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A New Framework to estimate Pedestrians' Transit Demand from Discrete Mode Choice Modelling applied toward the Prioritization of Pedestrian Infrastructure Investments in Knoxville, TN

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To the Graduate Council:

I am submitting herewith a thesis written by Dua Ahmad Mohammad Abdelqader entitled "A New Framework to estimate Pedestrians' Transit Demand from Discrete Mode Choice Modelling applied toward the Prioritization of Pedestrian Infrastructure Investments in Knoxville, TN." I have examined the final electronic copy of this thesis for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Master of Science, with a major in Civil Engineering.

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DEDICATION

To my Family

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ABSTRACT

The potential social, economic and environmental benefits associated with transit oriented developments encourage investments to enhance transit service, pedestrian infrastructure and parking opportunities. Boosting transit ridership, reducing traffic and congestion, supporting mixed land uses and improving public mobility are among a long list of benefits of a well-developed transit system. Understanding the travel behaviors within the studied areas is the key to finding the best methods to be utilized to attain these benefits. Many studies have focused on locating transit service areas to forecast ridership and apply the appropriate modifications to the existing or planned systems using travel behaviors of transit riders from transit on-boards surveys. Buffer distances were then used to confine service areas of potential transit demand. The bias associated with using transit users' demographics and the exclusion of demand beyond buffer distances motivated the search for a new method to estimate the demand for transit. Utilizing a mode choice model in estimating transit demand excludes some of the limitations found in other methods. This model was used to estimate potential walk to transit trips from each residential household for home-based work trips for Knox County using estimated probabilities of walking to transit and work trip production rates. The total walk-to - transit trips were associated with the street segments utilized to reach a transit stop. These weights of total trips were then used to prioritize pedestrian infrastructure investments at higher transit demand segments. This method can also be utilized in the prioritization of other service enhancements and stop locations.

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CHAPTER I
INTRODUCTION

The overall goal of reducing vehicle miles travelled by the transportation system users and the associated energy consumption rates and effects on the environment and public welfare, forced the implementation of fuel efficiency regulations and supported the transition to alternative modes.

Using a shared passenger transport service like public transit is one effective approach to reduce the number of vehicle-miles traveled on US roadways. Consequently, this reduction supported the mitigation of a large portion of the impacts on energy consumption and emissions. A study by the American Public Transportation Association showed that the effect of a single person, commuting alone by car, switching a 20-mile round trip to public transit results in a 10% reduction in all greenhouse gases produced by a typical two-adult, two-car household (APTA, 2008). For this transition to be encouraged, an efficient, effective and reliable transit system should exist and investments to improve this system to the required levels of service is the key to accomplish this transition. Despite its existence, few of the targeted groups of users end up using this system resulting in low ridership with a few exceptions. To fully understand the manner in which these investments and other improvements would be implemented, population densities, demographics, land uses and trip purposes are among a long list of factors included in these analyses.

For decades, attempts to understand the travel behaviors of the transportation system users have led to the diversified models and analysis tools that were derived from extensive surveys and controlled by many assumptions and base variables. A small discipline of such models concentrated on identifying public transit systems ridership based on the demographic characteristics of riders and the quality of service provided. These studies presented a wide range of models that can be applied to general or specific situations on small and large scales of analysis.

A better understanding of all the aspects related to the transit system requires proper knowledge, forecast and estimation of the users and riders in order to identify the quantitative

and qualitative features of the available or planned systems. Therefore, identifying the area around stops, stations and overall routes from which potential users are drawn was one of the major focuses of this study.

These approaches used for delineating service areas were coupled with efforts to understand walking distances and walking environments encountered by the users and their effects on the propensity to use the system. Buffer zone models, network ratio methods and/or models based on distance decay functions were used for this purpose and all have strengths and deficiencies and most are built on a stockpile of assumptions.

The exclusion of potential demand beyond the buffer distances and the bias associated with user demographics data from on-board surveys motivated the search for a new method to estimate transit demand and propensity to walk to transit.

In this study, we provide a new method to prioritize pedestrian infrastructure investments by highlighting locations with high demand for transit. Pedestrian transit demand was estimated by applying a mode choice model to calculate household probability of walking to transit for home-based work trips. Probabilities of walking to transit coupled with work trip production rates were used to estimate total walk to transit trips expected to be generated from each household. Each street segment was assigned the total of the walk to transit trips that will use this segment to reach transit stops. These weights of walk to transit trips were used to identify segments with high demand for transit and prioritize pedestrian infrastructure investments at these locations.

CHAPTER II
LITERATURE REVIEW

2.1 Transit Service Area

Delineating transit service areas around stops and stations is one of the highly implemented methods in identifying the population served by the transit system (El-Geneidy et al., 2014). When accurately delineated, service areas can be useful in determining the demand for transit and spotting gaps and redundancies in the offered service at the same or different transit routes. The purpose of delineating transit service areas is usually associated with the need to forecast future transit ridership and find the gaps in the system. These forecasts will be used in optimizing the service provided and maximizing the number of potential riders.

The most commonly known and largely used method to delineate the service area – based on a rule of thumb – is the buffer method. Usually a 0.25 mile and 0.5 mile buffer zones are defined around bus and rail stops, respectively, corresponding to a 5-10 minute walking time around these stops (O'Neill et al., 1992; Hsiao et al., 1997; Zhao et al., 2003; Upchurch et al., 2004; Kimpel et al., 2007). The populations within these buffers are considered to have access to transit service within walking distance as people are anticipated not to walk farther than these distances. Despite its acceptability among a wide body of researchers and practitioners, the buffer method relies on the assumption of uniform population densities and identical transit stops and stations for the same mode (El-Geneidy et al., 2014).

The Network Ratio method is another form of the buffer method that defines the service area around stops and stations based on real street network distances rather than Euclidean distances (O'Neill et al., 1992). This approach accounts for the overestimation of populations served by transit systems and includes only those populations around walking routes along street networks. According to this method, the population with access to transit is identified as the ratio of street network within walking distance from transit to the total length of the network in a specific analysis zone multiplied by the total population within this zone.

The application of this model to transit stops and stations attempts to eliminate the assumption of uniform population densities within the service area. On the other hand, other assumptions of proportionality between streets lengths and population and uniformity of population emerge.

A significant proportion of these assumptions were treated when researchers started using real survey data of transit riders walking distances to transit stops. Their findings ranged from lower to higher walking distances compared to the 0.25 and 0.5 mile distances used earlier. Autman-Hall et al. (1997) studied transit riders walking distances in Ontario, Canada and found that a mean of 300 m (0.19 mile) and a maximum of 600 m (0.37 mile) were the actual distances walked by these users and are different from the standard distances used as a rule of thumb. Moreover, Lam and Morrall (1982) found an average of 0.2 mile and a 75th percentile of 0.28 mile walking distances to bus stops in Calgary, Canada. In Sydney, Australia, Daniels and Mulley (2013) studied the walking distances to bus stops and found an average of 0.29 mile and a 75th percentile of 0.35 mile. On the other hand, higher walking distances – up to 1.88 miles with a 75th percentile of 0.68 mile – were found for San Francisco Bay area and Portland, Oregon (Agrawal et al., 2008).

In a more profound analysis of pedestrian’s propensity to walk to different destinations and other modes of transportation, a study by the Minnesota Department of Transportation surveyed walking distances for different modes and trip purposes and found that substantial shares of pedestrian travel exceeded the 0.25 mile threshold which were significantly affected by the type of service and trip purposes (Iacono et al., 2008).

The apparent under- and over-estimation of walking distances for different cities, transit routes and even different stops and stations forced the use of specific distance buffers for specific locations. Kimpel et al. (2007) used a 0.3 mile buffer around bus stations in an attempt to define more inclusive service areas based on the assumption that some users are willing to walk more than 0.25 mile to reach a stop or station.

These distances were used to find more representative buffers to estimate the populations within these catchment areas as an indicator of the expected demand for the studied transit stops

and stations. Within these buffers, population is usually assumed to be uniform and based on broader geographic resolution. The methods used to estimate and distribute populations differ among researchers. Zhao et al. (2003) used number of bedrooms from property tax data and total TAZ populations to estimate household size. Each parcel included in the analysis – within 0.5 mile buffer – was assigned the appropriate household size. The accumulated total population from all parcels within the network buffer was then used to forecast demand at each transit stop.

Similarly, Biba et al. (2010) overcame the assumption of uniform population distributions by assigning estimated populations to parcels, based on building areas, and creating walking distances from these parcels to the nearest transit facilities then compute the associated walking distances. This method highly improves the precision of the assigned populations but still relies on a more critical assumption of 0.25 mile walking distance to delineate the service areas.

Another approach by Pulugurtha et al. (1999) estimates the number of potential captive riders within a 0.25 mile buffer zone. They use an index of transit potential utilizing demographic variables such as age, income and auto ownership assumed to be uniformly distributed throughout the TAZ. This index was used to optimize transit service facilities locations by defining accessibility of potential captive riders.

2.2 The Distance Decay Function

The buffer method implicitly declares that all the population within the walking distances chosen for the buffer areas have the same level of willingness to walk to transit stops. Over time, researchers attempted to understand the manner in which the propensity to use the system changes when distance changes. This also resulted in a wide range of estimates for different cities and within the same system.

This distance decay effect is based on the commonly used geographical spatial interaction concept used to forecast trip distribution in transportation planning models and it explains the deterrence to move between two locations due to distance (Iacono et al., 2008). The level of deterrence differs based on the distance between the interacting locations and is often expressed

as an exponential function exp(-*bx*), where *b* is an empirically estimated level of impedance and *x* represents distance.

Ignoring the existence of variations in transit use probabilities within the same distance threshold in the existing models motivated the assignment of greater weights to areas that are near transit stations than for farther distanced areas with lower probabilities of transit use. In their study, Gutierrez et al. (2011) utilized 100 m width bands around transit stops and stations to cover a threshold derived from the surveyed walking distances. The population within each band was estimated and different weights were assigned to each based on their distance in order to forecast the overall population served by this station.

El-Geneidy et al. (2014) also used the concept of distance decay to study transit service areas based on survey data of walking distances to bus, metro and commuter train in the Montreal Metropolitan Region which presented varying exponential and linear functions for different modes. In their study, a multilevel regression model was used to estimate the effect of individual user characteristics on the walking distances to stops and stations. The outcome walking distance estimations were used to assign a mean walking distance for each transit stop. The variations in walking distance allowed the generation of different service areas around transit stops for the purpose of finding gaps and redundancies in the existing service.

Similarly, Kimpel et al. (2007) estimated distance decay parameters from an empirically analyzed negative logistic function that maximizes goodness of fit using data collected from Portland Metropolitan Region transit provider (TriMet) on boarding and alighting and service reliability data. The model was able to estimate probabilities of bus riding for dwelling units within a 0.3 mile walking distance which gives different weights to different walking distances. This approach uses boarding data to empirically estimate distance decay parameters and does not account for differences in demographics for the studied dwelling units and level of service of transit stops.

In the same manner Zhao et al. (2003) fitted an exponential curve to reflect the deterioration of transit use with distance using sample data from a transit on-board survey conducted in Southeast Florida. From this decay function, a maximum walking distance of 0.5

miles was selected. The probabilities associated with each walking distance were then used to calculate the potential demand from all the units included in the 0.5 mile catchment area for each transit stop or station.

2.3 Factors Affecting Transit Demand

The focus on one factor such as walking distance when estimating transit demand might be significant when choice riders are the only contributors to the overall ridership or in situations where the offered transit system serves a geographic location where populations comprise similar demographic characters and/or travel behaviors. Therefore, considering all the factors that can be associated with the decision of using transit is crucial to the accurate estimation of transit use probabilities.

These variables might be related to the users, the system and/or external factors of weather and topography. Individual socio-economic characteristics might be the most determining factors with regard to the individual's propensity to use the transit system. Household income (McLeod et al., 1991; Liu, 1993; Hsiao et al., 1997; Pulugurtha et al., 1999; Daniels and Mulley, 2013) the density of households under poverty levels (Ambruster, 2010), household size (Hsiao et al., 1997; Cohn, 1999; Zhao et al., 2003; Daniels and Mulley, 2013), employment types and rates (Gomez, 1996, Pulugurtha et al., 1999; Hobbs et al., 2002; TCRP, 2007), age and the percentage of senior population (Pulugurtha et al., 1999; Hobbs et al., 2002; Zhao et al., 2003; TCRP, 2007; Daniels and Mulley, 2013), auto ownership and the number of autos per household (McLeod et al., 1991; Liu, 1993; Hsiao et al., 1997; Kain and Liu, 1999; Pulugurtha et al., 1999; TCPR, 2007; Daniels and Mulley, 2013), ethnicity and minority populations (Cohn, 1999; Hobbs et al., 2002; TCRP, 2007) and gender and physical disabilities (Daniels and Mulley, 2013) were found to be the most influential among the individual and household characteristics.

The effect of these variables varies significantly. Some factors might directly force the individual to use the transit system as when no auto is available for use or the income is not

sufficient to cover the high cost of driving. This casts extra weight to these factors when the overall demand is estimated.

Combining the individual characteristics with adjustments to the quality of the provided transit service is expected to significantly increase transit demand. These internal adjustments are applied to station characteristics and route features (El-Geniedy et al., 2014), most importantly service frequency and coverage (Kain and Liu, 1999; Hobbs et al., 2002; TCRP, 2007). Moreover, a reliable on-time performance of the system is a significant contributor to higher use rates (TCRP, 2007). User information (Hobbs et al., 2002), comfort and convenience (TCRP, 2007), station safety (Kain and Liu, 1999) and parking availability (Hobbs et al., 2002; TCRP, 2007) are other factors that might be of lower significance but found to have a noticeable effect on ridership. Average fare was also found to affect ridership specifically if applied to a system with a majority of low income users (Kain and Liu, 1999; Hobbs et al., 2002).

The majority of research that included the effect of these variables associates walking distances and different demographics from on-board survey data. These data are used to estimate regression models of walking distance and user demographics relationship (Zhao et al., 2003; El-Geneidy et al, 2014) and applied to identify forecasts of current and future transit demand.

2.4 Literature Review Conclusion

Transit demand estimation is driven largely by arbitrary distance buffers. Few of these studies modelled the effect of other demographics and system characteristics that were expected to have a significant effect on ridership. They were mainly generated from data provided by on-board surveys conducted by transit agencies. This data are expected to be biased to system users and it lacks comparable data from the overall demographic structure of the geographic locations they serve. Moreover, delineating service areas by a predetermined boundary, which is also based on data from actual users, eliminates the demand from potential users with longer walking distances. So-called captive riders, for example, have certain socio-demographic properties that make transit the best travel mode choice for them regardless of long walking distances. Moreover, scoping the analysis to TAZ levels comprises deficiencies with the introduction of

population distribution uniformity and the exclusion of the variation of the demographic characteristics of the studied areas.

These conclusions support the search for a new methodology to forecast service areas based on walking distances that accounts for individual differences and applies to certain locations with unique characteristics. This paper proposes a new method to address some of the shortcomings of previous work and develop more robust approaches to prioritize transit and pedestrian investments to support transit ridership.

CHAPTER III
FRAMEWORK TO ESTIMATE WALKING TO TRANSIT PROBABILITY

For the purpose of providing the best service for pedestrian riders and reaching the overall goal of a pedestrian oriented transit system, studying the previous research helped in highlighting the limitations associated with the ridership forecasting approaches and motivated the search for a new method to estimate walking to transit trips. Forecasting the numbers of walking trips will support defining locations with higher probabilities and focus service enhancement, pedestrian infrastructure prioritization, transit stop location optimization, and other improvements at these locations without the limitation of a bounded service area. Moreover, a more disaggregate scope of analysis at parcel level will be utilized considering the characteristics of the transit system, the individual and/or household, and the transit trip.

The basic theoretical framework for the suggested model to estimate household transit riding probabilities comprises of two steps. The first step is the estimation of a mode choice model from household travel survey data, which includes Transit (Walk Access) as an independent alternative mode utilizing household, individual and trip characteristics. The second step is the preparation of household data for the geographic locations under study to be applied to the previously estimated model. The results of this step include the utilities and probabilities associated with each household or parcel.

The mode choice model estimation process (Step 1) and the process for the estimation of walk to transit probabilities (Step 2) are illustrated in Figure 1 and 2, respectively.

The following sections discuss the modelling approach, input variables used in the model and data preparation approaches.

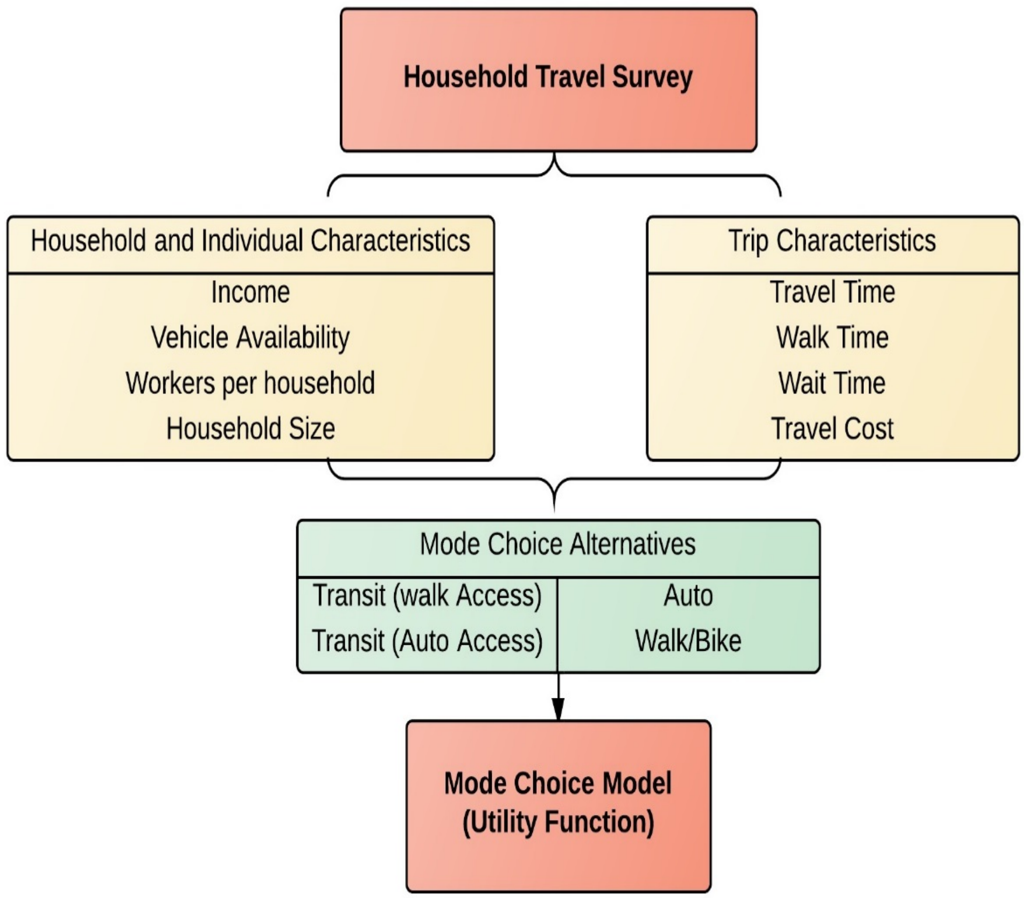


Figure 1. Modelling Approach- Step 1: Mode Choice Model Estimation

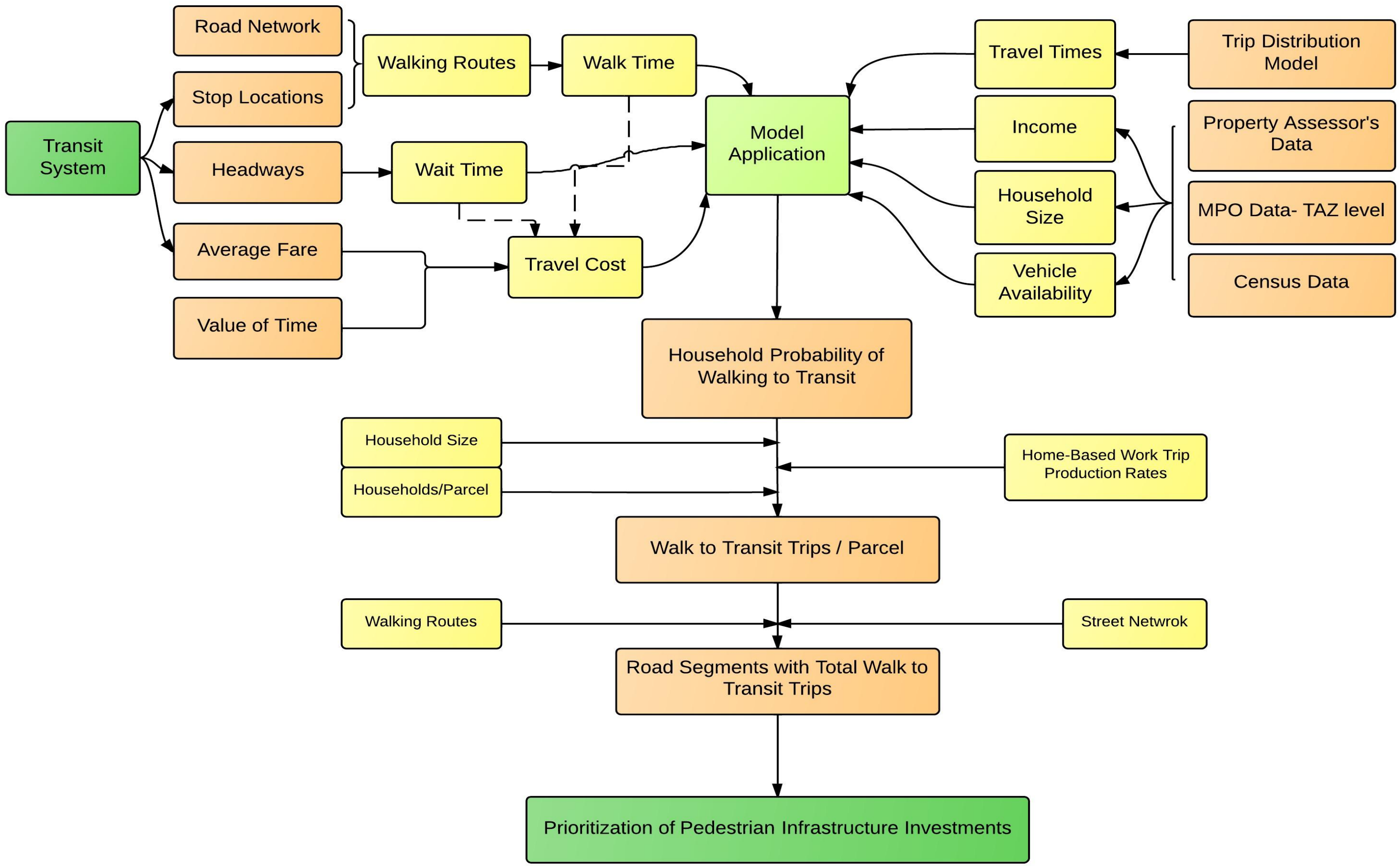


Figure 2. Modelling Approach- Step 2: Data Preparation and Model Application to Estimate Walk to Transit Probability

