Multimodal Trip Reduction Rates for Traffic Impact Analysis

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16. Abstract

The research aims to develop vehicle trip reduction rates for Traffic Impact Analysis (TIA) reviews by collecting and analyzing data from 21 sites across nine cities in North Carolina. Factors such as land use, infrastructure density, and proximity to trip generators guided the selection of sites. Data collection utilized ground-based cameras, manual counting, and mobile device data to capture variations in travel behavior.

Overall, 85.7% of all trips observed were made by vehicles, with walking (13.6%) as the most common non-auto mode. Public transit and cycling were minimally observed. A comparison of field data and Institute of Transportation Engineers (ITE) trip generation estimates found that field data reported fewer trips, especially in the AM, reflecting localized variations in travel behavior not captured by ITE data and models. The study also identifies proximity to the central business district (CBD) as a significant factor influencing multimodal usage and walkability. Sites with higher Walk Scores (between 50 and 90) exhibited more multimodal activity. Locations with higher walkability and those closer to or within the CBD are more likely to have a higher proportion of non-auto trips, while more remote areas with lower Walk Scores tend to rely less on multimodal trips. These findings underscore the importance of built-environment characteristics in promoting sustainable, multimodal transportation and provide recommendations for incorporating multimodal considerations into TIA reviews.

The research team recommends considerations of the Walk Score and location relative to the Central Business District (CBD) for sites being reviewed for a TIA. As a continuous variable on a scale of 0 to 100, the Walk Score showed promise as an indicator of multimodal trips in the sites evaluated for this study. As an example of Walk Score and non-auto trip percentages, at the four sites with Walk Scores rounded to 50, the non-auto percentage was 8% (AM) and 11% (PM), while the five sites with Walk Scores rounded to 90, the non-auto percentage was 32% (AM) and 31% (PM). Considering the locations relative to the CBD as a binary variable of proximity to the CBD, the average non-auto percentage observed was 27% (AM) and 30% (PM) for sites in or adjacent to the CBD, and 6% (AM) and 8% (PM) for sites outside or not adjacent to the CBD. To refine these estimates, the research team also recommends additional data collection at sites in and adjacent to CBDs to expand on the 11 sites observed in this study.

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Executive Summary

The North Carolina Department of Transportation (NCDOT) requires a Traffic Impact Analysis (TIA) for developments that meet a minimum threshold to assess the potential traffic impacts and mitigation needs based on trip generation estimates. Accurate trip generation is critical for site planning, particularly in areas with multimodal transportation options. Recent TIAs have included vehicle trip reductions in areas with multimodal options, but there is limited documentation on appropriate reduction rates in North Carolina. Multimodal trip generation, which integrates multiple forms of transportation, including auto (vehicles) and non-auto (walking, cycling, public transit, and driving), is an essential consideration for development review and impact analysis.

This study focuses on multimodal trip generation, analyzing walking, cycling, public transit, and driving to better understand how these modes influence travel behavior. The research aims to refine auto trip reduction rates for NCDOT in its review of TIAs by examining observed data from 21 sites across nine cities in North Carolina. Key factors like land use, infrastructure density, and proximity to trip generators were considered in site selection. Data were collected using ground-based cameras, manual counting, and mobile device data.

Key findings highlight distinct differences in trip making during AM and PM peak periods. The AM period had fewer trips, with a higher percentage of autos entering office buildings or retail-oriented sites, while the PM period recorded increased trips as autos exited, indicating greater vehicular departures. Despite some use of multimodal transportation, 85.7% of all trips were made by auto, with walking (13.6%) being the most common alternative mode. Public transit and biking were less commonly observed. A comparison of field data and Institute of Transportation Engineers (ITE) Trip Generation estimates revealed that the field data reported fewer trips, especially in the AM, suggesting that localized trip making variations are not fully captured by standard models.

The study concludes that proximity to the Central Business District (CBD) significantly influences multimodal transportation and walkability. Proximity to the CBD correlated with higher multimodal use and walkability, while suburban areas were more reliant on personal vehicles. Walk Scores also positively correlated with multimodal percentages, particularly in the PM period. Locations with Walk Scores between 50 and 90 generally exhibited non-auto percentages above 20%, whereas sites with scores below 50 saw much lower non-auto usage. These findings emphasize the importance of built-environment characteristics in promoting sustainable transportation options and inform recommendations for incorporating multimodal considerations into TIA reviews.

Table of Contents

List of Tables

List of Figures

1. Introduction

1.1 Background

In North Carolina, the North Carolina Department of Transportation (NCDOT) requires a Traffic Impact Analysis (TIA) for some developments based on the site trip generation estimates, site context, or at the discretion of the NCDOT District Engineer. An accurate TIA is essential to appropriately plan for a specific development and its expected impacts, along with any relevant mitigation factors. Many aspects of the TIA build on the trip generation estimates, which means that the trip generation process of a TIA is a critical component and receives substantial attention and review from both NCDOT and the developer.

The typical TIA methodology is to estimate impacts that new developments will have on the surrounding roadway network based on expected new traffic entering and exiting the development at daily or hourly levels of analysis. In general, it is assumed that new developments will induce traffic, thus a "trip generation rate" is applied for TIA studies. The standard TIA methodology consists of a few steps but can vary between states, counties, and municipalities. Traffic counts are performed to establish a baseline existing traffic condition. These existing traffic volumes are then grown at a certain rate to account for growth in traffic due to general traffic growth in the area. The growth rate is typically agreed upon by the preparer of the TIA and the review organization. Additionally, the projected traffic from TIAs performed for other nearby developments are added on top of this background growth. All of these traffic volumes are added together to establish a future year baseline traffic condition. This future year baseline condition does not include the projected site traffic from the development of interest. Finally, trips are estimated for the development based on the proposed land use intensities (number of residential units, office square footage, retail square footage, hotel rooms, etc.) and rates provided by the Institute of Transportation Engineers (ITE) for various land uses to determine how much traffic is expected to enter and exit the new development. The primary purpose of trip reduction programs is to give commuters alternative options to reduce single occupancy automobile trips by offering resources, incentives, or disincentives to stimulate carpool or public transport usages. Trip reduction strategies work to reduce the impacts of traffic on air pollution, greenhouse gas emissions, and congestion through the development, implementation, and maintenance of a trip reduction program.

1.2 Problem Statement

As North Carolina's population continues to urbanize (over half of the state's population was living in only 13 of the state's 100 counties and 99% of the state's growth is projected to occur in counties that belong to either metropolitan or micropolitan areas), more development is occurring in locations with multimodal options (such as transit and bicycle/pedestrian facilities). As a result, auto trips may be reduced by developments in locations with multimodal options as compared to developments without these options. In current practice, there are several issues with estimating and applying multimodal trip generation/reduction rates *(De Gruyter 2019)*, including but not limited to: the lack of sufficient multimodal trip generation data particularly with non-auto modes, standardization of multimodal trip generation data collection methods, validation of the accuracy of multimodal trip generation estimates in TIAs, etc. Although recent TIAs in these locations commonly include auto trip reductions, a thorough documentation and examination of reasonable auto trip reduction rates is not available in North Carolina.

1.3 Objectives and Scope

This research aims to assist NCDOT by developing a better understanding of the application of auto trip reduction rates for sites with probable multimodal usage in the context of a TIA. Using data from North Carolina sites, the research provides estimates of auto trip reduction rates for sites with probable multimodal usage (based on common location types with expected trip reduction requests in TIAs). Specifically, the objectives of this project include the following:

- Develop a better understanding of the application of auto trip reduction rates for sites with probable multimodal usage in the context of Traffic Impact Analysis (TIA)
- Using data from North Carolina sites, estimate auto trip reduction rates for sites with probable multimodal usage for the application of auto trip reduction rates for NCDOT in the review of TIAs (based on common locations with trip reduction requests)
- Recommendations for the application of auto trip reduction rates for NCDOT in the review of TIAs
- Recommendations for NCDOT and municipalities who may be intentionally focused on designs and developments that encourage multimodal transportation uses and options in their planning and land use processes

2. State-of-the-Practice

2.1 Multimodal Trip Generation Studies

In current practice, there is no commonly accepted methodology in the U.S. for estimating multimodal trip-generation rates, which makes it challenging for practitioners to accurately estimate the traffic impacts of mixed-use developments that involve walking, biking, and transit facilities. The *ITE Trip Generation Manual (2021)* has been widely used as the industry standard for predicting trips that would be produced by or attracted to a particular land use. ITE provides guidance on how to estimate internally-captured traffic within the development. Internal capture represents trips between different use types within the development (i.e., residential and retail). These internally-captured trips are subtracted from the overall total new trips entering and exiting the site since they only enter the site once but visit at least two uses within the site. Another reduction is taken for what is called a “pass-by trip,” which is a vehicular trip that is already on the adjacent road system that is anticipated to now enter and exit the site. The assignment of site trips to the street network is typically based on existing traffic patterns, location of complementary land uses (i.e., location of employment centers for new residential development), routes to highways/freeways, and other available information. However, it represents auto trip rates in areas with single-use, low density zoning and land uses, typically with limited or no pedestrian, bicycle and/or transit amenities. By following existing guidelines which typically are only applicable in contexts where auto access is the dominant mode, transportation engineers often over-prescribe automobile infrastructure in such locations, resulting in wider roadways, more turning lanes, and more parking spaces than necessary. In addition, there is a lack of an established approach to recommend adequate pedestrian, bicycle, or public transit facilities that may improve conditions for travel by these modes.

Currently, multimodal transportation systems have gained significant attention as a means to reduce reliance on single-occupancy autos and mitigate traffic congestion, air pollution, and energy consumption. One important aspect of evaluating the effectiveness of multimodal transportation initiatives is the measurement of multimodal trip reduction rates, which can be challenging due to various factors, including data availability, survey methods, and the complexity of behavioral change. Moreover, the effectiveness of multimodal transportation initiatives can be influenced by factors such as land use patterns, accessibility, and the integration of various transportation modes within a region.

The most recent edition of the ITE Trip Generation Manual is addressing the need for comprehensive data on multimodal trip generation rates, aiming to bridge this existing gap in the transportation literature. To provide insights into multimodal travel rates, Table 1 offers a concise overview of the multimodal trip generation rates associated with different land use categories, shedding light on the diverse transportation patterns observed in varying urban contexts.

Table 1. ITE Trip Generation Rates for Various Land Use Categories

Land Use Category	Land Use Code	Trip Generation Rates (Per 1000 Sq. Ft. GFA)			
		Vehicle	Pedestrian	Bike	Transit
Port and Terminal					
Intermodal Truck Terminal	30	2.14	-	-	-
Park-and-Ride Lot	90	1.77	-	-	-
Residential					
Single-Family Attached Housing	215	0.52	0.11	0.01	-
Multifamily Housing (Low-Rise)	220	0.38	0.03	0	0
Multifamily Housing (Mid-Rise)	221	0.48	0.05	0	0.01
	221 CTR	0.58	0.12	0.01	0.02
Multifamily Housing (High-Rise)	222	0.34	0.09	0.01	-
	222 CTR	0.38	0.16	0.01	-
Affordable Housing	223	1.97	-	-	-
Off-Campus Student Apartment (Low-Rise)	225	-	0.15	-	-
Off-Campus Student Apartment (Mid-Rise)	226	-	0.16	-	-
Low-Rise Residential with Ground-Floor Commercial	230	2.17	0.34	0	0.92
	231 (1-25k)	-	0.1	0.01	0.11
	231 (25-65k)	-	0.16	0.01	0.24
Senior Adult Housing - Multifamily	252	0.45	-	-	-
Congregate Care Facility	253	0.32	-	-	-
Lodging					
Business Hotel	312	0.74	0.01	-	-
Recreational					
Golf Course	430	2.11	-	-	-
Bowling Alley	437	1.73	0.03	-	-
Bingo Hall	470	0.23	0	-	-
Racquet/Tennis Club	491	1.47	-	-	-
Health/Fitness Club	492	2.53	0.27	-	-
Recreational Community Center	495	2.32	0.03	-	-

Note: Sq. Ft. GFA = Square Feet of Gross Floor Area

In addition to the ITE manual, a number of follow-up studies have been conducted to include multimodal trip generation rates at mixed-use developments.

Handy et al. (2013) developed a tool to estimate multi-modal trip generation rates for proposed smart-growth land use development projects in California, which included three key steps: the identification and evaluation of existing tools, the development and implementation of a data collection methodology, and the development of the trip generation method. Field data such as the mode, time of day, origin and destination, length of trips, vehicle occupancy, were collected at smart growth development locations with a single land use via a combination of door counts and intercept surveys. It was found that in comparison with the traditional methods that count automobiles entering and exiting access points, the proposed method is more suitable in urban areas with mixed-use developments, mixed-use buildings, and a variety of parking arrangements. In summary, at the study locations, 27% of the person-trips were made by walking, 21% by transit, and 3% by bicycle.

Westrom et al. (2017) proposed a model for calculating urban trip generation from mixed-use developments that includes both trip rate overall and trip rate by mode. The model considers elements that are site-specific and sensitive to the local environment. It first calculated total person trips independently of mode choice; and then calculated the mode choice with sensitivity to the amount of on-site parking. Using data from the District Department of Transportation, the model was proven to more accurately estimate the anticipated trip generation from proposed developments and the impacts that it would have on the transportation system.

De Gruyter (2019) presented a global analysis of multimodal trip generation related to land use development through literature review. The synthesis identified several problems in estimating and applying multimodal trip generation rates, and pointed out major directions to steer future practice and policy in the area of multimodal trip generation, including: 1) a fundamental paradigm shift to recognize the necessity of systematically accounting for the origination of multimodal trips; 2) creating a global trip generation database for multimodal transportation; 3) move to the use of multimodal trip generation rates in TIAs is needed; 4) developing more sensitivity testing and scenario planning to estimate the transportation consequences of new land use developments due to the substantial of variability in trip production rates.

Another study by *De Gruyter et al. (2021)* further investigated the various site factors that influence the rates at which multimodal trips are generated at residential projects. Using trip generation data from 933 residential developments in the United Kingdom and Ireland, the research examined the relationship between site features and multi-modal trip generation rates by mode and time period. Results showed that the key factors that affect multi-modal trips include geographic and housing characteristics like apartment developments and housing size, population density, car ownership, distance to neighborhood amenities like the closest corner store, quality of the public transportation service, on-site parking spaces/dwellings, as well as various travel plan initiatives.

The ITE Multimodal Transportation Impact Analysis for Site Development (MTIASD) *(ITE, 2023)* provides key considerations for practitioners preparing multimodal transportation impact analysis as well as new approaches for agencies to proactively plan for multimodal transportation when reviewing site developments. The MTIASD recommended practice updates the transportation impact analysis guidelines to incorporate considerations for walking, bicycling, and public transit in transportation impact studies in addition to autos. The update is intended to provide the user with a broader overview of key considerations for complex topics in identifying and mitigating multimodal transportation impacts. This publication also describes the effect of site layout and design on multimodal travel demand, impacts of projected motor vehicle trips on safe and convenient transit and human-powered transportation, trip-reduction tools, and peak spreading.

Based on the review of the multimodal trip reduction studies, a summary of the methodologies for collecting and analyzing multimodal trip data as well as major findings from each study is presented in Table 2. In summary, the literature indicates that multimodal trip reduction rates achieved through the promotion of alternative transportation modes vary across different programs and contexts. Further research and evaluation are needed to better understand the factors that contribute to successful multimodal transportation programs and to develop more accurate measurement methodologies for trip reduction rates.

Table 2. Summary of Multimodal Trip Reduction Studies

Study	Area / Region	Survey Method	Modeling Approach	Findings
Handy et al (2013)	USA	Combination of door counts and intercept surveys	Linear regression equations	Addressed the need for a methodology that practitioners can use to estimate multimodal trip-generation rates for proposed smart-growth land use development projects
Westrom (2017)	USA	Intercept survey	Multimodal accessibility (MMA) and the District DOT MXD+ method	Person trip observations in Washington, D.C. were significantly (30% to 50%) higher than the limited person trip data presented in the ITE vehicle trip generation resources
De Gruyter (2019)	Worldwide	Literature	State-of-the-practice review	Recommended to consistently account for multimodal trip generation and develop an international multimodal trip generation database
De Gruyter et al. (2021)	UK and Ireland	Online database of trip generation data	Bivariate analysis and Multivariate analysis	Multi-modal trip generation rates are associated with a range of site characteristics at residential developments
ITE (2023)	Worldwide	Literature	State-of-the-practice review	Collection techniques in travel surveys

2.2 Trip Generation Data Collection

This section summarizes the literature related to trip data collection for trip generation models and a review of the key context variables that affect trip generation and mode split. The available tools for predicting travel impacts of urban development are not as reliable as they could be. DOTs have relied on a variety of data sources, including Institute of Transportation Engineers' (ITE) trip generation rates, Census data, etc. when assessing the impact of a new development on the transportation system. It has been consistently shown that even when put together, these sources fail to provide a perfectly precise estimate of a development's trip generation due to a variety of underlying reasons and issues.

Recently, *Mukherjee and Kadali (2022)* provided a comprehensive review of studies related to the impact of land use on trip rates, data collection techniques and modeling approaches, major challenges associated with the modeling of trip generation included the unavailability of standard reference databases for multimodal trip generation, consideration of land use changes, full consideration of machine learning modeling approaches, and the feasibility of using emerging data collection techniques in travel surveys. In summary, a significant variation in travel behavior was observed for different land use characteristics, and the quantification of land use and its evolution over time is a serious challenge for researchers and practitioners.

Drawing upon an extensive review of the existing literature, a summary of the methodologies employed to collect and analyze trip generation data, alongside the prominent findings derived from each study, is compiled and presented in Table 3. This comprehensive synthesis not only exposes the diverse approaches adopted in studying trip generation but also offers a consolidated view of the significant outcomes and key insights gleaned from these comprehensive investigations.

Table 3. Summary of Trip Generation Data Collection and Modeling Methodologies

Study	Area / Region	Survey Method	Modeling Approach	Findings
Srinivasan and Roger (2005)	India	Face-to-face interview	Discrete choice	The frequency of travel was influenced by the location
Greenwald (2006)	USA	Household travel survey	Multinomial logit	With an increase in retail activity in the home zone, fewer journeys are anticipated
Sillaparcharn (2007)	Thailand	Census data	Comparative analysis	The trip prices were determined to be comparable to those specified in the USDOT
Guevara and Thomas (2007)	Chile	Origin-Destination survey	Multiple Classification analysis (MCA)	MCA models can be used to simulate the generation of trips
Bochner et al. (2011)	USA	Intercept survey	Internal Capture Estimation Methodology	This research provided recommendations for modifications to existing ITE procedures
Mirmoghtadaee (2012)	Iran	Questionnaire	Comparative analysis	Lane use features provide a more accurate forecast of travel demand
Shay and Khattak (2012)	USA	Computer-assisted telephone interview	Negative binomial regression model	Increased total trips as a result of walkability and accessibility
Silva et al. (2012)	Portugal	Web-based survey	Structural equation model	Land use has a considerable impact on travel behavior
Schneider et al. (2013)	USA	Door counts and intercept surveys	ITE method	Total person trip generation at the smart-growth study locations was similar to those estimated from ITE data; Larger shares of person trips were made by walking, bicycling, or public transit.
Calabrese et al. (2013)	USA	Mobile phone trace data	Multivariate regression	The average journey rate for weekdays and weekends was determined
Clifton et al. (2013)	USA	Intercept survey	Regression	Incorporating land use variables improves accuracy
Gulden et al. (2013)	USA	Manual count	Regression	The reduction in car trips ranges from 6.3 to 7.9% due to mixed land use
Wang (2013)	USA	DOT Database	Recursive SEM	Significant effects were observed for land use, job density, and intersection density
Weinberger et al. (2014)	Worldwide	Literature	State-of-the-practice review	Limited data on urban, multimodal trip generation at the individual site level; Developed a protocol for collecting trip generation by mode at the site level.
Ma et al. (2014)	China	HTS	Ordered logit model	There is a strong link between socio-demographic characteristics
Subbarao and Rao (2014)	India	Travel activity diary information	Multivariate analysis	Demographic factors have an impact on travel decisions
Tian et al. (2015)	USA	Regional HTS	Hierarchical modelling approach	Internal trips accounted for 19.7% of all developed trips
Colak et al. (2015)	Brazil	Call record data (CDR)	n/a	CDR provides precise estimates of trip production and attraction
Izanloo et al. (2017)	Iran	O-D Survey	Multivariate regression	The impact of land use was found to be significant

Study	Area / Region	Survey Method	Modeling Approach	Findings
Dibaj et al. (2017)	Iran	Questionnaire	Multivariate analysis	Walking trips was found to be the most common
Ewing et al. (2017)	USA	Intercept survey	Comparative analysis	Reduction in trips observed because of transit oriented development
Jayasinghe et al. (2017)	Sri-Lanka	Literature	Multivariate analysis	Trip attraction rates were significantly influenced by land use
Molla et al. (2017)	USA	O-D survey	Multinomial logit	Models based on activities can more accurately reflect travel behavior
Salini et al. (2017)	India	HTS	Fuzzy C-mean and fuzzy subtracting	Fuzzy subtracting model showed better performance in forecasting trips
Sun and Yang (2017)	China	Intercept survey	SEM	The most major influence on commuting is the occupation
Tian and Ewing (2017)	USA	HTS	Negative binomial hurdle model	Sociodemographic characteristics are found to be significant predictors
Currans and Clifton (2018)	USA	ITE database	Regression	Significant variation in trip rates observed with age
Hong and Thakuriah (2018)	UK	HTS and application based data	Comparative analysis	Auto travels increase as household size grows, but Public Transport trips decrease
Pani et al. (2018)	India	Face to face Interview	Linear regression	Employment based model performed better in dense area
Shams et al. (2018)	USA	HTS	Multinomial logit	Significant change in travel behavior was observed with socio-economic characteristics
Clifton and Currans (2019)	USA	Intercept survey and archived transportation counts	Multivariate statistical methods	For mixed-use sites, limited information to capture a significant relationship between vehicle or person trip rates and a range of built environment variables
Tian et al. (2019)	USA	Travel diary data	Multilevel logistic regression model	Density, demographics, and distance to transportation have a significant impact on the trips created
Zhang et al. (2019)	USA	HTS	Negative binomial regression	Measures of the built environment had a favorable impact on trip generation
Ahmed et al. (2020)	Bangladesh	Intercept Survey	Regression	The highest rates were in commercial and healthcare land use type
Mukherjee and Kadali (2022)	Worldwide	Literature	State-of-the-practice review	Challenges in modeling trip generation included the unavailability of data for multimodal trip generation, consideration of land use evolvement, less explored machine learning modeling approaches, and the feasibility of using emerging data collection techniques in travel surveys

(Courtesy: Adapted from Mukherjee and Kadali, 2022)

3. Data Collection

Trip generation data collection methodologies are essential for understanding the trip generation characteristics for a particular land use, development, subarea. These methodologies are used to estimate the number and types of trips a site will generate, often for transportation planning, traffic impact studies, and urban development projects. The data collection supporting this research started with the identification of representative sites with characteristics expected to affect multimodal trip generation, and then employed various methods for trip generation data collection.

3.1 Site Selection

The research team coordinated with the NCDOT steering committee and was informed with other relevant information from the literature review to select sites that provide sufficient variation in the types of locations consistent with multimodal trip generation in North Carolina. A variety of built-environment characteristics informed the site selection and was included as data collection/analysis factors.

Based on this knowledge, the selection of field data collection sites considered the following development characteristics and/or environmental factors:

- Development/land use type (e.g., single land use, multi-land uses)
- Density and availability of pedestrian, bicycle, and transit infrastructure
- Presence of trip generators/attractors in the vicinity of the sites
- Availability and prevalence of parking
- Steering committee input and literature review guidance

A total of 21 sites from 9 cities in North Carolina were visited for field data collection. An overview of the visited sites is illustrated in Figure 1, along with a detailed description of the development name and land use attributes of each site in Table 4. A more precise location of each site is presented in Appendix A.

