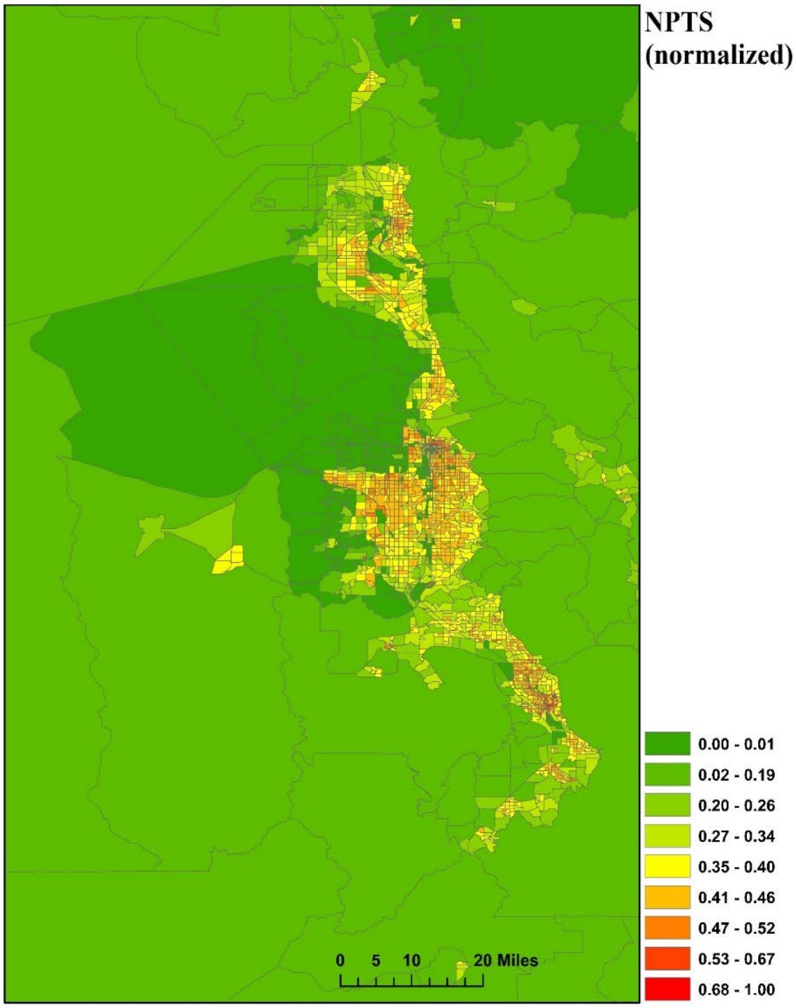


Figure 5.3 NPTS for Each TAZ

The NPTS and WATT were further combined to measure PTAG. TAZs with relatively high PTAG denote areas that have high demand (dependency) for transit services and poor PTA. As shown in Figure 5.4, Provo, Orem, Ogden, and Tooele experience the highest PTAG and consequently the highest gap between NPTS and PTA. High PTAG in rural (less urbanized) areas was expected due to the remote access to high potential opportunities in these locations, yet some rather more urbanized areas, such as South Jordan, also demonstrated high PTAG.

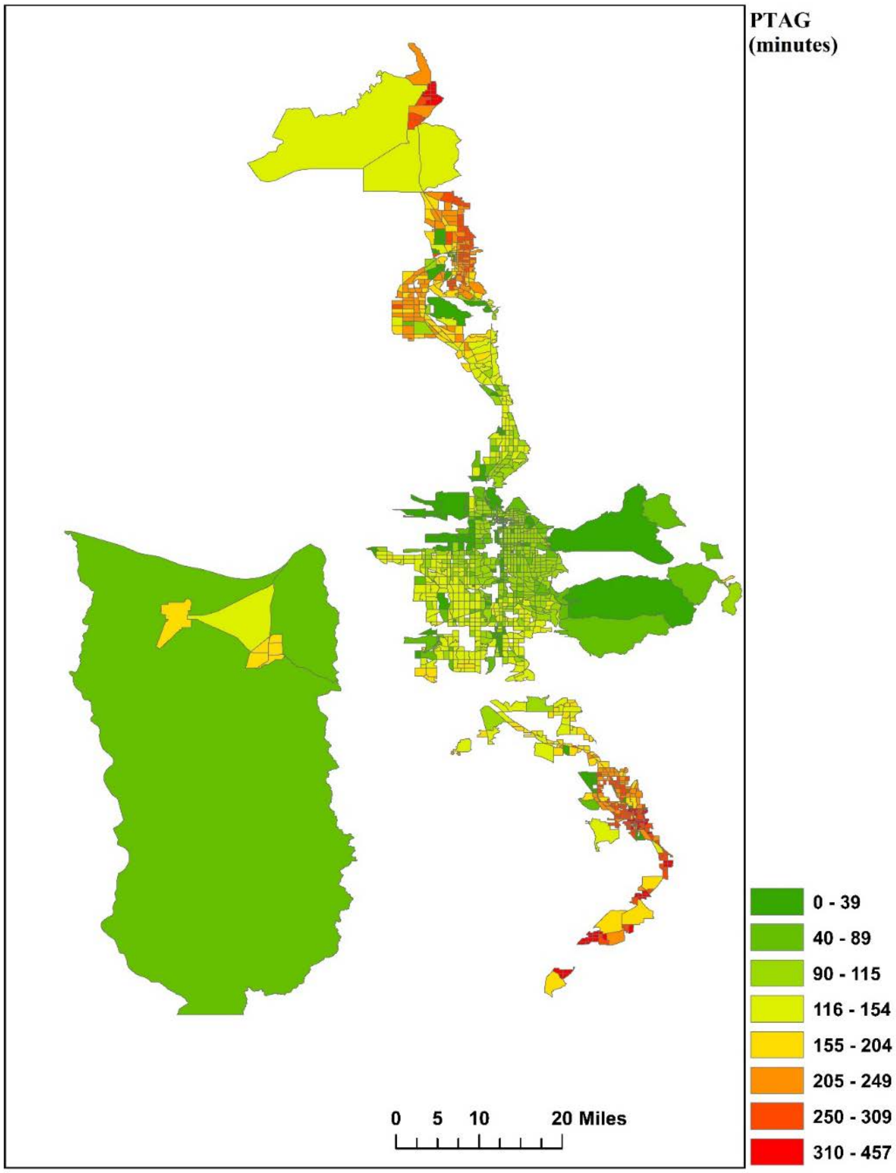


Figure 5.4 PTAG for Each TAZ Served by Public Transit

It is important to reiterate that AMWR reflects the temporal variability of transit service. As shown in Figure 5.5, areas on the edge of the network usually experience larger temporal fluctuation of PTA. This is because inner TAZs are usually served by several transit routes resulting in more frequent service, while outskirts experience limited transit service (e.g., one route). Consequently, a single route at these outskirt locations could serve as the only option for accessing different locations within the network and frequency of access is confined to the frequency of that route [e.g., Figure 4.1 (d)].