3.1 Modelling Approach

Transportation planning depends significantly on the transportation models forecasts and estimates of future travel demands. The four-step model is the commonly used approach to model travel flows, and we will be focusing on the mode choice part of this model to highlight the effect of socio-demographic characteristics and system levels of service on travel behavior and mode choice.

The choice of riding the transit system emerges after an expectedly comprehensive comparison of the available alternative modes by the potential user. This comparison is assumed to produce the choice with the highest utility to the user.

Ben-Akiva and Lerman (1985) identified the elements involved in the process of choosing the mode of travel. The elements shown in Figure 3 describe this process in which the decision makers are the main factor and the variability in the attributes related to them is the generator of the outcome decision. The individual or household would consider the physically and timely available alternatives, whose feasibility and existence are known at the time of the decision, based on their attractiveness (travel time, cost and comfort and convenience) and using a decision rule that best fulfills their needs. A choice that is better for at least one attribute and not worse for the other attributes would dominate among other alternatives and support the elimination of inferior ones. These processes can be used simultaneously or generalized to include the maximization of utility rule that combines the attributes for each alternative to specify an overall utility value. The final choice would be based on a comparison between the alternatives to find the ones with the maximum utility.

Therefore, a new approach to forecasting the potential demand of transit systems was needed. This motivated the search for an alternative framework that is capable of objectively estimating populations with higher transit riding probabilities, at the parcel level. The approaches used in this study will support the elimination of biased walking distances and demographic characteristics estimated by on-board travel surveys, or by relying on low resolution TAZ data. The implementation of the utility maximization process for the individuals' travel mode choice is the basis for this study and will perform as the major assumption for the suggested framework.

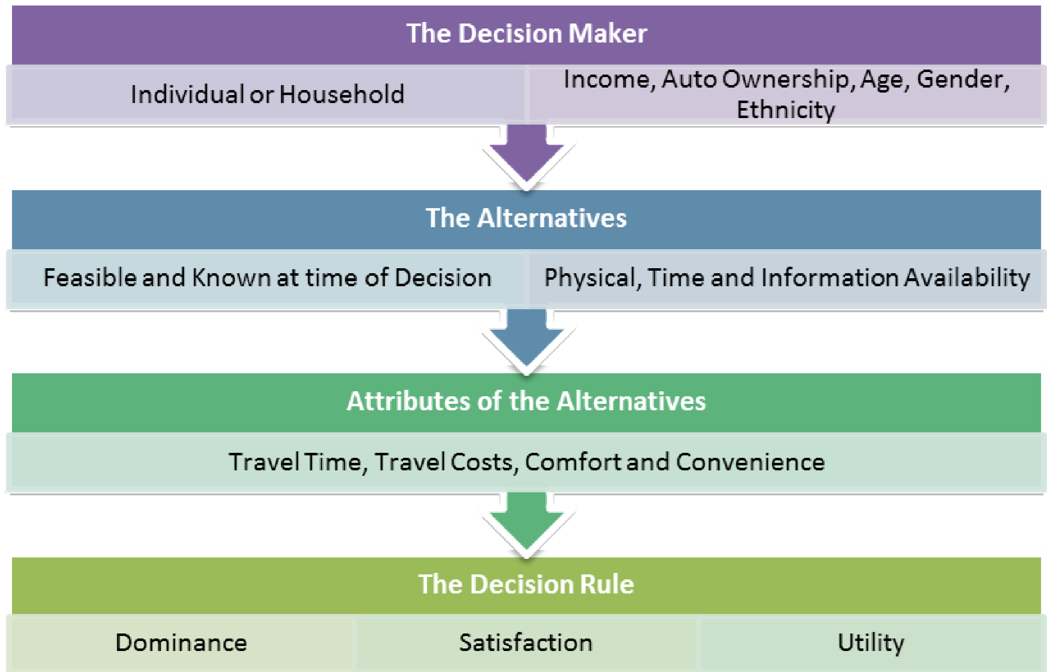


Figure 3. Mode of Travel Choice Process (Ben-Akiva and Lerman, 1985).

3.2 Model Inputs

The next sections of this chapter discuss the processes in which the inputs used in this model are obtained and applied to estimate the required probabilities.

3.2.1 Discrete Mode Choice and Utility Function

As discussed in the previous section, the decision of using the appropriate alternative would be best described by finding the alternative whose attributes would maximize the following utility function (Ben-Akiva and Lerman, 1985):

where

Within each individual utility, the attributes of the alternatives determine their levels. When travel time and cost are the only determinants of the mode utility, then their utilities would take the following form (Ben-Akiva and Lerman, 1985):

$$U_1 = U(t_1, c_1) = \beta_1 t_1 + \beta_2 c_1$$

$$U_2 = U(t_2, c_2) = \beta_1 t_2 + \beta_2 c_2$$

where

t: travel time

c: travel cost

β: parameters that represent the attributes of the decision maker

A probabilistic approach can be used to identify the probability of choosing an alternative. It can be described as the probability that the utility of this alternative is larger than that of the other alternatives. For two alternative modes auto (a) and transit (t), the probability of choosing any alternative takes the following form:

$$p_n(a) = p_r(U_{an} \geq U_{tn})$$

$$p_n(t) = p_r(U_{tn} \geq U_{an})$$

where

$p_n(a)$: The probability of person n choosing auto

$p_n(t)$: The probability of person n choosing transit

To estimate these probabilities, a linear model showed deficiencies with the non-normality and heteroscedastic variances of its errors and incapability in providing a probability within the 0-1 range. The Logit model, on the other hand, overcomes these deficiencies in taking logistic distributed variances. The most widely used Logit Model for mode choice modelling and probability estimation takes the following form (Ben-Akiva and Lerman, 1985):

$$p_n(i) = \frac{e^{\beta V_{in}}}{e^{\beta V_{in}} + e^{\beta V_{jn}}}$$

where

$p_n(i)$: The probability of individual n choosing mode i

V_{in}, V_{jn}: The systematic utility term for modes i and j

β: a scalar parameter

Unlike in linear regression parameter estimation, least squares method is not capable of producing minimum variance unbiased estimators for the actual parameters in a logistic regression model (Czepiel, 2002). Therefore, finding the set of parameters that gives the greatest probability of the observed data using maximum likelihood estimation is used for the Logit model and processed through a data analysis and statistical software.

The main purpose when estimating mode choice models, for researchers and agencies, is to understand the main contributors and the significant indicators to the individual's choice of travel mode. The emerging outcomes of the mode choice model have the potential to be exploited to benefit the construction of such models. The capability of producing these probabilities appealed this model to be used as the basis to forecasting pedestrian transit demand. To best generate and utilize this model, the following inputs will be applied to estimate the required probability function.

3.2.2 Factors Affecting Mode Choice

Factors that affect demand for transit are believed to be significantly correlated to the factors affecting the propensity to walk to transit, especially in a system that relies heavily on pedestrians as riders and has lower "park and ride" opportunities. A person with high reliance on the existence of the transit system is expected to have the willingness to walk longer distances to reach the system compared to other users.

Therefore, understanding the effect of these factors supports the understanding of users' willingness to walk to transit stops and stations.

The significant factors associated with the individual attribute, household attributes and the service attributes provided by the transit system should be included in the mode choice model to ensure the representative estimations of demand. In the reviewed literature, household income and the density of households under poverty levels, household size, employment types and rates, age and the percentage of senior population, auto ownership and the number of autos per household have high influence on transit demand. Moreover, factors related to the provided service such as service frequency and coverage, are significant in estimating the probability of using transit. Average fare, on the other hand, might have lower influence on medium-high income users but is significant to others with lower incomes specifically if under poverty levels.

The inclusion of the most significant factors from the above mentioned, is essential to the estimation of the structure of the mode choice model. Therefore, to best identify the influential factors that would be utilized in the model, travel surveys that investigate the household, individual and trip characteristics are needed to generate trip mode choice models in association with different demographics.

3.2.3 Travel Surveys

Collecting the appropriate data is an essential part of the modelling process. Therefore, controlled and carefully designed surveys can be an integral element in collecting representative sample data that will support the accuracy of the outcome models. With the limitations and/or errors in the available data come the deficiencies of the developed models.

For transportation planning purposes, planners have long used a wide range of travel surveys attempting to capture the attributes, choices and opinions of the surveyed individuals or households.

Transit agencies for instance rely mostly on on-board travel surveys to control, modify and apply the proper investments to their transit systems. In their surveys they collect data on

boarding and alighting numbers, socio-economic characteristics of riders, origins and destinations, trip purposes and opinions on the quality of service. As mentioned earlier, some of the approaches used to find transit service areas and model distance decay curves relied on the recorded walking distances to stops and stations of real transit users.

The distance decay functions estimated from these surveys would be representative of the distances walked by actual users and includes all stops and routes without the consideration of demographic and system variations.

Studying the demand of the transit system should not rely solely on data derived from individuals with very high probabilities of using the system (actual users). This approach assigns higher weights to certain attributes associated with the system users that might not be related to their propensity to use transit but rather to the overall demographic form of their demand areas. On the other hand, surveys that account for the differences between users and non-users of the transit system based on their trip mode choices, such as household travel surveys, can emphasize those attributes that are strongly correlated to the individual's transit choice.

The reported travel behaviors in these surveys include trip counts, lengths and purposes, mode of transportation and travel times of each trip associated with the recorded demographics of each household. Among these variables, significant contributors to the mode choice are used to construct the model considering all the possible combinations from these variables.

3.2.4 Summary of Model Structure

The form that the anticipated mode choice model would take relies on the travel behaviors within the studies areas. A binary or a multinomial model can be used depending on the number of alternative modes that are considered in the analysis. The transit mode will be categorized by access type to walk and auto access. The walk to transit mode is used to estimate the utilities of this alternative for each household under study.

From the household travel survey and in association with the influential factors of ridership, all the possible combinations of significant factors would be utilized to estimate the

final structure of the model. For the purpose of estimating walking to transit trips, walking distance is expected to be a highly significant parameter describing the disutility if increases in distances from transit stops.

In general, a model would include parameters such as in-vehicle travel time, out-of-vehicle travel time including waiting and walking times, level of service of the transit system represented by waiting time from service headways and trip costs from average fares. A highly significant part of the model is represented by the socio-demographic characters of individuals and households usually exemplified by income, auto availability and employment. The expected utility function will take a similar form to the following:

$$
\begin{aligned}
U_{Walk\ to\ Transit} \\
&= \beta_1 InVehtt + \beta_2 Walking\ Time + \beta_3 Waiting\ Time + \beta_4 Travel\ Cost \\
&+ \beta_5\ HHsize + \beta_6 Autos + \beta_7 LowIncome + \beta_8 Med\ Income \\
&+ \beta_9 HighIncome + Constant
\end{aligned}
$$

where

InVehtt: travel time in transit vehicle
Walking Time: time spend walking from home to bus stop or station
Waiting time: time spend waiting to ride transit at stop or station
Travel Cost: total cost of transit trip
HHsize: household size
Autos: available autos per household
Low, Med, High Income: a dummy variable for the income category of each household
$B_{1,2,3,\ldots}$: Estimated coefficients of the Logit Regression

To apply trip data to the model, each trip will be connected to the appropriate data on the individual who made that trip, the household in which he/she is a member and all the previously discussed characters of the trip. On the other hand, the utility functions for other alternative modes will also be modelled in the same form to be applied to the probability estimation function to find the overall probability of walking to transit model.

Moreover, an activity based utility function which describes trips of a specific purpose like work, college, shopping or recreational trips is specified for each and used to estimate different utility functions. In the following chapters, home-based work trips will form the basis for the estimation and application processes of the utility model.

3.3 Model Application

Collecting the data that would be applied to the utility model estimated from the household travel survey is a challenging process. The unavailability of data for such a disaggregate level of analysis is expected and can be limiting to the application of this model. Moreover, incompatibility of data from different sources can also hinder the full utilization of this model.

The following sections will discuss the suggested processes to be used in compiling and preparing the data applied to the mode choice model which is consistent with the significant variables that are used in its structure. These sections assume the ability to collect and process all the listed data for the accurate application of the suggested model.

3.3.1 Scope of Analysis (Parcel and Household Data)

From the previously discussed approaches to identifying transit service areas and forecasting future ridership, traffic analysis zone was the widely used scope for analysis. Data for such a geographic boundary can be obtained from most MPOs. For our model, a more disaggregate level of analysis that is based on each individual household for transit trip production will be utilized. The data necessary for the application of the model are collected and processed for each parcel by applying TAZ data and property data provided by the TPO and the local property assessor's office for all locations included in the analysis. Methods described below are used to devolve TAZ data to the parcel level.

The data provided for each unit are used to approximately estimate household demographic variables needed in the application of the mode choice model. The processes used to prepare this data for application are discussed in the following sections.

3.3.2 Household Size

The property assessor's data includes all dwelling units including multifamily and detached housing. Detailed information on the number of bedrooms for each unit will be used to estimate bedroom occupancies and household size using the following equations:

$$Bedroom\ Occupancy = \frac{Total\ Population\ in\ TAZ}{Total\ Number\ of\ Bedrooms\ in\ TAZ}$$

$$HH\ Size = Bedroom\ Occupancy \times Number\ of\ Bedrooms\ in\ HH$$

3.3.3 Vehicles per Household

For the estimation of the number of vehicles per household, number of garage spaces for each unit from property data and total number of registered vehicles from TAZ data will be used in the following equations:

$$Garage\ Occupancy = \frac{Total\ Number\ of\ Registered\ Vehicles\ in\ TAZ}{Total\ Number\ of\ Garage\ Spaces\ in\ TAZ}$$

$$Vehicles\ per\ HH = Garage\ Occupancy \times Number\ of\ Garage\ Spaces\ in\ HH$$

3.3.4 Household Income

As an indicator of household income, the assessed and appraised property values will be collected from the property assessors' office. These data can be used to segment the market into categories without the estimation of associated income values where each category represents a different income group. On the other hand, income can be estimated by applying a percentage to the property values, believed to be related to mortgage rates, from data observed within the studied areas. For rented units, monthly rent rates can be estimated from the apartment size and

location. A proper rent to income ratio will be applied to estimate the associated income values for each household.

3.3.5 Census Data (TAZ Data)

The TAZ data will be used where parcel data are not available or difficult to generate. Total population, household size, workers per household, vehicles per household and average median income per household might be used for each parcel when associated to the appropriate TAZ data. These data are less accurate but can be representative for smaller or low parcel count TAZs.

3.3.6 Travel Time

In vehicle travel time, the time spent in the transit vehicle during the entire trip, depends on the length of the produced trip to reach destination. The trip distribution models generated from household travel surveys and usually using a gravity model for estimation, provide the distribution of trips between production and attraction zones and travel time distribution based on trip lengths. The trip distribution can also be modelled to present the effect of different socio-demographic characteristics on trip attractions and eventually average trip lengths. If such a demographic-based trip distributions can be easily estimated or are available for the area under study then a representative different trip lengths can be associated with the household that comprise matching attributes. Otherwise, applying the average travel time for each TAZ or the overall travel time within the whole survey area is a less comprehensive alternative to the distribution model.

3.3.7 Walking Distance

The origin of each walking trip to the nearest transit stop or station is a centroid point of either a parcel or a building footprint. To ensure that the walking paths produced for each parcel/building resemble, to a high extent, the actual walking paths for each individual, all parcels should be connected to their address streets before generating walking routes.

The process in which each parcel is connected to transit stop/s depends on the type of transit system under consideration. A more complicated analysis process is needed to assign each parcel to a stop when a competitive multiple route transit system is under study.

For a simpler transit system, where there is little redundancy in the service, connecting each parcel to the nearest stop can best describe the possible behavior of riders and representative routes that are applied in the mode choice function. Using the closest facility network analyst tool in ArcGIS, each building/parcel point is connected by a route along the street network provided for that geographic area to the nearest transit stop from the system under study. The length of each route is also generated in the process and used as the walking distance when applied to the model.

Walking can be represented as time or distance, depending on the type of survey data provided for analysis. These walking distances can be easily converted to walking times by using standard average pedestrian walking speeds.

3.3.8 Wait Time

Wait time at transit stops or stations was found to be a significant contributor in the probability of using transit system and an indicator of the level of service of the transit system. The expected average wait time was found to have a value close to half of the headway (Holroyd and Scraggs, 1966), based on the assumptions of random passengers arrivals and regular vehicle arrivals. On the other hand, other researchers argued with the assumption of regular service and stated that its inclusion can be problematic to the estimation of average waiting times. They suggested different estimation functions considering the variability in service headways. Moreover, for longer headways, passengers would attempt to plan their arrival times to minimize waiting times weakening the assumption of random passenger arrivals (Fan and Machemehl, 2002).

For the purpose of our research, we will be utilizing the half headway model of waiting times depending on the transit service under consideration applied to different routes with different service characteristics.

3.3.9 Travel Cost

To estimate the cost associated with riding transit for each specific trip, average fares can be collected from the transit system agency. Including all types of rides and special passes for all available routes is essential to the estimation of a representative average fare. To simplify the analysis, an average fare could be applied to the model under the assumption that all studied trips are work commuter trips and use the commuter pass, monthly pass or any other form of all-day pass approximated to a single trip cost for a daily two trips itinerary. For transit systems with variable rates, the estimated in vehicle travel times that relate to specific distances can be used to generate different travel costs for each individual based on their projected destinations.