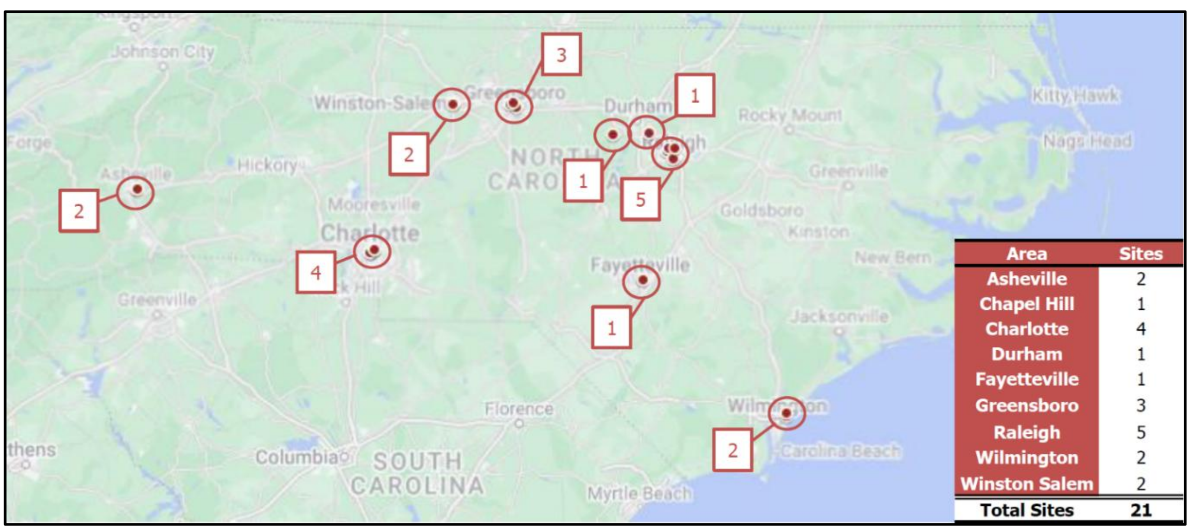


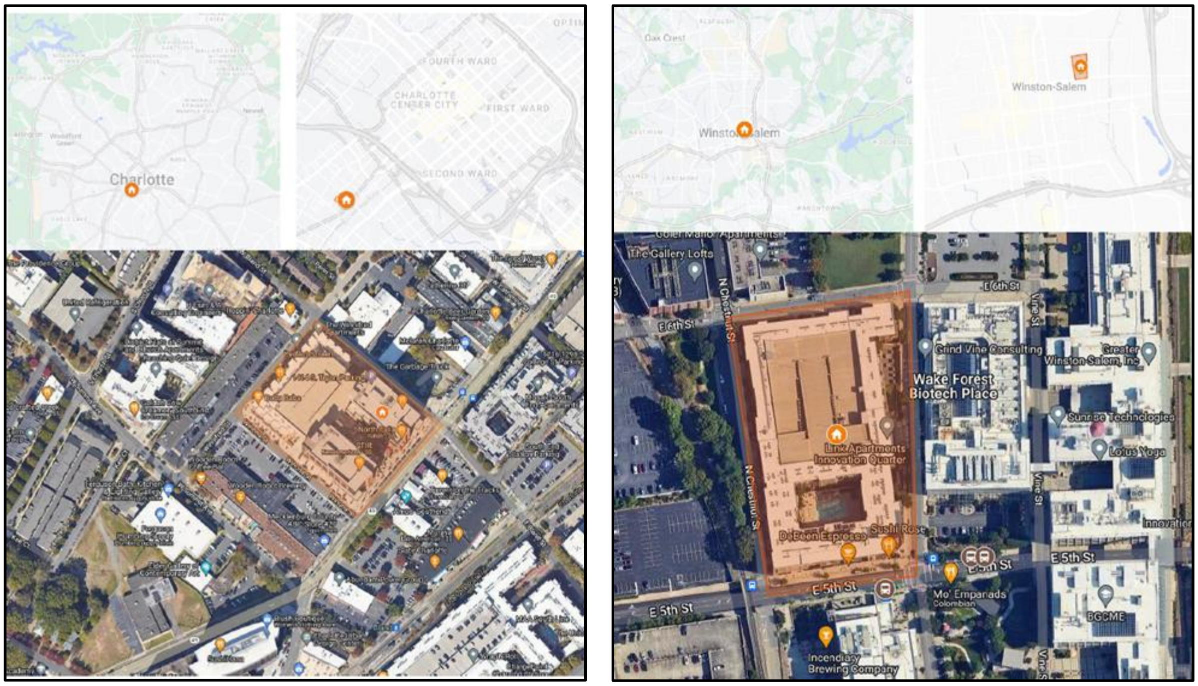
Figure 1. Overview of Field Data Collection Sites

Table 4. Development Type and Characteristics of Each Site

City	Name of the Development	Land Use Type		Site Characteristics			
		Site Specific	Surrounding Area	Gross Floor Area (1,000 SqFt)	On-site Parking Spaces	Bus/Light Rail Stops	Walking Attractions
Asheville	The Patton	Mixed	Mixed	150	Yes, with parking garage	Yes	Public schools, Museums, Grocery stores, Ashville visitor center
	55 Market	Residential	Mixed	75	Yes, with parking garage	Yes	Parks and Gardens, Grocery stores,
Chapel Hill	Berkshire 54	Residential	Mixed	272	Yes, about 450 spaces	Yes	Shopping plaza; Parks and greenways
Charlotte	Uptown 550	Mixed	Mixed	560	Yes, with parking garage	Yes	Public schools, Parks, Stadium, Grocery stores
	RailYard South End	Mixed	Mixed	329	Yes, with parking garage	Yes	Parks, Stadium, Grocery stores, Public schools, Churches
	Optimist Hall	Commercial	Mixed	147	Yes, about 120 spaces	Yes	Parks and greenways, Grocery stores, Restaurants
	Cortland NoDa	Residential	Mixed	350	Yes, with parking garage	Yes	Parks and greenways, Grocery stores, Restaurants
Durham	Amazon RDU5	Commercial	Commercial	325	Yes, about 200 spaces	Yes	N/A
Fayetteville	Cross Creek Pointe	Residential	Mixed	380	Yes	Yes	Parks and greenways, Grocery stores, Restaurants
Greensboro	Greenway at Fisher Park	Residential	Mixed	180	Yes, about 300 spaces	Yes	Grocery stores, Restaurants, Greenway, Stadium Park
	Hawthorne at Friendly	Residential	Mixed	245	Yes, with parking garage	Yes	Shopping plaza, Botanical Garden
	Kirkwood Place	Mixed	Mixed	80	Yes, about 150 spaces	Yes	Shopping plaza
Raleigh	Lake Boone	Commercial	Mixed	32	Yes, about 500 spaces	Yes	Hospital, Restaurants, Art Museum, Grocery stores
	Crabtree Commons	Mixed	Mixed	500	Yes, one garage per unit plus visitor parking	Yes	Shopping plaza, Elementary school, Business offices
	The Dillon	Mixed	Mixed	422	Yes, with parking garage	Yes	Park, Grocery stores, Restaurants, Museums
	Fairweather Condos	Mixed	Mixed	80	Yes, with parking garage	Yes	Park, Grocery stores, Restaurants, Museums
	North Hills East	Mixed	Mixed	1,715	Yes, with parking garage	Yes	Shopping plaza, Grocery stores, Restaurants
Wilmington	Mayfaire Flats	Residential	Mixed	304	Yes, about 160 spaces	No	Shopping plaza
	Arboretum Village	Residential	Mixed	150	Yes	Yes	Grocery stores, Restaurants, Parks
Winston Salem	Link Apts. Innovation Qtr.	Mixed	Mixed	356	Yes, with parking garage	Yes	Restaurants, Greenway
	The Easley	Residential	Mixed	310	Yes, with parking garage	Yes	Grocery stores, Stadium Park, Restaurants

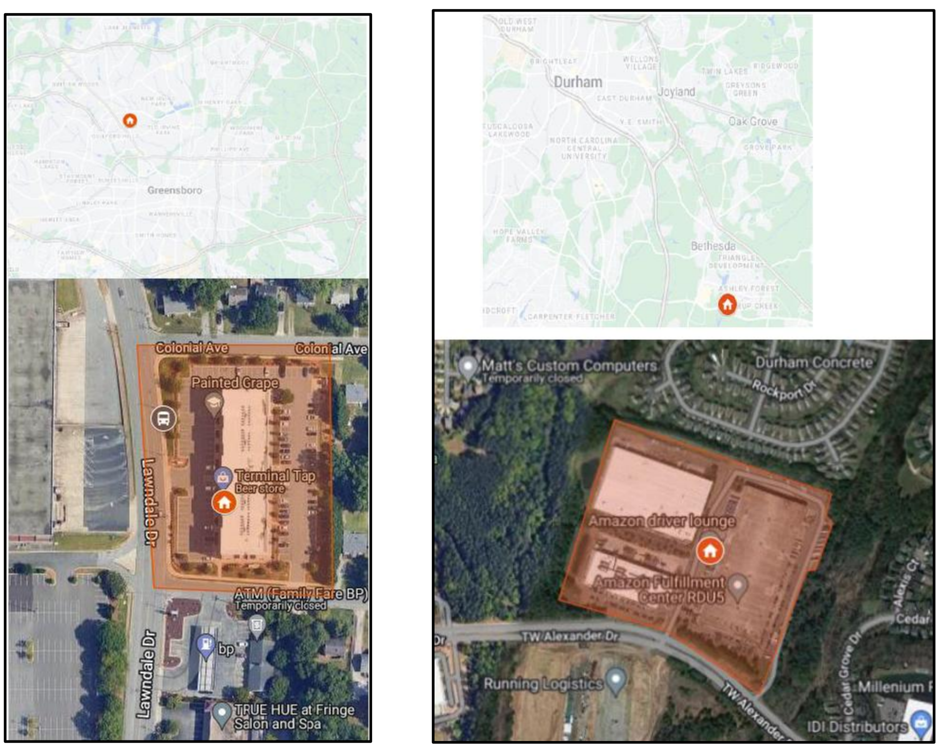
Data collection sites with an expectation of high and low trip reduction rates were included in the sample. High trip reduction sites are specific land uses, locations, or developments where the number of auto trips generated is expected to be lower than the typical rates for similar uses. This is due to the incorporation of various factors that encourage non-automobile travel modes or reduce the reliance on personal autos. The purpose of recognizing high trip reduction sites is to adjust traffic estimates and develop strategies for mitigating traffic impacts more accurately. Typical factors that contribute to a site being considered a high trip reduction site include mixed-use development, proximity to public transit, pedestrian and bicycle-friendly facility, traffic demand management strategies such as parking restrictions, urban vs. suburban locations, etc. In practice, these factors are accounted for by adjusting the trip generation rates for the site, often using lower rates than the typical values provided by sources like the Institute of Transportation Engineers (ITE) Trip Generation Manual to ensure that the traffic analysis better reflects actual conditions. Examples of high trip reduction sites are illustrated in Figure 2.

In comparison, low trip reduction sites are locations or developments where the potential to reduce auto trips is expected to be minimal. These sites are likely to generate a higher number of auto trips compared to typical trip generation rates because they lack the factors that encourage alternative modes of transportation or reduce auto dependency. Several common characteristics of low trip reduction sites are summarized as follows: limited public transit access, low-density suburban or rural development with long distances between destinations, single-use zoning that only offers one type of land use, poor pedestrian and bicycle infrastructure, etc. Low trip reduction sites are likely to have higher auto trip generation rates, reflecting the high number of auto trips. These types of sites often require more robust traffic mitigation strategies because they tend to put more strain on surrounding road networks. Examples of low trip reduction sites are illustrated in Figure 3.



(a) (b)

Figure 2. Examples of Expected High Trip Reduction Sites: (a) The RailYard South End in Charlotte, (b) The Link Apartment Innovation Quarter in Winston-Salem



(a) (b)

Figure 3. Examples of Expected Low Trip Reduction Sites: (a) The Kirkwood Place in Greensboro, (b) The Amazon Fulfillment Center RDU5 in Durham

3.2 Data Acquisition

Based on the unique characteristics of each site, the research team employed a diverse range of methodologies and technologies to collect and analyze trip data. These included the use of ground-based cameras for capturing detailed vehicular and pedestrian movements; and manual counting techniques to provide direct observational data. Additionally, the team utilized boarding and alighting data obtained from local transit agencies to assess public transportation usage. Other local data sources were also integrated into the analysis to provide a comprehensive understanding of automobile, pedestrian, and transit activity across different locations. This multi-modal approach ensured accurate and context-specific measurements of transportation patterns.

In addition, anonymized mobile device data from the StreetLight Data platform, which is a data analytics solution designed for transportation and urban planning professionals, were gathered at each of the 21 locations to facilitate comparison and validation of trip patterns observed through other data collection methods. The StreetLight Data platform provides real-time, data-driven insights into traffic patterns, mobility trends, and transportation behaviors by leveraging data from various sources, including GPS, mobile apps, connected vehicles, and IoT sensors *(StreetLight, 2024)*. The purpose of this validation effort was to assess whether the StreetLight data could reliably and accurately capture non-auto trip behavior, including vehicular, pedestrian, and transit movements. By comparing the StreetLight data with on-site measurements, the research team aimed to determine the effectiveness of this data source in representing non-auto transportation activity and its potential utility for future trip generation analysis.

3.2.1 Field Data Collection Methodology

For each of the data collection sites, the research team defined boundaries that encapsulated all of the features included at the development. For example, if an apartment complex had ground floor commercial that extended out from the apartment buildings footprint but was still a part of the development, it would be included in the defined boundary. The boundaries were used as a cordon line for determining trips entering and exiting. Ground cameras were deployed temporarily on-site to record video footage on the boundary for each site, being sure to cover areas of interest including adjacent transit stops and all entrances and exits. The ground cameras were set to record both of the peak 2-hour periods (7am to 9am & 4pm to 6pm) from which the peak hour would be determined. An example of a site boundary (orange) and ground camera arrangement (blue) at Link Apartments Innovation Quarter in Winston-Salem, NC is shown in Figure 4. Examples of ground camera hardware at various sites as well as views captured by the cameras are illustrated in Figure 5. Privacy masks were implemented on cameras that were directly adjacent to residential buildings to provide security for the residents in the area in and around the collection sites. These privacy masks blocked the view into private dwelling spaces and could be customized by cameras and sites depending on the proximity to residential buildings.

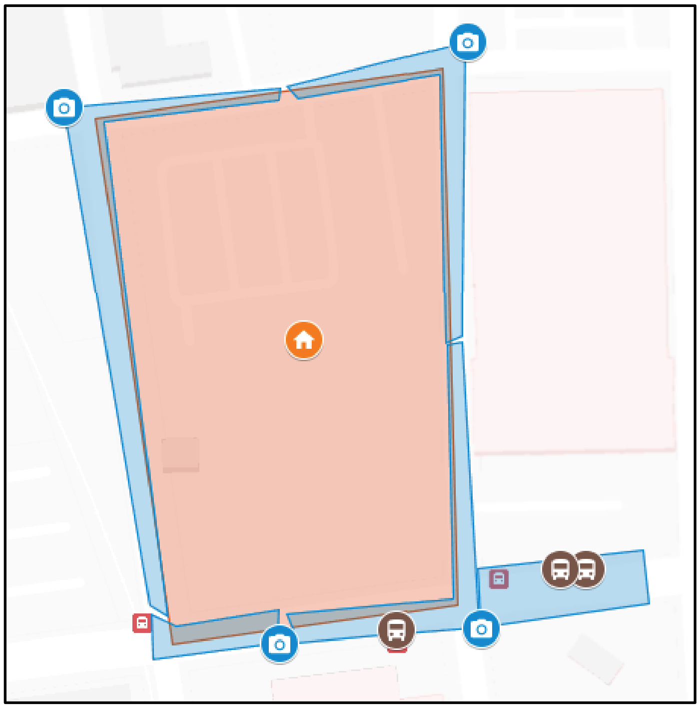


Figure 4. Example of Site Boundary (Orange) and Ground Camera Arrangement for Field Data Collection

Figure 5. Examples of Ground Camera Hardware at Various Sites

3.2.2 Video Data Reduction

The data from the ground cameras was manually reduced using individual recordings from different cameras as well as custom multi-view videos from the cameras when necessary to observe trips in, out, and through the site boundaries. Each trip by a person or auto to or from the site was recorded noting the timestamp it occurred at, direction (entering or exiting), and mode of travel. The categories of travel modes selected for data collection were either “auto” or “non-auto”, which included bus, light rail, bike and walk. Scooters, skateboards and other similar travel modes were included in the “bike” mode. Individuals walking pets were only included as a “walk” trip if the origin or destination exceeded the extent of the site collection boundaries to exclude trips that are solely for the pet to relieve themselves. The data reducers also noted if autos appeared to be commercial or privately owned autos; examples of commercial autos are presented in Figure 6.

The peak hour for both the morning and evening collection periods for each site were determined by sorting the individual sets of trip data chronologically and then computing a running total spanning 1-hour. The maximum 1-hour running total trips was found to be during the peak hour of each 2-hour collection period (i.e., morning peak period from 7 to 9AM, and afternoon peak period from 4 to 6PM). Detailed peak hour data collection time frame for each site is listed in Table 5.

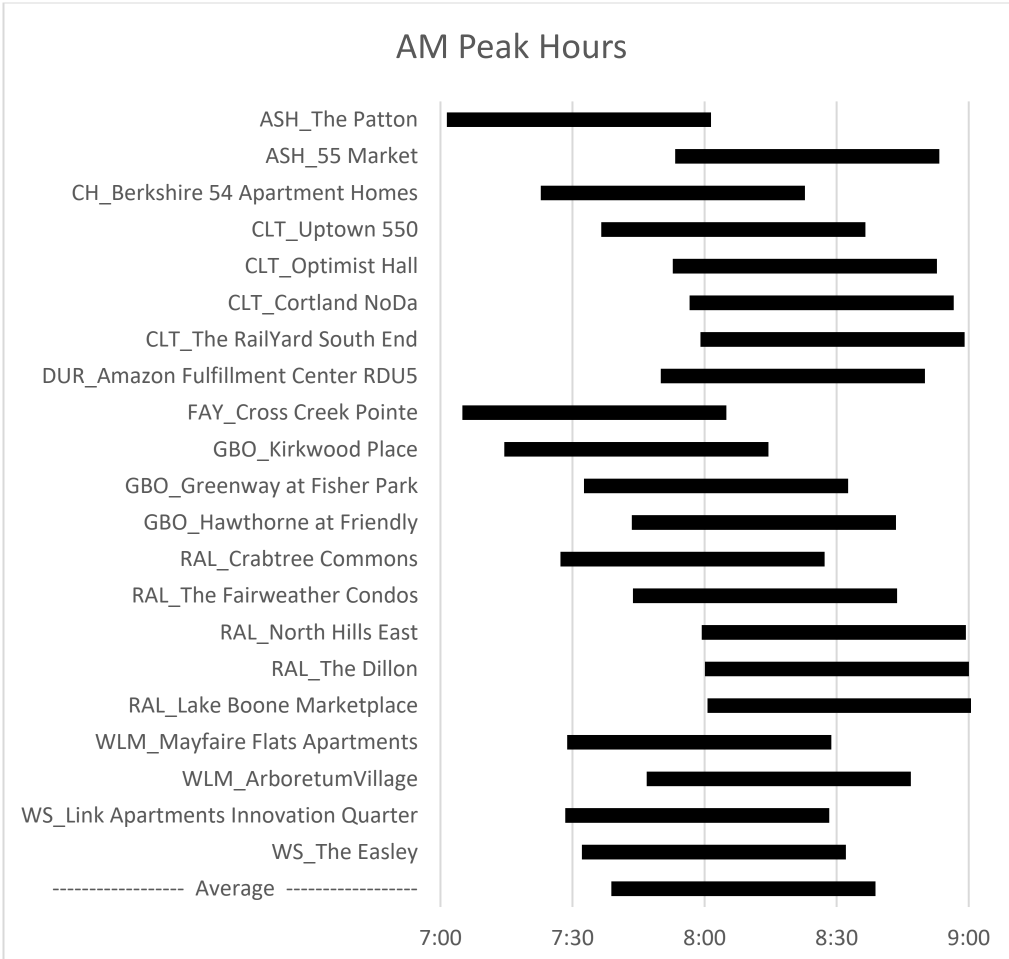
Figure 6. Examples of Commercial Vehicles

The videos were viewed in their entirety multiple times to capture individual modes and entrances as well as to identify vehicles that cut-through the site that would not be included in the dataset. The reduced data was then crosschecked by another research team member for quality assurance and quality control. Reviewing the videos multiple times and using the custom multi-view videos improved the continuity of the traffic counts by better determining unique patterns for parking or pedestrians, while simultaneously reducing the risk of duplicates in the data where a vehicle or individual might pass by multiple cameras and be counted in each. To further reduce the chance of duplicates, the camera view where a trip was observed was noted in the data as well for use in the cross-referencing method for quality assurance and quality control.

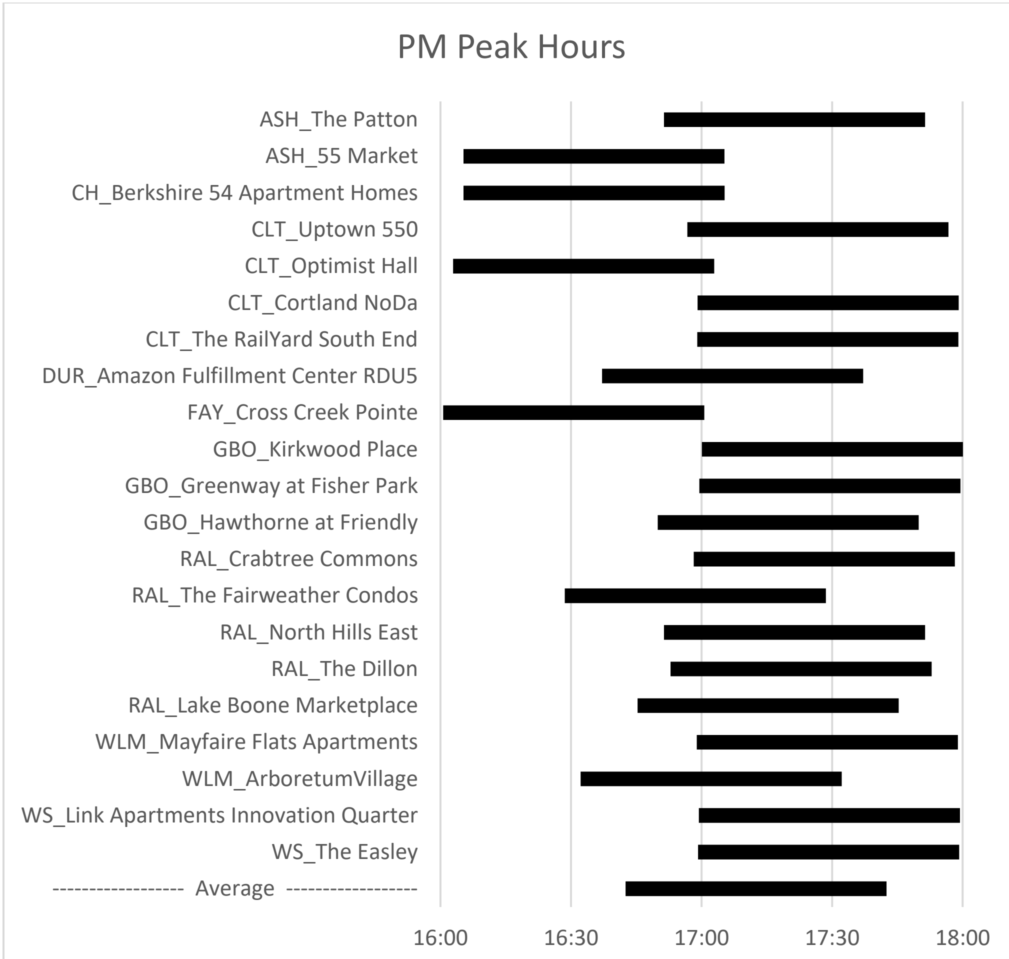
Table 5 summarizes information on the start of peak hours for various developments across different cities. The average peak hour start time for the sites was 7:38 AM for the morning peak and 16:42 PM for the afternoon peak. The distributions of the peak hours for each development are presented in Figure 7.