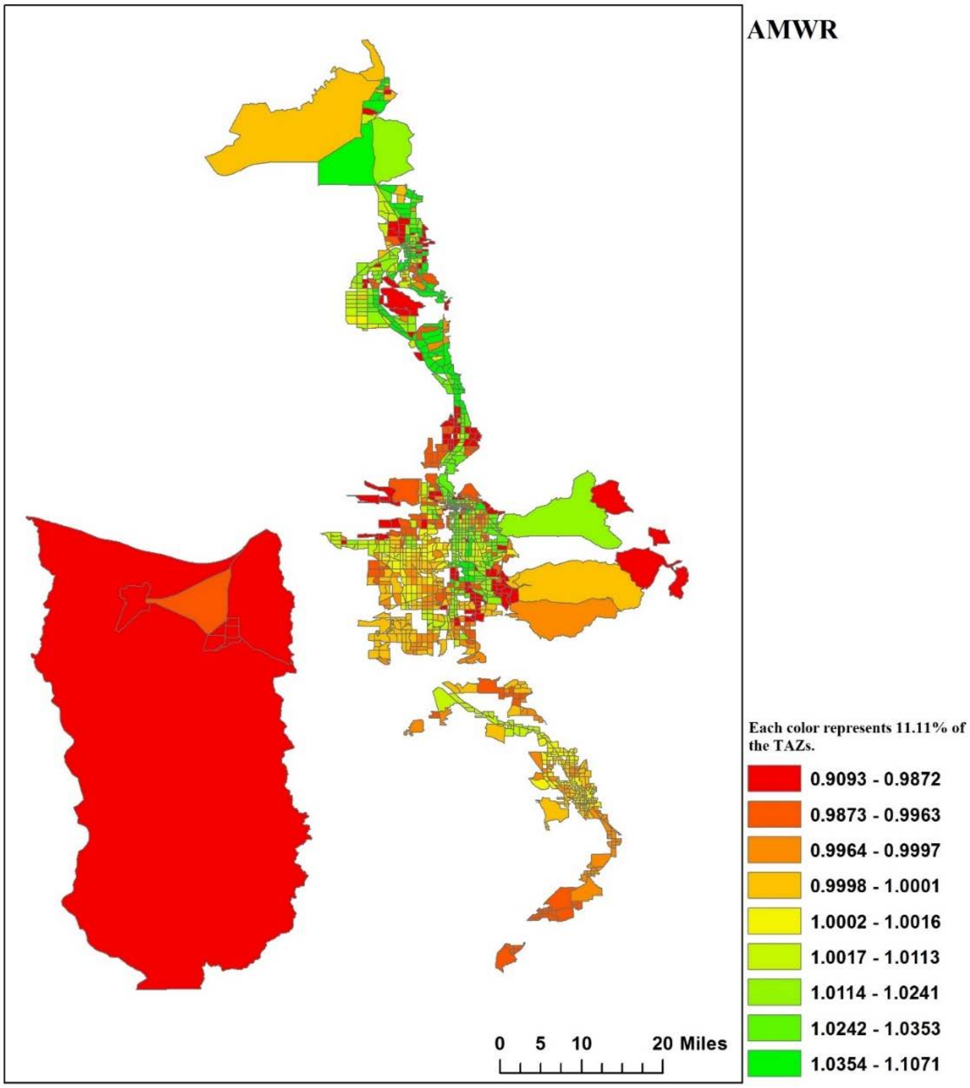


Figure 5.5 AMWR for Each TAZ Served by Public Transit

Finally, NPTI was calculated using Equation (5) to distinguish TAZs with poor public transit service and high PTAG. Figure 5.6 shows that Tooele is among the top priorities for public transit service improvements. Tooele is a small city located on the western side of the Oquirrh Mountains. Because of its close proximity to Salt Lake City, many Tooele residents regularly commute to Salt Lake City for work. The UTA network serves Tooele with only four bus routes for limited hours during the day. As a result, the area has high demand (dependency) for transit, yet relatively poor PTA and, more importantly, high temporal fluctuation of PTA, creating the highest needs for public transit improvements.

Several areas in Ogden also demonstrate high NPTI. Even with the operation of commuter rail in Ogden, these areas still appear to have high NPTI. The TAZs in and around Ogden are connected to commuter rail by one or two transfers, and the transfer buses are operating at a minimum headway of 30 minutes. This increases the temporal variability of access to commuter rail and consequently decreases the AMWR. As a result, these TAZs become high priorities for improvement. There are several TAZs in south and east Murray that require attention as well. The high NPTI values at these locations are mainly caused by limited numbers of routes operating at large headways.