For the mode choice model used, the effect of cost on the mode of travel is highly associated with the income group of each rider. Therefore, different parameters can be applied to different income groups giving the lower income individuals higher sensitivities to the cost of travel. Moreover, the value of time is included in the overall cost and will have different values depending on the income group of each household.

3.4 Home-Based Work Trips Productions

To estimate the number of trips generated for these probabilities, a production (generation) model estimated from the household travel survey will be applied to find the total number of Home-Based Work Trips (HBWT) produced by each household. The total number of expected trips is then multiplied by the probability of walking to transit to find the potential number of walk to transit trips for each household. These trips will be integrated to include all households within each parcel for multi-family residential parcels.

CHAPTER IV
ESTIMATION OF WALK TO TRANSIT PROBABILITIES AND TRIPS IN KNOXVILLE, TN

The application of our framework is highly dependent on the available data for the area under study. The compatability of data within all participating sources is the key to the harmonic compilation of all essential variables to the model framework. Moreover, the level of analysis is more flexible and can include fine dissagregated analysis units to more aggregate ones depending on the available data.

To illustrate the outcomes of this model, data compiled from the Knoxville GIS (KGIS), Tennessee Department of Transportation (TDOT), Knoxville Area Transit (KAT), TAZ data from the Transportation Planning Organization (TPO) and the property assessor's office of Knox County will be utilized as a case study for the Knoxville Area Transit system.

4.1 The Study Area

The study area includes Knox County specifically the city of Knoxville where the transit service primarily operates. Within the five hundred traffic analysis zones included in the analysis, almost 140,000 parcels are residential, including single and multi-family and other residential land uses. For each parcel, the unit of analysis is disaggregated to include detached homes, apartments, or condominiums based on the building footprint and property data provided from KGIS and the property assessor's database. Figures 4 and 5 illustrate the area included in the analysis with traffic analysis zones and residential parcels.

4.2 KAT Transit System

The transit system within the City of Knoxville includes fixed route bus service with varying times and fare options. Figure 6 highlights the transit system routes and stops under study.

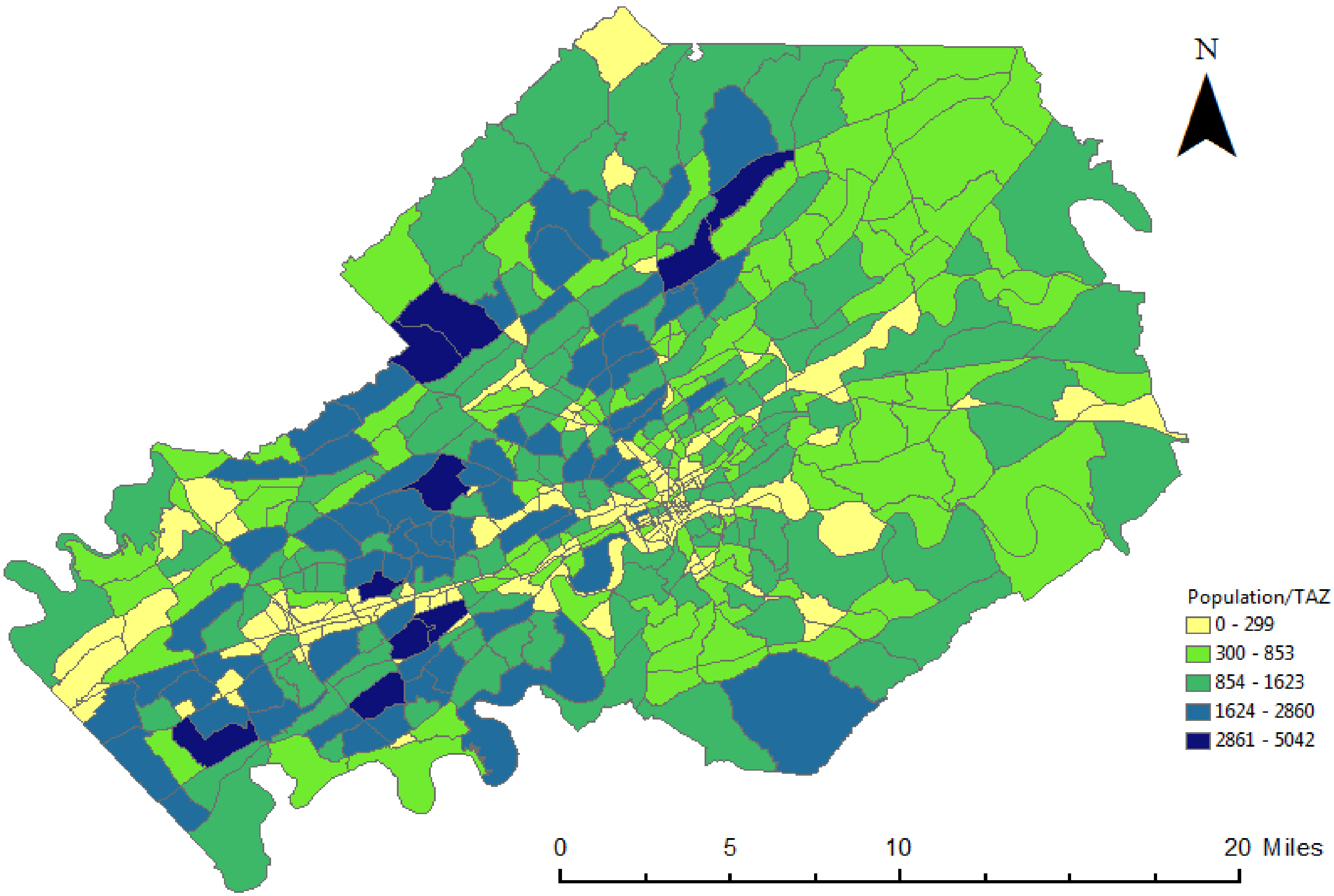


Figure 4. Traffic Analysis Zones in Knox County by Household Population.

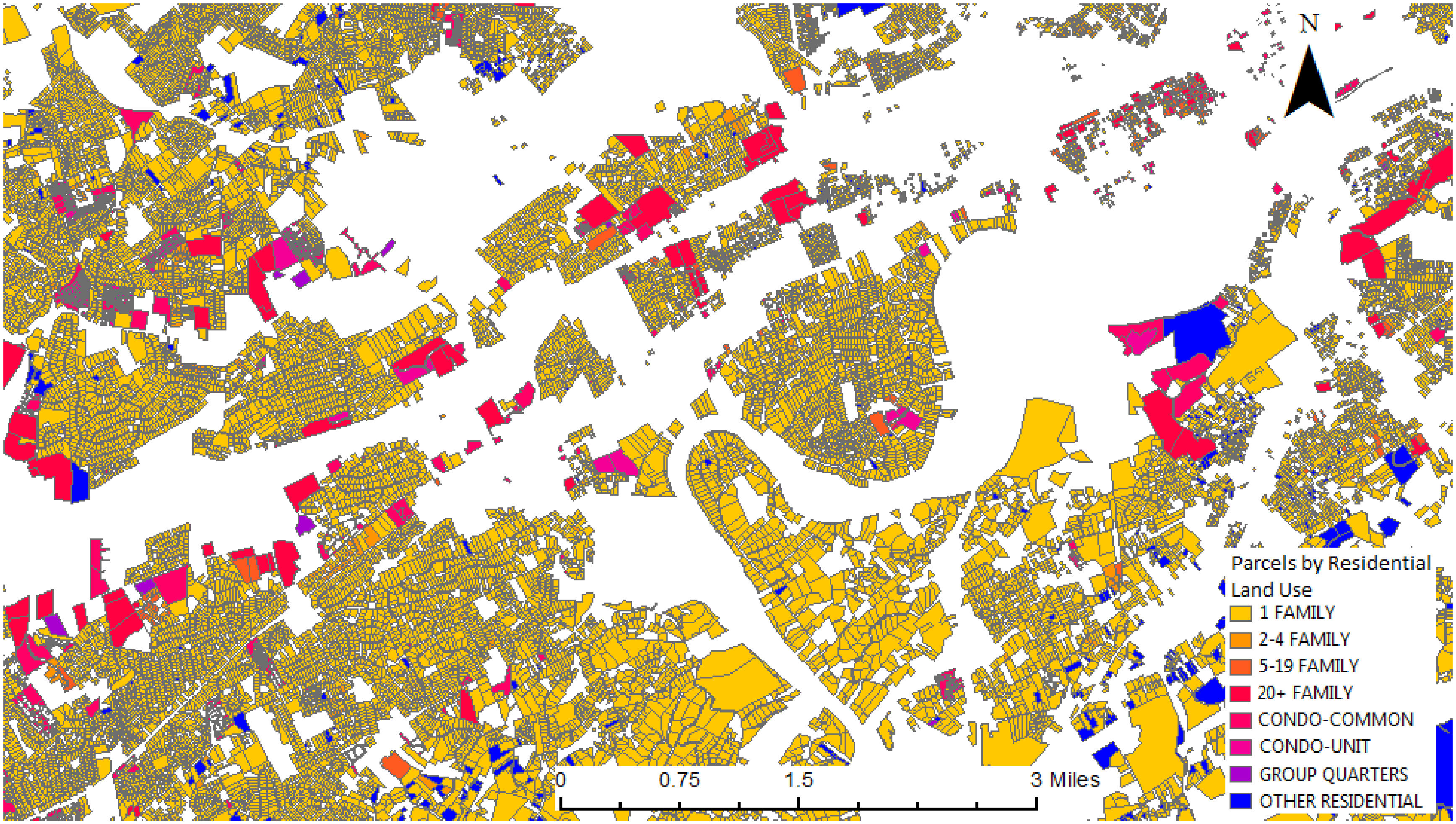


Figure 5. Residential Parcel Map within Knox County.

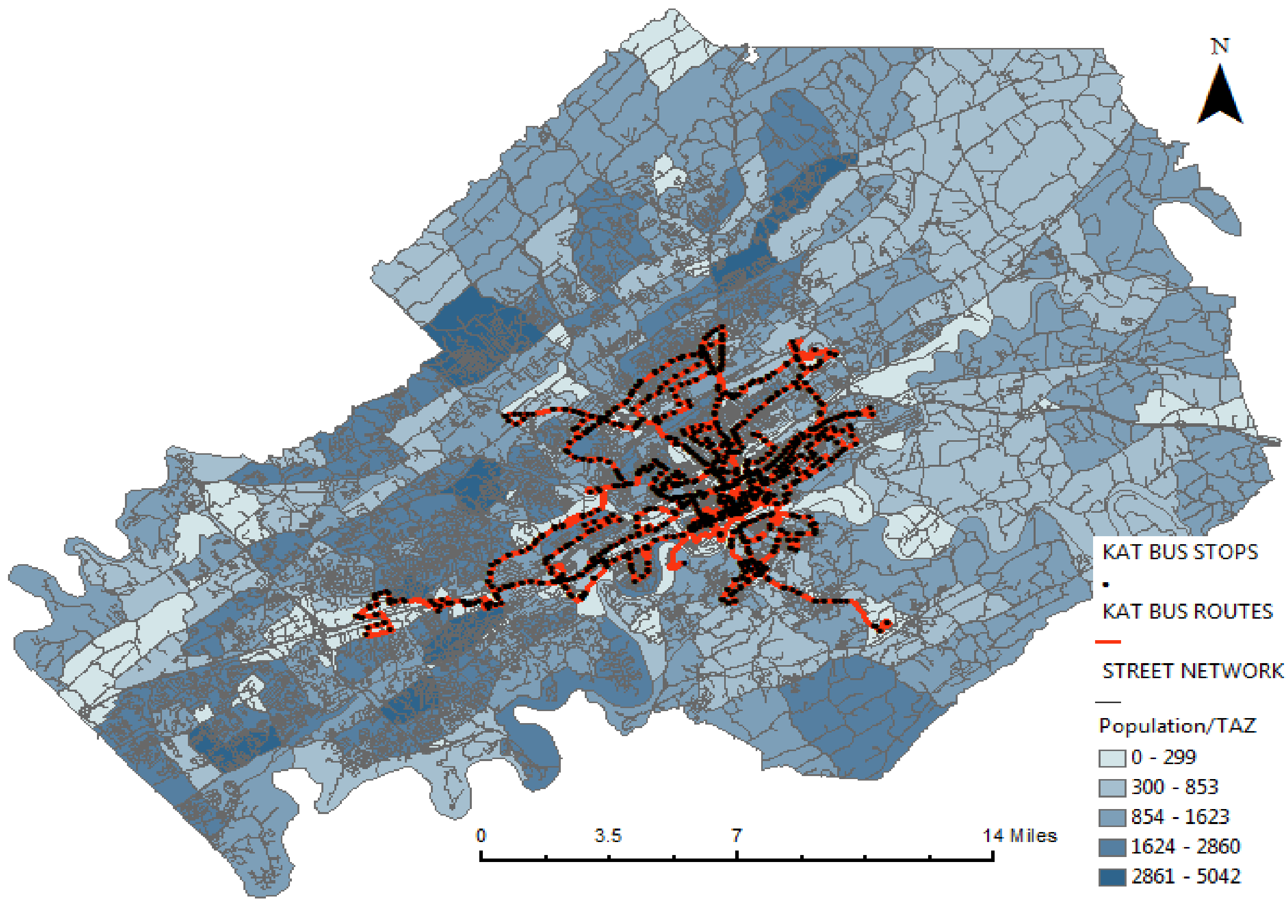


Figure 6. Knoxville Area Transit Routes and Stops.

4.3 Travel Survey and Mode Choice Model

To estimate the best travel demand model that specifies a representative mode choice utility function, significant trip, household and individual data from the household travel survey should be available. Household travel surveys that form the basis for this model and usually conducted by Metropolitan Planning Organizations (MPOs) could be deficient or insignificant – if available – for a specific geographic location. For the City of Knoxville, a household travel survey was conducted to include ten counties (most without transit service) within the Transportation Planning Organization's (TPO) jurisdiction and this caused the insignificance of transit trips data, which were eventually excluded from the mode choice model. Therefore, the estimated mode choice model does not include the transit utility function for specific transit trips but considers transit in a tour based mode choice model. The transit tour represents any tour that includes a transit trip but can include any other mode of transportation within the same tour. This level of estimation to the mode choice model is not representative of the specific demographics related to transit use and cannot be utilized to estimate the probabilities of walk to transit expected for the application of the conceptual model.

On the other hand, similar models estimated for different cities with similar travel behaviors and transportation systems can substitute these models. The search for such a model conducted by other transportation organizations resulted in finding models that include users' demographics but lack data on walking distances and vice versa.

A travel demand model was conducted for the Washington State Department of Transportation and the Puget Sound Regional Council by Cambridge Systematics Inc. (PSRC, 2007). The mode choice part of this model was able to resemble the expected utility function among all studied models. The collected and prepared data for Knox County are applied to the utility function provided by this model.

Despite the variability in demographics and transit service between both locations, the model is used for the purpose of application and does not necessarily resemble the actual travel behaviors and utility parameters that would be found for Knox County. The estimated walk to transit trips from this model will be useful in comparing households' demand for transit within

the city for the purpose of prioritizing pedestrian infrastructure investments and not as absolute estimates.

The following structure of a nested mode choice model is used to estimate the utility and ultimate probability of the walk to transit mode, for each parcel. The model includes sociodemographic characteristics, transit system, and road network specific parameters discussed in the previous chapters. This model is a multinomial model that includes seven different alternative modes within the Puget Sound area. Table 1 illustrates the form of the utility function including all the available alternatives.

As discussed in the preceding chapters, the utility model structure that defines the individual's choice among travel modes includes the characteristics of the trip, the trip maker and the available modes of travel. The structure provided by PSRC explicitly identifies the effect of all these variables on the utility of each mode.

To further identify the sensitivity of the travel cost on each specific trip maker, income was found to have the dominant effect on travel cost. Therefore, the travel cost parameter was estimated for four income level groups in which the coefficients were found to have different values representing the increasing effect of cost on a lower income individual when choosing the most satisfying mode of travel.

Moreover, a household classification by car competition categories was used as a market segmentation parameter to reflect the effect of lower car availability on the probability to choose transit or other modes like car sharing. In Table 2, four categories were used in market segmentation to include households with no available autos, households with more workers than available autos, households with fewer workers than autos where each worker has at least one available auto, and households with one worker only with available autos.

To apply the market segmentation parameters for each category and mode, every household included in the estimation process will be categorized based on the number of workers and autos calculated using data preparation processes specific for Knox County data.

Table 1. Home-Based Work Mode Choice Model Parameters (PSRC, 2007)

Variable	Drive Alone	Shared Ride 2	Shared Ride 3+	Transit-Auto Access	Transit-Walk Access	Bicycle	Walk
Level of Service							
In-Vehicle Travel Time	-0.0253	-0.0253	-0.0253	-0.0253	-0.0253		
Out-Vehicle Travel Time-Walk Time and Wait Time <7 minutes				-0.0633	-0.0633		
Out-Vehicle Travel Time-Walk Time and Wait Time>7 minutes				-0.0506	-0.0506		
Number of Transit Boardings				-0.3060	-0.3060		
Walk Time							-.0788
Bicycle Time						-0.102	
Ratio of Drive Time to Total Time				-6.0000			
Travel Cost (cents)-Low Income HH (Income 1)	-0.0038	-0.0038	-0.0038	-0.0038	-0.0038		
Travel Cost (cents)-Low-Med Income HH (Income 2)	-0.0021	-0.0021	-0.0021	-0.0021	-0.0021		
Travel Cost (cents)-Med-High Income HH (Income 3)	-0.0014	-0.0014	-0.0014	-0.0014	-0.0014		
Travel Cost (cents)-High Income HH (Income 4)	-0.0011	-0.0011	-0.0011	-0.0011	-0.0011		
Socioeconomic							
Market Segmentation Parameter				See Table 2			
CBD Variable		0.199	-0.268	2.167	0.593	0.173	1.688
Alternative-specific constant		-2.355	-3.968	-0.169	0.351	-1.151	0.491

Table 2. Market Segmentation Parameters (PSRC, 2007)

Variable	Car Class 1 0-Car HH	Car Class 2 Workers > Cars	Car Class 3 Workers ≤ Cars	Car Class 4 1-Worker HH
Drive Alone				
Income 1	-4.0	-0.2	0.3	0.0
Income 2	-4.0	-0.2	0.3	0.0
Income 3	-3.5	0.3	0.8	0.5
Income 4	-3.0	0.8	1.3	1.0
Shared Ride 2	0.0	0.9	-0.5	-0.4
Shared Ride 3+	0.0	1.3	-0.6	-0.7
Transit-Walk Access				
Income 1	2.4	4.4	-1.3	0.5
Income 2	1.9	3.9	-1.8	0.0
Income 3	1.4	3.4	-2.3	-0.5
Income 4	0.9	2.9	-2.8	-1.0
Transit-Auto Access				
Income 1	-4.5	-0.9	-2.1	-1.6
Income 2	-4.0	-0.4	-1.6	-1.1
Income 3	-3.5	0.1	-1.1	-0.6
Income 4	-3.0	0.6	-0.6	-0.1
Walk	0.5	1.2	-1.6	-0.1
Bicycle	0.2	0.7	-1.0	0.2

4.4 Knox County Data Preparation

As discussed in the previous sections, the available travel demand model estimated by the regional transportation planning organization has some deficiencies in providing a representative trip generation, distribution and mode choice models. Due to these limitations in data availability, some of these variables were approximately specified from applying average data and/or scaling TAZ data. The following sections discuss the specific processes used to estimate Knox County data needed for application which differ in some aspects from the suggested processes discussed earlier in the data preparation section.

4.4.1 In Vehicle Travel Time

The distribution of travel times within the County was not available from the travel demand model. Instead, an overall average travel time for each travel mode was provided for all the counties within the regional jurisdiction. These data provided an average of 20 minutes travel time for auto and public transit modes to 45 minutes bike time. The distribution of travel times over geographic areas or for certain demographics is not available from the travel survey. Therefore, average commute times for each ZIP code within the county collected from census data and illustrated in Figure 7, were used to approximately represent the differences in commute times and their effect on the utility function (Transportation Nation (WNYC), 2014).

Each parcel is associated with the appropriate address ZIP code and given an average commute time accordingly. Despite the large area of commute time distribution, this differentiation will represent, to a degree, the sensitivity of the estimated utilities to travel time variations compared to the overall average for the entire county.