Table 5. Peak Hour Start Time at Each Site

City	Name of the Development	AM Peak Hour Started	PM Peak Hour Started
Asheville	The Patton	7:01	16:51
	55 South Market	7:53	16:05
Chapel Hill	Berkshire 54 Apartment Homes	7:22	16:05
Charlotte	The Railyard South End	7:36	16:56
	Cortland NoDa	7:52	16:02
	Optimist Hall	7:56	16:59
	Uptown 550	7:59	16:59
Durham	Amazon Fulfillment Center RDU5	7:50	16:37
Fayetteville	Cross Creek Pointe	7:04	16:00
Greensboro	Greenway at Fisher Park	7:14	17:00
	Hawthorne at Friendly	7:32	16:59
	Kirkwood Place	7:43	16:49
Raleigh	Crabtree Commons	7:27	16:58
	Lake Boone Marketplace	7:43	16:28
	North Hills East PD	7:59	16:51
	The Dillon	8:00	16:52
	The Fairweather Condos Raleigh NC	8:00	16:45
Wilmington	Arboretum Village	7:28	16:58
	Mayfaire Flats Apartments	7:46	16:32
Winston Salem	Link Apartments Innovation	7:28	16:59
	The Easley	7:32	16:59
Average		**7:38**	**16:42**


AM Peak Hours
ASH_The Patton
ASH_55 Market
CH_Berkshire 54 Apartment Homes
CLT_Uptown 550
CLT_Optimist Hall
CLT_Cortland NoDa
CLT_The RailYard South End
DUR_Amazon Fulfillment Center RDU5
FAY_Cross Creek Pointe
GBO_Kirkwood Place
GBO_Greenway at Fisher Park
GBO_Hawthorne at Friendly
RAL_Crabtree Commons
RAL_The Fairweather Condos
RAL_North Hills East
RAL_The Dillon
RAL_Lake Boone Marketplace
WLM_Mayfaire Flats Apartments
WLM_ArboretumVillage
WS_Link Apartments Innovation Quarter
WS_The Easley
------------------ Average ------------------
7:00
7:30
8:00
8:30
9:00

(a)



(b)

Figure 7. Peak Hour Data Collection Time Frame for Each Site:
(a) AM Peak Period; (b) PM Peak Period

3.2.3 StreetLight Data

In addition to field data, this research reviewed the StreetLight platform and established a methodology to evaluate car, bus, bicycle, and pedestrian counts as a potential source of auto trip reduction data and information. This involved developing an understanding of the tool and its functionality. Items that the research team reviewed included, pass-through vs non pass-through definitions (i.e., a pass-through zone is used to count only trips that go through the zone, but do not stop within it; while a non-pass-through zone is used to only count trips that start or end within the zone), directional settings and angles, and analysis output. Key features of the StreetLight platform include:

- Traffic and Mobility Analyses: modal usage including synthesized vehicle, bicycle, and pedestrian traffic flows across regions, cities, or specific streets.

- Origin-Destination (O-D): analysis of where trips are starting and ending, which is useful for understanding commuting patterns, and optimizing public transit routes.
- Demographics: Information about travelers and their travel behavior such as trip frequency or travel times.
- Project and Scenario Analysis: modeling the impact of proposed infrastructure projects, such as new roads, bike lanes, or transit systems, by analyzing projected traffic patterns and shifts in mobility behavior.

Based on the research study locations, seven StreetLight zones were developed, including five sites in Raleigh, one in Durham, and one in Charlotte, as shown in Figure 8. These sites were selected due to their likelihood of multimodal trip generation. Data for each study location during the peak time periods of 7-9am and 4-6pm on Tuesday, Wednesday, and Thursday were analyzed. An initial site was selected as a pilot to test the data collection setup and analysis techniques. The North Hills East PD development was selected for the pilot due to the high volume of vehicle and pedestrian data in the field collected counts. The purpose of this analysis was to determine if vehicle, bus, bicycle, and pedestrian counts could be reliably estimated through the StreetLight platform to obtain multimodal trip rates.

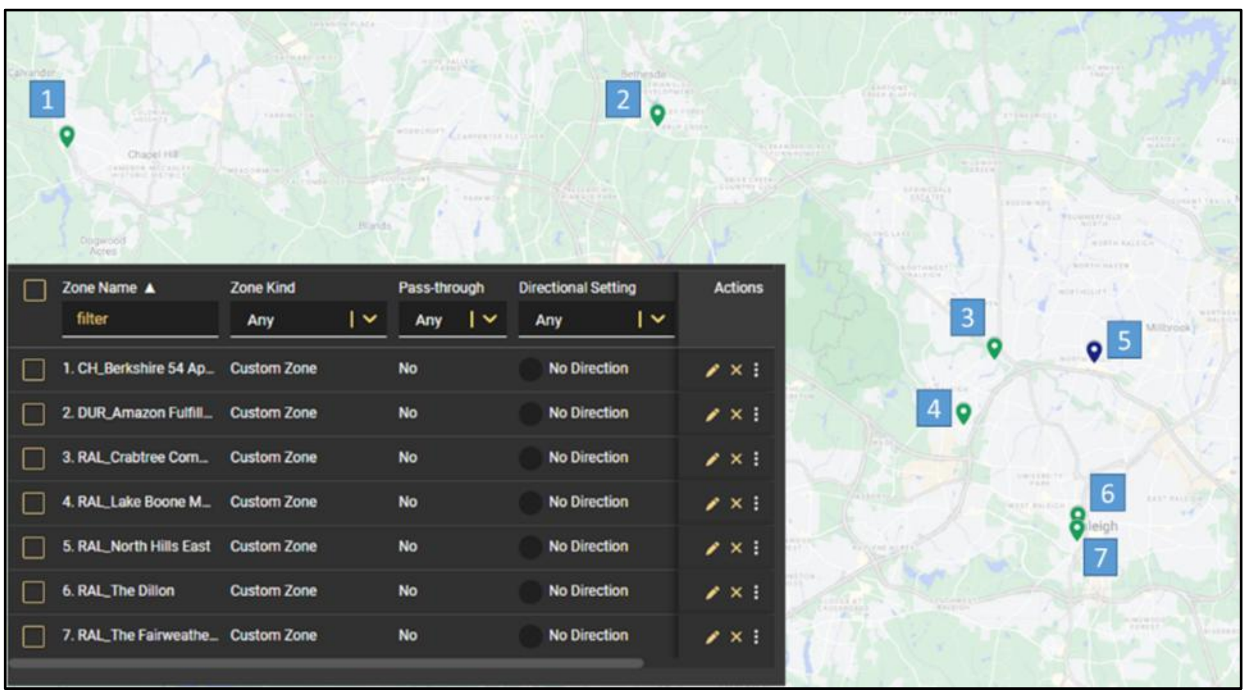


Figure 8. Initial Set of Zones Developed for Study Locations

To do this, the research team exported all types of travel mode (all vehicles, bicycle, bus and pedestrian) based on the initial seven selected locations for further review and comparison to field data. StreetLight vehicle data were available for the four-year period from 2018 to 2021, and other data were available for the three-year period from 2019 to 2021. The research team found no missing data for vehicles and pedestrians during these time periods, however the amount of missing data for sites in StreetLight for bus and bicycle was substantial. Furthermore, the research team noticed an overestimation in the volume of pedestrians compared to field data. Consequently, through the data exploration phase, the research team determined that the non-auto data are limited. In some instances, pedestrian, bike, and bus data were not available for specific areas or time periods.

Based on the review of the StreetLight output data, the research team found that the StreetLight platform overestimated the pedestrian usage in the North Hills area. After discussions with StreetLight representatives, it was determined that the StreetLight values were likely being overestimated for two reasons: (1) slow moving vehicles were being confused for pedestrians (at the North Hills location, vehicles move at slow speeds through parking lots to find parking and safely maneuver through a mixture of vehicular, pedestrian, and bicycle traffic) and (2) location based transmissions may have confusion distinguishing between people in retail locations and pedestrians walking in nearby locations.

The StreetLight team had two suggestions to address the overestimation. The first method involved removing any existing pedestrian retail shoppers and slow-moving vehicles within the area of interest through a process of drawing multiple gates. The second method involved conducting an origin-destination (O-D) analysis within the zone, which effectively removed any existing retail shoppers or slow-moving vehicles through subtraction. However, even with these countermeasures, pedestrian estimates were still overrepresented.

- *Gates Method:* This method involved drawing gates around the entry points and exit points for a given polygon, examining the total counts at those gates, and using those as the actual value of counts for each mode. For this method, all gates were set up manually and were created to capture all possible access routes. Counts were determined by using the polygon tool within the StreetLight platform and then by obtaining the pedestrian volumes through the StreetLight platform data export.
- *O-D Zone Analysis within Zone Method:* This method involved conducting an O-D analysis of people coming to the zone from within the zone. Those counts were then subtracted from the counts in the existing polygon (non pass-through zone analysis). To complete this method, the pedestrian counts were calculated using three processes. First, counts were obtained for trips coming into the zone and terminating in that zone (demarcated by the yellow arrows in Figure 9). Second, counts were obtained for trips starting in the zone and terminating outside the zone (demarcated by the red arrows in Figure 9). Third, counts are obtained for trips originating and terminating within the zone (demarcated by the blue arrows in Figure 9). The counts originating and terminating within the zone were subtracted from the total to get the actual number of trips for each mode.

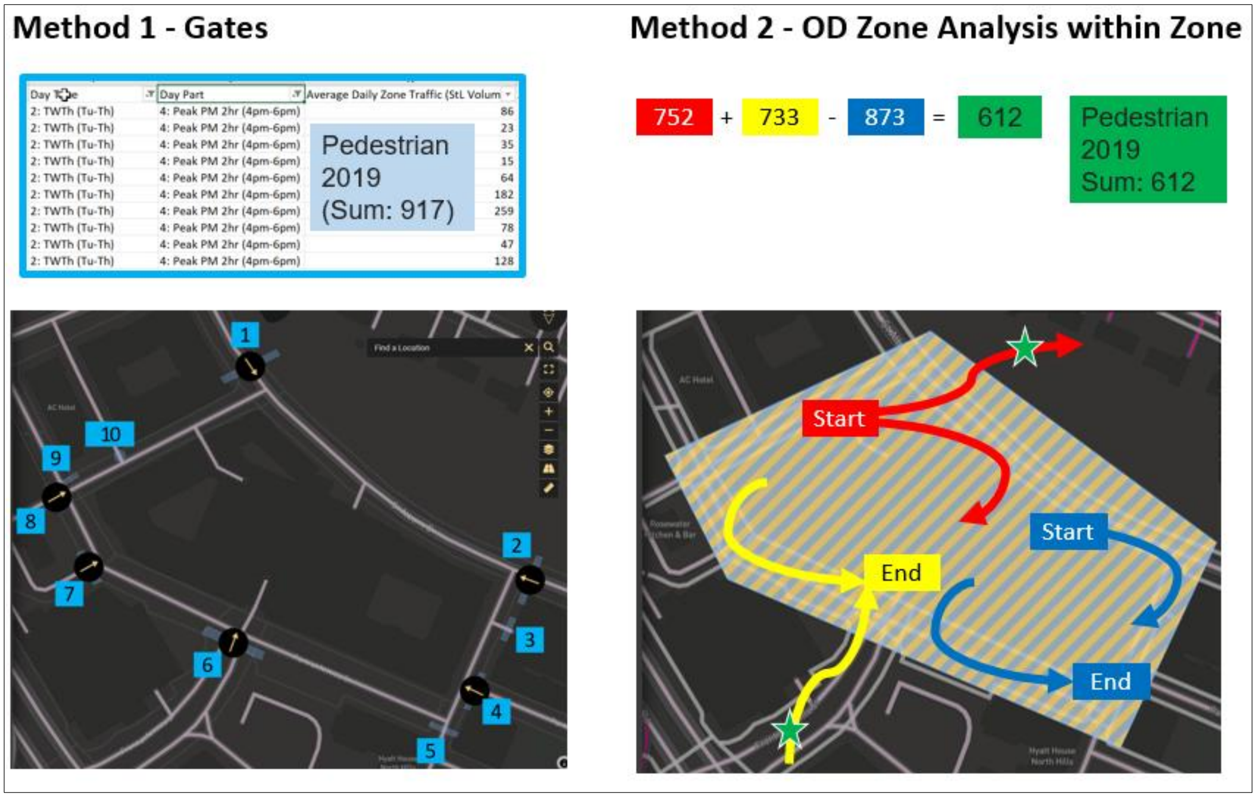


Figure 9. Methods for Addressing Overestimation of Pedestrian Volumes within StreetLight

Despite the challenges of StreetLight bicycle and pedestrian count estimation and methodology, the research team moved forward to test if StreetLight could operate as a viable platform for estimating multimodal trips through calibration methods. The research team received Charlotte Pyro sensor data and used these data to validate StreetLight count estimates. The Pyro sensor data consisted of pedestrian data collected over three years within ten sites in the Charlotte downtown area. Count estimates within the StreetLight platform were matched to those of the ten sites. The research team conducted a trend analysis to see if StreetLight data consistently overrepresented counts, underrepresented counts, or exhibited another counting estimation flaw that could be systematically addressed.

Through this analysis, the research team found that StreetLight data tended to be higher than the pyro sensor data ranging between 15 and 61 percent. Additionally, there was not a way to determine a cause for why StreetLight overestimated in some instances and not in others. Based on these findings, the research team concluded that the StreetLight platform is not a viable solution for estimating multimodal trip rates for the purposes of this study. Issues with pedestrian estimation could not be rectified through calibration. Additionally, if StreetLight were to change its internal methodology for count estimation, anticipated via legislative changes for increased data privacy, the platform would lose its ability to estimate corridor-level pedestrian counts altogether.

Considering the inconsistency between StreetLight pedestrian data and the Pyro sensor data, the research team had a discussion with NCDOT Integrated Mobility Division (IMD) on the limitations of the platform and cautioned against the use of StreetLight for estimating bicycle, pedestrian, or bus counts for the purposes of this study. These issues are noted below:

- There were inconsistencies in how pedestrian counts were assigned to adjacent facilities. For example, at a cross section that includes a street next to a sidewalk and a side path, there were some inconsistencies or confusion about how those counts were assigned across those different facilities. Additionally, pedestrians walking in hallways and buildings adjacent to roadways can be misassigned to the sidewalk. Moreover, some slow car trips can be misclassified as pedestrian trips.
- It is anticipated that StreetLight will change its count estimation methodologies, where existing segment-level aggregation algorithms will be replaced by new methodologies with less corridor granularity and will be implemented starting in 2024. This further impacts the viability of using StreetLight as a platform to estimate multimodal trips at the site-level and to conduct before and after studies.

4. Data Analysis

4.1 Descriptive Statistics

4.1.1 Vehicular Trips

Table 6 presents the number of vehicular trips observed from the research sites during both the AM and PM periods, along with the percentage of autos entering each site during those times. Results show that during AM period, sites tend to have fewer trips relative to the PM period, with a higher percentage of autos entering, especially at workplace or retail-oriented sites such as Amazon Fulfillment Center (80%) and The RailYard South End (77%). In comparison, during the PM period, there is typically a higher number of trips with lower entering percentages at many sites, indicating that more autos are exiting during this time. Notable exceptions include residential areas, where the PM period sees more entering traffic, such as The Fairweather Condos and The Patton in Asheville.

Table 6. Total Peak One Hour Vehicular Trips from Data Collection

City/Area	Development	Total Vehicular Trips from Data Collection			
		AM	% Entering	PM	% Entering
Asheville	The Patton	28	21%	50	66%
Asheville	55 Market	7	43%	16	56%
Chapel Hill	Berkshire 54 Apartment Homes	108	30%	109	59%
Charlotte	Cortland NoDa	72	28%	98	56%
Charlotte	Uptown 550	135	28%	167	53%
Charlotte	Optimist Hall	139	91%	361	42%
Charlotte	The RailYard South End	331	77%	370	31%
Durham	Amazon Fulfillment Center RDU5	148	80%	135	19%
Fayetteville	Cross Creek Pointe	86	34%	138	43%
Greensboro	Greenway at Fisher Park	57	18%	108	58%
Greensboro	Hawthorne at Friendly	58	28%	76	53%
Greensboro	Kirkwood Place	37	11%	76	55%
Raleigh	Crabtree Commons	101	32%	217	65%
Raleigh	Lake Boone Marketplace	190	68%	422	52%
Raleigh	The Dillon	213	80%	286	44%
Raleigh	The Fairweather Condos	9	44%	16	69%
Raleigh	North Hills East	2071	70%	3031	43%
Wilmington	Mayfaire Flats Apartments	76	29%	103	51%
Wilmington	Arboretum Village	42	24%	62	60%
Winston Salem	Link Apartments Innovation Quarter	129	49%	143	54%
Winston Salem	The Easley	57	21%	116	62%

4.1.2 Multimodal Trips

Tables 7 and 8 provide a comparative analysis of transportation modal splits across the studied sites, focusing on non-auto trips (walking, biking, bus, and light rail), passenger auto usage, and the percentage of commercial autos. Field collected data highlights notable differences in transportation patterns, with some sites demonstrating a more diverse modal split, while others remain largely auto-dependent.

In terms of non-auto transportation usage, during AM peak period, the non-auto trips were highest at "CLT_The RailYard South End" with 206 individuals, while several sites, such as "ASH_55 Market" and "DUR_Amazon Fulfillment Center RDU5," reported minimal non-auto trips, with no non-auto user or just a single trip. During the PM peak period, sites with the highest non-auto usage include "RAL_The Dillon" (337 users) and "CLT_The RailYard South End" (234 users). In contrast, sites such as "DUR_Amazon Fulfillment Center RDU5" reported minimal non-auto usage (1 user) during that period.

Most sites exhibit a high dependence on autos during both AM and PM peak periods. Sites such as "DUR_Amazon Fulfillment Center RDU5" and "RAL_Lake Boone Marketplace" reported nearly exclusive auto usage at 99%. While others, like "RAL_The Fairweather Condos," showed a much lower auto dependency with 27% vehicular trips. The percentage of commercial autos varies significantly across sites. During AM peak period, "RAL_The Fairweather Condos" has the highest commercial auto presence at 33%, and the highest percentage of commercial autos (21%) during PM peak was found at "DUR_Amazon Fulfillment Center RDU5". Sites like "RAL_The Dillon" and "WS_Link Apartments Innovation Quarter" had no observable commercial auto presence during the study.

Table 7. Total AM Peak One Hour Trips

Development (City Code & Name)	Non-Auto [Persons]					Passenger Auto [Vehicles]		Commercial Auto %
	Walk	Bike	Bus	Light Rail	Total	Count	Percent	
ASH_The Patton	19	0	1	0	20	28	58%	4%
ASH_55 Market	0	0	0	0	0	7	100%	0%
CH_Berkshire 54 Apartment Homes	8	0	1	0	9	108	92%	9%
CLT_Cortland NoDa	9	0	0	15	24	72	75%	6%
CLT_Uptown 550	15	0	0	0	15	135	90%	1%
CLT_Optimist Hall	8	0	0	4	12	139	92%	7%
CLT_The RailYard South End	202	2	2	0	206	331	62%	4%
DUR_Amazon Fulfillment Center RDU5	0	0	1	0	1	148	99%	20%
FAY_Cross Creek Pointe	6	0	0	0	6	86	93%	1%
GBO_Greenway at Fisher Park	10	0	0	0	10	57	85%	2%
GBO_Hawthorne at Friendly	3	0	0	0	3	58	95%	2%
GBO_Kirkwood Place	3	0	0	0	3	37	93%	3%
RAL_Crabtree Commons	6	0	0	0	6	101	94%	11%
RAL_Lake Boone Marketplace	2	0	0	0	2	190	99%	3%
RAL_The Dillon	93	0	0	0	93	213	70%	3%
RAL_The Fairweather Condos	23	1	0	0	24	9	27%	33%
RAL_North Hills East	114	7	2	0	123	2071	94%	3%
WLM_Mayfaire Flats Apartments	7	1	0	0	8	76	90%	1%
WLM_Arboretum Village	4	0	0	0	4	42	91%	0%
WS_Link Apartments Innovation Quarter	113	2	0	0	115	129	53%	0%
WS_The Easley	4	0	1	0	5	57	92%	0%

Table 8. Total PM Peak One Hour Trips

Development (City Code & Name)	Non-Auto [Persons]					Auto [Vehicles]		Commercial
	Walk	Bike	Bus	Light Rail	Total	Count	Percent	Auto %
ASH_The Patton	12	0	0	0	12	50	81%	0%
ASH_55 Market	10	0	0	0	10	16	62%	0%
CH_Berkshire 54 Apartment Homes	11	0	2	0	13	109	89%	3%
CLT_Cortland NoDa	33	1	0	10	44	98	69%	1%
CLT_Uptown 550	30	0	0	0	30	167	85%	4%
CLT_Optimist Hall	30	6	0	11	47	361	88%	2%
CLT_The RailYard South End	224	10	0	0	234	370	61%	2%
DUR_Amazon Fulfillment Center RDU5	0	0	1	0	1	135	99%	21%
FAY_Cross Creek Pointe	18	0	0	0	18	138	88%	7%
GBO_Greenway at Fisher Park	26	0	0	0	26	108	81%	3%
GBO_Hawthorne at Friendly	10	0	0	0	10	76	88%	1%
GBO_Kirkwood Place	7	0	0	0	7	76	92%	1%
RAL_Crabtree Commons	7	2	0	0	9	217	96%	0%
RAL_Lake Boone Marketplace	10	0	0	0	10	422	98%	2%
RAL_The Dillon	334	3	0	0	337	286	46%	0%
RAL_The Fairweather Condos	14	1	0	0	15	16	52%	13%
RAL_North Hills East	106	1	1	0	108	3031	97%	1%
WLM_Mayfaire Flats Apartments	18	1	0	0	19	103	84%	2%
WLM_Arboretum Village	7	2	0	0	9	62	87%	0%
WS_Link Apartments Innovation Quarter	106	1	1	0	108	143	57%	0%
WS_The Easley	11	2	0	0	13	116	90%	1%

More detailed comparisons of the multimodal splits at the sites during AM and PM peak periods are illustrated in Figures 10 and 11. Overall, most sites show a high reliance on autos, with walking being the most common alternative mode of transport and minimal observable usage of public transit or biking.

In addition to the peak hour trip counts presented in this section, the two-hour trip counts are documented in Appendix B. In summary, across all sites, 85.7% of trips were made by auto, with the remaining 14.3% distributed across walking (13.6%), biking (0.3%), bus (0.1%), and light rail (0.3%).