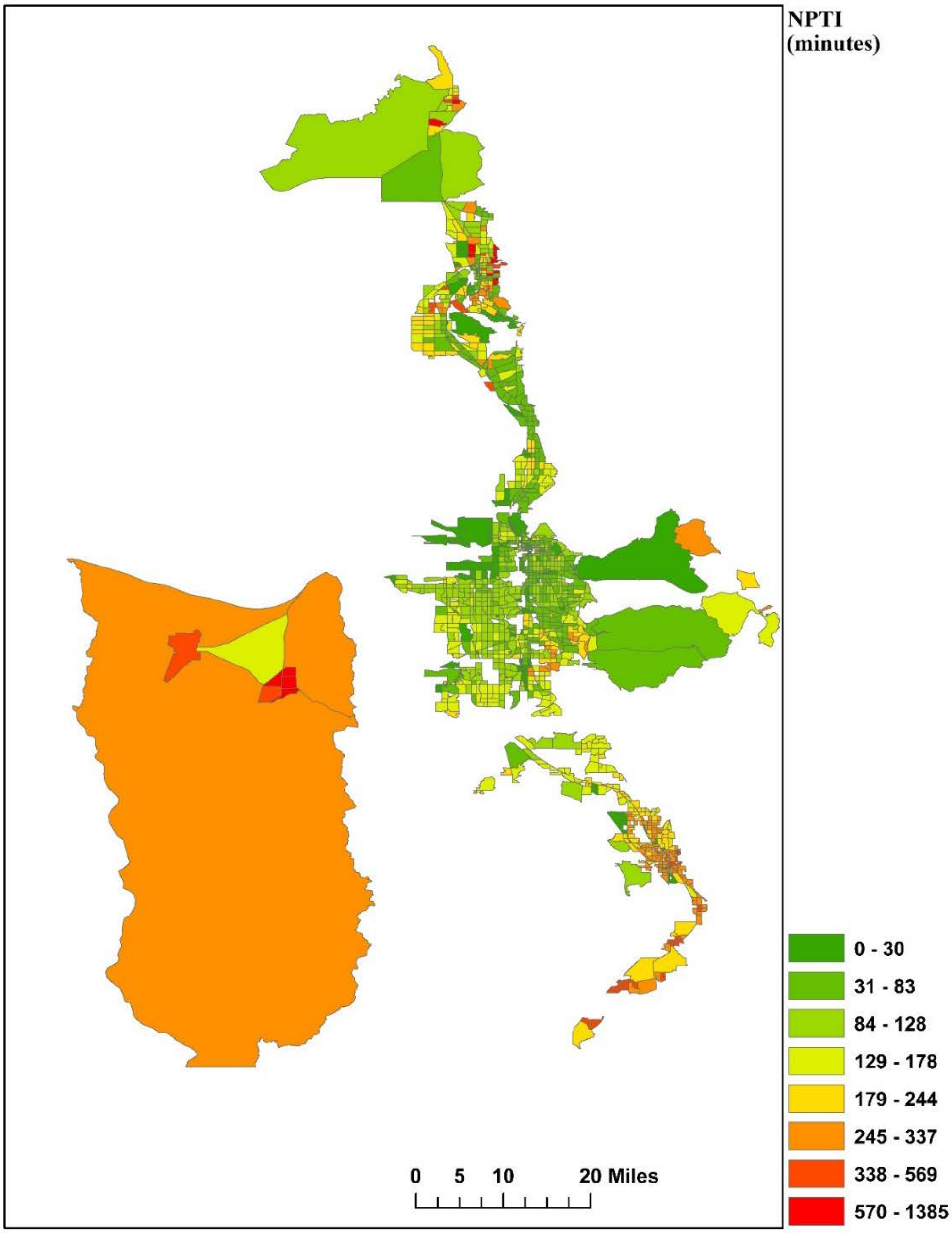


Figure 5.6 NPTI for Each TAZ Served by Public Transit

The NPTI results show that UTA is providing a reasonably good service in West Valley City. This is partly because of the operation of a BRT line in the area since 2008, providing efficient access to light rail stops. This can be observed in Figure 5.2, where the green area extended more widely to the west side of Salt Lake City when compared with the east side. Figure 5.5 shows that AMWR is higher in TAZs where BRT operates than the neighboring TAZs. Moreover, commuter rail has stretched the green area to the south and north sides of Salt Lake City. Figure 5.5 also indicates that, along the commuter rail route, the temporal fluctuation in PTA is lower than in neighboring TAZs. This is partly due to the relatively faster access to desired locations provided by the frequent service of commuter rail. The same trend can be observed for TAZs served by light-rail routes. This shows the positive impact of fast public transit routes on accessibility. However, the high NPTI of some neighboring TAZs shows the importance of feeder routes. Specifically, feeder routes operating on long headways in high demand areas will significantly compromise the benefits of fast public transit services (e.g., BRT, light rail, commuter rail).

The importance of geographical location on PTA can be better observed by comparing Figures 5.4 and 5.6. For example, Provo and Orem are experiencing relatively high PTAG, yet moderate NPTI, indicating good transit service provisions already. As a result, the gaps (i.e., poor PTA and high NPTS) are mainly due to the relatively long distances between these areas and Salt Lake City (where most opportunities are located). In such cases, improving transit service (e.g., frequent and larger coverage) will only provide marginal benefits to the area and might not be a cost effective investment.

The temporal fluctuation of PTA can be further analyzed at a stop level (Figure 4.1) to investigate possible flaws (e.g., incoordination) in existing services. For example, Figure 4.1(d) is a stop served by only one feeder route that works on a one-hour headway. The local minimums for the WATTs represent the time when the bus is approaching the stop. The differences between the peaks (local minimums) are mainly due to the wait time at the stop (counted as first transfer). The larger the time gap between peaks, the less synchronization there is between the feeder bus and fast transit service. In the case of Figure 4.1(d), no significant incoordination is observed.

The average WATT within the entire UTA network across the day is shown in Figure 5.7. Note that lower WATT (higher PTA) is observed between 5:30 to 7:30 AM, which corresponds to lower headways during morning peaks towards the denser job areas. The same lower trends occur from 3:30 PM to 5:30 PM when more frequent services are offered in the opposite direction of the morning commute. These results indicate that the current transit services meet the need of daily commute patterns. However, for people who work on night shifts, commuting by public transit becomes much less convenient.

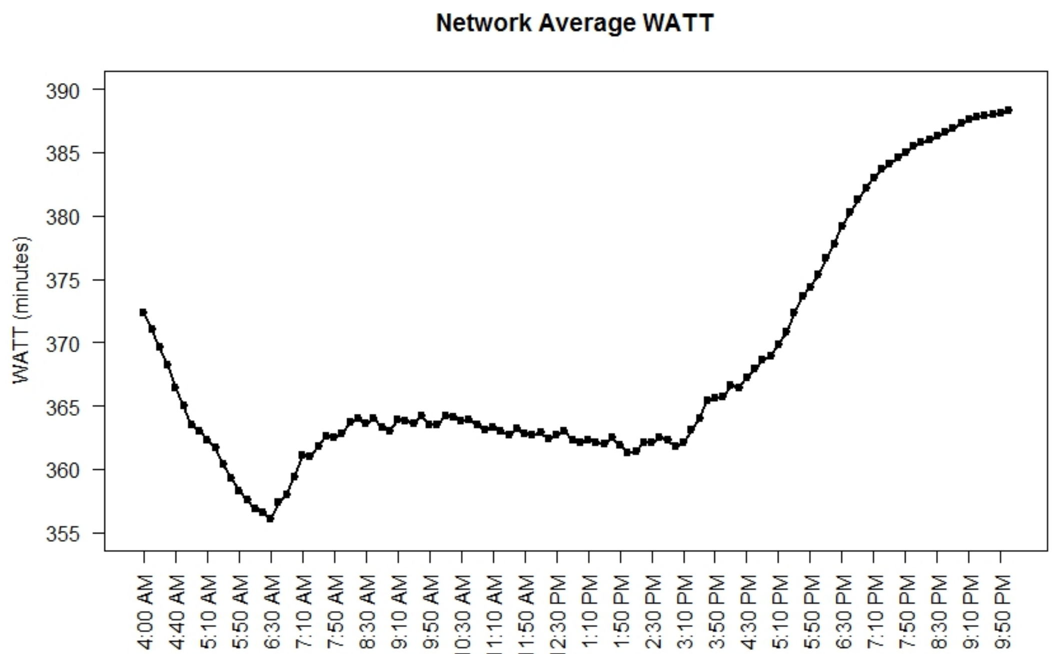


Figure 5.7 Average WATT of All Stops in UTA's Network

6. CONCLUSIONS

Several PTA measures have been developed over the past several decades. Yet the usage of travel time in PTA measures has only emerged with the introduction of GTFS. Dynamic PTA, considering the spatiotemporal dimensions in accessibility variation, has gained popularity as a result. Yet, analyzing the temporal fluctuation of PTA remains challenging due to the computational inefficiency and added temporal dimensions. Additionally, inadequate public transit service has generally been assumed to be the cause of poor PTA, without fully considering the potential geographical disadvantage of areas in study.