4.4.2 Out-of-Vehicle Travel Time

Waiting and walking times were calculated to represent the out of vehicle travel time. Walking distances were specified for each household to the nearest bus stop using ArcMAP closest facility analysis tool. For each walking distance, the associated walking time was calculated from a rule of thumb of 5 minutes for a 0.25 mile walk which produces a walking speed of 264 ft/min (3 mph) (Levinson, 1992). These points are generated for each Parcel using ArcGIS and data provided by KGIS. Figure 8 illustrates a sample of generated routes from parcel points to the nearest transit stop points along the existing street network.

Half of the headway of the transit service was used to represent waiting times for each stop. The KAT stop data are not associated to the appropriate route they serve. Therefore, for this analysis each stop was connected to the nearest route and to the proper average service headway from KAT bus schedules.

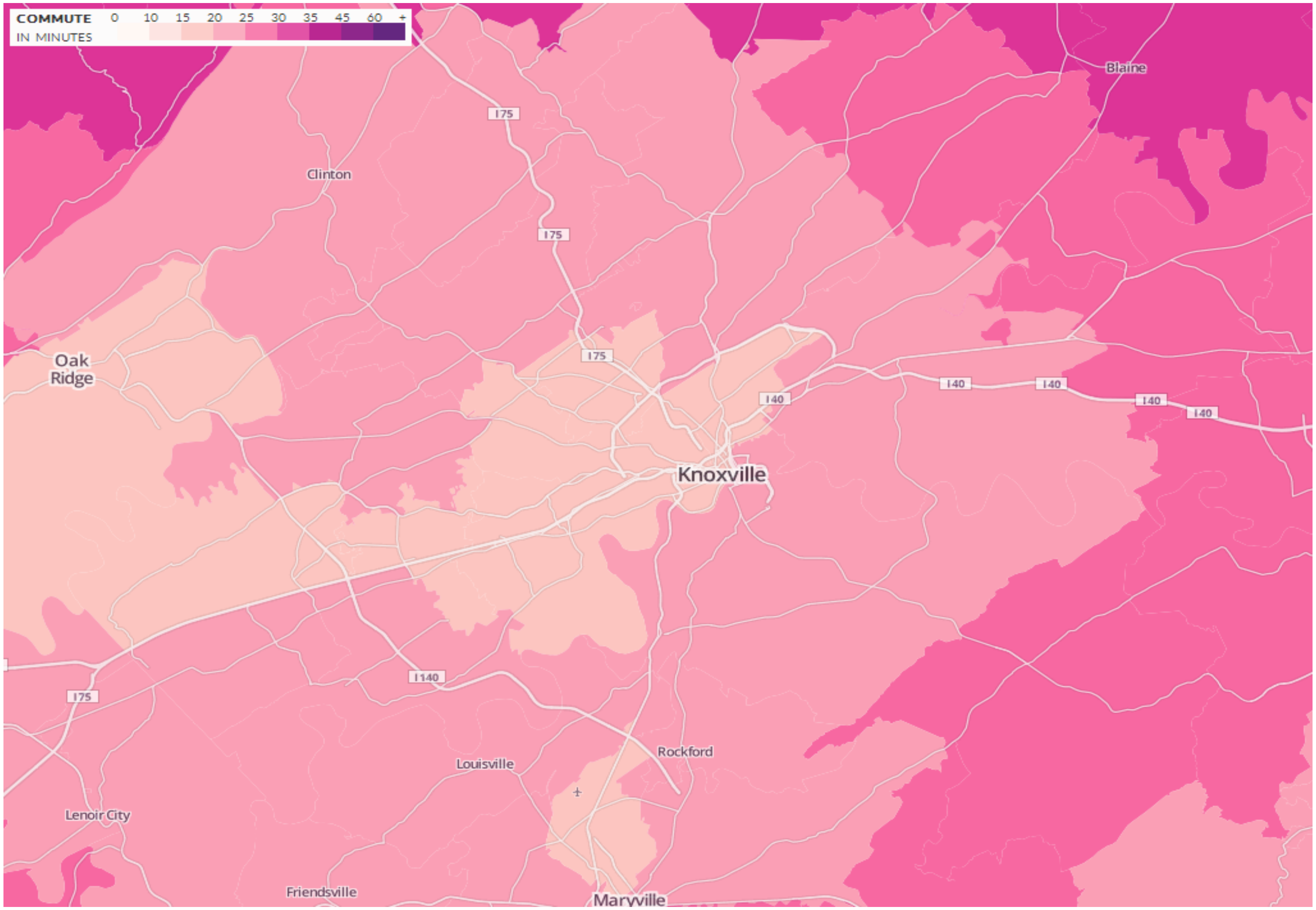


Figure 7. Average Commute Time (In Minutes) by ZIP Code. (Transportation Nation (WNYC), 2014)

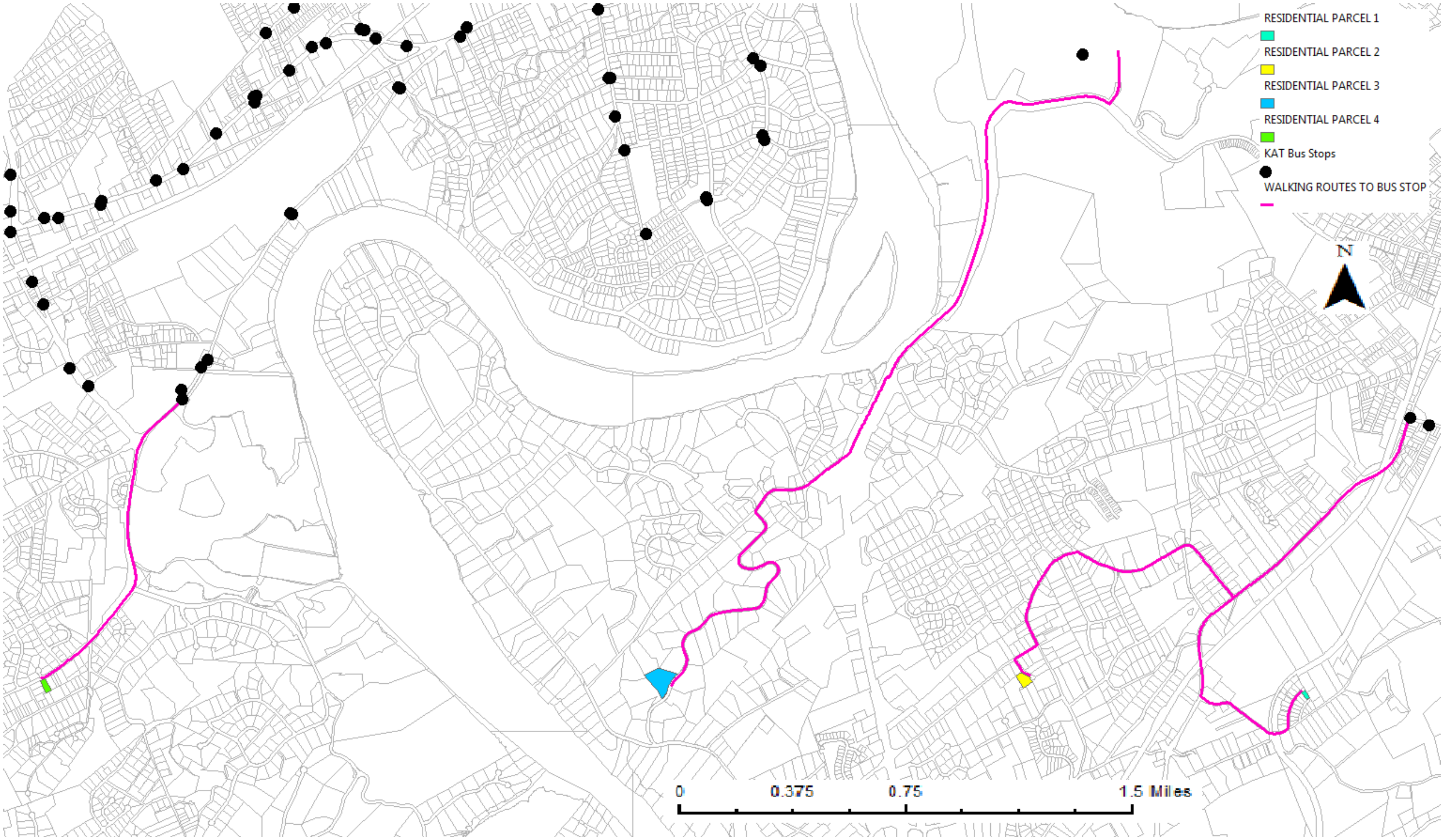


Figure 8. Illustration of Generated Walking Routes to Transit for Selected Parcels.

4.4.3 Market Segmentation Parameters and HH Size

The property data collected from Knox county property assessors' office were used to estimate income from property values. Income was estimated as 30% of the property value based on a rule of thumb of mortgage affordability of 2.5-3 times gross income (McWhinney, 2014).

For rented apartments, we used ZIP code median rent values collected from Zillow listings (Zillow, 2014). Each unit was associated with median rent for the ZIP code in which they are located. An approximate 25%-30% rent to income ratio collected from Kwelia maps and shown in Figure 9 was used to calculate the associated income values (Kwelia, 2014). Moreover, from census data on income distribution, four income groups were generated from percentile data and used in the market segmentation process as income groups 1-4, corresponding to income values of < \$25,000, \$25,000-\$50,000, \$50,000-\$80,000 and >\$80,000, respectively. The total number of bedrooms in each TAZ was used to find bedroom occupancy and household size using the following equations:

$$Bedroom\ Occupancy = \frac{Average\ HH\ size\ in\ TAZ}{Average\ HH\ bedrooms\ in\ TAZ}$$

$$HH\ Size = Bedroom\ Occupancy \times No.of\ Bedrooms\ in\ HH$$

Average workers and vehicles per household for each TAZ were multiplied by household size to find number of workers and vehicles for each household.

4.4.4 Travel Cost

As this analysis includes home based work trips and assumes commuter users, the average fare from 30-day passes offered by the KAT agency was used to represent the travel cost of a daily trip (am or pm) from a potential round trip every workday. The cost associated with the walking, waiting and in-vehicle travel times was also included based on the average value of time for each income category. Table 3 lists the value of time used for each income category from the PSRC model utilizing the Federal Transit Administration (FTA) guidelines (Ryan, 2004).

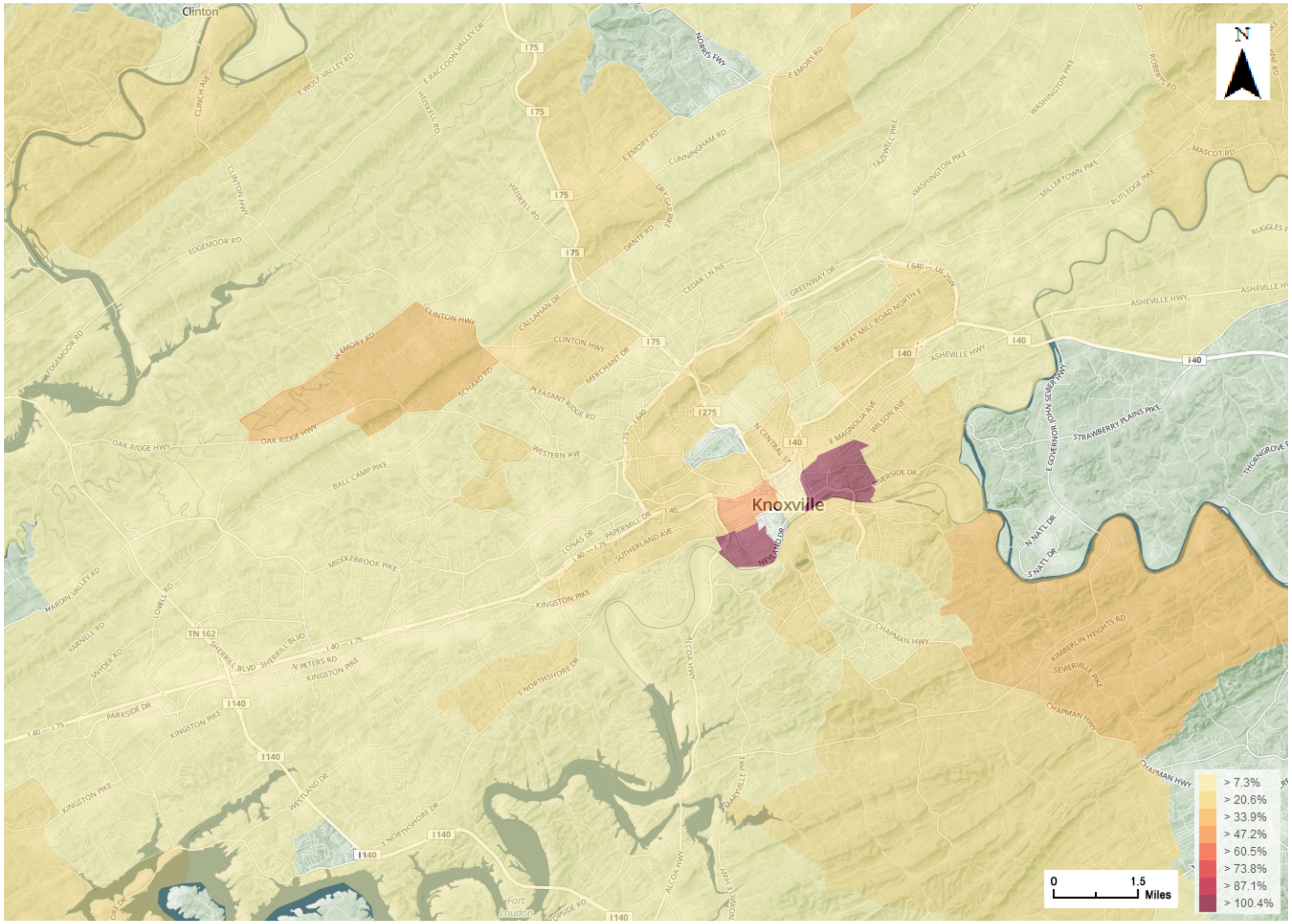


Figure 9. Percentage of Median Apartment Rent to Median Income. (Kwelia, 2014).

Table 3. Recommended Value of Time for Home-Based Work Trips (PSRC, 2007)

Income Category	Value of Time
Low Income	$4.00
Low-medium Income	$7.23
Medium-High Income	$10.48
High Income	$14.00

4.4.5 CBD Variable

The parcels that are located within the CBD boundary were selected and assigned a CBD variable which gives higher utility to parcels within the CBD area. Moreover, households within the dense Fort Sanders and UT areas where most of the students reside were included in the CBD area and assigned a CBD variable to give higher probabilities of walk to transit.

4.4.6 Trip Productions

As discussed in the previous chapter, production rates for the estimation of total number of trips and eventually walk to transit trips expected to be generated from each household will support the prioritization process using walk to transit trip maximization. For this purpose, HBWT productions per household, estimated by the PSRC study, were used to estimate total work trips for each household and applied to the generated probabilities to find the number of walk to transit trips. Moreover, for multi-family parcels the total number of trips for all units was used to account for the higher weight of these parcels. Table 4 shows the HBWT productions per household for PSRC that were used in the analysis.

Table 4. Home-Based Work Trip Productions per Household. (PSRC, 2007)

Household Size	Number of Workers in Household	Income				
		Less than $15,000	$15,000 - $24,999	$25,000 - $44,999	$45,000 - $74,999	$75,000 and Above
1 Person	0	0.02	0.01	0.07	0.26	0.19
	1	0.75	1.02	1.17	1.37	1.30
2 Persons	0	0.00	0.07	0.01	0.15	0.33
	1	0.08	0.41	0.62	1.06	1.24
	2	1.24	1.57	1.78	2.22	2.40
3 Persons	0	0.00	0.00	0.15	0.11	0.21
	1	0.2	0.4	0.77	0.99	1.09
	2	1.33	1.52	1.89	2.12	2.21
	3	2.52	2.72	3.09	3.31	3.41
4+ Persons	0	0.00	0.17	0.09	0.22	0.17
	1	0.47	1.10	1.02	1.15	1.10
	2	1.07	1.71	1.62	1.75	1.71
	3+	2.62	3.26	3.17	3.30	3.26

4.5 Results

4.5.1 Probability and Trip Estimation

This model was used to estimate the probability of walk trips to transit for each household analyzed. This probability was estimated based on the level of utility of walk to transit mode and an assumed value of zero for all other alternatives. This assumption is used due to the unavailable data of other modes and for the purpose of normalizing utility values for the application of household size. A zero value was picked to account for higher utilities expected for auto modes compared to a majority of negative utilities found for transit (walk access) mode.

The multiplication of a negative utility value by household size will result in a higher negative value corresponding to a lower utility level. To eliminate this effect, an approach to normalize all values according to the minimum and maximum utilities was needed. The use of a

conventional linear normalization approach does not account for the exponential variation of the estimated utilities. The best way believed to generate representative normalized values is in assuming a utility value for all other modes and apply the utility function to find the probability of walk to transit, accordingly. The application of zero utility for other alternative modes is illustrated in the following equations:

$$p_{Walk\ to\ Transit}(i) = \frac{e^{V_{Walk\ to\ Transit}}}{e^{0} + e^{V_{Walk\ to\ Transit}}}$$

$$p_{Walk\ to\ Transit}(i) = \frac{e^{V_{Walk\ to\ Transit}}}{1 + e^{V_{Walk\ to\ Transit}}}$$

where

$P_{Walk\ to}$ Transit (i): probability of walk to transit trips for household i
$V_{Walk\ to\ Transit}$ (i): estimated utility of walking to transit trips for household i

The probabilities resulted from this estimation can be used for the comparison between different households. Figure 10 illustrates the generated probabilities for each household within Knox County. The accumulations of higher probabilities at closer distances from transit stops, locations within the CBD area and lower income neighborhoods can be observed. To illustrate these differences, Figures 11-13 show the variations in probabilities for East and West Knoxville, University of Tennessee and Fort Sanders. These variations account for the deficiencies associated with other methods which assume the uniformity of the probability to walk to transit within the same distances without the consideration of demographic variations. In East Knoxville, the area within the dashed circle in Figure 11 represents high variability in walk to transit probability for the households represented in red. This effect was found to be due to higher numbers of workers per household for the traffic analysis zone to which they are associated. This caused higher probabilities and total transit trips to be estimated. This observation offers two conclusions to our method of analysis; data availability and accuracy highly affect the resulting probabilities and high variability and/or anomalies are easily observable and fixable in this model.