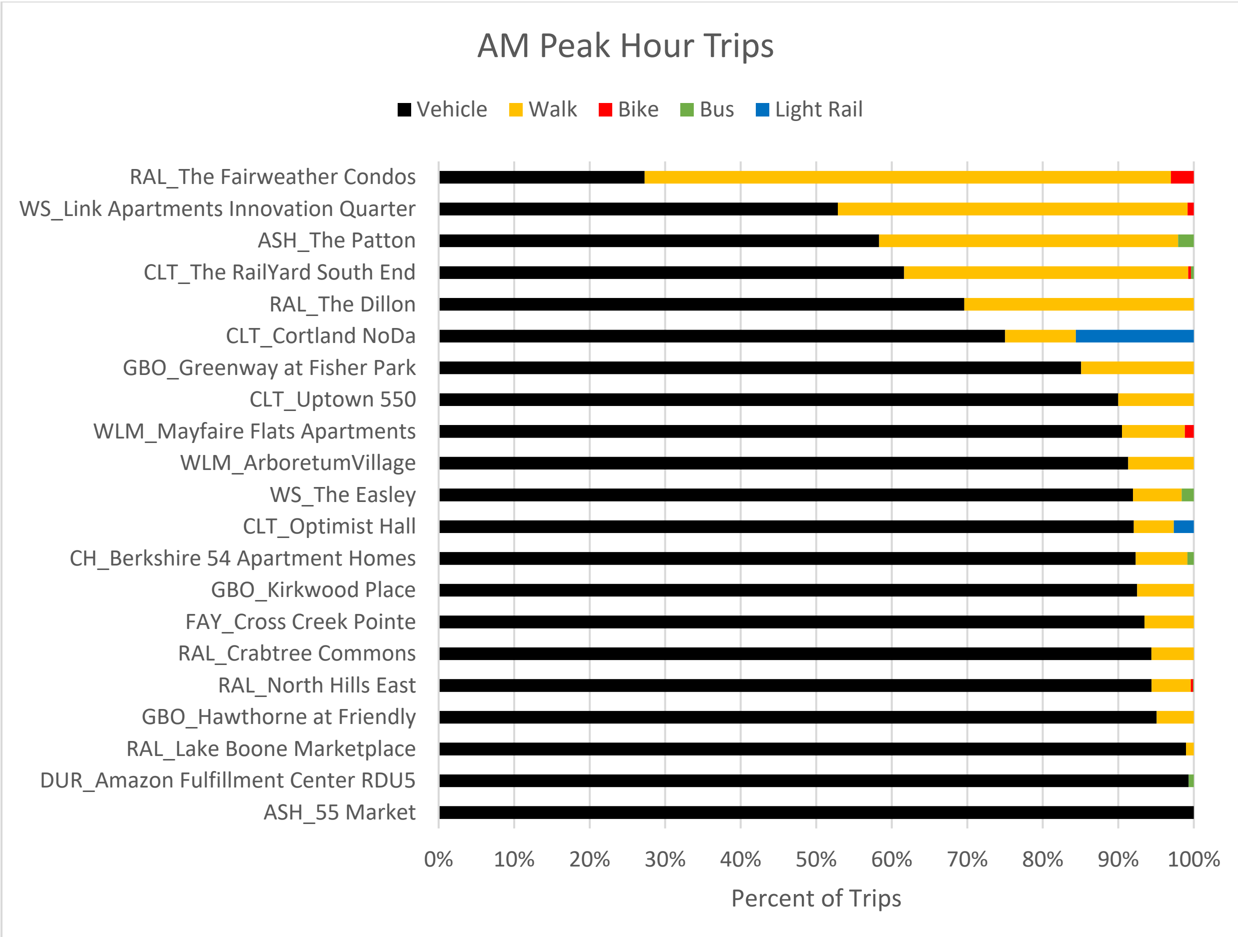


Figure 10. Percent of Multimodal Trips during AM Peak Hour

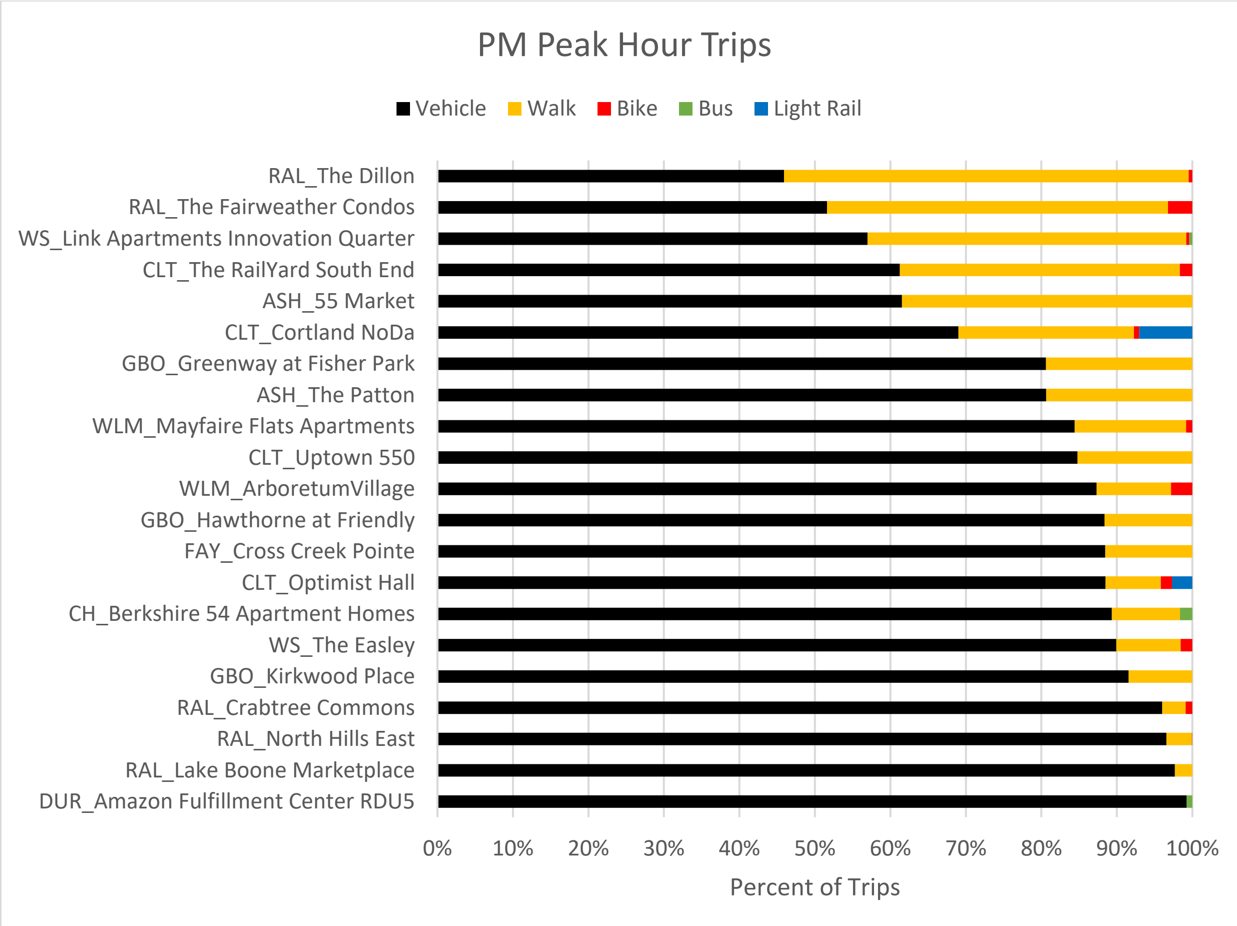


Figure 11. Percent of Multimodal Trips during PM Peak Hour

4.2 Trip Generation Analysis

The ITE Trip Generation Manual analysis method compared auto trips estimated from the ITE procedures against auto trips from the field collected data. Details on the ITE trip generation method are documented in Appendix C.

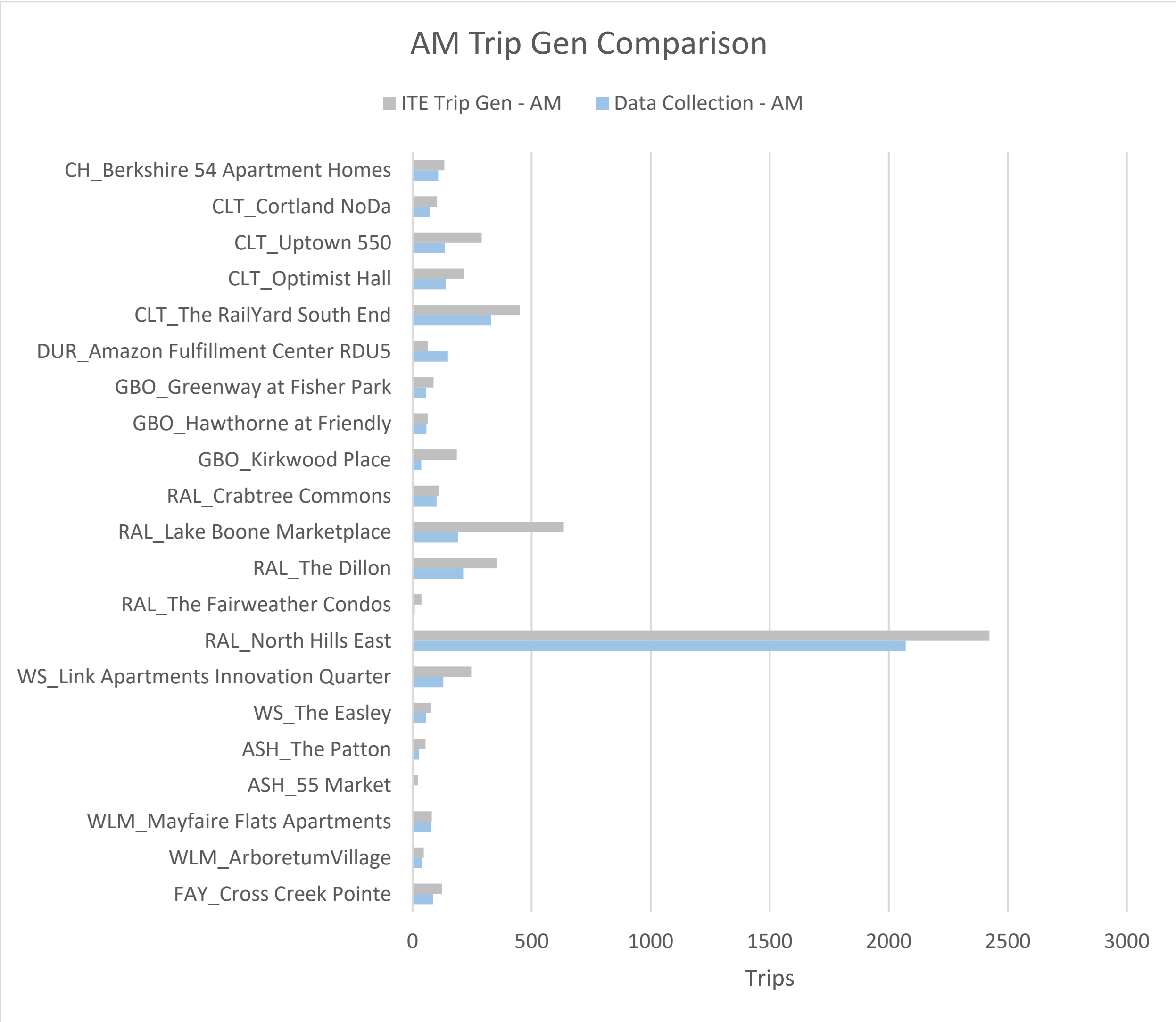
Table 9 and Figure 12 compare auto trips for the developments in the study. The counts are broken down into AM and PM trip periods. Overall, field collected data tends to show fewer trips compared to the standard ITE Trip Generation estimates, especially in the AM period for many developments. The discrepancies between the two methods may reflect localized factors or variations in travel behavior that the ITE Trip Generation Manual doesn't capture or be reflective of low sample sizes in the ITE Trip Generation Manual. In Table 9, positive values indicate that the ITE estimates exceed the actual field data, while negative values indicate that the field data surpasses the ITE estimates. Overall, the table reveals considerable variability in the accuracy of ITE Trip Generation estimates compared to actual field data. In several cases, ITE overestimates vehicular trips, particularly in the AM period, though some developments show underestimation (such as the DUR_Amazon Fulfillment Center RDU5). These differences highlight the potential need for localized trip generation studies to improve the level of confidence in traffic impact studies.

Table 9. Vehicular Trips - ITE Trip Generation Manual and Field Data Collection

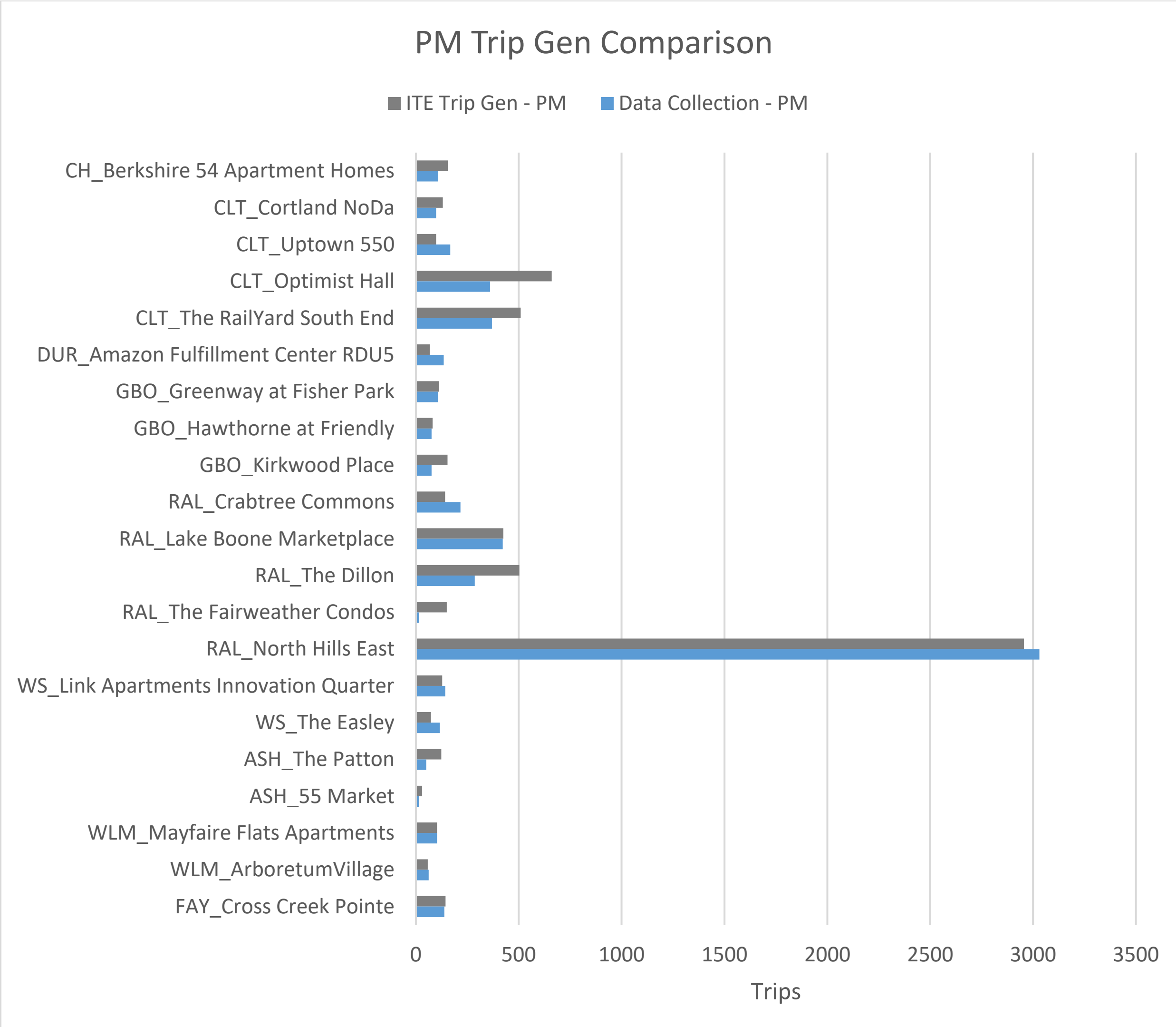
City	Development	Utilized ITE Setting(s)*	Total Vehicular Trips from ITE Trip Gen		Total Vehicular Trips from Field Data		Difference between ITE Trip Gen and Field Data**	
			AM	PM	AM	PM	AM	PM
Asheville	The Patton	GUS	54	124	28	50	93%	148%
Asheville	55 Market	GUS	23	30	7	16	229%	88%
Chapel Hill	Berkshire 54 Apartment	GUS	134	155	108	109	24%	42%
Charlotte	Cortland NoDa	GUS	103	131	72	98	43%	34%
Charlotte	Uptown 550	GUS, DMU	290	98	135	167	115%	-41%
Charlotte	Optimist Hall	GUS	216	660	139	361	55%	83%
Charlotte	The RailYard South End	GUS, DMU	451	509	331	370	36%	38%
Durham	Amazon RDU5	GUS	65	67	148	135	-56%	-50%
Fayetteville	Cross Creek Pointe	GUS	123	144	86	138	43%	**4%**
Greensboro	Greenway at Fisher Park	GUS	88	112	57	108	54%	**4%**
Greensboro	Hawthorne at Friendly	GUS	64	81	58	76	**10%**	**7%**
Greensboro	Kirkwood Place	GUS	185	154	37	76	400%	103%
Raleigh	Crabtree Commons	GUS	112	142	101	217	**11%**	-35%
Raleigh	Lake Boone Marketplace	GUS	635	425	190	422	234%	**1%**
Raleigh	The Dillon	GUS, CCC	356	503	213	286	67%	76%
Raleigh	The Fairweather Condos	GUS, DMU	37	150	9	16	311%	838%
Raleigh	North Hills East	GUS	2423	2955	2071	3031	**17%**	**-3%**
Wilmington	Mayfaire Flats Apartments	GUS	81	103	76	103	**7%**	**0%**
Wilmington	Arboretum Village	GUS	47	58	42	62	**12%**	**-6%**
Winston Salem	Link Apts. Innovation Qtr.	GUS, DMU	246	128	129	143	91%	**-10%**
Winston Salem	The Easley	DMU	79	74	57	116	39%	-36%
Average Difference			276.8	324.0	195.0	290.5	42.0%	11.5%

Notes:
*The following acronyms are used for the ITE settings utilized in ITE trip-gen analysis: GUS = General Urban-Suburban, DMU = Dense Multi-use Urban, CCC = Center City Core. These settings were chosen to represent the true site setting as closely as possible that also suggests to use a "rate" or "equation", as opposed to "local data".
****Bold numbers** indicate lower than 20 percent difference between ITE trip generation and field data

The Mann-Whitney U test statistical test was used to evaluate if there are significant differences in the total vehicular trips estimated from ITE trip generation manual and field collected across both AM and PM periods. The Mann-Whitney U test results for AM period show a z-score of 1.22005 and a p-value of 0.2225. Since the p-value is greater than 0.05, we can conclude that there is no statistically significant difference in the average total vehicular trips estimated by the ITE trip generation manual and field collected. The U test results for PM period show a z-score of 0.60374 and a p-value of 0.5485. Since the p-value is greater than 0.05, indicating that there is no statistically significant difference in the average total vehicular trips estimated from ITE trip generation manual and collected from field.


AM Trip Gen Comparison
ITE Trip Gen - AM
Data Collection - AM
CH_Berkshire 54 Apartment Homes
CLT_Cortland NoDa
CLT_Uptown 550
CLT_Optimist Hall
CLT_The RailYard South End
DUR_Amazon Fulfillment Center RDU5
GBO_Greenway at Fisher Park
GBO_Hawthorne at Friendly
GBO_Kirkwood Place
RAL_Crabtree Commons
RAL_Lake Boone Marketplace
RAL_The Dillon
RAL_The Fairweather Condos
RAL_North Hills East
WS_Link Apartments Innovation Quarter
WS_The Easley
ASH_The Patton
ASH_55 Market
WLM_Mayfaire Flats Apartments
WLM_ArboretumVillage
FAY_Cross Creek Pointe
0
500
1000
1500
2000
2500
3000
Trips

(a)



(b)

Figure 12. Vehicular Trips - ITE Trip Generation Manual and Field Data Collection: (a) AM Peak Period; (b) PM Peak Period

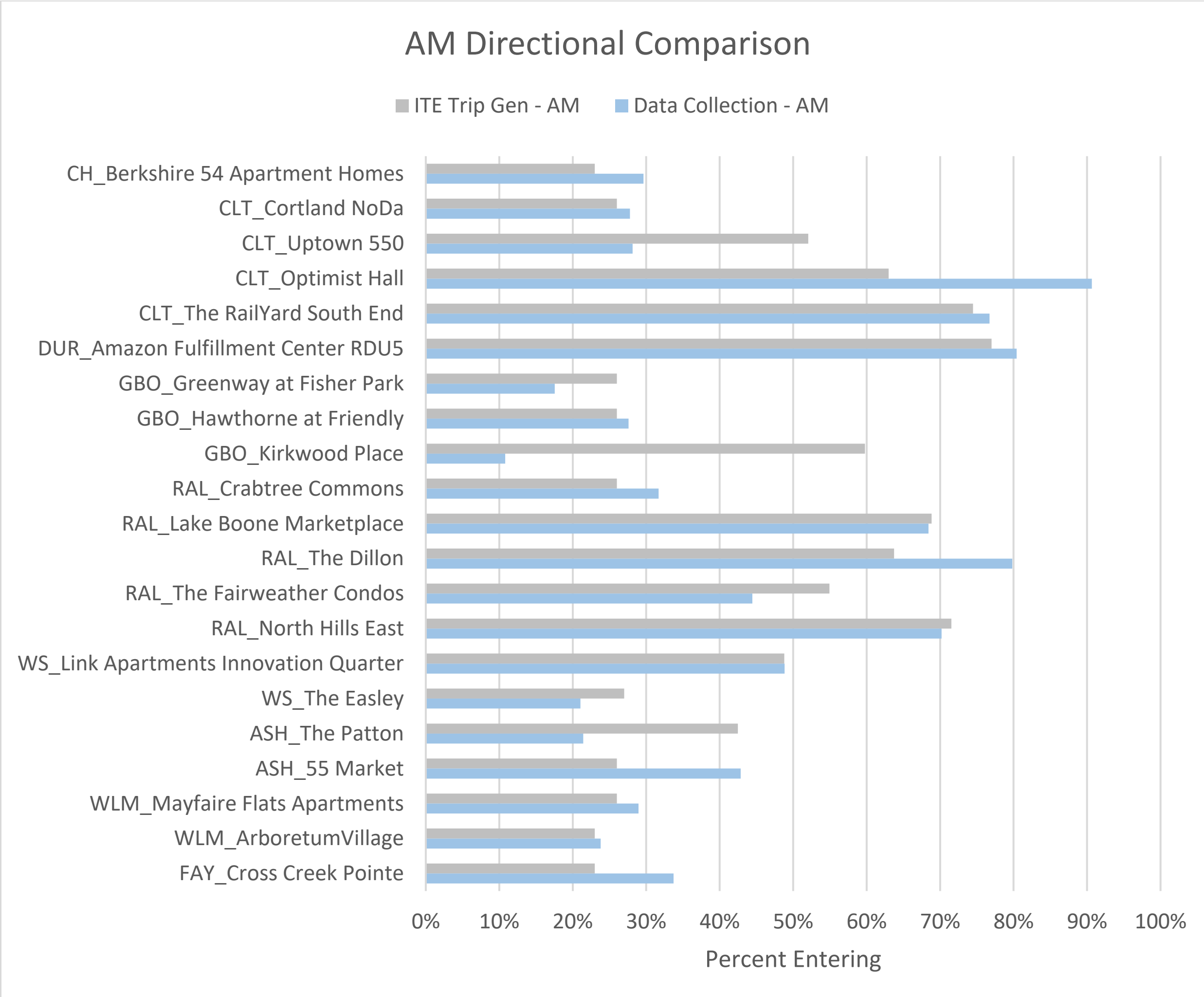
Moreover, Table 10 and Figure 13 compare the vehicular entering percentage for each development; the percentages represent the share of total passenger auto trips that are entering the development during AM and PM peak periods. In general, it was found that during AM peak period, for many developments, field data tends to show either higher or more varied entering percentages compared to the ITE estimates. In some cases, such as CLT_Optimist Hall and GBO_Kirkwood Place, the difference is substantial. During the PM peak period, the entering percentages of the field collected data are often lower than those predicted by ITE, suggesting a higher proportion of exiting trips during this period in these observations.