In this project, we showed that a dynamic PTA analysis can be implemented in an efficient manner using a computationally elegant algorithm. The algorithm enables the measurement of travel time at multiple departure times throughout the day. The time resolution was selected in such a way to reflect all possible waiting times and schedule variations. WATT was adopted in this study as a gravity-based PTA measure. Using UTA's transit network as a case study, the results indicated that PTA is generally higher in downtown Salt Lake City and trends downward as the areas extend to city outskirts. This is consistent with findings in previous studies and shows the importance of geographical location in PTA. AMWR was developed to capture the quality of transit service and its temporal fluctuation throughout the day. A higher AMWR (>1) implies relatively consistent transit service and constant WATT. A lower AMWR (<1), on the other hand, indicates high variability in transit service and PTA. The results show that AMWR is generally lower in TAZs that are located at the edge of network due to the limited feeder routes connecting them to the inner loop. A series of indicators that are intuitive to interpret were developed to identify the varying causes of poor PTA and areas with immediate needs for transit service improvements. NPTS was measured based on employment density and income in each TAZ. NPTS and WATT were then jointly used to identify the gaps in the existing services (PTAG). NPTI was developed to uncover the convoluted causes of poor PTA.

The analysis on UTA's network shows the positive impact of fast transit services, such as commuter rail, BRT, and light rail, on improving transit accessibility. The spatial inconvenience can also significantly jeopardize PTA of the study area. As an example, Provo and Orem, cities located approximately 45 miles away from downtown Salt Lake City, have large transit accessibility gaps (high PTAG), yet good transit service is provided within the area. Further improving transit service (e.g., frequent and larger coverage) will only provide marginal benefits to the area and might not be a cost effective investment.

The PTA analysis, as demonstrated in the project, can be conducted at high resolution (stop level) as well. As shown in Figure 4.1(d), a feeder stop WATT can help identify the incoordination between the feeder route and the connected faster transit service. The proposed method is solely based on publicly available datasets, including GTFS and CTPP. The analytical framework presented is reproducible for any public transport network and can help unveil the causes of inefficient PTA and areas in need of service investment. Based on the above discussion, two intriguing topics emerge. First, as a follow-up research on the result, it is necessary to incorporate a salary profile of transit users to further refine the potential opportunity measurement and NPTS, providing more insights on how PTA affects different transit users. Second, it might be interesting to perform pattern matching by categorizing transit stops based on their PTA to identify the mismatch between existing services and transit agencies' expectation.

REFERENCES

AASHTO, CTPP, 2016. <http://ctpp.transportation.org/Pages/default.aspx>.

Beimborn, E., Greenwald, M. and Jin, X., 2003. "Accessibility, connectivity, and captivity: impacts on transit choice." *Transportation Research Record: Journal of the Transportation Research Board*, (1835), pp.1-9.

Benenson, I., Martens, K. and Rofé, Y., 2010. "Measuring the gap between car and transit accessibility: estimating access using a high-resolution transit network geographic information system." *Transportation Research Record: Journal of the Transportation Research Board*, (2144), pp.28-35.

Besser, L.M. and Dannenberg, A.L., 2005. "Walking to public transit: steps to help meet physical activity recommendations." *American Journal of Preventive Medicine*, *29*(4), pp.273-280.

Brown, B.B. and Werner, C.M., 2008. "Before and after a new light rail stop: resident attitudes, travel behavior, and obesity." *Journal of the American Planning Association*, *75*(1), pp.5-12.

Bhat, C., Handy, S., Kockelman, K., Mahmassani, H., Chen, Q. and Weston, L., 2000. *Development of an urban accessibility index: literature review. Texas Department of Transportation Technical Report*. TX-01/7–4938–1.

Bhat, C.R., Bricka, S., La Mondia, J., Kapur, A., Guo, J.Y. and Sen, S., 2006. *Metropolitan area transit accessibility analysis tool* (No. Report No. 0-5178-P3).

Boyer, K.K., Prud'homme, A.M. and Chung, W., 2009. "The last mile challenge: evaluating the effects of customer density and delivery window patterns." *Journal of Business Logistics*, *30*(1), pp.185-201.

Burns, L.D., 1980. Transportation, temporal, and spatial components of accessibility.

Cao, J., Liu, X.C., Wang, Y. and Li, Q., 2013. "Accessibility impacts of China's high-speed rail network." *Journal of Transport Geography*, *28*, pp.12-21.

Coffel, K., 2012. *Guidelines for providing access to public transportation stations* (Vol. 153). Transportation Research Board.

De Smith, M.J., Goodchild, M.F. and Longley, P., 2007. Geospatial analysis: a comprehensive guide to principles, techniques and software tools. Troubador Publishing Ltd.

Dhondt, S., Kochan, B., Beckx, C., Lefebvre, W., Pirdavani, A., Degraeuwe, B., Bellemans, T., Panis, L.I., Macharis, C. and Putman, K., 2013. "Integrated health impact assessment of travel behaviour: model exploration and application to a fuel price increase." *Environment International*, *51*, pp.45-58.

Edwards, R.D., 2008. "Public transit, obesity, and medical costs: assessing the magnitudes." *Preventive Medicine*, *46*(1), pp.14-21.

EPA, 2008a. *Emission Facts: Average Annual Emissions and Fuel Consumption for Gasoline-Fueled Passenger Cars and Light Trucks*. (EPA420-F-08-024). Office of Transportation and Air Quality, United States Environmental Protection Agency.

EPA, 2008b. *Emission Facts: Average In-Use Emissions from Heavy-Duty Trucks*. (EPA420-F-08-027). Office of Transportation and Air Quality, United States Environmental Protection Agency.

EPA, 2008c. *Emission Facts: Idling Vehicle Emissions for Passenger Cars, Light-Duty Trucks, and Heavy-Duty Trucks*. (EPA420-F-08-025). Office of Transportation and Air Quality, United States Environmental Protection Agency.

El-Geneidy, A., Levinson, D., Diab, E, Boisjoly, G., Verbich, D., and Loong, C., 2016. "The cost of equity: Assessing accessibility by transit and social disparity using total travel cost." *Transportation Research Part A: Policy and Practice*, 91, 302-2016.

Fan, Y., Guthrie, A. and Levinson, D.M., 2010. "Impact of light rail implementation on labor market accessibility: A transportation equity perspective." *Journal of Transport and Land use*, *5*(3).

Farber, S. and Páez, A., 2011. "Running to stay in place: the time-use implications of automobile oriented land-use and travel." *Journal of Transport Geography*, *19*(4), pp.782-793.

Farber, S., Ritter, B. and Fu, L., 2016. “Space–time mismatch between transit service and observed travel patterns in the Wasatch Front, Utah: A social equity perspective.” *Travel Behaviour and Society*, *4*, pp.40-48.

Farber, S. and Fu, L., 2016. “Dynamic Public Transit Accessibility Using Travel Time Cubes: Comparing the Effects of Infrastructure (Dis) investments over Time.” In *Transportation Research Board 95th Annual Meeting* (No. 16-1457).