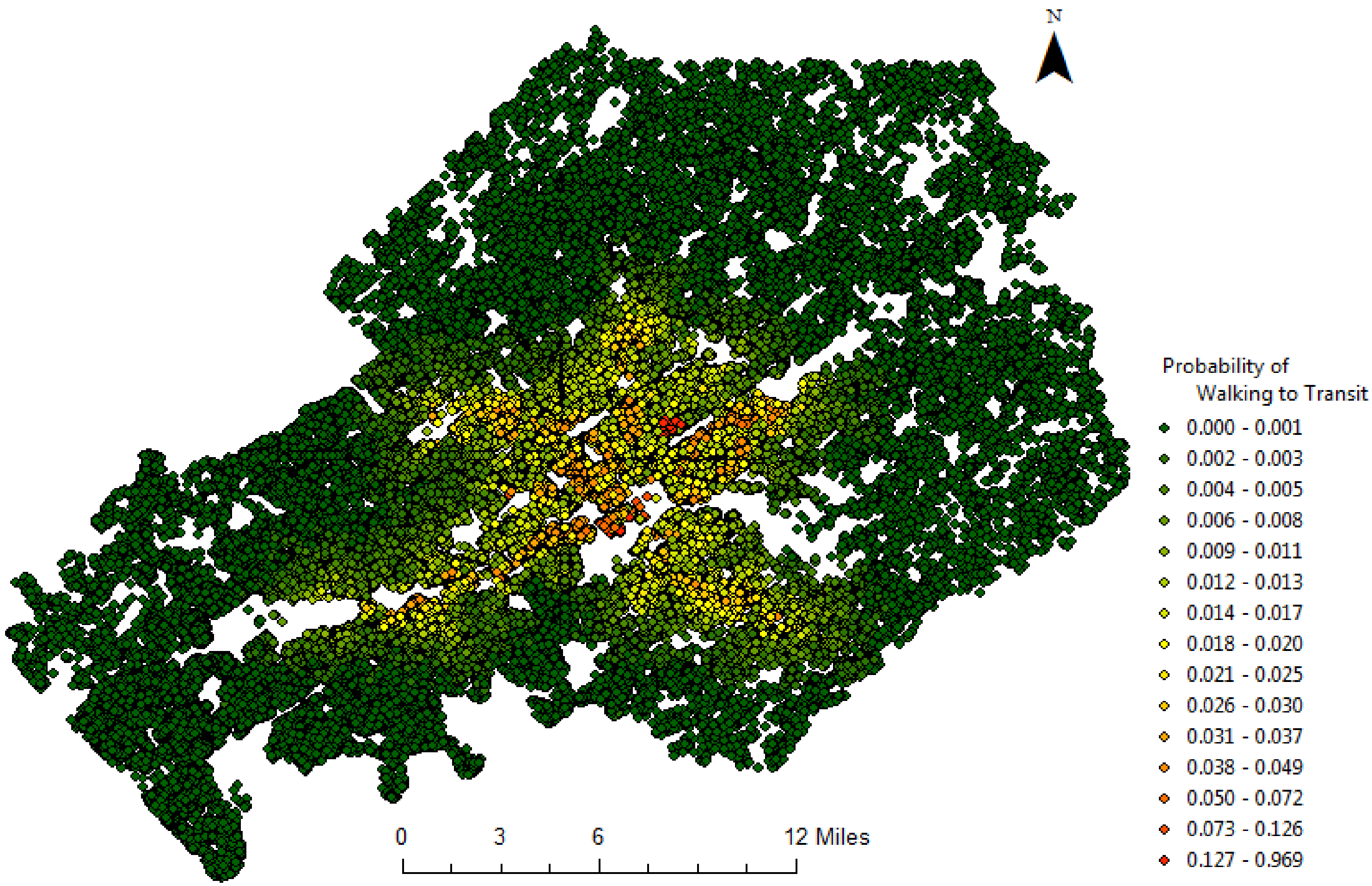


Figure 10. Households' Probability of Walking to Transit

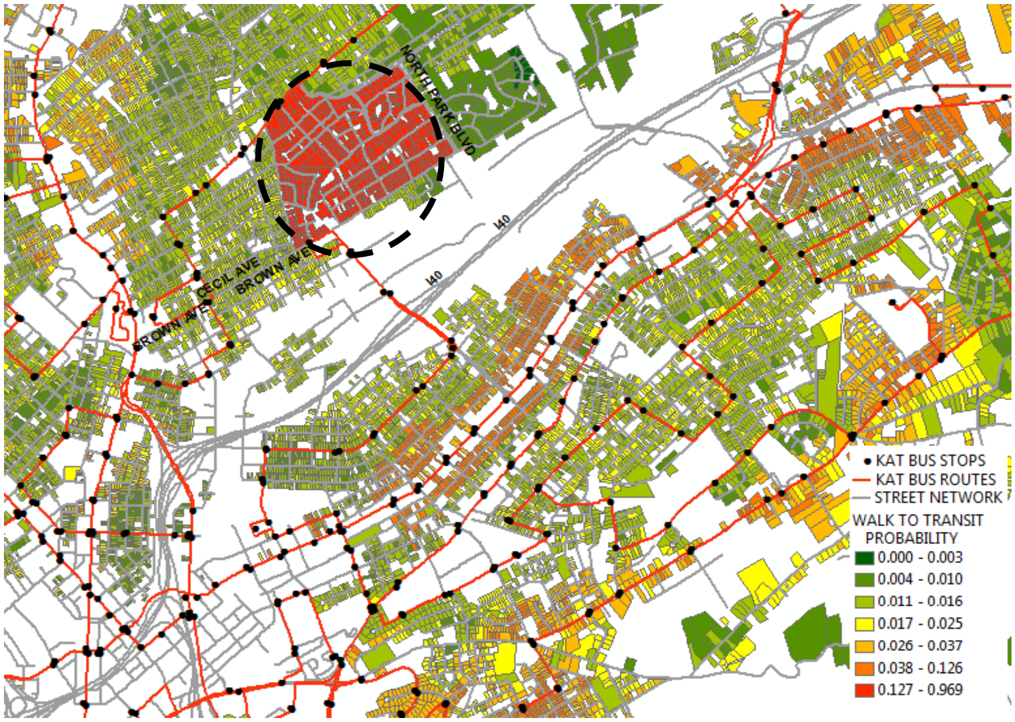


Figure 11. Probability of Walking to Transit in East Knoxville

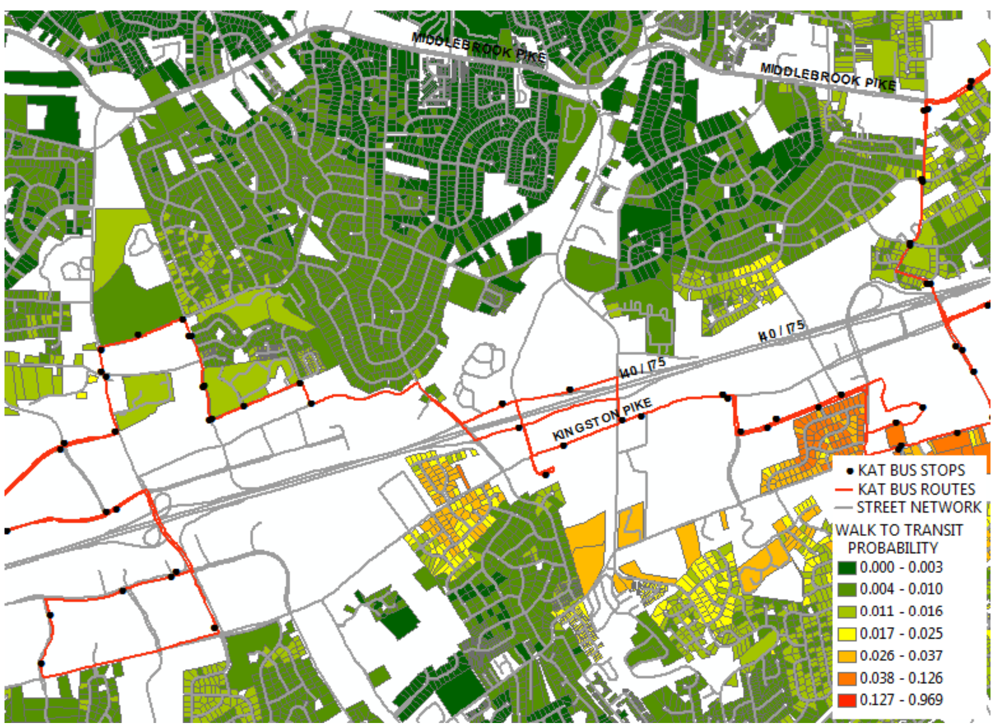


Figure 12. Probability of Walking to Transit in West Knoxville

Figure 13. Probability of Walking to Transit in UT and Fort Sanders

Moreover, to show the effect of different demographics on the walking probability and walking distance relationship, Figures 14-16 represent the differences in probabilities by walking distances for different demographics. From these figures, the variations in probabilities for the same walking distances from transit stops are noticeable. It can also be noticed that some households have very high probabilities compared to others as highlighted in Figure 14. This effect is due to their location within the CBD area which is associated with a CBD parameter. Moreover, the previously mentioned data anomaly of TAZ #1051 with high number of workers per households compared to neighboring TAZs contributed to these higher probabilities. This is almost certainly a data or sampling error.

Excluding these high probabilities and focusing on the ones that are not affected by the CBD parameter, different distance decay functions were formed for different demographic categories, observed in Figure 15 as separate bands of distance decay functions.

A more profound illustration of these bands is represented in Figure 16. The 3-D projection of walking distance, household income, and the resulting probabilities show the effect of income categories on the probability of walking to transit for households with the same walking distance from transit stops. The differences in income levels support the formation of different probability bands as shown with red, yellow and black dashed lines for incomes of less than $25,000, $25,000-$50,000 and $50,000-$80,000, respectively. Moreover, different bands within the same income category were formed due to other variables included in the utility function in addition to the demographic variables as seen in the difference between red and blue dashed lines for income category 1 (< $25,000).

Although one variable cannot be singled out as the only contributor to this effect, waiting time from service headway was noticed to have a significant effect on the formation of bands within the same market segmentation parameters.

These figures were set to show probabilities for walking distances up to 1 mile which is used to illustrate the differences in observations and not to delineate the service area or force a maximum walking distance.

Moreover, trip production rates for each household were used to estimate HBWTs for each household utilizing household size, number of workers and income. These trips were then multiplied by the probability of walking to transit estimated for each household to find the number of work trips that are expected to use transit (walk access). The estimated walk to transit trips will be used in prioritizing pedestrian infrastructure as discussed in the following chapter. Figures 17-19 represent walk to transit trip numbers considering single and multi-family dwellings in East and West Knoxville and UT and Fort Sanders. Using work trip numbers reduced the differences between households noticed in the probability analysis part. This is due to the highly variable trip production rates from PSRC as a result of chained work trips that were excluded during estimation (PSRC, 2007). Therefore, for households with higher numbers of

workers, noticeably higher numbers of work trips that affected the overall potential walk to transit trips were estimated and used for analysis. This estimation will help in the prioritization of pedestrian infrastructure analysis in the following chapter.

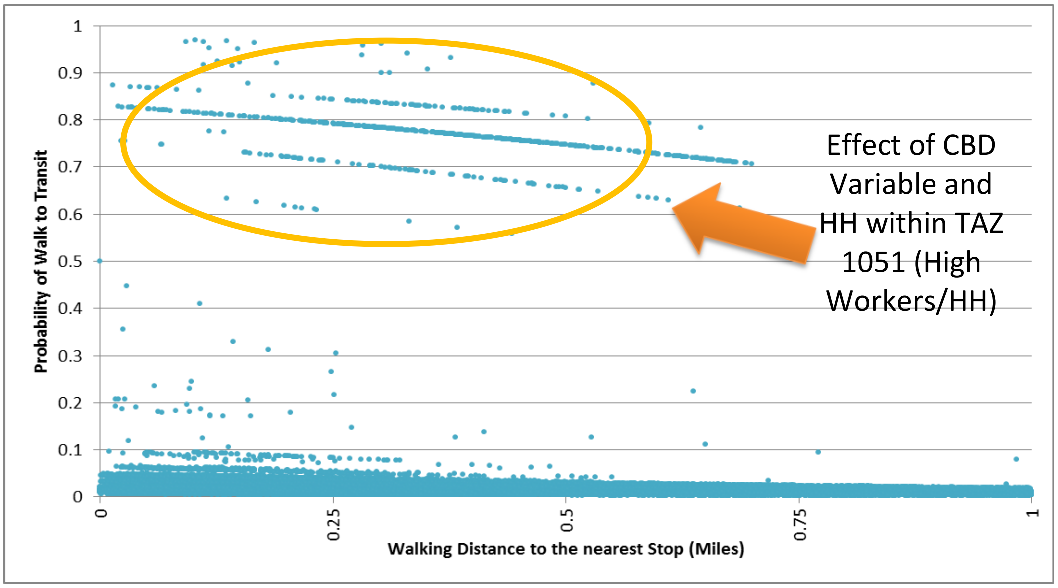


Figure 14. Probability of Walking to Transit by Walking Distance

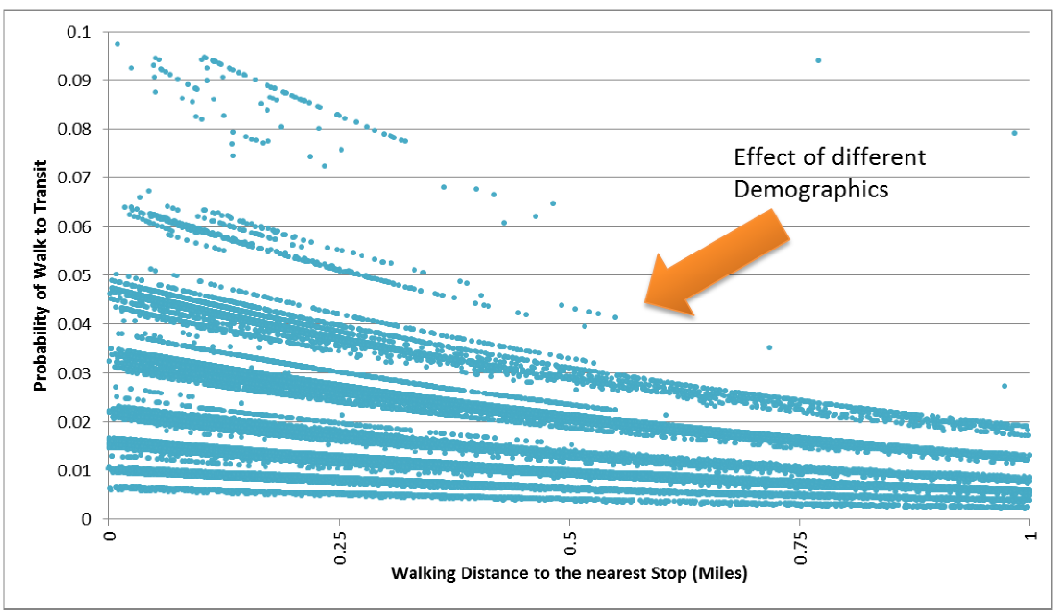


Figure 15. Probability of Walking to Transit (Up to 0.1) by Walking Distance.

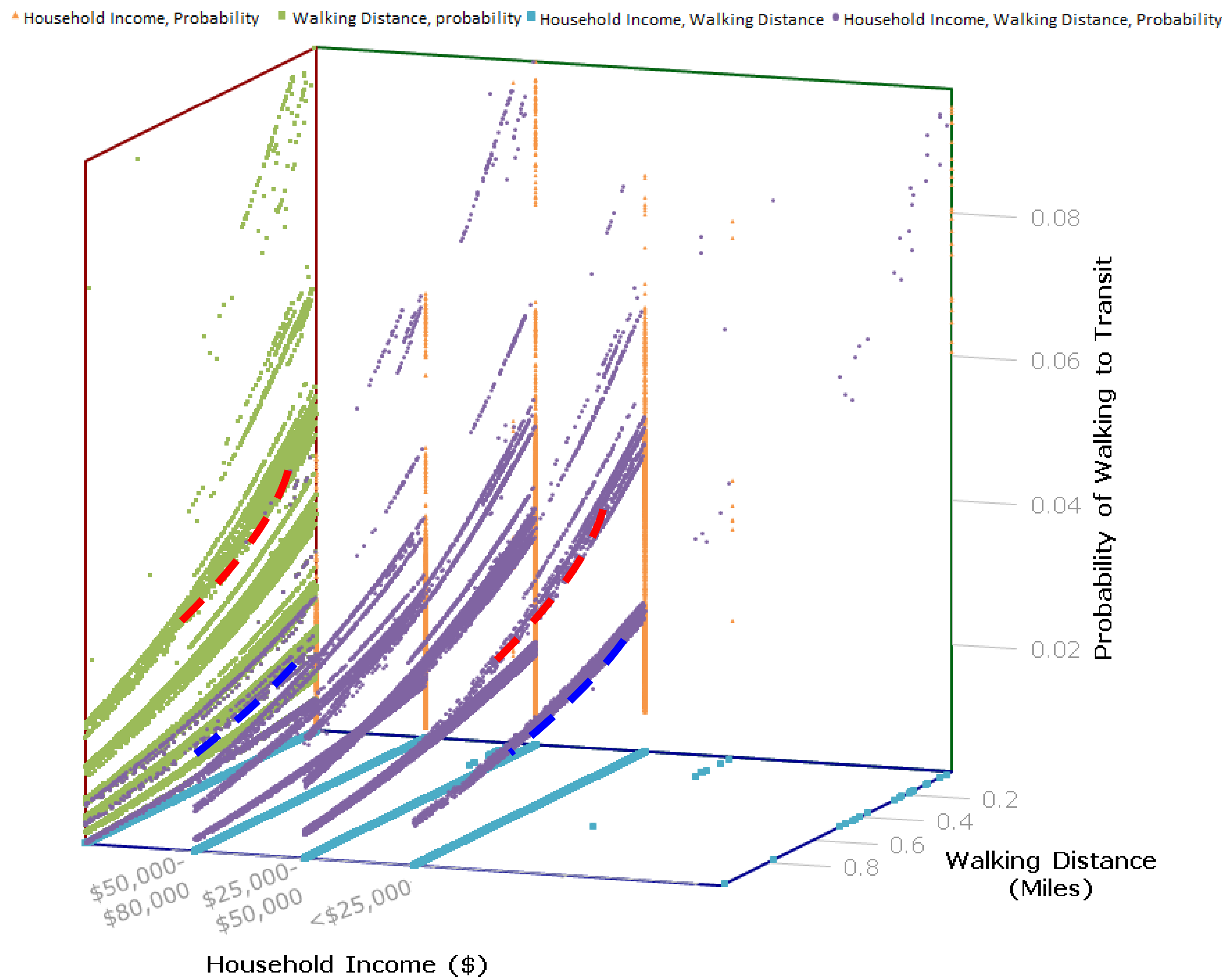


Figure 16. Walking Distance, Income Category and Probability of Walking to Transit Relationship

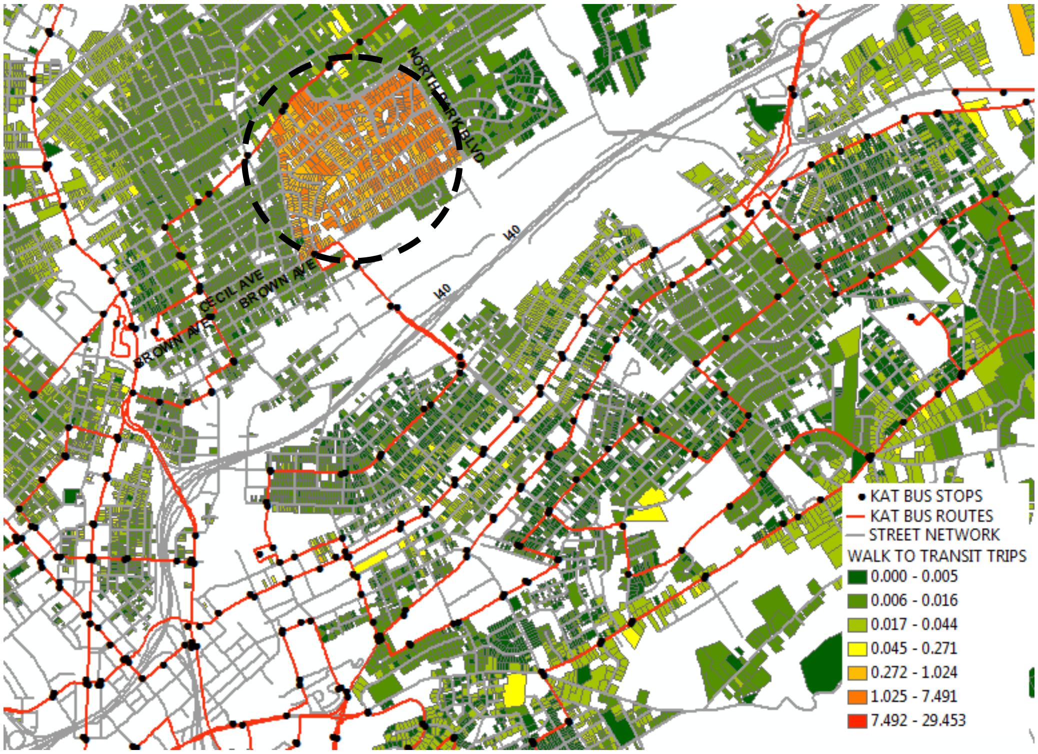


Figure 17. Total Walk to Transit Trips for HBWTs in East Knoxville

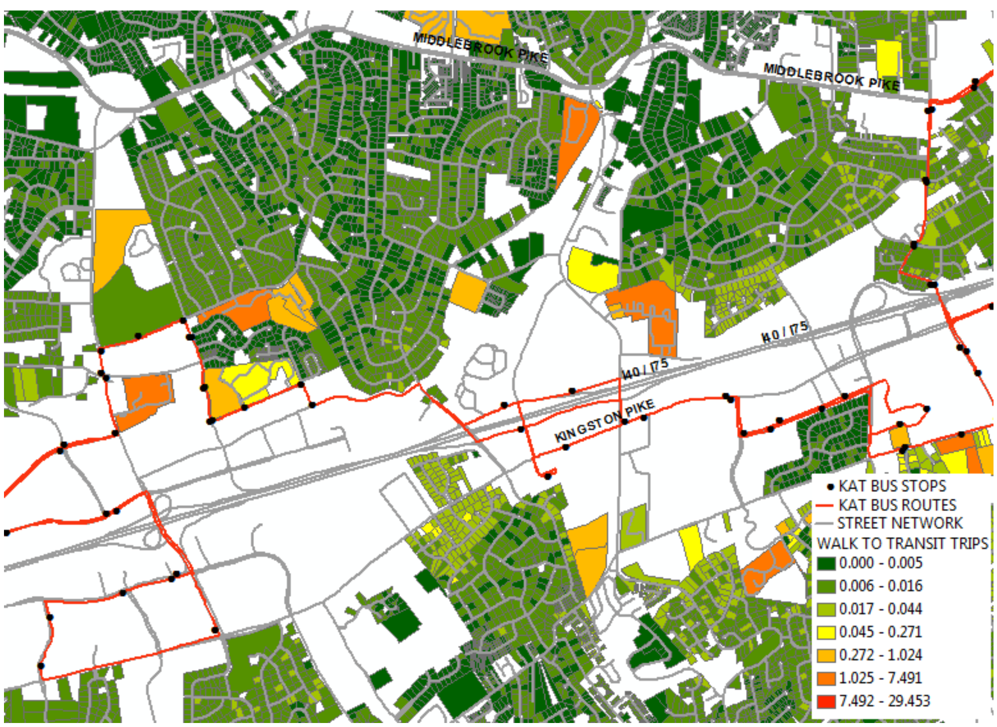


Figure 18. Total Walk to Transit Trips for HBWTs in West Knoxville

Figure 19. Total Walk to Transit Trips for HBWTs in UT and Fort Sanders.