Similar to the total vehicular trips, the table also illustrates varying degrees of alignment between ITE Trip Generation estimates and actual vehicular entering percentages observed in the field. While some developments show strong alignment (i.e., differences less than 20%), others exhibit significant deviations, particularly in Asheville and Greensboro. Again, these findings suggest that while ITE estimates may serve as useful guidelines, localized data collection is crucial for improving the level of confidence in traffic impact studies.

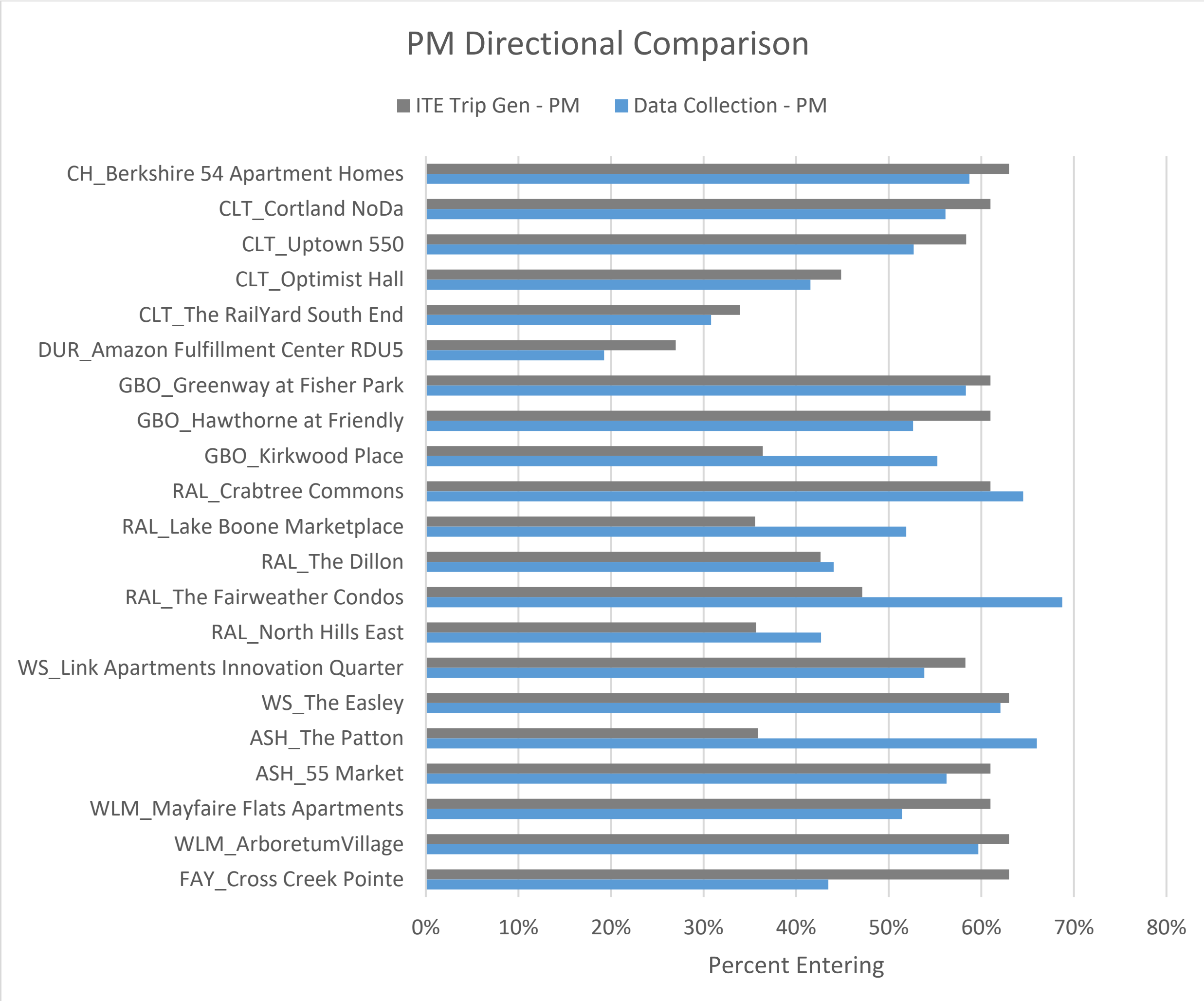
Table 10. Comparisons of Total Vehicular Entering Percentages from ITE Trip Generation Manual and Field Data Collection

City	Development	Total Vehicular Entering Percentage from ITE Trip Gen		Total Vehicular Entering Percentage from Fire Data		Difference between ITE Trip Gen and Field Data	
		AM	**PM**	**AM**	**PM**	**AM**	**PM**
Asheville	The Patton	42%	36%	21%	66%	100%	-45%
Asheville	55 Market	26%	61%	43%	56%	-40%	**9%**
Chapel Hill	Berkshire 54 Apartment Homes	23%	63%	30%	59%	-23%	**7%**
Charlotte	Cortland NoDa	26%	61%	28%	56%	**-7%**	**9%**
Charlotte	Uptown 550	52%	58%	28%	53%	86%	**9%**
Charlotte	Optimist Hall	63%	45%	91%	42%	-31%	**7%**
Charlotte	The RailYard South End	74%	34%	77%	31%	**-4%**	**10%**
Durham	Amazon Fulfillment Center RDU5	77%	27%	80%	19%	**-4%**	42%
Fayetteville	Cross Creek Pointe	23%	63%	34%	43%	-32%	47%
Greensboro	Greenway at Fisher Park	26%	61%	18%	58%	44%	**5%**
Greensboro	Hawthorne at Friendly	26%	61%	28%	53%	**-7%**	**15%**
Greensboro	Kirkwood Place	60%	36%	11%	55%	445%	-35%
Raleigh	Crabtree Commons	26%	61%	32%	65%	**-19%**	**-6%**
Raleigh	Lake Boone Marketplace	69%	36%	68%	52%	**1%**	-31%
Raleigh	The Dillon	64%	43%	80%	44%	**-20%**	**-2%**
Raleigh	The Fairweather Condos	55%	47%	44%	69%	25%	-32%
Raleigh	North Hills East	72%	36%	70%	43%	**3%**	**-16%**
Wilmington	Mayfaire Flats Apartments	26%	61%	29%	51%	**-10%**	**20%**
Wilmington	ArboretumVillage	23%	63%	24%	60%	**-4%**	**5%**
Winston Salem	Link Apartments Innovation Quarter	49%	58%	49%	54%	**0%**	**7%**
Winston Salem	The Easley	27%	63%	21%	62%	29%	**2%**
Average Difference		44.2%	51.1%	43.1%	52.0%	2.5%	-1.6%

Note: **Bold numbers** indicate lower than 20 percent difference between ITE trip generation and field data


AM Directional Comparison
ITE Trip Gen - AM
Data Collection - AM
CH_Berkshire 54 Apartment Homes
CLT_Cortland NoDa
CLT_Uptown 550
CLT_Optimist Hall
CLT_The RailYard South End
DUR_Amazon Fulfillment Center RDU5
GBO_Greenway at Fisher Park
GBO_Hawthorne at Friendly
GBO_Kirkwood Place
RAL_Crabtree Commons
RAL_Lake Boone Marketplace
RAL_The Dillon
RAL_The Fairweather Condos
RAL_North Hills East
WS_Link Apartments Innovation Quarter
WS_The Easley
ASH_The Patton
ASH_55 Market
WLM_Mayfaire Flats Apartments
WLM_ArboretumVillage
FAY_Cross Creek Pointe
0%
10%
20%
30%
40%
50%
60%
70%
80%
90%
100%
Percent Entering

(a)



(b)

Figure 13. Comparisons of Total Vehicular Entering Percentages between ITE Trip Generation Manual and Field Data Collection: (a) AM Peak Period; (b) PM Peak Period

4.3 Correlation Analysis of Non-Auto Trips

This research further investigated the potential correlation between built-environment characteristics and non-auto trip percentages based on field collected data. Table 11 outlines the non-auto percentages, Walk Scores, demand estimations by NCDOT, and whether each site is located in or adjacent to a Central Business District (CBD). In this case, the non-auto trips capture walking, biking, and all modes of public transit. The Walk Score is a measure of walkability obtained online at www.walkscore.com provided by Redfin using a patented system by analyzing walking routes to nearby amenities. A higher Walk Score indicates closer access to amenities such as stores, restaurants, and parks by pedestrians (with amenities within a 5 minute walk receiving maximum points and no points received for amenities beyond 30 minutes). Pedestrian friendliness is also considered with the inclusion of population and infrastructure characteristics (such as block length and intersection density) *(Walk Score, 2024)*.

The NCDOT Demand Estimation value was collected from the pedestrian/bicyclist demand estimation map developed by NCDOT. The estimated demand is based on a weighted average of population, employment, and zero-vehicle household densities *(NCDOT, 2022)*.

In general, sites near or adjacent to the CBD show much higher non-auto trip percentages and walkability, such as The Dillon in Raleigh and Link Apartments in Winston Salem. In comparison, suburban developments, such as Crabtree Commons and Amazon Fulfillment Center, show lower non-auto percentages and are more dependent on travel by auto. Overall, the Walk Score generally correlates with higher non-auto percentages and proximity to the CBD, reflecting better access to a variety of transportation options in more urban settings.

Table 11. Study Site Characteristics and Non-auto Trip Percentage

Development (City Code & Name)	Non-Auto %		Walk Score	NCDOT Demand Estimation	CBD or Adjacent to CBD
	AM	PM			
CH_Berkshire 54 Apartment Homes	8%	11%	50	High	No
WLM_Mayfaire Flats Apartments	10%	16%	50	Medium	No
WLM_Arboretum Village	9%	13%	47	Medium	No
GBO_Kirkwood Place	8%	8%	70	Medium	No
FAY_Cross Creek Pointe	7%	12%	71	Medium	No
RAL_Crabtree Commons	6%	4%	45	Medium	No
RAL_North Hills East	6%	3%	76	Medium	No
GBO_Hawthorne at Friendly	5%	12%	62	Medium	No
RAL_Lake Boone Marketplace	1%	2%	72	Medium	No
DUR_Amazon Fulfillment Center RDU5	1%	1%	18	Medium	No
RAL_The Fairweather Condos	73%	48%	88	High	Yes
WS_Link Apartments Innovation Quarter	47%	43%	78	High	Yes
ASH_The Patton	42%	19%	87	High	Yes
RAL_The Dillon	30%	54%	97	High	Yes
GBO_Greenway at Fisher Park	15%	19%	74	High	Yes
CLT_Uptown 550	10%	15%	70	High	Yes
WS_The Easley	8%	10%	85	High	Yes
ASH_55 Market	0%	38%	89	High	Yes
CLT_The RailYard South End	38%	39%	91	Medium	Yes
CLT_Cortland NoDa	25%	31%	57	Medium	Yes
CLT_Optimist Hall	8%	12%	72	Medium	Yes

4.3.1 Impacts of Walk Score on Non-Auto Percentage

A scatter plot showing the relationship between multimodal percentage and Walk Score is presented in Figure 14, with two sets of data points representing different times of day: AM (orange diamonds) and PM (blue squares). Overall, there exists a positive correlation between Walk Score and non-auto percentage, particularly in the PM period, where higher Walk Scores tend to correspond with higher non-auto percentages. PM data points generally show a higher non-auto % compared to AM data points for the same Walk Score values. This suggests that in the evening, people tend to rely more on a variety of transportation options than in the morning. The majority of the data points are concentrated between Walk Scores of 50 and 90, with high non-auto percentages (above 50%) observed in this range. Locations with Walk Scores below 50 show lower non-auto percentages. A few outliers in the AM period show very high non-auto percentages (above 70%) for Walk Scores around 80-90, indicating potential high reliance on varied transportation options in these areas during the morning.

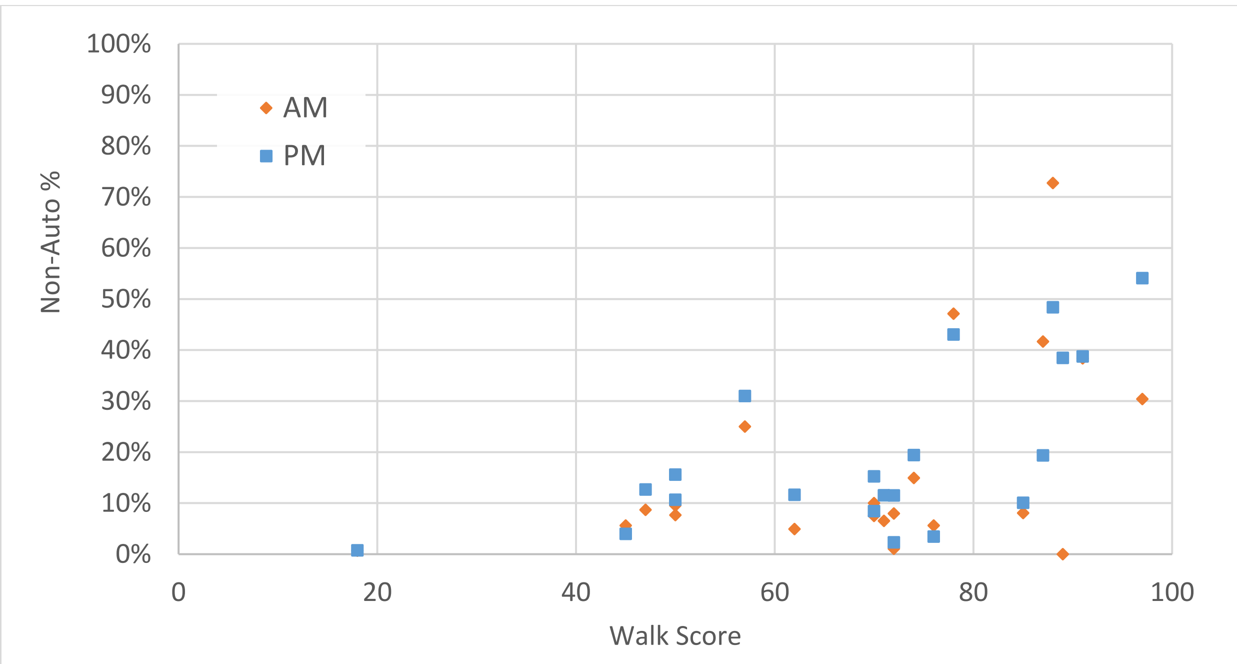


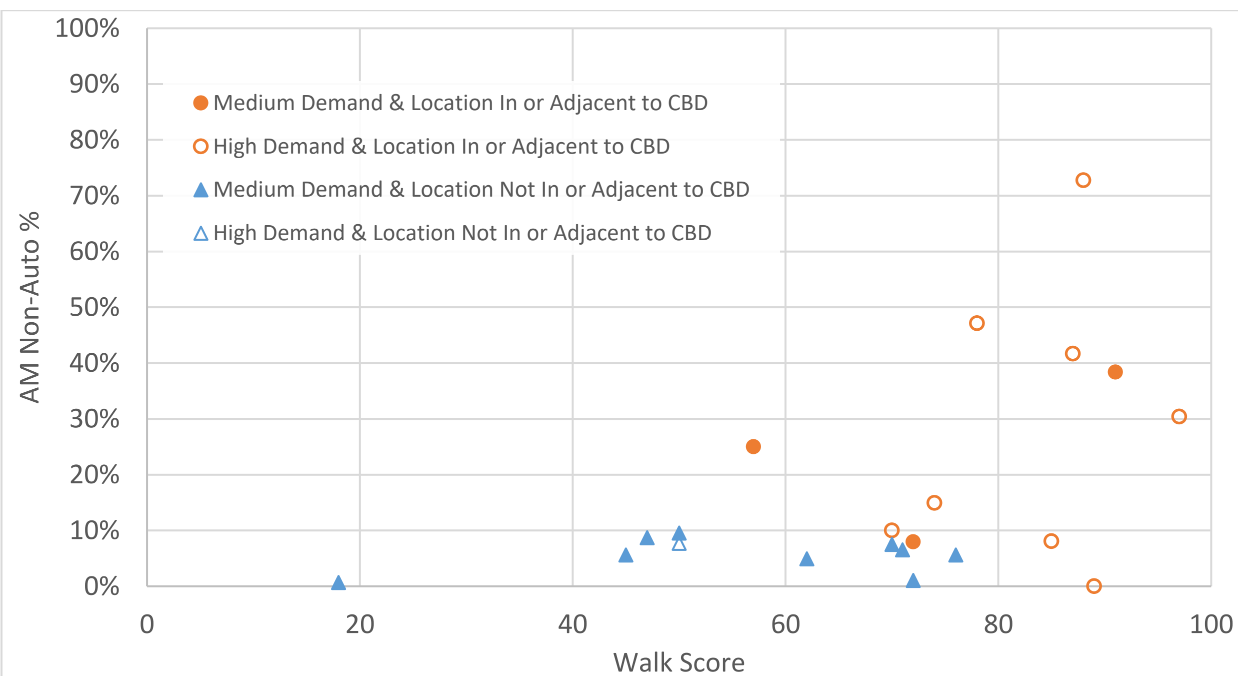
Figure 14. Scatter Plot of Non-auto Percentage and Walk Score

4.3.2 Impacts of Demand and Proximity to CBD on Non-Auto Percentage

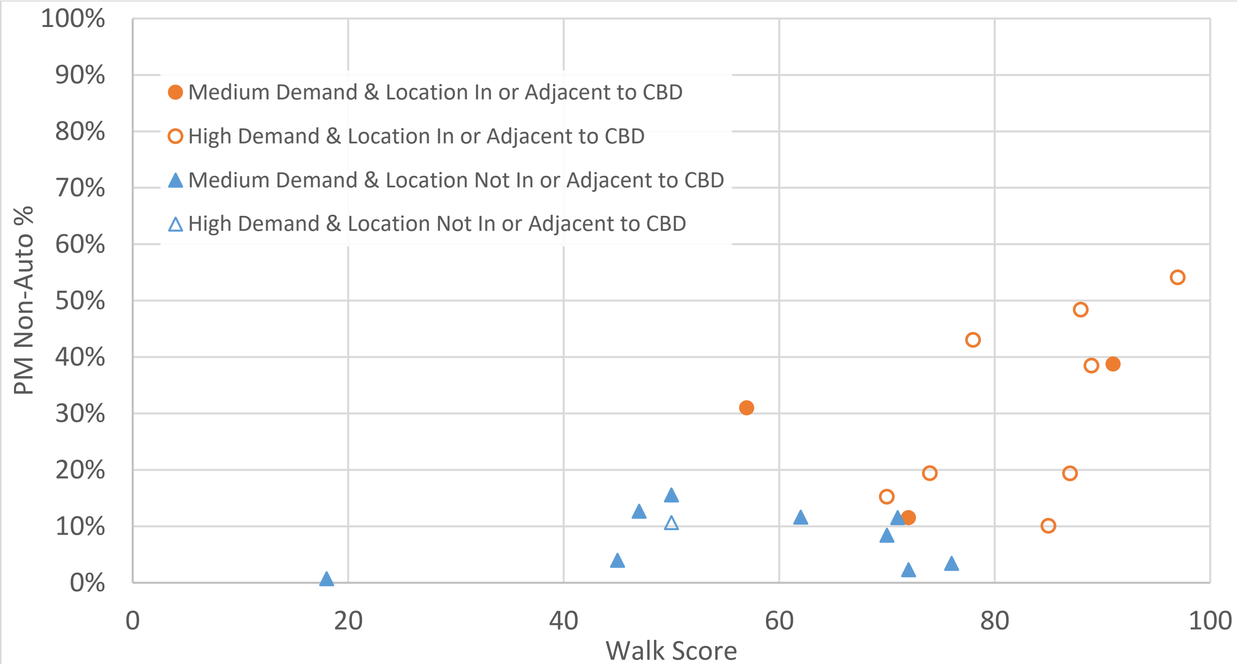
Figure 15 presents scatter plots that illustrates the relationship between Walk Score and the percentage of non-auto trips for various demand levels and location contexts. Four categories are represented in the figure:

- Medium Demand & Location In or Adjacent to CBD (filled orange circles)
- High Demand & Location In or Adjacent to CBD (open orange circles)
- Medium Demand & Location Not In or Adjacent to CBD (filled blue triangles)
- High Demand & Location Not In or Adjacent to CBD (open blue triangles)

In general, sites in or adjacent to the CBD (both medium and high demand) tend to have higher Walk Scores (ranging from 60 to 100) and display a positive correlation with non-auto percentages during both the AM and PM peak periods. Conversely, locations not in or adjacent to the CBD (both medium and high demand) exhibit lower Walk Scores (mostly below 80) and correspondingly lower non-auto percentages, clustering below 10% in the AM peak period and under 20% in the PM peak period. In terms of the impacts of demand level on non-auto percentage, high demand locations in or adjacent to the CBD consistently show higher non-auto percentages compared to medium demand locations in or adjacent to the CBD, especially during PM peak period and at sites with higher Walk Scores. In summary, the location factor (CBD proximity) appears to be a more significant determinant of both walkability and non-auto transport usage, while demand level does not seem to be a key contributing factor to non-auto percentage.