Fayyaz S., S. K., Liu, X. C., and Zhang, G. 2017. “An efficient General Transit Feed Specification (GTFS) enabled algorithm for dynamic transit accessibility analysis.” *PloS one*, *12*(10), e0185333.

Federal Transit Administration (FTA), 2011. *Final Policy Statement on the Eligibility of Pedestrian and Bicycle Improvements Under Federal Transit Law*. In *Federal Register,* 76, no. 161, pp. 52046-52053. Retrieved from http://www.gpo.gov/fdsys/pkg/FR-2011-08-19/html/2011-21273.htm

Foth, N., Manaugh, K. and El-Geneidy, A.M., 2013. “Towards equitable transit: examining transit accessibility and social need in Toronto, Canada, 1996–2006.” *Journal of Transport Geography*, *29*, pp.1-10.

Fransen, K., Neutens, T., Farber, S., De Maeyer, P., Deruyter, G. and Witlox, F., 2015. “Identifying public transport gaps using time-dependent accessibility levels.” *Journal of Transport Geography*, *48*, pp.176-187.

Geurs, K.T. and Ritsema van Eck, J.R., 2001. Accessibility measures: review and applications. Evaluation of accessibility impacts of land-use transportation scenarios, and related social and economic impact.

Giuliano, G., 2005. “Low income, public transit, and mobility.” *Transportation Research Record: Journal of the Transportation Research Board*, (1927), pp.63-70.

Google, Inc., 2016. Transit/GTFS. <https://developers.google.com/transit/gtfs/>.

Great Britain. Social Exclusion Unit (United Kingdom), 2003. Making the connections Final report on transport and social exclusion: summary.

Gutiérrez, J., González, R. and Gomez, G., 1996. “The European high-speed train network: predicted effects on accessibility patterns.” *Journal of Transport Geography*, *4*(4), pp.227- 238.

Gutiérrez, J., 2001. Location, economic potential and daily accessibility: an analysis of the accessibility impact of the high-speed line Madrid–Barcelona–French border. *Journal of Transport Geography*, *9*(4), pp.229-242.

Hansen, W.G., 1959. How accessibility shapes land use. *Journal of the American Institute of Planners*, *25*(2), pp.73-76.

Horner, M.W., 2004. “Spatial Dimensions of Urban Commuting: A Review of Major Issues and Their Implications for Future Geographic Research”. *The Professional Geographer*, *56*(2), pp.160-173.

Jacobsen, P.L., 2003. “Safety in numbers: more walkers and bicyclists, safer walking and bicycling.” *Injury Prevention*, *9*(3), pp.205-209.

Kawabata, M. and Shen, Q., 2006. “Job accessibility as an indicator of auto-oriented urban structure: a comparison of Boston and Los Angeles with Tokyo.” *Environment and Planning B: Planning and Design*, *33*(1), pp.115-130.

Kawabata, M., 2009. “Spatiotemporal dimensions of modal accessibility disparity in Boston and San Francisco.” *Environment and Planning A*, *41*(1), pp.183-198.

Kittelson, P.B., Quade, K. and Hunter-Zaworski, K.M., 2003. “Transit capacity and quality of service manual.” *Transportation Research Board, National Academy Press, Washington, DC*.

Koenig, J.G., 1980. “Indicators of urban accessibility: theory and application.” *Transportation*, *9*(2), pp.145-172.

Krizek, K.J., Iacono, M., El-Geneidy, A., Liao, C.F. and Johns, R., 2009. Access to destinations: Application of accessibility measures for non-auto travel modes.

Lindsay, G., Macmillan, A. and Woodward, A., 2011. “Moving urban trips from cars to bicycles: impact on health and emissions.” *Australian and New Zealand Journal of Public Health*, *35*(1), pp.54-60.

Lei, T.L. and Church, R.L., 2010. "Mapping transit-based access: integrating GIS, routes and schedules." *International Journal of Geographical Information Science*, *24*(2), pp.283-304.

Litman, T., 2003. "Integrating public health objectives in transportation decision-making." *American Journal of Health Promotion*, *18*(1), pp.103-108.

Mavoa, S., Witten, K., McCreanor, T. and O'Sullivan, D., 2012. "GIS based destination accessibility via public transit and walking in Auckland, New Zealand." *Journal of Transport Geography*, *20*(1), pp.15-22.

Ma, X. and Wang, Y., 2014. "Development of a data-driven platform for transit performance measures using smart card and GPS data." *Journal of Transportation Engineering*, 140(12), p.04014063.

Mineta Transportation Institute (MTI). 2014. Perceptions of Bicycle-Friendly Policy Impacts on Accessibility to Transit Services – The First and Last Mile Bridge.

MacDonald, J.M., Stokes, R.J., Cohen, D.A., Kofner, A. and Ridgeway, G.K., 2010. "The effect of light rail transit on body mass index and physical activity." *American Journal of Preventive Medicine*, *39*(2), pp.105-112.

Morency, C., Trépanier, M. and Demers, M., 2011. "Walking to transit: an unexpected source of physical activity." *Transport Policy*, *18*(6), pp.800-806.

Moniruzzaman, M. and Páez, A., 2012. "Accessibility to transit, by transit, and mode share: application of a logistic model with spatial filters." *Journal of Transport Geography*, 24, pp.198-205.

Newman, M.E., 2001. "Scientific collaboration networks. II. Shortest paths, weighted networks, and centrality." *Physical review E*, *64*(1), p.016132.

Newman, M.E., 2004. "Analysis of weighted networks." *Physical review E*,*70*(5), p.056131.

Opsahl, T., Agneessens, F. and Skvoretz, J., 2010. "Node centrality in weighted networks: Generalizing degree and shortest paths." *Social networks*, *32*(3), pp.245-251.

O'Sullivan, D., Morrison, A. and Shearer, J., 2000. "Using desktop GIS for the investigation of accessibility by public transport: an isochrone approach." *International Journal of Geographical Information Science*, *14*(1), pp.85-104.

O'Sullivan, S. and Morrall, J., 1996. "Walking distances to and from light-rail transit stations." *Transportation Research Record: Journal of the Transportation Research Board*, (1538), pp.19-26.

Owen, A. and Levinson, D., 2012. "Annual accessibility measure for the Twin Cities metropolitan area." *Minnesota Department of Transportation*.

Owen, A. and Levinson, D.M., 2015. "Modeling the commute mode share of transit using continuous accessibility to jobs." *Transportation Research Part A: Policy and Practice*, *74*, pp.110-122.

Partnership for Active Transportation, 2014. *What is Active Transportation?* http://www.partnership4at.org/why/what-is-active-transportation.

Polzin, S., Pendyala, R. and Navari, S., 2002. "Development of time-of-day-based transit accessibility analysis tool." *Transportation Research Record: Journal of the Transportation Research Board*, (1799), pp.35-41.

Rojas-Rueda, D., De Nazelle, A., Teixidó, O. and Nieuwenhuijsen, M.J., 2012. "Replacing car trips by increasing bike and public transport in the greater Barcelona metropolitan area: a health impact assessment study." *Environment International*, *49*, pp.100-109.