4.5.2 Sensitivity Analysis

With the assumptions utilized in the application of this model, an assessment of the effect of variations in real data from the assumed values of the included variables is needed. This assessment shows the sensitivity of the resulting probabilities to the changes in these variables. Some assumptions made earlier that might have an effect on probabilities include commute time, wait time and cost. These values were estimated based on average data for large demographic areas (ZIP Codes), a rule of thumb of half headway wait time and an average fare of a selected transit pass, respectively. Moreover, these variables were assumed to be consistent for all households within the same area and/or transit stop. To assess the effect of encountering

different ranges of possible values for the studied variables, the probability associated with different levels of the variable were compared to the base case assumption values and the percentage change was estimated accordingly. Figures 20-22 illustrate the results of these analyses including the ranges of value change, resulting statistics and associated box plot distributions.

The results of the sensitivity analysis show variability in probabilities of walking to transit when different average fares from other offered passes are used. When a single ride pass (150 ¢) or a 20-ride pass (125 ¢) are used, an average of (7% -11%) reduction in probability is expected compared to the base case of 30-day pass (100 ¢). Moreover, using the average fare from fare box revenue per ride reported by KAT bus (50 ¢) that includes all types of passes and discounts used by transit riders, is expected to raise the probability of walking to transit by an average of 8% (FTA, 2012). These results also show that the variability of the percentage difference in probability would be in the (-20% - 16%) range which is acceptable for the application of this model in ranking road segments for pedestrian infrastructure priority.

Variable			Quantiles				
	Mean	S.D.	Min	0.25	Mdn	0.75	Max
Base Case (30 Day Pass Fare)	0	0	0	0	0	0	0
Single Ride Fare	-11	4	-20	-12	-12	-8	-6
20 Ride Pass Fare	-7	2	-12	-7	-7	-5	-3
Average Farebox Revenue per Ride	8	3	4	6	9	9	16

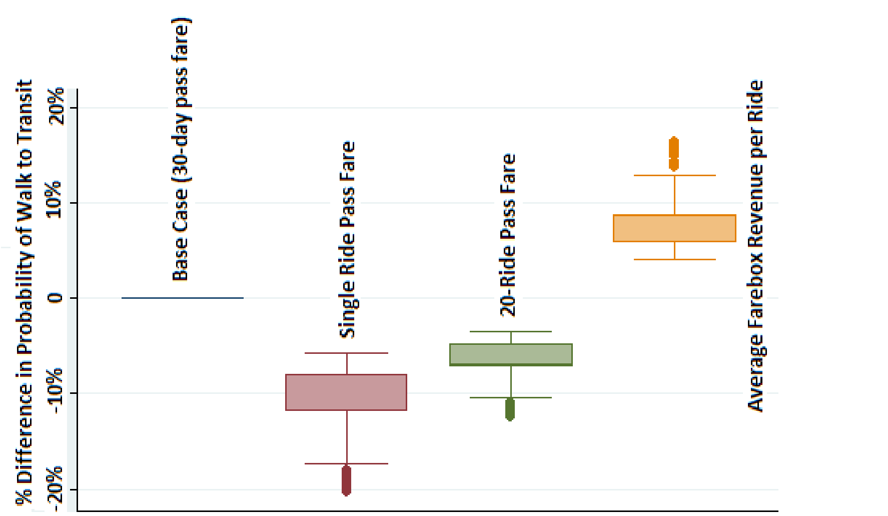
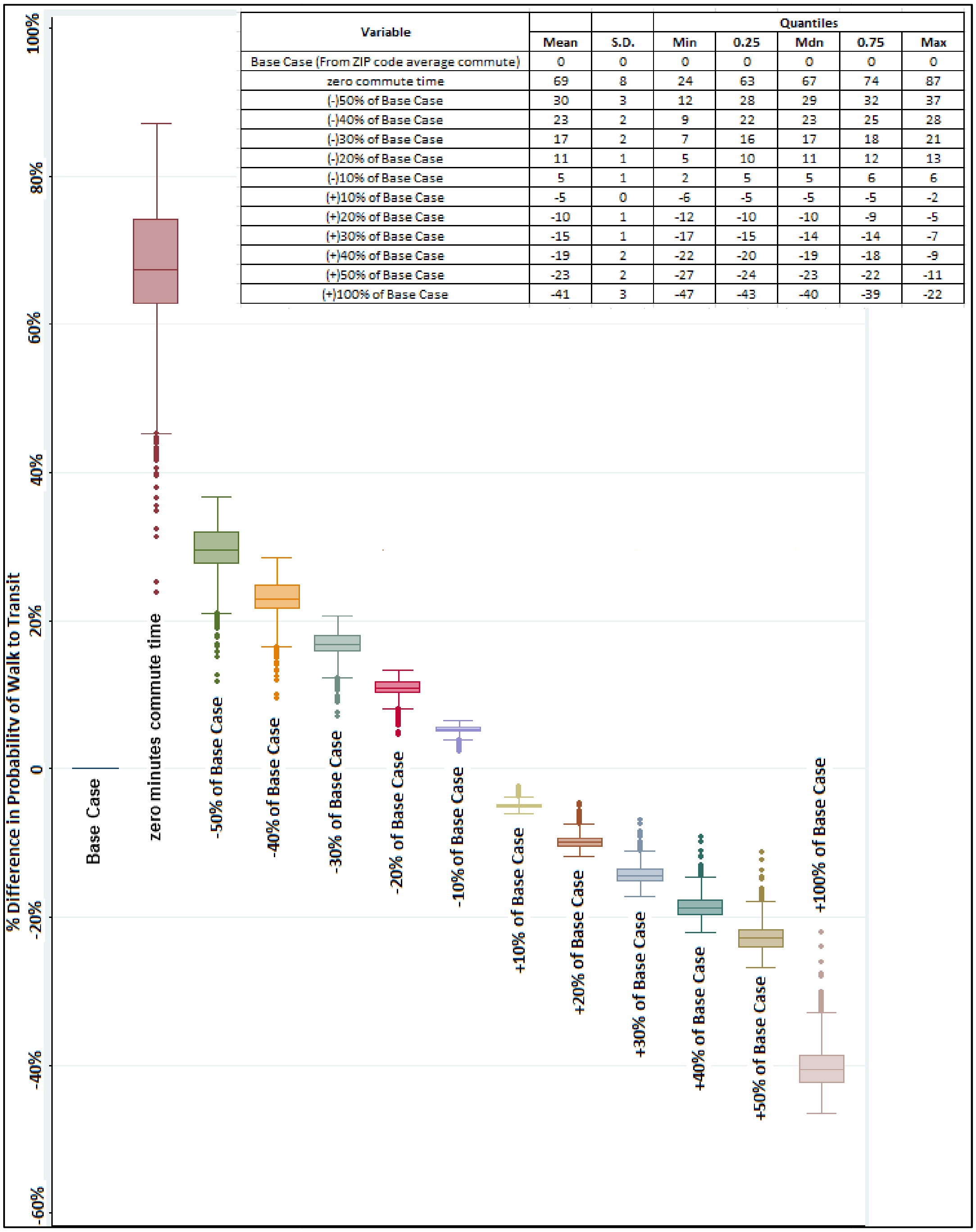
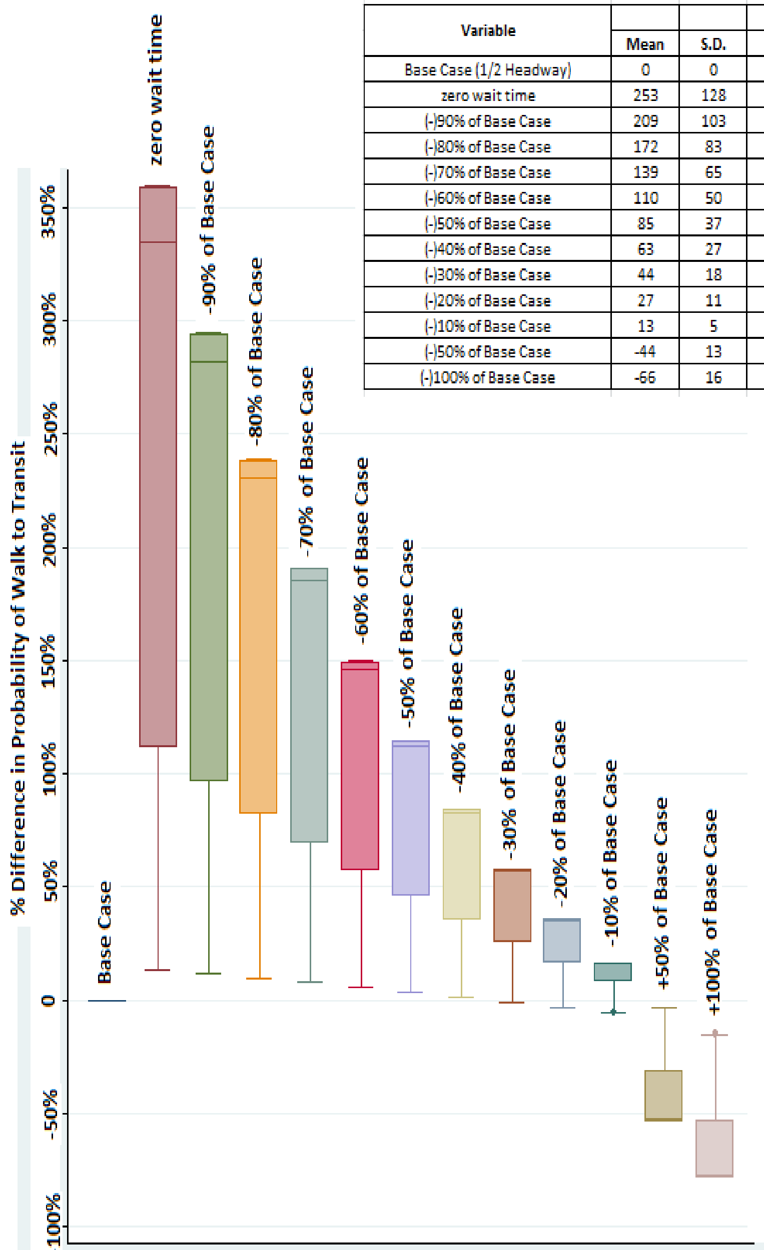


Figure 20. Percentage Difference in Probability of Walking to Transit for Different Fares (Box Plots and Statistics)



Variable	Mean	S.D.	Quantiles				
			Min	0.25	Mdn	0.75	Max
Base Case (From ZIP code average commute)	0	0	0	0	0	0	0
zero commute time	69	8	24	63	67	74	87
(-)50% of Base Case	30	3	12	28	29	32	37
(-)40% of Base Case	23	2	9	22	23	25	28
(-)30% of Base Case	17	2	7	16	17	18	21
(-)20% of Base Case	11	1	5	10	11	12	13
(-)10% of Base Case	5	1	2	5	5	6	6
(+)10% of Base Case	-5	0	-6	-5	-5	-5	-2
(+)20% of Base Case	-10	1	-12	-10	-10	-9	-5
(+)30% of Base Case	-15	1	-17	-15	-14	-14	-7
(+)40% of Base Case	-19	2	-22	-20	-19	-18	-9
(+)50% of Base Case	-23	2	-27	-24	-23	-22	-11
(+)100% of Base Case	-41	3	-47	-43	-40	-39	-22

Figure 21. Percentage Difference in Probability of Walking to Transit for Different Commute Times (Box Plots and Statistics)



Variable	Mean	S.D.	Quantiles				
			Min	0.25	Mdn	0.75	Max
Base Case (1/2 Headway)	0	0	0	0	0	0	0
zero wait time	253	128	14	112	335	359	360
(-)90% of Base Case	209	103	12	96	282	294	295
(-)80% of Base Case	172	83	10	82	230	238	239
(-)70% of Base Case	139	65	8	69	185	191	191
(-)60% of Base Case	110	50	6	57	146	150	150
(-)50% of Base Case	85	37	4	46	112	114	114
(-)40% of Base Case	63	27	1	35	82	84	84
(-)30% of Base Case	44	18	-1	25	57	58	58
(-)20% of Base Case	27	11	-3	16	35	36	36
(-)10% of Base Case	13	5	-6	8	16	16	16
(-)50% of Base Case	-44	13	-53	-53	-53	-31	-4
(-)100% of Base Case	-66	16	-78	-78	-78	-53	-14

Figure 22. Percentage Difference in Probability of Walking to Transit for Different Waiting Times (Box Plots and Statistics).

The assumption of average commute time from ZIP code data and uniformity across all households within these areas motivated testing the sensitivity of estimated probabilities to a wide range of possible commute time values. A range of zero commute time for workers who live near their work destinations to twice the assumed commute time was used for this analysis. The results show high sensitivity for those households with zero commute time of up to 70% change in probability of walking to transit. This result was expected and further analysis to identify some locations were similar instances might occur is recommended in future work. Moreover, the results from all other values show a percentage difference range of (-40% - 30%). This range is slightly higher than expected for the very low and very high commute times but is within the acceptable ranges for other values. A representative trip distribution model is expected to account for this variability by estimating more accurate commute times for different demographics based on surveyed travel behaviors.

Wait time variability showed high sensitivity and percentage difference of probability. Some values such as zero wait time at which a rider is served upon arrival to bus stop, give 2.5 times the probability of walking to transit compared to the assumption of half headway. This is due to a high number of routes that have service headways up to one hour within the KAT system. Riders are expected to plan their arrivals to stops and stations at larger service headways. To account for this large variability in the estimated probabilities, a model that can accurately estimate waiting times and modify the assumption of half headway is recommended in future application of this model.

The application of this model toward prioritizing pedestrian infrastructure locations requires a comparative weight that can be assigned to each segment to allow for their ranking based on the estimated probabilities. Therefore, the variability of the estimated values might not have a significant effect on the outcome ranking even when different values are utilized. A recommended approach to the understanding of the effect of variable sensitivity on the ranking of road segments is to test the differences in priority rank while changing one or more of these variables. This approach is recommended in the extended work of this model.

CHPATER V
MODEL APLICATION FOR PEDESTRIAN INFRASTRUCTURE PRIORITIZATION IN KNOXVILLE, TN

The suggested model offers a wide range of possible applications which would mostly rely on the probability and/or trip maximization for the purposes of prioritizing investments in any selected area of application. One of the possible applications is the prioritization of pedestrian infrastructure investments toward the enhancement of accessibility to transit stops and stations. With the budget constraints associated with these investments, selecting alternative locations with higher walk to transit probabilities and focusing the available money on those locations supports the overall purpose of improving accessibility along dedicated infrastructure where most demanded.

The following sections present the method used in the prioritization analysis process and results when applied to Knox County data.

5.1 Criteria for Infrastructure Prioritization

The probability model estimated in the previous chapters was used to assign a specific walk to transit probability for each household included in the analysis. These probabilities coupled with the total work trip productions per household were used to estimate total potential number of transit trips (walk access). When each segment of the road network is associated with the appropriate number of trips from all overlapping walking routes, each segment will have a certain weight and all segments can be compared accordingly. The existing pedestrian infrastructure network (sidewalks) is used to find gaps in transit accessibility where potential walking routes exist and sidewalks are not available. Each of these segments can be compared based on the transit (walk access) trips from all the passing routes for the purpose of prioritizing pedestrian infrastructure investments at locations with higher values when constrained budgets dominate.

5.2 Data Preparation and Application

All the walking routes generated from each parcel to the nearest bus stop were given a weight based on the associated number of trips for the parcel they serve. As the walking routes might share segments from neighboring parcels, the weight for some segments will take the total number of trips from all the parcels they serve. To further explain the process used to prioritize pedestrian infrastructure locations, the following steps illustrate the full procedure used in the analysis:

1. Walking Routes from each parcel were generated from the closest facility network analyst in ArcMAP as discussed in the previous chapter and illustrated in Figure 23.
2. Each route was joined with the appropriate total number of trips estimated from the probability model for each parcel they serve. Figures 24 and 25 illustrate the procedure used to join these attributes from a spreadsheet to the associated routes and results of the join process.
3. The walking routes layer was spatially joined with the existing Street Network layer using ArcMAP to find overlapping segments from both layers. Figures 26 and 27 illustrate the procedure and the results of this step.
4. All the generated overlapping segments from the spatial join were summed to give a total number of trips for each road segment using Dissolve with SUM option in ArcMAP. Figure 28 and 29 illustrate the procedure and results of the dissolve process.
5. The result is a road network with segments weighted based on the total number of trips that are expected to use that segment when walking to transit.