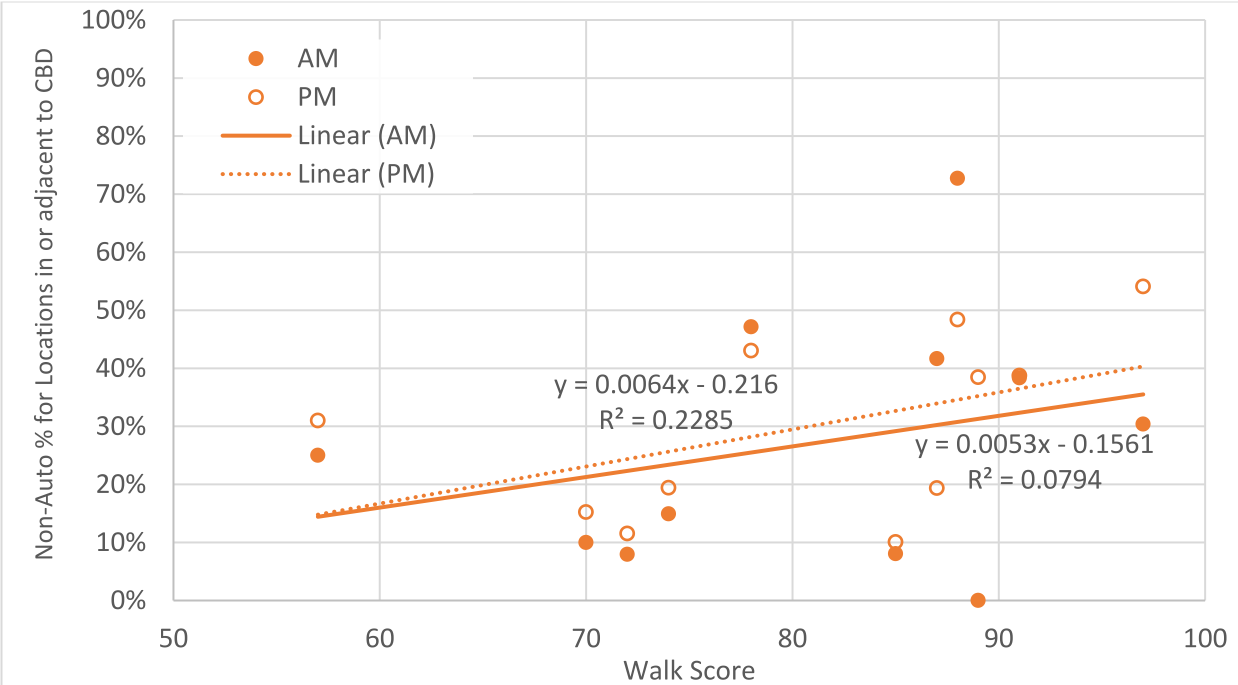
(a)



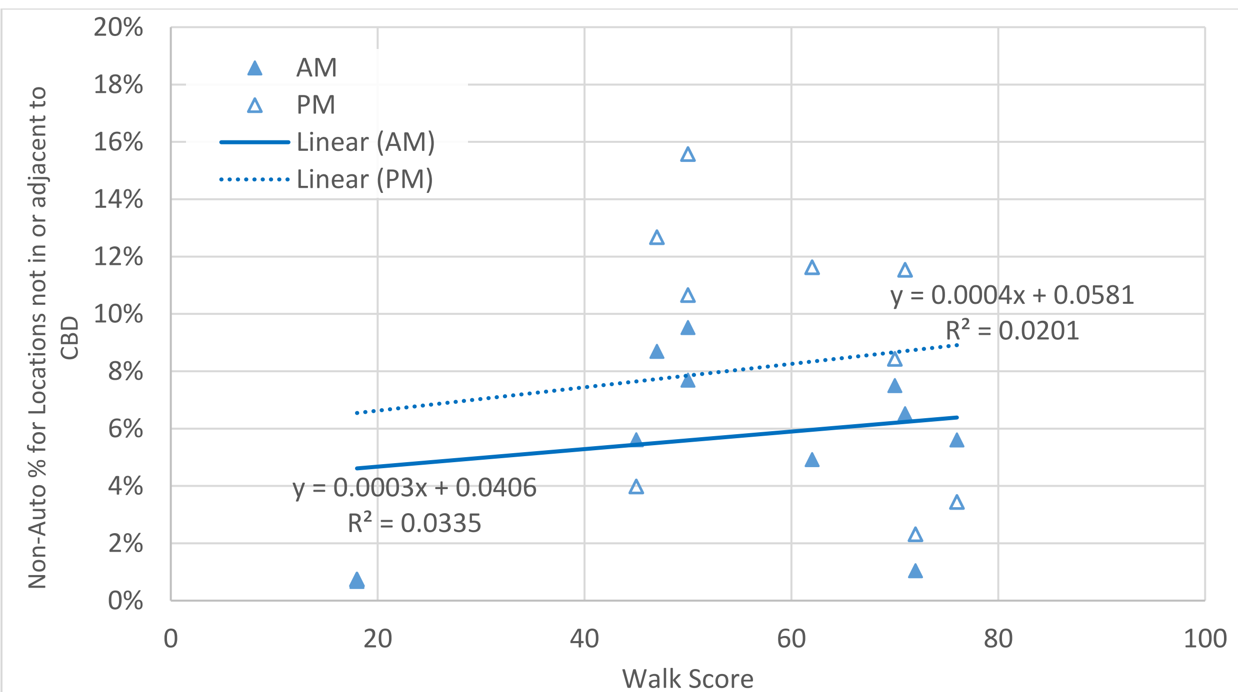
(b)

Figure 15. Scatter Plot of Non-auto Percentage and Demand and Proximity to CBD: (a) AM peak period; (b) PM peak period

In addition, this research tends to quantitatively identify the correlation between proximity to CBD and non-auto percentage, as shown in Figure 16. There is a slight positive correlation between Walk Score and non-auto percentage at locations in or adjacent to the CBD for both the AM and PM periods, and higher Walk Scores tend to associate with higher non-auto percentages. For sites not in or adjacent to CBD, both AM and PM periods show a very weak positive correlation between Walk Score and non-auto percentage. In summary, these findings suggest that locations with higher Walk Scores near or in the CBD tend to have higher non-auto usage, especially in the PM period. For sites outside or not adjacent to CBD, Walk Score has a minimal impact on the non-auto percentage with very weak correlations in both the AM and PM periods.



(a)



(b)

Figure 16. Correlation between Non-auto Percentage and Proximity to CBD: (a) In or Adjacent to CBD; (b) Not In or Adjacent to CBD

4.4 Summary of Data Analysis

This section summarizes the average non-auto trip percentages under different demand levels (High vs. Medium), site locations (In or Adjacent to CBD vs. Not in CBD), and site Walk Scores.

Table 12 presents the relationship between demand levels and the percentage of non-auto transportation use during both morning (AM) and afternoon (PM) peak periods. In general, results show that non-auto transportation use increases with higher demand levels and tends to be slightly higher during the PM period across all levels of demand. Specifically, at high demand levels, the average percentage of non-auto usage is 26% during the AM period and increases to 29% in the PM period. For medium demand levels, the average non-auto usage is lower, with 10% in the AM period and 13% in the PM period. The total average non-auto percentages across both demand levels indicate 17% non-auto usage in the AM peak period and 20% in the PM peak period.

Table 12. Summary of Non-auto Trip Percentages under Two Demand Levels

Demand Level	Average AM Non-auto %	Average PM Non-auto %
High	26%	29%
Medium	10%	13%
All Sites	**17%**	**20%**

Table 13 illustrates the variation in average non-auto transportation usage across two different site locations during AM and PM peak periods. At locations not in CBD, the average percentage of non-auto usage is relatively low, with 6% in the AM period and 8% in the PM period. For locations within or adjacent to the CBD, the average non-auto usage is significantly higher, with 27% in the AM period and 30% in the PM period. The overall averages across all locations reveal 17% non-auto usage in the AM period and 20% in the PM period. These findings suggest that proximity to the CBD is strongly associated with higher non-auto transportation usage, particularly in the PM period.

Table 13. Summary of Non-auto Trip Percentages for Two Different Locations

Site Location	Average AM Non-auto %	Average PM Non-auto %
Not in CBD	6%	8%
In or Adjacent to CBD	27%	30%
All Sites	**17%**	**20%**

Table 14 lists the average percentage of non-auto transportation use under different Walk Scores during AM and PM peak periods. For locations with a Walk Score of 20, the average non-auto usage is minimal, at 1% for both the AM and PM periods. Sites with a Walk Score between 50 and 70 show moderate non-auto usage, with 8% to 15% in the AM and 11% to 21% in the PM. Sites with higher Walk Scores (i.e., 80 and above) see significantly greater non-auto usage. For example, a Walk Score of 80 corresponds to 26% non-auto usage in the AM and 23% in the PM, while a Walk Score of 90 has the highest average usage in the AM (32%) with 31% usage in the PM. For locations with a perfect Walk Score of 100, non-auto use peaks dramatically in the PM period, reaching 54%. Overall, the total averages show 17% non-auto use in the AM period and 20% in the PM period. The data suggests a positive correlation between Walk Score and non-auto transportation use, with usage notably increasing as walkability improves, particularly during the PM period.

Table 14. Summary of Non-auto Trip Percentages under Different Walk Scores

Walk Score (Rounded)	**Average AM Non-auto %**	**Average PM Non-auto %**
20	1%	1%
50	8%	11%
60	15%	21%
70	8%	11%
80	26%	23%
90	32%	31%
100	30%	54%
All Sites	**17%**	**20%**

Lastly, a comprehensive analysis of the relationship between site location, transportation demand, walkability, and non-auto transportation usage during various time periods is summarized in Table 15. In general, sites located in or adjacent to CBD generally exhibit higher Walk Scores (ranging from 60 to 100) and a significantly greater reliance on non-auto transportation, with usage reaching up to 54% during the PM peak period. In contrast, sites not in CBD display lower Walk Scores and lower non-auto participation, with the highest usage being 12% during the PM peak period. These findings suggest a strong correlation between urban density, walkability, and the adoption of non-auto transportation, with central business areas fostering more sustainable transportation usages. The average non-auto usages across all locations and demand levels in the study are 17% in the AM and 20% in the PM, indicating a modest reliance on multiple transportation modes, with higher non-auto percentages in CBD-adjacent areas.

Table 15. Average Non-auto Percentages under Various Locations, Demand Levels and Walk Scores

Site Location	NCDOT Demand Estimation	Walk Score Rounded	Average Non-auto %	
			AM	PM
Not in CBD	High	50	8%	11%
	Medium	20	1%	1%
	Medium	50	8%	11%
	Medium	60	5%	12%
	Medium	70	5%	7%
	Medium	80	6%	3%
In or Adjacent to CBD	High	70	12%	17%
	High	80	47%	43%
	High	90	31%	29%
	High	100	30%	54%
	Medium	60	25%	31%
	Medium	70	8%	12%
	Medium	90	38%	39%
All Sites			**17%**	**20%**

A One-way Analysis of Variance (ANOVA) statistical test was used to evaluate if there are significant differences in the average non-auto usage under different site locations (i.e., Not in CBD vs. In or Adjacent to CBD) and NCDOT Demand Estimation levels (i.e., High vs. Medium) across both AM and PM periods. The ANOVA results for average non-auto percentage by site location show a F-statistic value of 31.4195 and a P-value of 0.0000. Since the p-value is less than 0.05, we can conclude that there is a statistically significant difference in the average non-auto percentage between the locations Not in CBD and In or Adjacent to CBD. The ANOVA results for average non-auto percentage by demand levels show a F-statistic value of 6.9252 and a P-value of 0.0146. Since the p-value is less than 0.05, indicating that there is a statistically significant difference in the average non-auto percentage between medium and high demand levels.

5. Conclusions and Recommendations

Multimodal trip generation, which integrates multiple forms of transportation, including auto (vehicles) and non-auto (walking, cycling, and public transit), is an essential consideration for development review and impact analysis. It reflects the complexity of mode choice in diverse environments, particularly in urban areas where individuals may switch between modes depending on convenience, cost, or accessibility. This research developed a better understanding of the application of vehicle trip reduction rates for sites with probable multimodal usage in the review of Traffic Impact Analysis (TIA) for NCDOT using field data from multiple sites in North Carolina.

The selection of field data collection sites considered a variety of built-environment characteristics and environmental factors, aimed at providing comprehensive insights into transportation patterns. Key factors in site selection included the type of land use (e.g., single or multi-use developments), the density and availability of pedestrian, bicycle, and transit infrastructure, the presence of trip generators or attractors, and the availability of parking. Ultimately, 21 sites across nine cities in North Carolina were chosen for field data collection. Data were gathered through ground-based cameras that captured detailed vehicular and pedestrian movements, as well as manual counting techniques.

Analysis of the data revealed notable differences in trip making behavior across different periods and site types. For instance, during the AM period, there were fewer non-auto trips, with a higher percentage of autos entering workplace or retail-oriented sites. In contrast, the PM period typically saw a higher number of non-auto trips, with more autos exiting many sites, indicating that most vehicular traffic in the afternoon involves departures at the observed locations. The data also showed a heavy reliance on personal autos during both the AM and PM peak periods, with walking emerging as the most common alternative mode of transport; nevertheless, public transit and biking were minimally utilized at the observed locations. Across all sites throughout the entire two-hour AM and PM peak periods, field data shows that, on average, **85.7%** of trips were made by passenger **auto**, with the remaining 14.3% distributed across **walking (13.6%)**, **biking (0.3%)**, **bus (0.1%)**, and **light rail (0.3%)**.

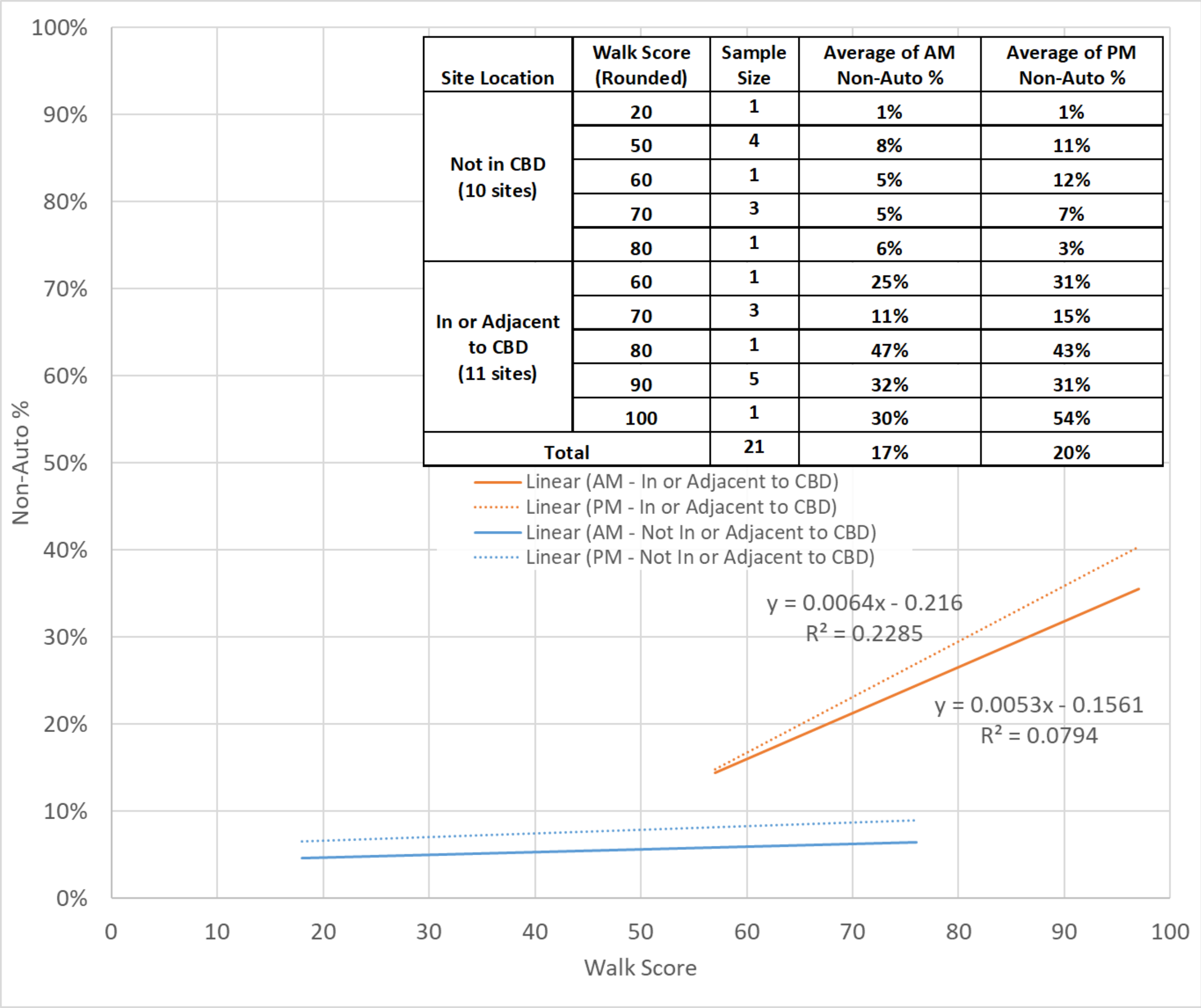
The research team recommends considerations of the Walk Score and location relative to the Central Business District (CBD) for sites being reviewed for a TIA. As a continuous variable on a scale of 0 to 100, the Walk Score showed promise as an indicator of multimodal trips in the sites evaluated for this study. As an example of the association between Walk Score and multimodal trip percentage, at the four sites with Walk Scores rounded to 50, the non-auto percentage was 8% (AM) and 11% (PM), while the five sites with Walk Scores rounded to 90, the non-auto percentage was 32% (AM) and 31% (PM). Considering the locations relative to the CBD as a binary variable of proximity to the CBD, the average non-auto percentage observed was 27% (AM) and 30% (PM) for sites in or adjacent to the CBD, and 6% (AM) and 8% (PM) for sites outside or not adjacent to the CBD. A summary of the results is shown in Figure 17. Figure 17 does not include an equation for the trendlines for the sites that were outside/not adjacent to the CBD because of the weak relationship between Walk Score and non-auto percentage. To refine these estimates, the research team also recommends additional data collection at sites in and adjacent to CBDs to expand on the 11 sites observed in this study.

Furthermore, a comparison of field-collected data and standard ITE Trip Generation estimates showed that the former tended to report fewer trips, especially in the AM period. This discrepancy suggests that localized factors or variations in trip making behavior might not be fully captured by the ITE model at the studied locations.

The research also explored the correlation between built-environment characteristics and non-auto trip percentages. Findings indicated that sites in or adjacent to Central Business Districts (CBD) exhibited higher non-auto trip usage and walkability, whereas suburban developments were more dependent on travel by passenger auto.

Walk Scores generally positively correlated with higher non-auto percentages and proximity to the CBD, reflecting better access to transportation options in urban settings. Particularly, PM data showed a higher non-auto percentage compared to AM data for the same Walk Score values, indicating that people rely more on multiple transportation options in the evening. The majority of the data points were concentrated between Walk Scores of 50 and 90, with non-auto percentages exceeding 60% in this range. Locations with Walk Scores below 50 had significantly lower non-auto percentages, though a few outliers in the AM period showed high non-auto usage for Walk Scores around 80-90.

Proximity to the CBD appeared to be a significant determinant of walkability and a variety of transportation modes. These findings emphasize the importance of considering built-environment characteristics when planning for transportation and land use to encourage multimodal travel.



Site Location	Walk Score (Rounded)	Sample Size	Average of AM Non-Auto %	Average of PM Non-Auto %
Not in CBD (10 sites)	20	1	1%	1%
	50	4	8%	11%
	60	1	5%	12%
	70	3	5%	7%
	80	1	6%	3%
In or Adjacent to CBD (11 sites)	60	1	25%	31%
	70	3	11%	15%
	80	1	47%	43%
	90	5	32%	31%
	100	1	30%	54%
Total		21	17%	20%

Figure 17. Walk Score and Non-Auto Percentage by Time Period (AM/PM) and Proximity to CBD (In or Adjacent to CBD; Not In or Adjacent to CBD)[1]

[1] These results are representative of data collected at 21 sites from 9 cities in North Carolina during the AM peak (7am to 9am) and PM peak (4pm to 6pm). Equations are shown for each linear trendline of the data for each time period and proximity to the central business district (CBD). Additionally, a table within the graph shows the average non-auto percentage for each combination of site location and Walk Score.

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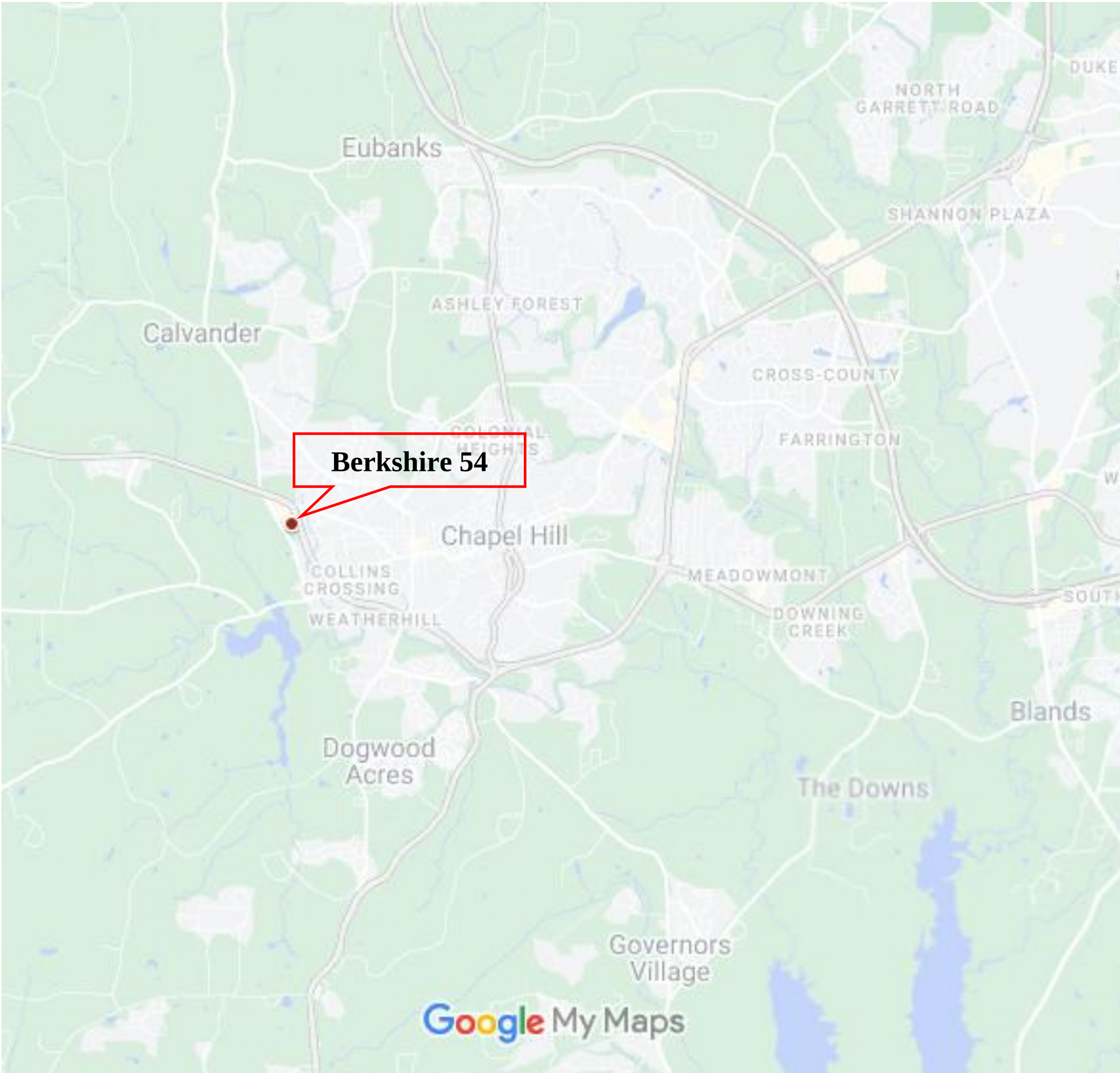
Appendices