Rojas-Rueda, D., De Nazelle, A., Teixidó, O. and Nieuwenhuijsen, M.J., 2013. "Health impact assessment of increasing public transport and cycling use in Barcelona: a morbidity and burden of disease approach." *Preventive medicine*, *57*(5), pp.573-579.

Rood, T. and Sprowls, S., 1998. *The local index of transit availability: An implementation manual*. Local Government Commission.

Ryus, P., Ausman, J., Teaf, D., Cooper, M. and Knoblauch, M., 2000. "Development of Florida's transit level-of-service indicator." *Transportation Research Record: Journal of the Transportation Research Board*, (1731), pp.123-129.

Stokes, R.J., MacDonald, J. and Ridgeway, G., 2008. “Estimating the effects of light rail transit on health care costs.” *Health & Place*, *14*(1), pp.45-58.

Southern California Association of Governments (SCAG), 2013. *Draft First Last Mile Strategic Plan – Path Planning Guidelines*.

Tumlin, J., Walker, J., Hoffman, J. and Hutabarat, R., 2005. “Performance measures for the urban village transit network.” In *84th Annual Meeting of the Transportation Research Board. Transportation Research Board, Washington, DC*.

Utah Transit Authority, 2013. UTA Network Study Next Tier Program Final Report.

Vickerman, R.W., 1974. “Accessibility, attraction, and potential: a review of some concepts and their use in determining mobility.” *Environment and Planning A*, *6*(6), pp.675-691.

Wachs, M. and Kumagai, T.G., 1973. “Physical accessibility as a social indicator.” *Socio-Economic Planning Sciences*, *7*(5), pp.437-456.

Washington Metropolitan Transit Authority (Metro), 2010. *Metrorail Bicycle & Pedestrian Access Improvements Study*.

Widener, M.J., Farber, S., Neutens, T. and Horner, M., 2015. “Spatiotemporal accessibility to supermarkets using public transit: an interaction potential approach in Cincinnati, Ohio.” *Journal of Transport Geography*, 42, pp.72-83.

Wu, B.M. and Hine, J.P., 2003. “A PTAL approach to measuring changes in bus service accessibility.” *Transport Policy*, *10*(4), pp.307-320.

APPENDIX

Health/Environment Effects Sketch Planning Tool

Spreadsheet User Guide

SPREADSHEET QUICK GUIDE

Introduction & Purpose

This spreadsheet was created as a sketch-planning tool to quickly estimate the health and environmental effects of physical activity associated with transit use. Health effects are estimated using a simplified version of a health impact assessment (HIA), which is a generalized framework for estimating the potential health effects of a policy, program, or project, similar to environmental impact assessments applied in transportation planning and design. Environmental effects are estimated using average per-mile emission rates and estimated changes in vehicle-miles traveled (VMT).

This spreadsheet tool adopts a simplified HIA methodology based on the Health Economic Assessment Tool (HEAT) developed by the World Health Organization (WHO, 2014) to estimate mortality effects of physical activity. Further modifications were adapted from an HIA conducted in Barcelona, Spain (Rojas-Rueda et al., 2013), to incorporate morbidity effects associated with physical activity.

The first portion of this document is a quick guide for using the spreadsheet tool, describing its inputs and outputs and some general guidelines for interpreting estimates. The second portion of this document describes the modeling methodology demonstrated in the spreadsheet tool.

General Spreadsheet Details & Organization

The spreadsheet tool has three worksheets. The following table offers a brief summary of their uses and interaction. More detailed descriptions are provided after the table.

Worksheet	Description
Report Input-Output	• Contains all major inputs related to station and trip attributes **(Provided by the user)** • Presents major outputs describing estimated health benefits, emissions, VMT reductions, and economic costs associated with changes in boardings and mode shares • Describes all modeling assumptions applied in this analysis • Can be printed and used as a report for each station analyzed
Methodological Inputs	• Contains fundamental inputs used to calculate health benefits, emissions, and economic costs • Generally, users should not change inputs in this worksheet without justification (i.e., region-specific inputs, adjustments for inflation)
Intermediate Calculations	• Contains most calculations for changes in VMT, emissions, health benefits, and economic costs using inputs from the other worksheets

Report Input-Output Worksheet

This worksheet is the primary interface through which most users will interact with this sketch planning tool. Users enter input values about the station and trips in the **Input Data** section (highlighted in red in **Figure A.1**), and estimated annual benefits are presented in tables in the **Analysis Results** section (highlighted in blue in **Figure A.1**). All input data are to be provided by the user. For input data descriptions, please refer to **Input Data Definitions**. Output data descriptions can be found in the **Output Data** Definitions.

The second half of this worksheet explains the modeling assumptions applied using the analysis methodology described in this document. These modeling assumptions are further explained in the **Methodology** & Modeling Assumptions section, with additional information provided within the context of the modeling methodology implemented in this spreadsheet.

This worksheet can also be used as a station analysis report for inclusion in larger reports and interactions with decision-makers. The **Title Block** (highlighted in green in **Figure A.1**) at the top of the worksheet allows the user to input the facility name being analyzed, the organization for which the analysis is being performed, and the analysis date. The spreadsheet is designed to print the Title Block, Input Data, and Analysis Results on a single page to simplify the process for creating analysis reports.

Health Effects Sketch Planning Analysis Tool	
Transit Facility Name:	**Insert Name Here**
Organization:	**Insert Name Here**
Date:	**Insert Date Here**

Input Data

Station Trip Information	Before Treatment	After Treatment
Boardings Per Day	800	1000
Percent Commuter Boardings	80%	80%
Average Trip Length to Destination (miles)	10	10

Trip Attributes to/from Station	Before Treatment	After Treatment
Walk Mode Share (%)	50%	60%
Bike Mode Share (%)	10%	10%
Drive Mode Share (%)	10%	10%
Average Walk Distance (miles)	0.6	0.6
Average Bike Distance (miles)	2.1	2.1
Average Drive Distance (miles)	4	4
Average Number of Biking Days Per Year	124	124

Analysis Results (Annual Benefits)

Estimated Lives Saved	Before Treatment	After Treatment	Due to Treatment
Walking	0.14 (0.05 - 0.21)	0.20 (0.07 - 0.32)	0.07 (0.02 - 0.11)
Bicycling	0.02 (0.01 - 0.03)	0.03 (0.02 - 0.04)	0.01 (0.00 - 0.01)
Total Estimated Lives Saved	0.16 (0.06 - 0.24)	0.23 (0.09 - 0.35)	0.07 (0.03 - 0.11)

Estimated Number of Illnesses Prevented	Before Treatment	After Treatment	Due to Treatment
Cardiovascular Disease	0.18 (0.11 - 0.23)	0.25 (0.16 - 0.33)	0.08 (0.05 - 0.10)
Type 2 Diabetes	0.43 (0.23 - 0.63)	0.62 (0.33 - 0.91)	0.18 (0.10 - 0.27)