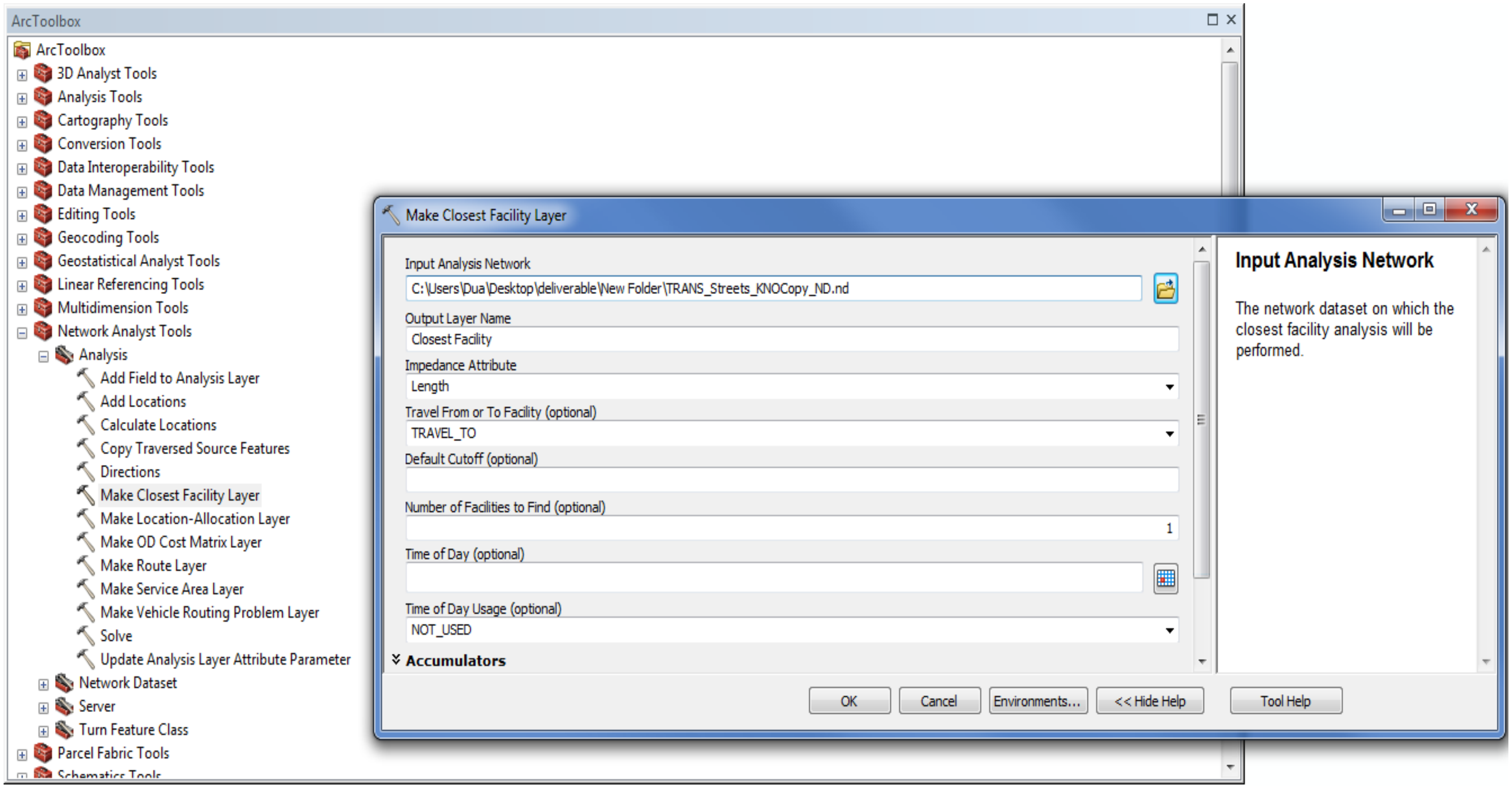


Figure 23. Generating Walking Routes Using ArcMAP Closest Facility Network Analyst Tool

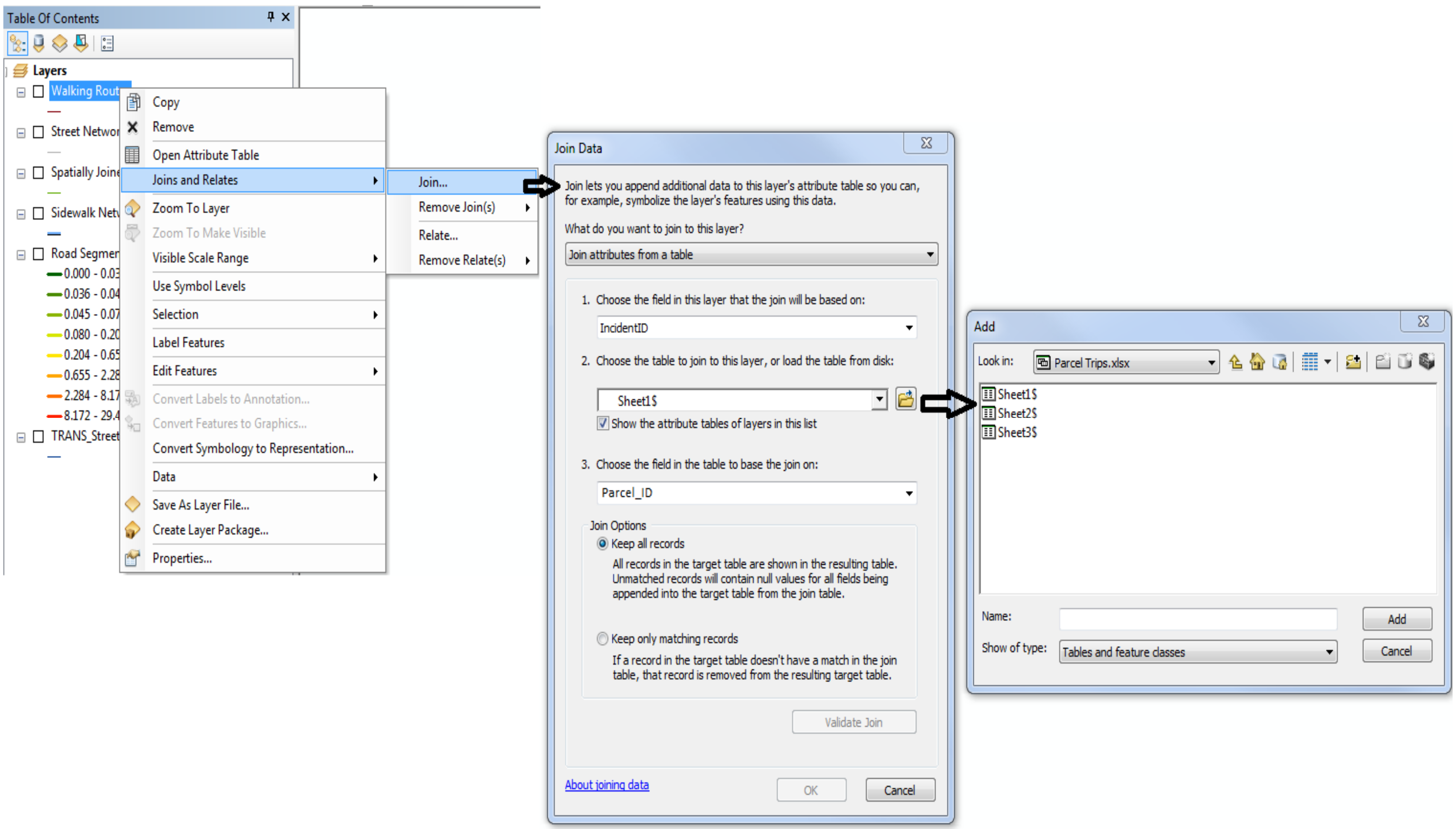


Figure 24. Joining Walking Trips For Each Parcel To Their Generated Walking Routes

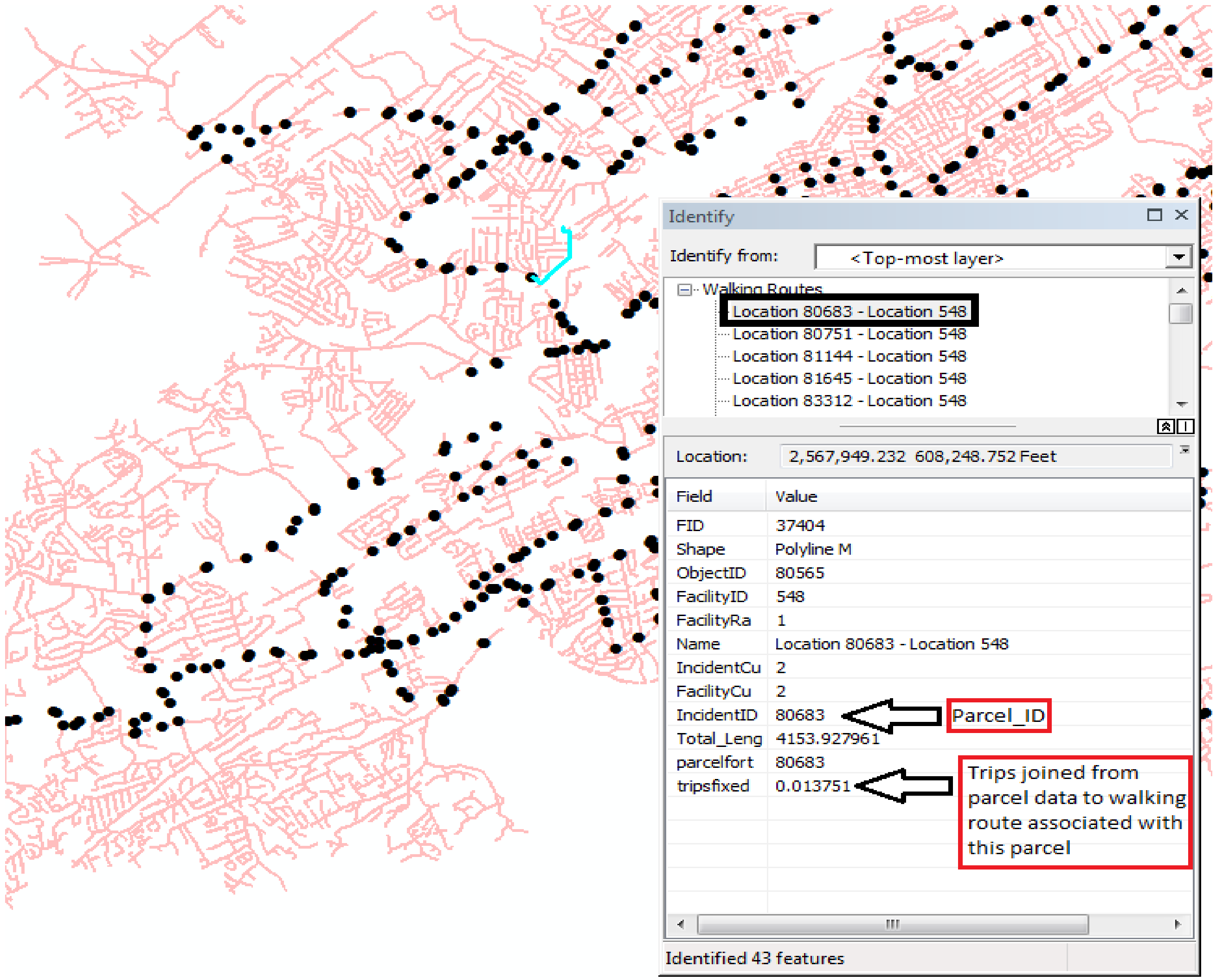


Figure 25. Results of Joined Walking Routes with Walk to Transit Trips

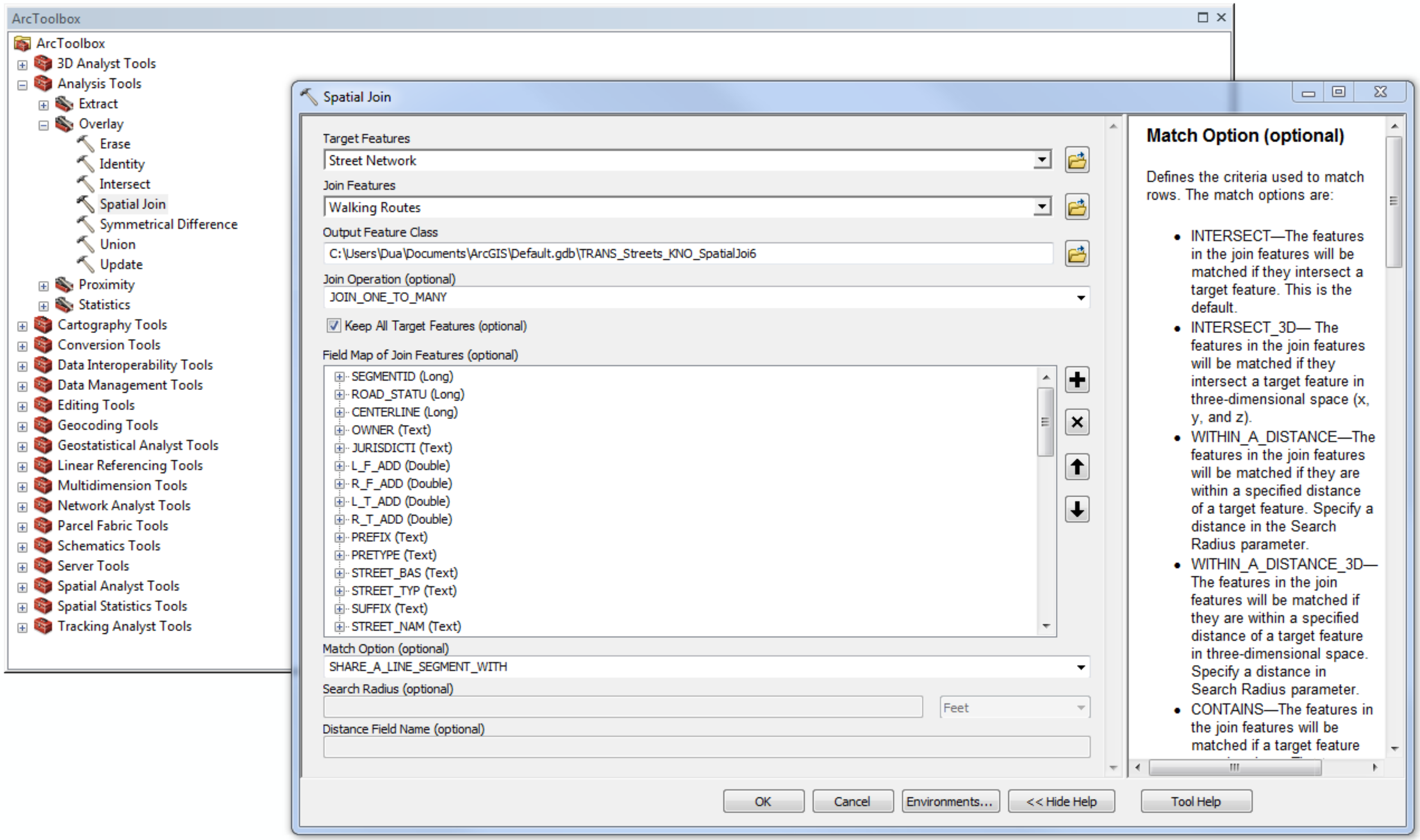


Figure 26. Joining Street Network with Walking Routes Using Spatial Join Tool

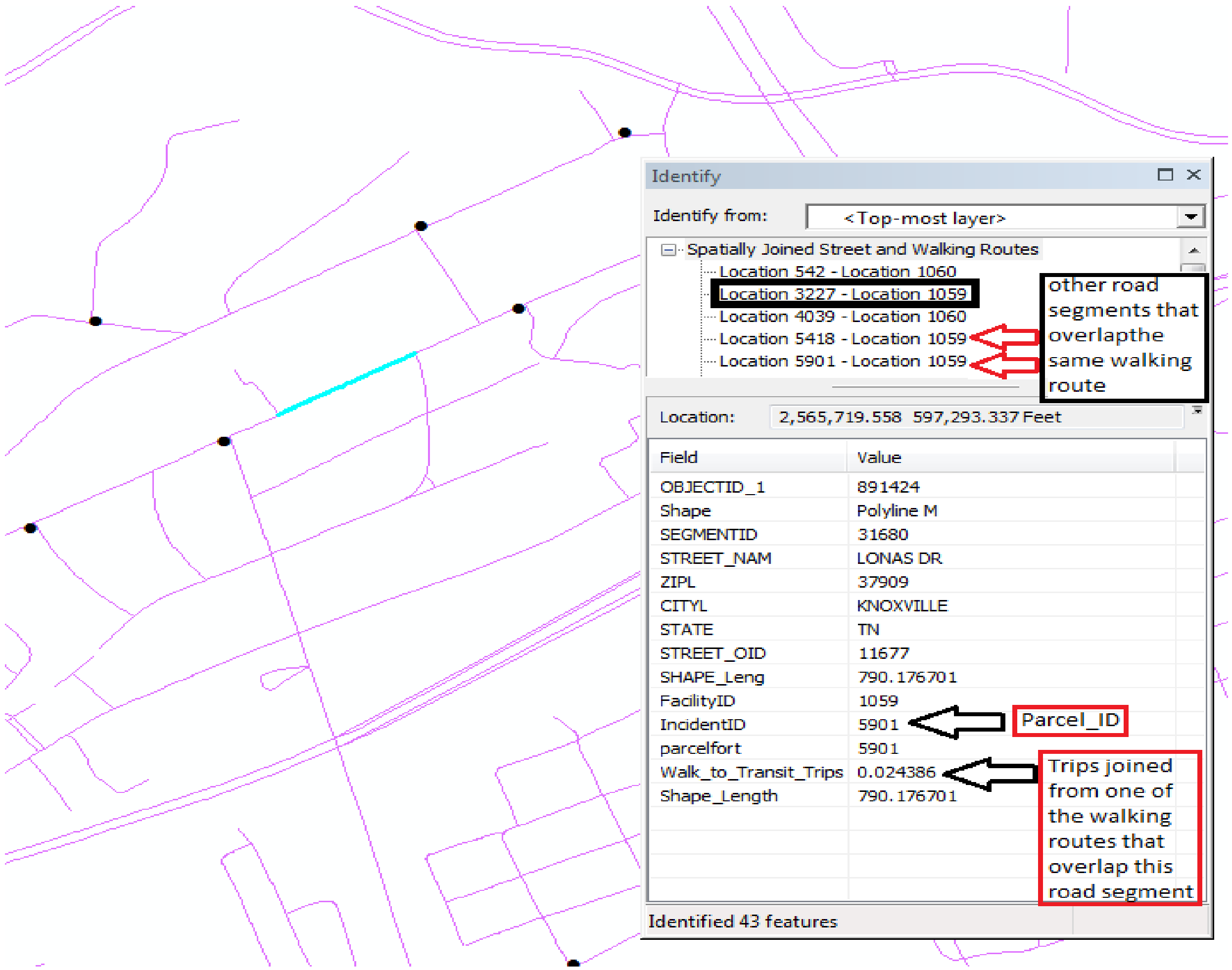


Figure 27. Results of Spatially Joined Street Network Layer with Walking Routes

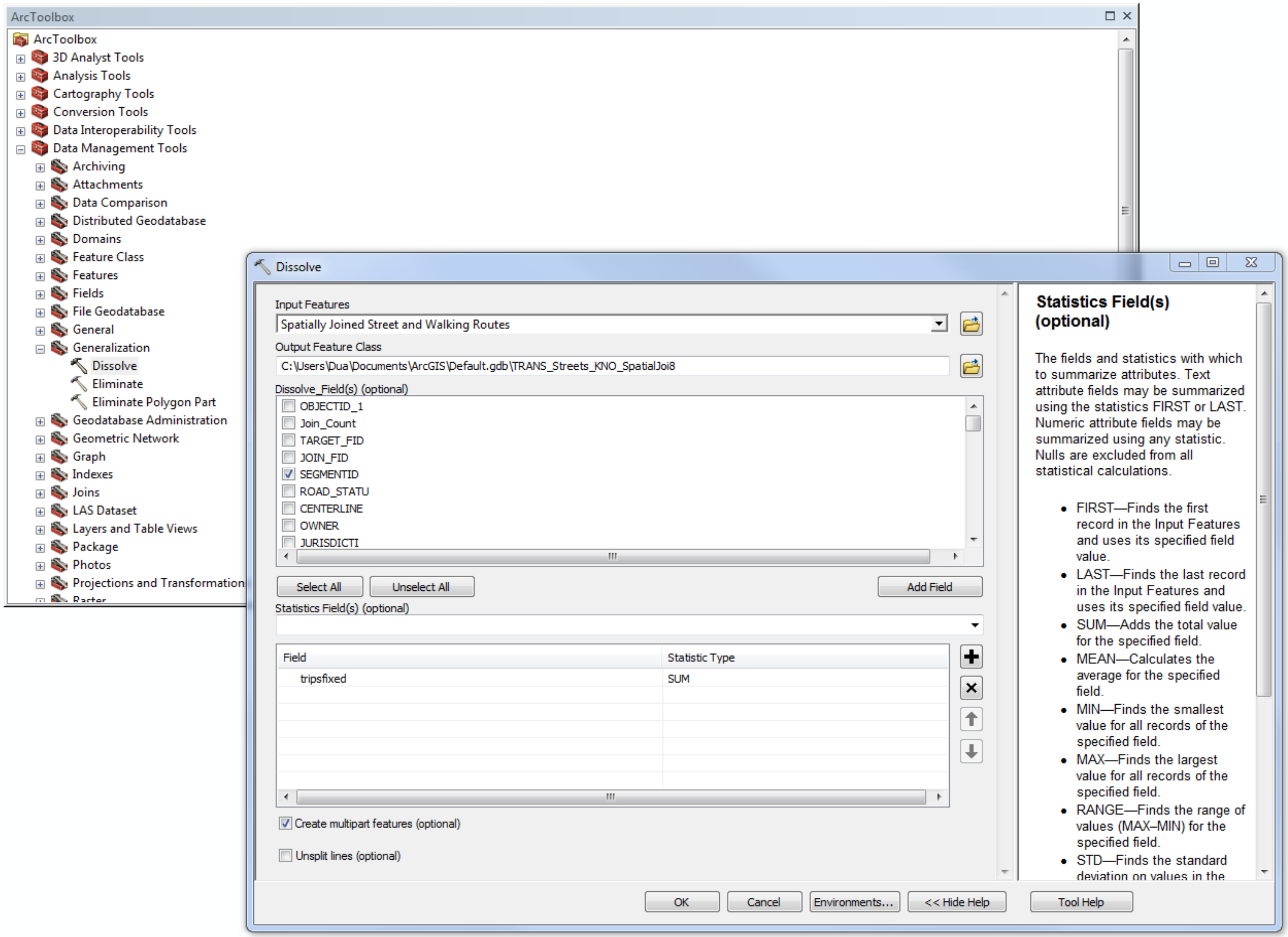


Figure 28. Aggregation of All Overlapping Walking Routes to Each Road Segment Using Dissolve Tool