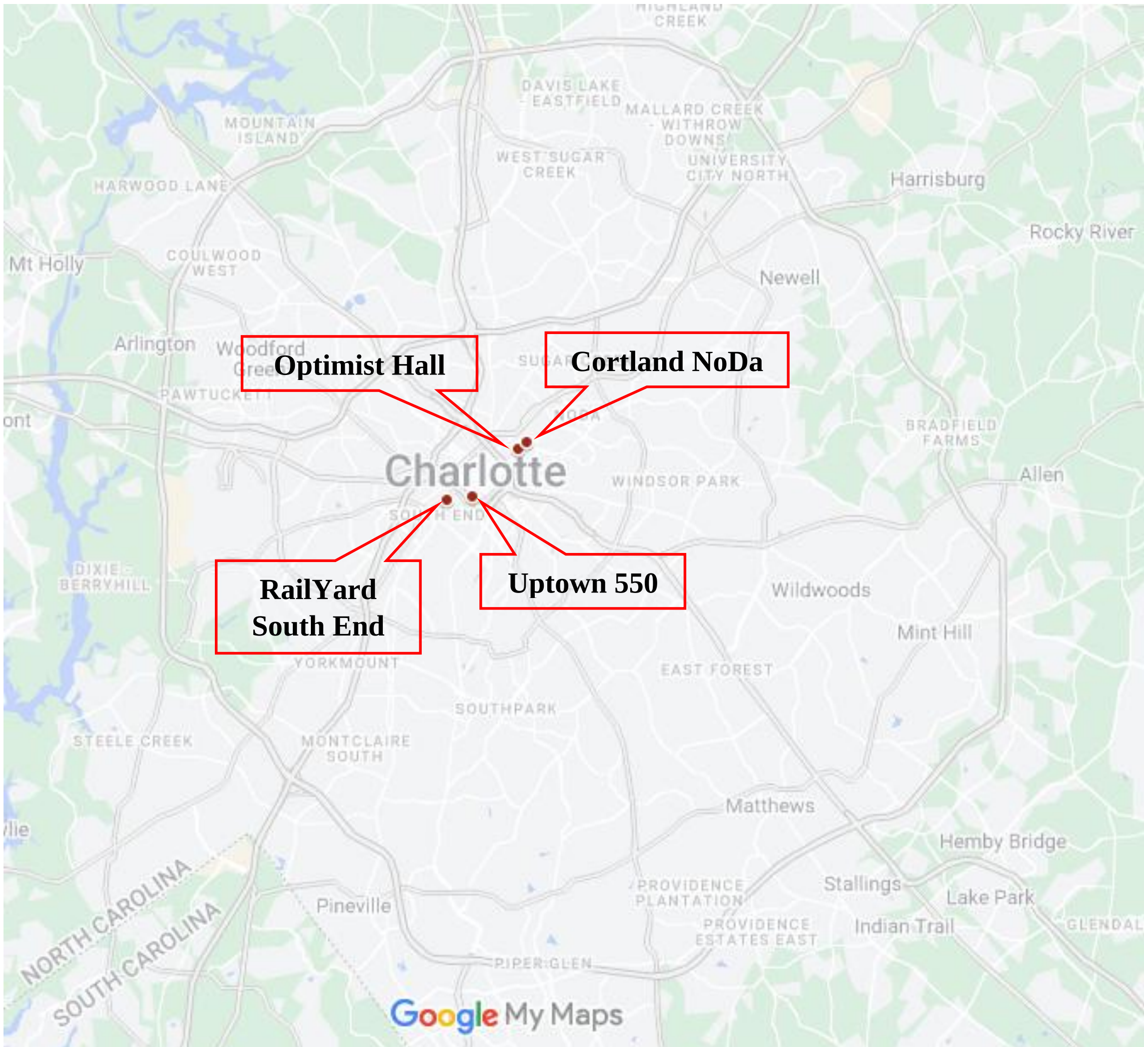
Appendix A. Final Site Selection

Asheville, NC

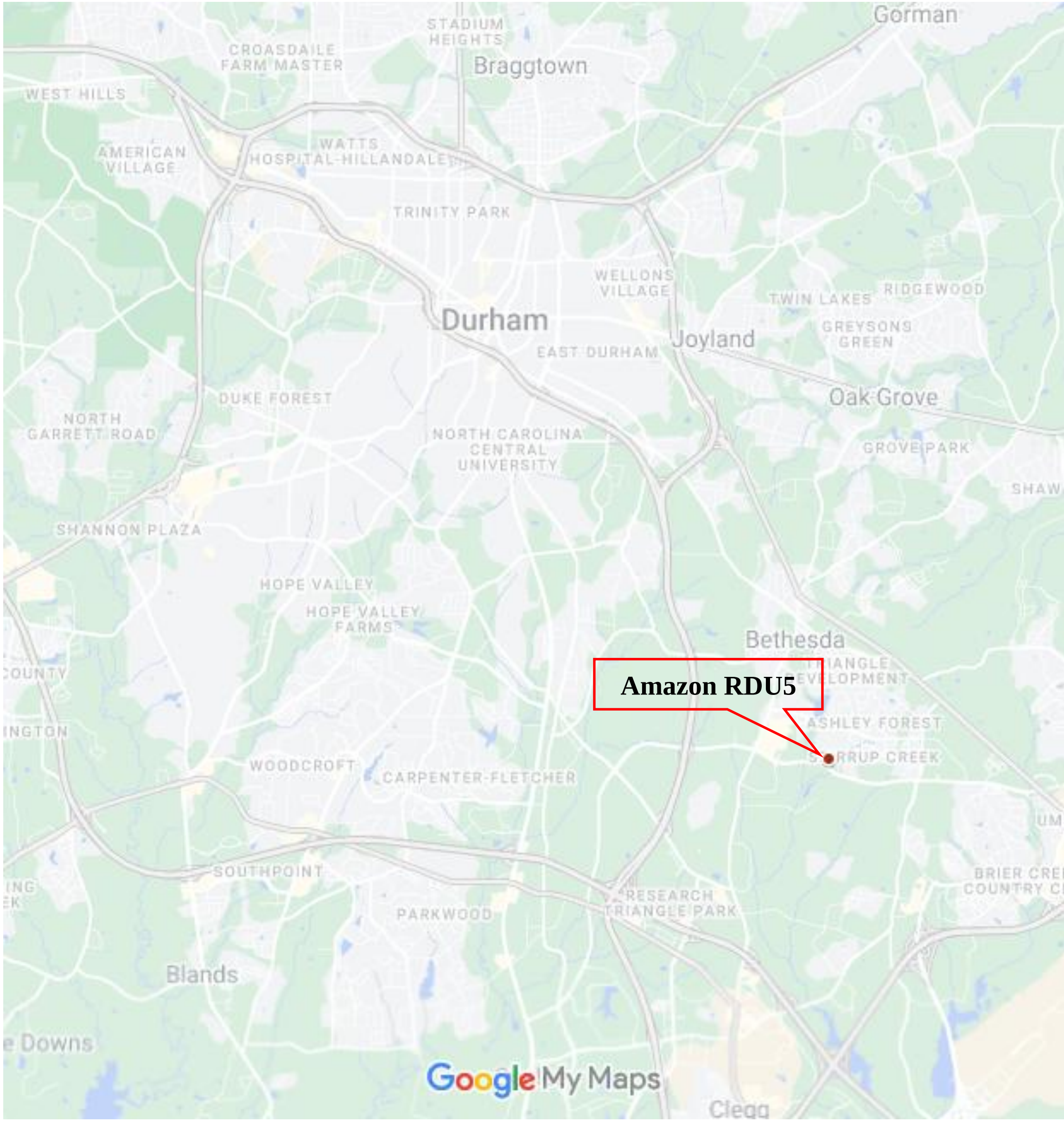
Chapel Hill, NC



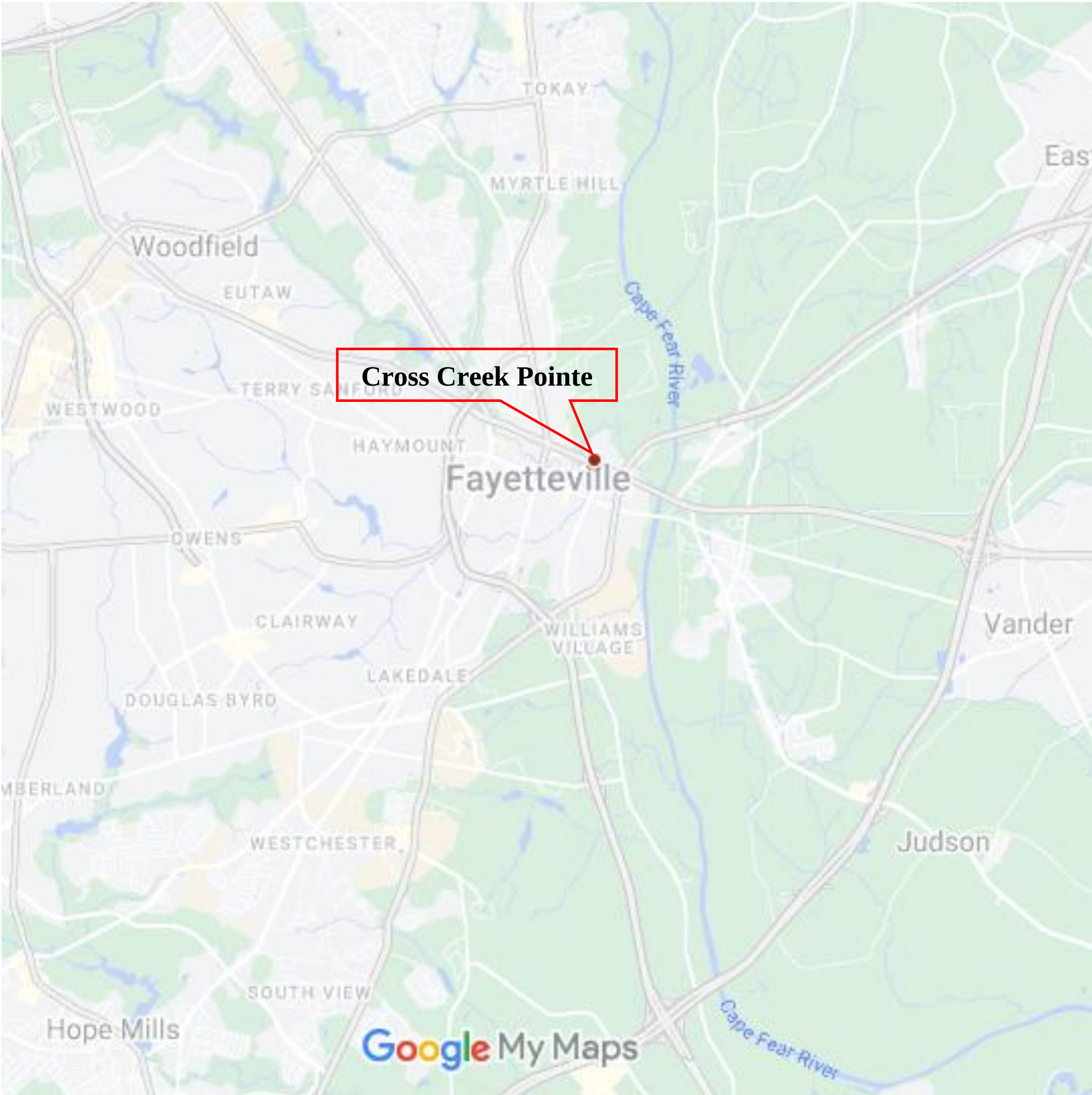
Charlotte, NC



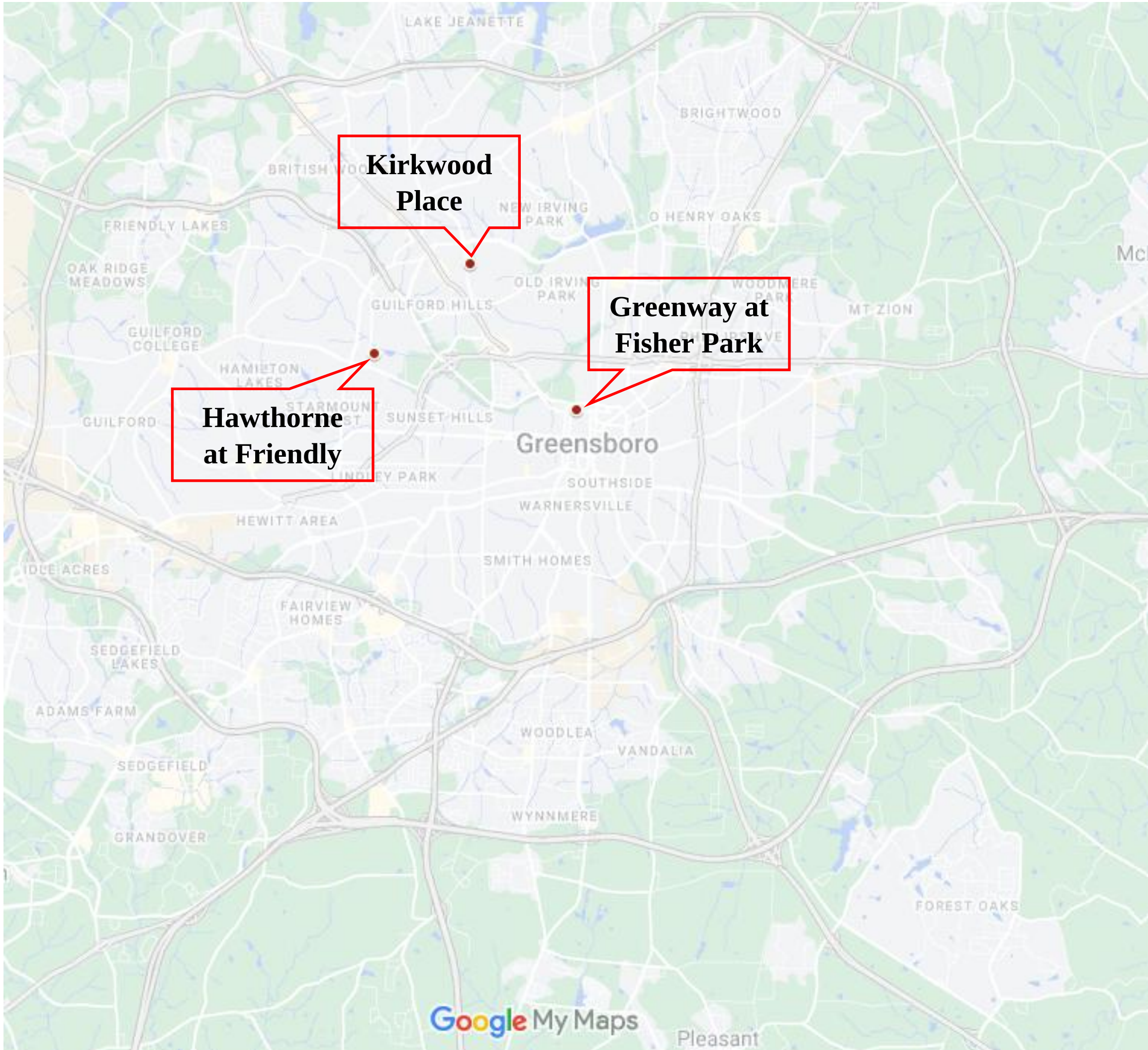
Durham, NC


Amazon RDU5
Durham
Gorman
Braggtown
STADIUM HEIGHTS
CROASDAILE FARM MASTER
WEST HILLS
AMERICAN VILLAGE
WATTS HOSPITAL-HILLANDALE
TRINITY PARK
WELLONS VILLAGE
TWIN LAKES
RIDGEWOOD
GREYSONS GREEN
EAST DURHAM
Joyland
Oak Grove
DUKE FOREST
NORTH GARRETT ROAD
NORTH CAROLINA CENTRAL UNIVERSITY
GROVE PARK
SHANNON PLAZA
HOPE VALLEY
HOPE VALLEY FARMS
Bethesda
ASHLEY FOREST
WOODCROFT
CARPENTER-FLETCHER
SOUTHPOINT
PARKWOOD
RESEARCH TRIANGLE PARK
Blands
Clegg
Google My Maps

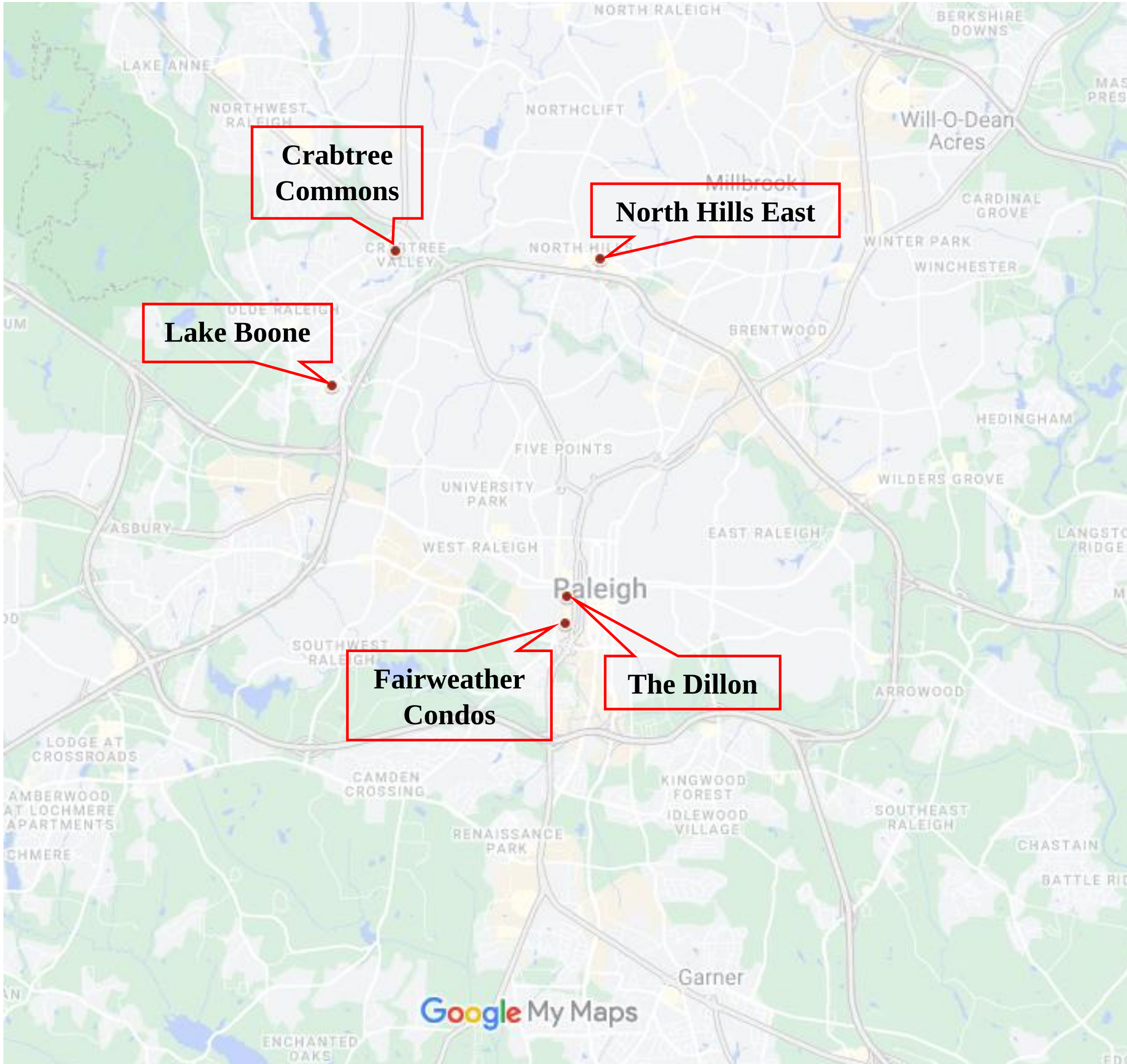
Fayetteville, NC



Greensboro, NC



Raleigh, NC


Crabtree Commons
North Hills East
Lake Boone
Fairweather Condos
The Dillon
Raleigh
Garner
Google My Maps

Wilmington, NC

Winston-Salem, NC

Appendix B. Two-Hour Trip Counts

Table B1. Two-hour Trips Counts

Site	Counts					Grand Total	% Vehicle
	Vehicle	Walk	Bike	Bus	Light Rail		
RAL_Lake Boone	**1,007**	**26**		**1**		**1,034**	97%
AM	274	5				279	98%
PM	733	21		1		755	97%
RAL_Crabtree Crossing	**530**	**33**	**2**			**565**	94%
AM	167	12				179	93%
PM	363	21	2			386	94%
CLT_Uptown 550	**492**	**71**				**563**	87%
AM	212	29				241	88%
PM	280	42				322	87%
DUR_Amazon RDU5	**465**			**4**		**469**	99%
AM	239			2		241	99%
PM	226			2		228	99%
CH_Berkshire 54	**375**	**31**	**2**	**5**		**413**	91%
AM	161	13		2		176	91%
PM	214	18	2	3		237	90%
CLT_RailYard SouthEnd	**1,166**	**718**	**19**	**2**		**1,905**	61%
AM	505	296	5	2		808	63%
PM	661	422	14			1,097	60%
RAL_The Dillon	**767**	**645**	**6**			**1,418**	54%
AM	298	130				428	70%
PM	469	515	6			990	47%
RAL_Fairweather Condos	**50**	**60**	**2**			**112**	45%
AM	20	35	1			56	36%
PM	30	25	1			56	54%
GBO_Greenway at Fisher Park	**269**	**57**				**326**	83%
AM	94	14				108	87%
PM	175	43				218	80%
GBO_Hawthorne at Friendly	**206**	**28**	**2**			**236**	87%
AM	89	7				96	93%
PM	117	21	2			140	84%
GBO_Kirkwood Place	**207**	**18**				**225**	92%
AM	64	10				74	86%
PM	143	8				151	95%
WS_Link Apts. Innovation Qtr.	**462**	**386**	**3**	**1**		**852**	54%
AM	212	191	2			405	52%
PM	250	195	1	1		447	56%

WS_The Easley	**263**	**27**	**2**	**1**		**293**	90%
AM	97	9		1		107	91%
PM	166	18	2			186	89%
CLT_Optimist Hall	**902**	**61**	**8**		**20**	**991**	91%
AM	238	9	1		6	254	94%
PM	664	52	7		14	737	90%
CLT_Cortland NoDa	**287**	**75**	**1**		**36**	**399**	72%
AM	128	26			19	173	74%
PM	159	49	1		17	226	70%
ASH_The Patton	**113**	**46**	**4**	**1**		**164**	69%
AM	50	26	3	1		80	63%
PM	63	20	1			84	75%
ASH_55 Market	**36**	**13**				**49**	73%
AM	9					9	100%
PM	27	13				40	68%
FAY_CrossCreekPoint	**415**	**34**				**449**	92%
AM	152	11				163	93%
PM	263	23				286	92%
WLM_MayfaireFlats	**305**	**41**	**4**			**350**	87%
AM	127	15	3			145	88%
PM	178	26	1			205	87%
WLM_ArboretumVillage	**177**	**13**	**2**			**192**	92%
AM	78	4				82	95%
PM	99	9	2			110	90%
RAL_North Hills East	**9,070**	**408**	**10**	**5**		**9,493**	96%
AM	3,607	230	7	3		3,847	94%
PM	5,463	178	3	2		5,646	97%
Grand Total	**17,564**	**2,791**	**67**	**20**	**56**	**20498**	**86%**

Table B2. Two-Hour Multimodal Trip Splits during AM Peak Period

Site	Vehicle	Walk	Bike	Bus	Light Rail
RAL_The Fairweather Condos	36%	63%	2%	0%	0%
WS_Link Apartments Innovation Quarter	52%	47%	0%	0%	0%
CLT_The RailYard South End	63%	37%	1%	0%	0%
ASH_The Patton	63%	33%	4%	1%	0%
RAL_The Dillon	70%	30%	0%	0%	0%
CLT_Cortland NoDa	74%	15%	0%	0%	11%
GBO_Kirkwood Place	86%	14%	0%	0%	0%
GBO_Greenway at Fisher Park	87%	13%	0%	0%	0%
WLM_Mayfaire Flats Apartments	88%	10%	2%	0%	0%
CLT_Uptown 550	88%	12%	0%	0%	0%
WS_The Easley	91%	8%	0%	1%	0%
CH_Berkshire 54 Apartment Homes	91%	7%	0%	1%	0%
GBO_Hawthorne at Friendly	93%	7%	0%	0%	0%
FAY_Cross Creek Pointe	93%	7%	0%	0%	0%
RAL_Crabtree Commons	93%	7%	0%	0%	0%
CLT_Optimist Hall	94%	4%	0%	0%	2%
RAL_North Hills East	94%	6%	0%	0%	0%
WLM_ArboretumVillage	95%	5%	0%	0%	0%
RAL_Lake Boone Marketplace	98%	2%	0%	0%	0%
DUR_Amazon Fulfillment Center RDU5	99%	0%	0%	1%	0%
ASH_55 Market	100%	0%	0%	0%	0%