Estimated Change in Emissions (Kilograms)	Before Treatment	After Treatment	Due to Treatment
Carbon Dioxide (CO_2)	-563,000	-704,000	-141,000
Carbon Monoxide (CO)	-14,300	-17,900	-3,600
Total Hydrocarbons (THC)	-1,600	-2,000	-400
Volatile Organic Compounds (VOC)	-1,500	-1,900	-400
Nitrogen Oxides (NO_x)	-1,000	-1,300	-300
PM_{10}	-6.7	-8.4	-1.6
$PM_{2.5}$	-6.2	-7.8	-1.5
VMT Reduction	1,530,000	1,910,000	380,000

Economic Benefits	Before Treatment	After Treatment	Due to Treatment
Social Value of Lives Saved (per year)	**$1,470,000**	**$2,150,000**	**$680,000**
Lower Range:	$587,000	$848,000	$261,000
Upper Range:	$2,220,000	$3,250,000	$1,030,000
Medical Cost Savings from Prevented Illnesses	**$11,400**	**$16,300**	**$4,900**
Lower Range:	$6,800	$9,700	$2,900
Upper Range:	$15,600	$22,200	$6,600

Figure A.1 Report Input-Output Worksheet Layout

Methodological Inputs Worksheet

The Methodological Inputs worksheet contains fundamental inputs, which are used to calculate health benefits, emissions, and economic costs. More specifically, this worksheet contains the following information:

- Conversion rates for metabolic equivalent tasks (METs)
- Relative risks for morbidity and mortality
- Morbidity and mortality incidence rates
- Per-mile emissions rates
- Medical costs of illnesses and the value of statistical life for economic calculations

Users should not change inputs in this worksheet without justification. Changes to relative risks and MET conversion rates should be informed by a review of epidemiological studies and research. Advanced users may wish to change these inputs based on the year of analysis (e.g., adjustments for inflation) and/or to provide region-specific estimates (morbidity and mortality incidence rates, medical/social costs).

Intermediate Calculations Worksheet

This worksheet combines the input data from the previous two worksheets to calculate the estimated changes in VMT, emissions, health benefits, and economic costs displayed on the Report Input-Outputs worksheet. The calculations here follow the methodology explained in **Methodology & Modeling Assumptions** section of this document. This worksheet should only be changed as part of an effort to develop and expand this sketch planning tool.

Input Data Definitions

Variable Name	Description
Trips Originating From Station (Per Day)	Number of travelers beginning their trip from the analyzed station each day
Percent Commuter Trips	Percentage of the total number of trips for which the trip purpose is to travel to work, or to home from work (home-based work trip)
Average Trip Length to Destination (miles)	Average distance traveled between the origin and destination for commuter trips from this station
Walk Mode Share (%)	Percentage of travelers approaching station by walking
Bike Mode Share (%)	Percentage of travelers approaching station by bicycle
Drive Mode Share (%)	Percentage of travelers approaching station using a personal vehicle
Average Walk Distance (miles)	Average distance traveled to the station by walking travelers
Average Bike Distance (miles)	Average distance traveled to the station by bicycling travelers
Average Drive Distance (miles)	Average distance traveled to the station by driving travelers
Average Number of Biking Days Per Year	The average number of days each year that commuters most commonly use their bicycles. For example, out of 260 working days per year, the average bicycling commuter may only use their bike on 124 of those days.

Output Data Definitions

Variable Name	Description
Estimated Lives Saved	The estimated (mean) number of lives saved each year due to additional physical activity associated with walking and bicycling to/from a station. Estimates are provided for the effects of both walking and cycling, as well as a combined estimate. A range describing the upper and lower bound estimates is included (Min – Max).
Estimated Number of Illnesses Prevented	The estimated (mean) number of illnesses prevented each year due to additional physical activity associated with walking and bicycling to/from a station. Estimates are provided for each illness (currently cardiovascular disease and Type 2 Diabetes). A range describing the upper and lower bound estimates is included (Min – Max).
Estimated Change in Emissions (Kilograms)	The estimated amount (mass) of various air pollutants prevented from being released from personal automobiles due to transit use at a station. This estimate assumes that the traveler would have driven to their destination otherwise, and considers their travel mode to the station. Estimates are currently provided for carbon dioxide (CO_2), carbon monoxide (CO), nitrogen oxides (NO_x), Volatile Organic Compounds (VOC), Total Hydrocarbons (THC), and PM_{10} and $PM_{2.5}$.
VMT Reduction	Estimated vehicle-miles traveled (VMT) reduced due to the transit use, including the main leg of their journey and their trip to/from the station.
Social Value of Lives Saved (per year)	The estimated social value of lives saved each year (based on value of statistical life) due to reductions in mortality associated with increased physical activity. A range describing the upper and lower bound estimates is included.
Medical Cost Savings from Prevented Illnesses	The estimated medical expenses saved (based on treatment costs) due to reductions in morbidity associated with increased physical activity. A range describing the upper and lower bound estimates is included.

All health-related estimates include upper and lower bounds to describe the range of potential health effects. These upper and lower bounds represent estimates calculated using the estimated upper and lower confidence bounds (95^{th} percentile confidence interval) for the relative risks associated with morbidity and mortality effects. As a result, these upper and lower bound estimates should represent a 95^{th} percentile confidence interval for an average change in physical activity.

Guidelines for Interpreting Results

1. Ranges should always be used when describing output data from this sketch planning tool. These ranges help frame the context in which the estimates are provided and encourage careful consideration in their application.

2. The health effects are only calculated for trips starting at each transit facility. As a result, this analysis estimates the health effects for the trips between the trip origin and a transit facility (e.g., from home to transit, from transit to home), but it does not account for the health effects for the subsequent trips between another transit facility and the trip destination (e.g., from transit to work, from work to transit). As a result, analyzing a single transit facility should produce a very conservative estimate of the health benefits, but analyzing all facilities in a transit network will provide a best-quality estimate. As the percentage of stations in the transit network being analyzed approach 100%, the estimate will become less conservative.

3. It is important to note that there is no correction for the existing level of physical activity in the population being analyzed. Research has shown that, if a group of individuals already undertake a high level of physical activity, they see fewer health benefits associated with an incremental increase in activity compared with individuals with lower levels of physical activity. As a result, this analysis methodology is not intended to evaluate health benefits for a very active study group. Ridership populations with very high levels of existing physical activity (e.g., more than six hours of physical activity per week) may produce unreliable health benefit estimates.
4. When analyzing the effects of a treatment, it is possible to overestimate the health/environmental effect due to the estimated change in travelers using the station. In this case, to prevent overestimating health and emissions benefits, the number of trips reported after the treatment should only include the additional trips which are assumed to be caused by the treatment. This can be easily accommodated when using estimates for testing, but the effect can also potentially be accounted for in measured data by considering the effects of ridership time-series trends.