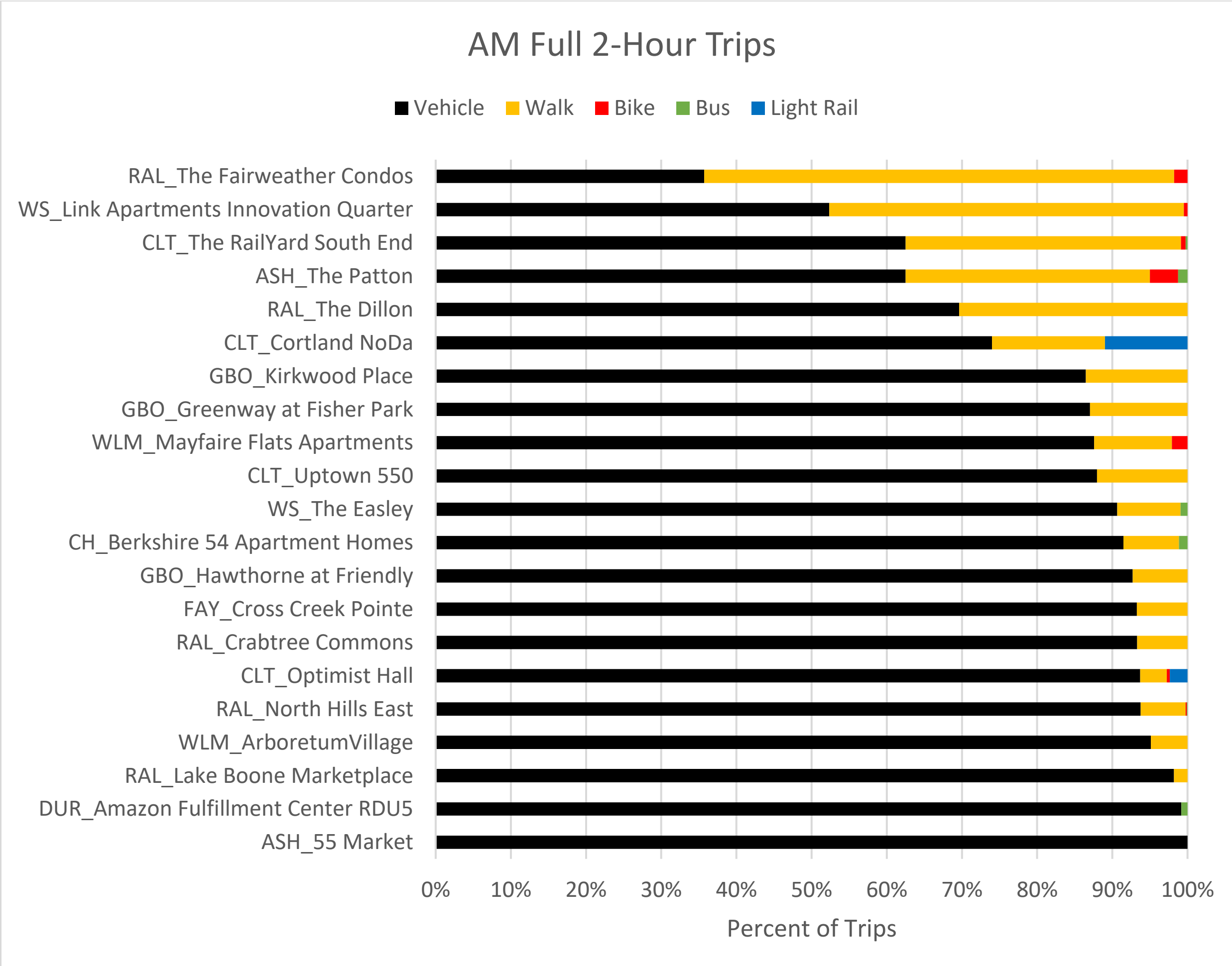


Figure B1. Percent of Trips during AM Peak Period

Table B3 - Two-Hour Multimodal Trip Splits during PM Peak Period

Site	Vehicle	Walk	Bike	Bus	Light Rail
RAL_The Dillon	47%	52%	1%	0%	0%
RAL_The Fairweather Condos	54%	45%	2%	0%	0%
WS_Link Apartments Innovation Quarter	56%	44%	0%	0%	0%
CLT_The RailYard South End	60%	38%	1%	0%	0%
ASH_55 Market	68%	33%	0%	0%	0%
CLT_Cortland NoDa	70%	22%	0%	0%	8%
ASH_The Patton	75%	24%	1%	0%	0%
GBO_Greenway at Fisher Park	80%	20%	0%	0%	0%
GBO_Hawthorne at Friendly	84%	15%	1%	0%	0%
WLM_Mayfaire Flats Apartments	87%	13%	0%	0%	0%
CLT_Uptown 550	87%	13%	0%	0%	0%
WS_The Easley	89%	10%	1%	0%	0%
WLM_ArboretumVillage	90%	8%	2%	0%	0%
CLT_Optimist Hall	90%	7%	1%	0%	2%
CH_Berkshire 54 Apartment Homes	90%	8%	1%	1%	0%
FAY_Cross Creek Pointe	92%	8%	0%	0%	0%
RAL_Crabtree Commons	94%	5%	1%	0%	0%
GBO_Kirkwood Place	95%	5%	0%	0%	0%
RAL_North Hills East	97%	3%	0%	0%	0%
RAL_Lake Boone Marketplace	97%	3%	0%	0%	0%
DUR_Amazon Fulfillment Center RDU5	99%	0%	0%	1%	0%

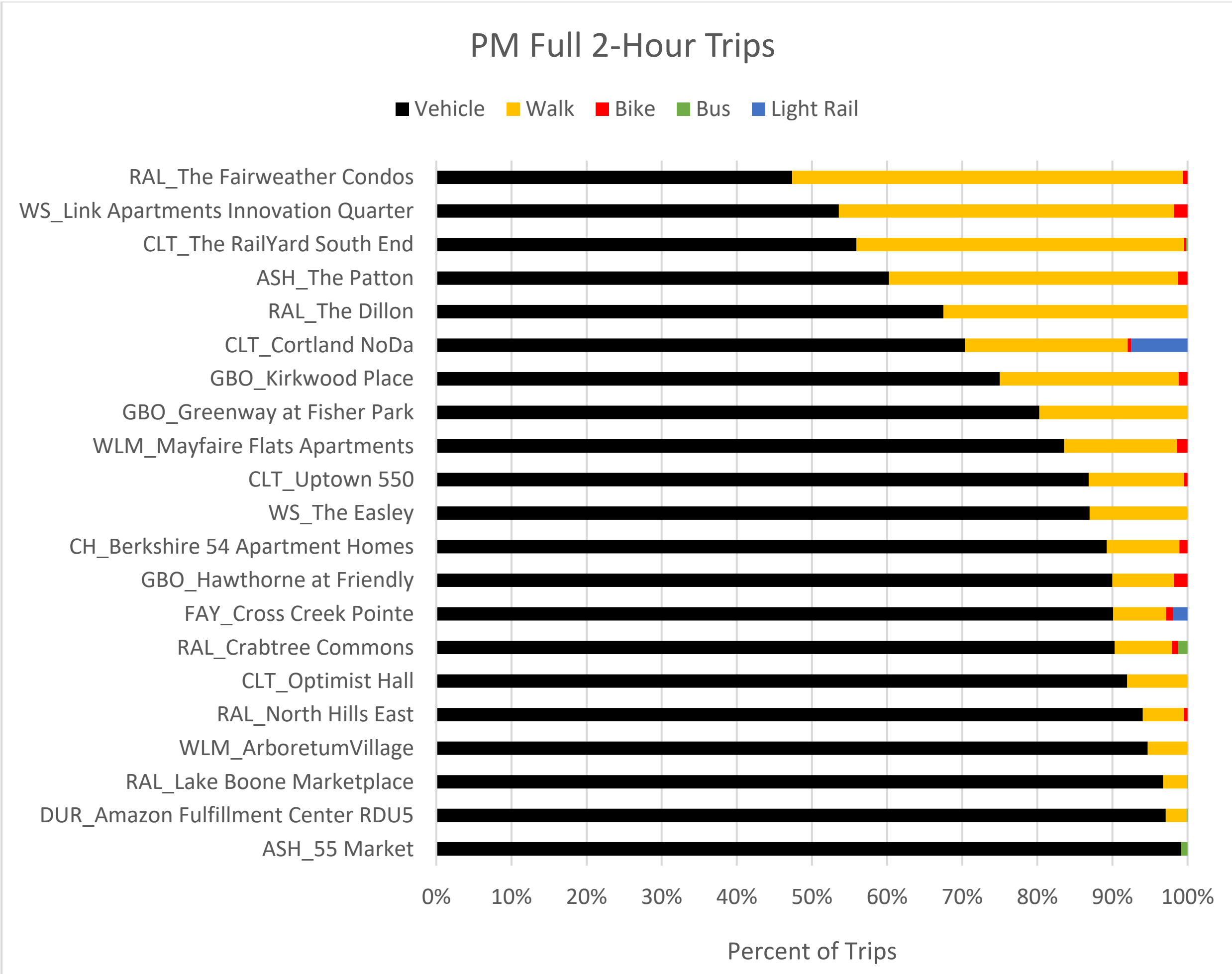


Figure B2. Percent of Trips during PM Peak Period

Appendix C. ITE Trip Generation Analysis Procedure

When estimating trip generation at each site, the ITE Trip Generation Manual method used the applicable LUC from the ITE Trip Generation Manual. However, a large percentage of the initial LUCs used directly from ITE Trip Generation Manual required the use of LOCAL data that was not available. The ITRE research team developed a method of determining LUCs that would still allow for the comparison between ITRE field analysis data (a form of LOCAL data) and the calculated estimate from the ITE Trip Generation Manual. Instead of using the initial LUC according to the ITE Trip Generation Manual, the ITRE Estimate method used the next closest LUC that utilized EQN or RATE to avoid using a LUC that resulted in the need for LOCAL data. Figure C1 illustrates an example of the Greensboro Kirkwood Place in terms of the location and land use of the development. Then, Table C1 presents comparisons between initial and estimated Land Use Codes (LUCs) for different types of occupants, highlighting both their descriptions and how they are classified in the ITE manual and ITRE estimate methods.

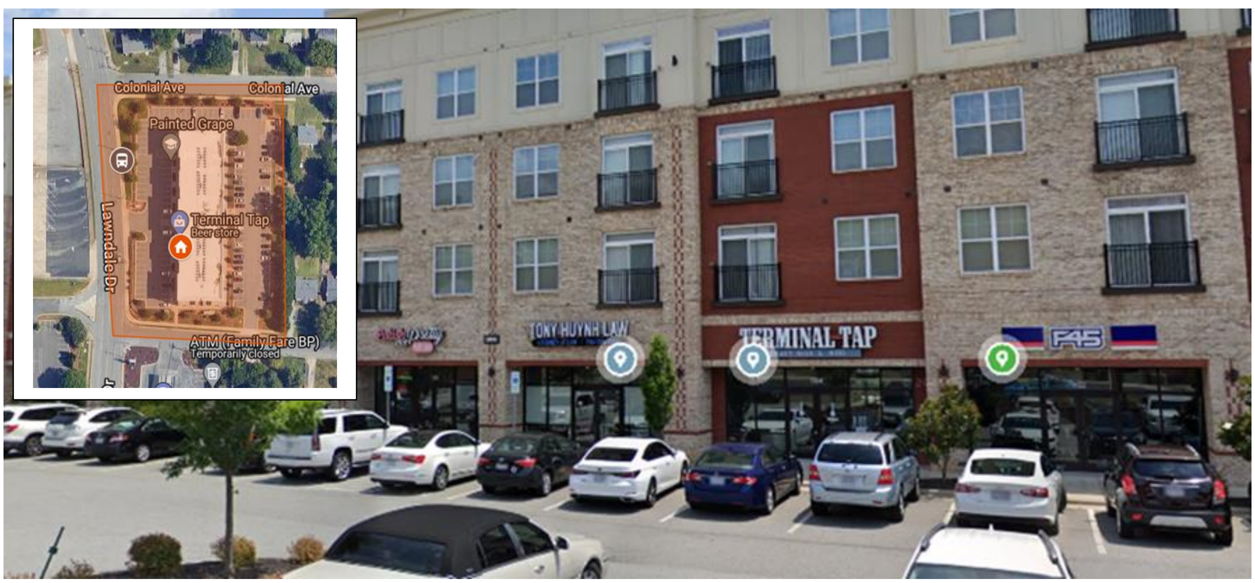


Figure C1. Kirkwood Place Example

Table C1. Comparison of Land Use Codes between ITE Manual and ITRE Method

Occupant	ITE Manual		ITRE Estimate Method	
	LUC	Description	LUC	Description
Kirkwood Place Apts.	*231*	*Mid-Rise Residential with 1st-Floor Commercial*	221	Multifamily Housing (Mid-Rise)
DS Studios Beauty Salon	*918*	*Hair Salon*	820	Shopping Center [treated as general retail]
Polish Me Pretty Nail Spa	*918*	*Hair Salon*		
Terminal Tap Taproom	*925*	*Drinking Place*		
F45 Gym	*492*	*Health/Fitness Club*		
Tony Huynh Law Office	712	Small Office Building [suggested to include LOCAL]	710	General Office Building [treated as general office]

Note: Italic means local data are required for estimating trip generation

Specifically, the Kirkwood Place Apts. was Initially classified as LUC 231, "Mid-Rise Residential with 1st-Floor Commercial," it is re-estimated as LUC 221, "Multifamily Housing (Mid-Rise)," suggesting a shift in how the residential component is treated. DS Studios Beauty Salon and Polish Me Pretty Nail Spa were originally listed under LUC 918, "Hair Salon," they were reclassified under LUC 820, "Shopping Center" in the ITRE estimate method, indicating their treatment as general retail for trip generation estimation. Similarly, Terminal Tap Taproom and F45 Gym, initially classified under LUC 925 "Drinking Place" and LUC 492 "Health/Fitness Club" in the ITE manual, were also reclassified under LUC 820, "Shopping Center" in the ITRE estimate method. Tony Huynh Law Office was initially classified under LUC 712, "Small Office Building" and recommended for inclusion of local data to improve accuracy; was re-estimated as LUC 710, "General Office Building" by the ITRE estimate method. These adjustments were made for better trip generation estimates, particularly for mixed-use and general retail establishments. More detailed LUCs are summarized below:

Land Use Type 1

Land Use Type 1												
ITE Trip Gen Manual			NCDOT Selection of Variable				Local	ITE Manual				
Source	***LUC***	***Description***	***Setting/Location***	***IND VARIABLE***	***PK HR TYPE***	***METHOD***	***Units***	***AM Trip Gen Estimate***	***% Entering***	***PM Trip Gen Estimate***	***% Entering***
ITE Manual	220	Multifamily Housing (Low-Rise)	GENERAL URBAN-SUBURBAN	Dwelling Units	Adjacent	EQN	296	133.73	23%	155.15	63%
ITE Manual	221	Multifamily Housing (Mid-Rise)	GENERAL URBAN-SUBURBAN	Dwelling Units	Adjacent	EQN	309	103.41	26%	130.84	61%
ITRE Estimate	222	Multifamily Housing (High-Rise)	DENSE MULTI-USE URBAN	Dwelling Units	Adjacent	EQN	426	84.41	12%	74.00	70%
ITE Manual	820	Shopping Center [Data Range: 16-1500]	GENERAL URBAN-SUBURBAN	1000 GLA	Adjacent	EQN	112.12	207.84	62%	591.39	48%
ITRE Estimate	221	Multifamily Housing (Mid-Rise)	DENSE URBAN-SUBURBAN	Occupied DUs	Adjacent	EQN	80	24.13	27%	18.93	63%
ITE Manual	150	Warehousing	GENERAL URBAN-SUBURBAN	1000 GFA	Adjacent	EQN	328.45	64.73	77%	67.23	27%
ITE Manual	221	Multifamily Housing (Mid-Rise)	GENERAL URBAN-SUBURBAN	Dwelling Units	Adjacent	EQN	263	88.30	26%	112.09	61%
ITE Manual	221	Multifamily Housing (Mid-Rise)	GENERAL URBAN-SUBURBAN	Dwelling Units	Adjacent	EQN	188	63.54	26%	81.21	61%
ITRE Estimate	221	Multifamily Housing (Mid-Rise)	GENERAL URBAN-SUBURBAN	Dwelling Units	Adjacent	EQN	57	19.73	26%	25.82	61%
ITE Manual	221	Multifamily Housing (Mid-Rise)	GENERAL URBAN-SUBURBAN	Dwelling Units	Adjacent	EQN	336	112.25	26%	141.80	61%
ITE Manual	820	Shopping Center [Data Range: 16-1500]	GENERAL URBAN-SUBURBAN	1000 GLA	Adjacent	EQN	2.58	153.07	62%	36.28	48%
ITRE Estimate	221	Multifamily Housing (Mid-Rise)	CENTER CITY CORE	Occupied DUs	Adjacent	EQN	275	70.45	31%	73.36	50%
ITE Manual	221	Multifamily Housing (Mid-Rise)	DENSE MULTI-USE URBAN	Occupied DUs	Adjacent	EQN	46	14.61	27%	73.36	63%
ITRE Estimate	221	Multifamily Housing (Mid-Rise)	GENERAL URBAN-SUBURBAN	Dwelling Units	Adjacent	EQN	794	260.74	26%	323.76	61%
ITRE Estimate	221	Multifamily Housing (Mid-Rise)	DENSE MULTI-USE URBAN	Occupied DUs	Adjacent	EQN	326	93.01	27%	87.81	63%
ITE Manual	221	Multifamily Housing (Mid-Rise)	DENSE MULTI-USE URBAN	Occupied DUs	Adjacent	EQN	275	78.73	27%	73.53	63%
ITE Manual	221	Multifamily Housing (Mid-Rise)	GENERAL URBAN-SUBURBAN	Dwelling Units	Adjacent	EQN	117	39.92	26%	51.51	61%
ITE Manual	221	Multifamily Housing (Mid-Rise)	GENERAL URBAN-SUBURBAN	Dwelling Units	Adjacent	EQN	67	23.12	26%	30.16	61%
ITE Manual	221	Multifamily Housing (Mid-Rise)	GENERAL URBAN-SUBURBAN	Dwelling Units	Adjacent	EQN	240	80.72	26%	102.66	61%
ITE Manual	220	Multifamily Housing (Low-Rise)	GENERAL URBAN-SUBURBAN	Dwelling Units	Adjacent	EQN	98	46.79	23%	58.01	63%
ITE Manual	220	Multifamily Housing (Low-Rise)	GENERAL URBAN-SUBURBAN	Dwelling Units	Adjacent	EQN	272	123.41	23%	143.91	63%

Land Use Type 2

Land Use Type 2												
ITE Trip Gen Manual			NCDOT Selection of Variable				Local	ITE Manual				
Source	***LUC***	***Description***	***Setting/Location***	***IND VARIABLE***	***PK HR TYPE***	***METHOD***	***Units***	***AM Trip Gen Estimate***	***% Entering***	***PM Trip Gen Estimate***	***% Entering***
ITRE Estimate	710	General Office Building [Data Range: 10-900]	DENSE MULTI-USE URBAN	1000 GFA	Generator	EQN	1	53.27	87%	20.97	19%
ITRE Estimate	710	General Office Building	GENERAL URBAN-SUBURBAN	1000 GFA	Generator	EQN	3.302	8.26	88%	69.02	18%
ITE Manual	820	Shopping Center [Data Range: 16-1500]	GENERAL URBAN-SUBURBAN	1000 GLA	Adjacent	EQN	31.995	167.78	62%	233.81	48%
ITRE Estimate	710	General Office Building [Data Range: 10-900]	GENERAL URBAN-SUBURBAN	1000 GFA	Generator	EQN	4.8	11.48	88%	70.67	18%
ITE Manual	820	Shopping Center [Data Range: 16-1500]	GENERAL URBAN-SUBURBAN	1000 GLA	Adjacent	EQN	18.53	161.05	62%	156.08	48%
ITE Manual	710	General Office Building [Data Range: 10-900]	CENTER CITY CORE	1000 GFA	Generator	EQN	220	107.8	88%	94.6	18%
ITRE Estimate	710	General Office Building	GENERAL URBAN-SUBURBAN	1000 GFA	Generator	EQN	10.372	22.61	73%	76.80	32%
ITE Manual	222	Multifamily Housing (High-Rise) [Data Range: 75-500]	GENERAL URBAN-SUBURBAN	Dwelling Units	Adjacent	EQN	657	196.82	24%	231.94	61%
ITE Manual	820	Shopping Center [Data Range: 16-1500]	GENERAL URBAN-SUBURBAN	1000 GLA	Adjacent	EQN	2.976	153.27	62%	40.33	48%
ITRE Estimate	710	General Office Building	GENERAL URBAN-SUBURBAN	1000 GFA	Generator	EQN	6.23	14.44	88%	72.24	18%

Land Use Type 3

Land Use Type 3												
ITE Trip Gen Manual								NCDOT Selection of Variable				
Source	**LUC**	**Description**	**Setting/Location**	**IND VARIABLE**	**PK HR TYPE**	**METHOD**	**Units**	**AM Trip Gen Estimate**	**% Entering**	**PM Trip Gen Estimate**	**% Entering**
ITRE Estimate	820	Shopping Center [Data Range: 16-1500]	GENERAL URBAN-SUBURBAN	1000 GLA	Adjacent	EQN	2	152.78	62%	3.40	48%
ITRE Estimate	710	General Office Building	DENSE URBAN-SUBURBAN	1000 GFA	Generator	EQN*	303.21	258.77	87%	256.69	19%
ITRE Estimate	820	Shopping Center [Data Range: 16-1500]	GENERAL URBAN-SUBURBAN	1000 GLA	Adjacent	EQN	4.8	154.18	62%	57.44	48%
ITE Manual	820	Shopping Center [Data Range: 16-1500]	GENERAL URBAN-SUBURBAN	1000 GLA	Adjacent	EQN	4.72	154.14	62%	56.73	48%
ITE Manual	820	Shopping Center [Data Range: 16-1500]	GENERAL URBAN-SUBURBAN	1000 GLA	Adjacent	EQN	52	177.78	62%	334.93	48%
ITE Manual	255	Continuing Care Retirement Community [Data Range: 2500-2200]	GENERAL URBAN-SUBURBAN	Occupied Units	Adjacent	EQN	379	68.50493417	65%	73.28875764	39%

Land Use Type 4

Land Use Type 4											
ITE Trip Gen Manual			NCDOT Selection of Variable				Local	ITE Manual			
Source	***LUC***	***Description***	***Setting/Location***	***IND VARIABLE***	***PK HR TYPE***	***METHOD***	***Units***	***AM Trip Gen Estimate***	***% Entering***	***PM Trip Gen Estimate***	***% Entering***
ITRE Estimate	710	General Office Building	GENERAL URBAN-SUBURBAN	1000 GFA	Generator	EQN	100.55	166.90	88%	176.00	18%
ITE Manual	310	Hotel [Data Range: 75-425]	GENERAL URBAN-SUBURBAN	Rooms	Adjacent	EQN	272	130.66	59%	177.98	51%

Land Use Type 5

Land Use Type 5											
ITE Trip Gen Manual			NCDOT Selection of Variable				Local	ITE Manual			
Source	***LUC***	***Description***	***Setting/Location***	***IND VARIABLE***	***PK HR TYPE***	***METHOD***	***Units***	***AM Trip Gen Estimate***	***% Entering***	***PM Trip Gen Estimate***	***% Entering***
ITRE Estimate	710	General Office Building [Data Range: 10-900]	GENERAL URBAN-SUBURBAN	1000 GFA	Generator	EQN	1260	1544.11	88%	1451.39	18%

Land Use Type 6

Land Use Type 6												
ITE Trip Gen Manual			NCDOT Selection of Variable				Local	ITE Manual				
Source	***LUC***	***Description***	***Setting/Location***	***IND VARIABLE***	***PK HR TYPE***	***METHOD***	***Units***	***AM Trip Gen Estimate***	***% Entering***	***PM Trip Gen Estimate***	***% Entering***
ITRE Estimate	820	Shopping Center [Data Range: 16-1500]	GENERAL URBAN-SUBURBAN	1000 GLA	Adjacent	EQN	140	221.78	62%	697.02	48%