METHODOLOGY & MODELING ASSUMPTIONS

Health Assessment

As mentioned above, this spreadsheet tool adopts a simplified HIA methodology based on the HEAT developed by the World Health Organization (WHO, 2014) and a HIA conducted in Barcelona, Spain (Rojas-Rueda et al., 2013). Generally, these methodologies estimate the change in health effects associated with increased physical activity by calculating a protective benefit. The protective benefit is a combination of the preventive fraction (PF) and a ratio of the exposure to a baseline exposure.

$$Protective\ Benefit = (1 - RR)\left(\frac{Exposure}{Baseline\ Exposure}\right)$$

The PF (1 – RR) describes the percentage of cases which can be prevented due to exposure to increased physical activity (measured in Metabolic Equivalent Tasks, or METs). In this case, the relative risk is the ratio of probability of disease/death in the exposed population (receiving a baseline MET exposure) to the probability of disease/death in the non-exposed population (not receiving the baseline MET exposure). The risk ratio is estimated by epidemiological studies for a specified baseline exposure of physical activity.

The HEAT model assumes a linear relationship between the exposure and the preventive effect. This means that for each increase in physical activity equivalent to the baseline exposure, there is a (1 – RR) percent decrease in disease/death incidence. In order to prevent estimating unreasonable changes in disease/death incidence, the percent decrease in incidence is typically limited to 30%-50%.
To calculate the number of lives saved or diseases prevented, the incidence rate is multiplied by the Protective Benefit.

$$Diseases\ or\ Deaths\ Prevented = (Incidence\ Rate)(Protective\ Benefit)$$

Exposure is related to walking and bicycling based on distance. This spreadsheet tool uses the following conversion rates to translate walking and bicycling distances to METs.

Walking = 1.341 METs/Mile	Bicycling = 0.782 METs/Mile

Methodological Inputs

Table A.1 Relative Risk Estimates from Epidemiological Literature

Relative Risk	**Low CI**	**Average**	**High CI**	**MET Reference (per Week)**	**Source**
Mortality (Walking)	0.83	0.89	0.96	11.25	WHO (2013)
Mortality (Bicycling)	0.87	0.9	0.94	11.25	WHO (2013)
Cardiovascular Disease	0.79	0.84	0.9	7.5	Hamer and Chida (2008)
Type 2 Diabetes	0.75	0.83	0.91	10	Jeon et al. (2007)

Table A.2 Estimated Disease and Death Incidence Rates

Incidence Rate	**Rate (per 100,000)**	**Year**	**Source**
Crude Mortality Rate	540	2012	Utah Department of Health (2013)
Cardiovascular Disease	229	2011	Centers for Disease Control and Prevention (2011)
Diabetes	700	2010	Centers for Disease Control and Prevention (2010)

Table A.3 Economic/Social Costs of Death and Medical Conditions, Adjusted to 2014 Dollars using Consumer Price Index (CPI)

Cost	**Year**	**Value**	**2014 Value**	**Source**
Value of Statistical Life	2014	$ 9,200,000	$ 9,200,000	Rogoff & Thomson (2014)
Cost of hospital admission for Ischemic Heart Disease	2000	$ 32,452	$ 44,858.20	Abt Associates Inc. (2012)
Cost of medical treatment per person attributable to Diabetes	2013	$ 7,888	$ 8,177.86	American Diabetes Association (2013)

Environmental Assessment

Environmental benefits are quantified in terms of the mass of different air pollutants. The mass of an air pollutant is calculated using the estimated VMT and the average per-mile emission rate for the pollutant, as shown in the equation below. The average per-mile emission rates used in the spreadsheet are shown in Table 4.4 below.

$$Emissions_{Pollutant} = VMT \times Avg.\ Operating\ Rate_{Pollutant}$$

Table 4.4 Average Per-Mile Emission Rates for Gasoline-Fueled Passenger Cars & Light Trucks (EPA, 2008)

Average Emission Rate	**Gram/Mile**	**Average Emission Rate**	**Gram/Mile**
VOC	1.034	PM10	0.0044
THC	1.077	PM2.5	0.0041
CO	9.4	CO2	368.4
NOx	0.693		

To calculate the emission reductions due to transit use, we estimate the VMT reduction associated with transit users based on their trip length and travel mode to the station. By calculating the emission reductions for the Before Treatment and After Treatment conditions, the change in emissions due to any kind of treatment will be the difference between those emission reductions.

$$Net\ Emissions_{Pollutant} = Emissions(After\ Treatment)_{Pollutant} - Emissions(Before\ Treatment)_{Pollutant}$$

REFERENCES

Abt Associates Inc. (2012). BenMAP: Environmental Benefits Mapping and Analysis Program: User's Manual: Appendices. Available: http://www.epa.gov/airquality/benmap/docs.html [accessed 9 July 2014].

American Diabetes Association. (2013). Economic costs of diabetes in the US in 2012. Diabetes Care, 36(4), 1033-1046.

Centers for Disease Control and Prevention. (2011). National Environmental Public Health Tracking Network. Available from http://ephtracking.cdc.gov/

Centers for Disease Control and Prevention. (2010). National Diabetes Surveillance System. Available from http://www.cdc.gov/diabetes/statistics

EPA. (2008). *Emission Facts: Average Annual Emissions and Fuel Consumption for Gasoline-Fueled Passenger Cars and Light Trucks*. (EPA420-F-08-024). Office of Transportation and Air Quality, United States Environmental Protection Agency.

Hamer, M., & Chida, Y. (2008). "Walking and primary prevention: a meta-analysis of prospective cohort studies." *British Journal of Sports Medicine*,*42*(4), 238-243.

Jeon, C. Y., Lokken, R. P., Hu, F. B., & Van Dam, R. M. (2007). "Physical Activity of Moderate Intensity and Risk of Type 2 Diabetes A systematic review." *Diabetes Care*, *30*(3), 744-752.

Rogoff, P. & Thomson, K. (2014). *Guidance on Treatment of the Economic Value of a Statistical Life – 2014 Adjustment*. Washington, DC: U.S. Department of Transportation. Retrieved from http://www.dot.gov/sites/dot.gov/files/docs/VSL_Guidance_2014.pdf

Rojas-Rueda, D., de Nazelle, A., Teixidó, O., & Nieuwenhuijsen, M. J. (2013). "Health impact assessment of increasing public transport and cycling use in Barcelona: A morbidity and burden of disease approach." *Preventive Medicine*, *57*(5), 573-579.

Utah Department of Health, Center for Health Data and Informatics. (2013). *Utah's Vital Statistics: Births and Deaths 2012*. (Technical Report No. 283). Salt Lake City, UT: Office of Vital Records and Statistics. Retrieved from http://health.utah.gov/vitalrecords/2012bx_Final_122013.pdf

World Health Organization. (2013). *Development of the health economic assessment tools (HEAT) for walking and cycling*.

World Health Organization (2014). *Health economic assessment tools (HEAT) for walking and for cycling: Methods and user guide, 2014 update: Economic assessment of transport infrastructure and policies*.