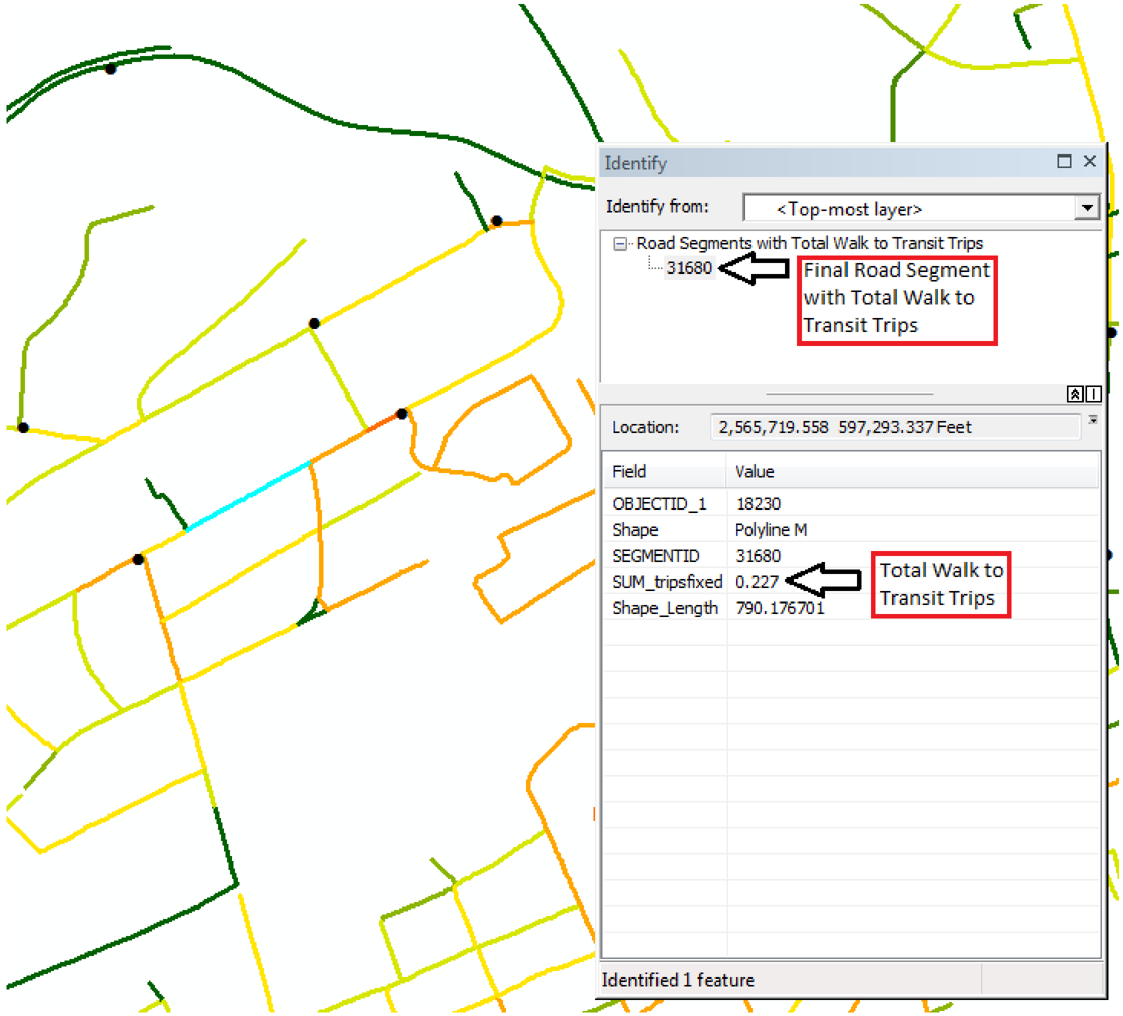


Figure 29. Results of Dissolving the Attributes of All Overlapping Waking Routes to the Road Segment.

5.3 Model Results

The result of this model is a road network with segments, as per the original GIS layer from KGIS, weighted according to the total number of trips generated from all parcels that share this segment of the road when walking to transit. Figure 30 illustrates a sample of the final results showing color coded road network segments based on the estimated weights (Total Trips) for a two mile distance from transit stops. This distance was used for sampling purposes (to speed computation time) and not as a buffer distance, as this was eliminated in the analysis by including all parcels within the county boundary.

This map represents the differences in the level of importance of the road segments. Red colors indicate higher total trips and priority for providing pedestrian infrastructure. These segments might be serving a higher number of parcels with potential walk to transit trips and/or parcels with higher numbers of walk to transit trips depending on the overall accumulated numbers associated with these segments.

A projection of the existing sidewalk network on the transit trips weighted road network is represented in Figure 31. This projection helps in finding gaps in the sidewalk system where higher walk to transit trips segments exist and lack infrastructure. The prioritization process of pedestrian infrastructure using the results of this model supports the efficient placement of sidewalks at forecasted locations within the specified budgets. To further explain the usage of the model, a roadway segment with high number of walk to transit trips at Wilson Road in Knoxville was selected as illustrated in Figure 32.

This segment of the roadway represents a gap in the pedestrian infrastructure (sidewalks) where higher probabilities of generating walk to transit trips are expected due to specific demographics of the population residing in this area. The higher trip numbers are supported by the existence of a residential complex as can be seen in the street view in Figure 33. The simplified selection of such high probability locations where observable discontinuities in the sidewalk network take place is a major advantage to this model and is useful in the fast allocation of road segments in need of immediate action.

After the selection of alternative locations for pedestrian infrastructure prioritization, the estimated costs for adding infrastructure will vary according to locations, topography and other variables within the construction sites. While these variables are necessary for the prioritization process, they are beyond the scope of our analysis and can be performed by public agencies as an advanced step after the application of results from this model.

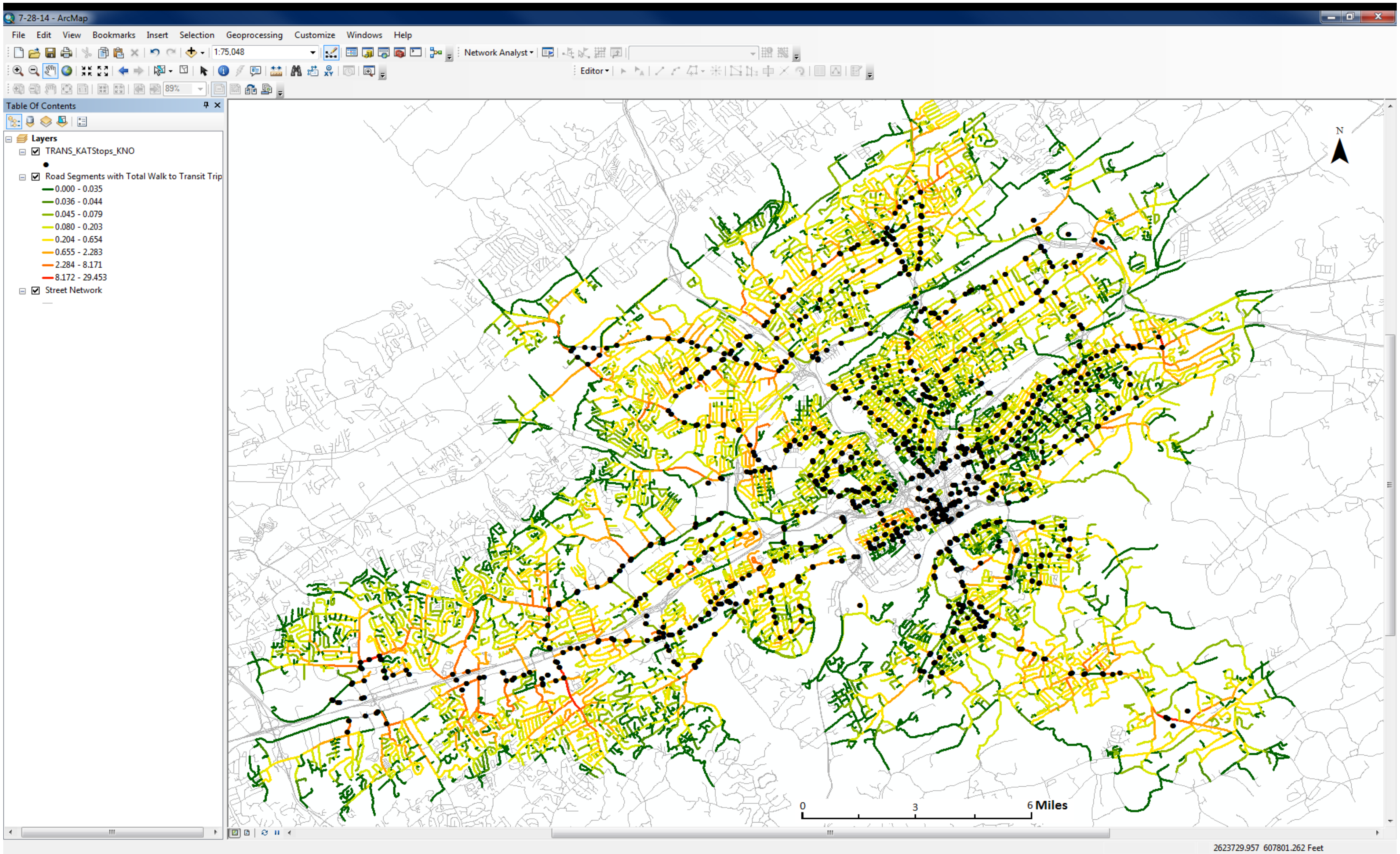


Figure 30. Sample of Dissolved Total Walk Trips to Transit for Some Road Segments in Knox County.

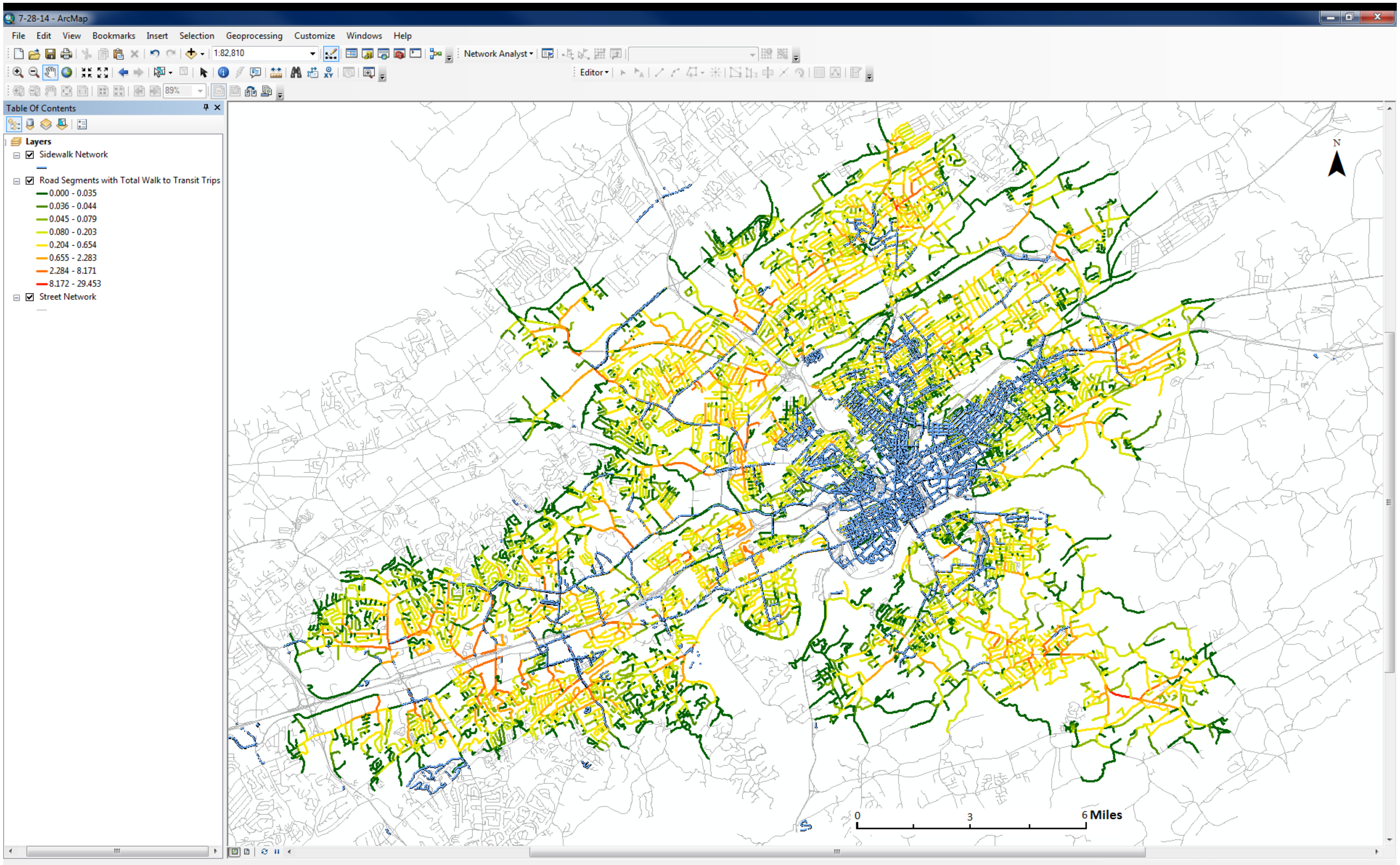


Figure 31. Road Network with Total Walk Trips to Transit for each Segment with existing Sidewalk Network.

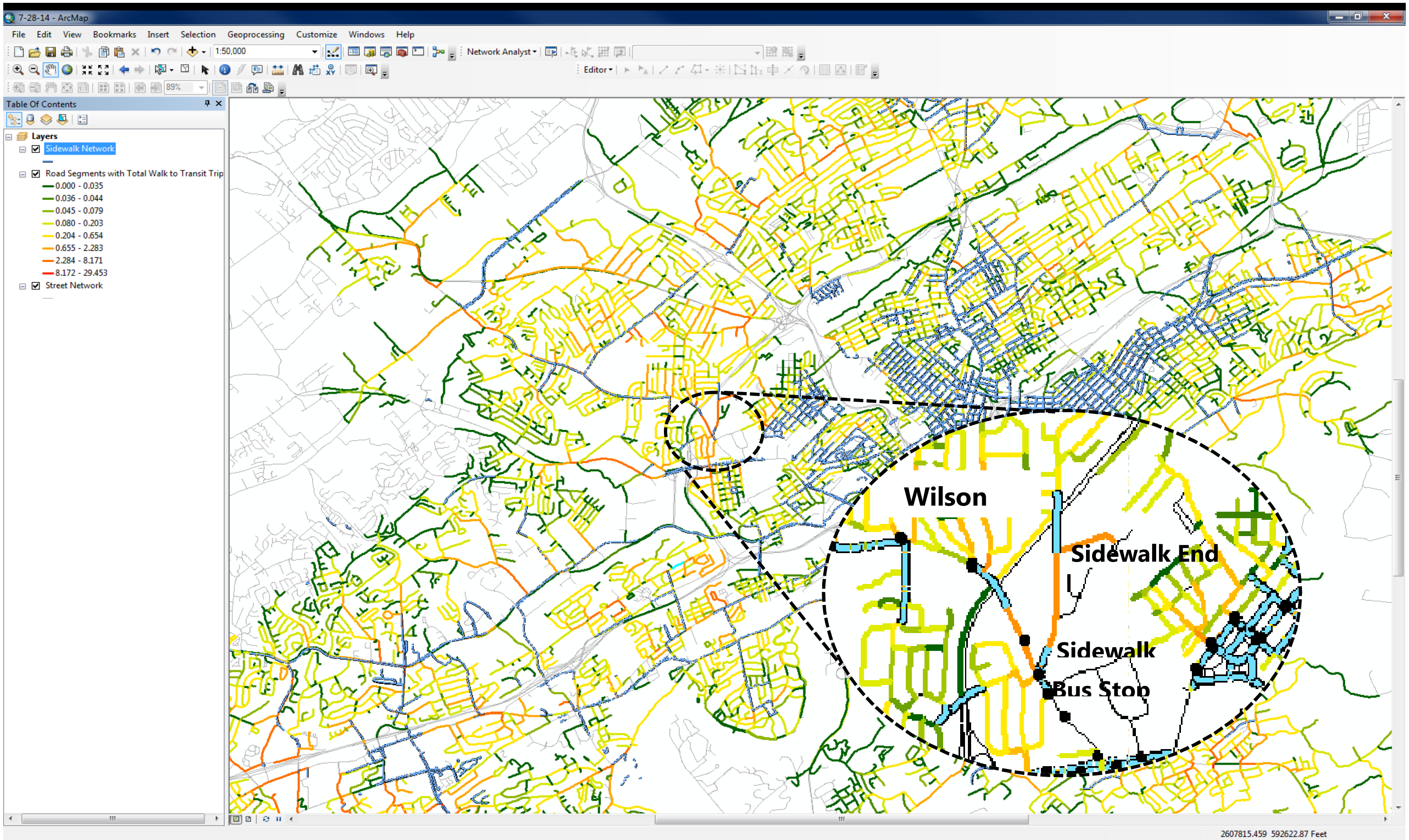


Figure 32. Example of a Road Segment with Gap in Pedestrian Infrastructure (Sidewalk) and High Number of Walk to Transit Trips.

Figure 33. Street View of the Gap in Pedestrian Infrastructure at Wilson Rd in Knoxville, TN.

CHPATER VI
SUMMARY AND CONCLUSION

The use of utility functions from discrete mode choice models to estimate walking to transit probabilities shows potential in understanding the differences in the probability to walk to transit. The estimation of walk to transit probabilities relied on data collected from household travel surveys. These surveys included data on the individual, household and trips for different modes and purposes. The inclusion of the behaviors of transit users and non-users in the estimation of the mode choice model offers a representative estimation of walking distance and demographics relationship. It also eliminates the bias associated with the use of transit on-board surveys which gives higher weights to certain demographics of transit riders.

Within the mode choice model, a distance decay function is defined by the walking distance variable given an estimated coefficient. The effect of this variable was apparent in the formed distance decay functions for different distances and user demographics. Therefore, this method was capable of utilizing the distance decay concept of deterrence to walk with higher walking distances.

Moreover, residential households served as the basis of this analysis with home-based work trips as the major trip purpose which account for 40 percent of transit trips surveyed by KAT agency. Demographic data and walking distances were estimated for each household and applied to the mode choice model. Therefore, the use of an arbitrary buffer distance was eliminated in the process.

The calculated walk to transit probabilities coupled with HBWT production rates were used to estimate potential walk to transit trip numbers for each household. These trips were then aggregated based on the walking routes to transit stops and each road segment was given a weight based on their associated total number of trips. This method was used in identifying segments with higher walk to transit trips to prioritize pedestrian infrastructure investments at these locations. Road segments can be ranked based on the associated walk to transit trips. A number of the highest ranked segments can be identified for infrastructure priority.

The estimated trip numbers can also be used to forecast ridership numbers and/or highlight locations with higher potential ridership and focus service enhancements, such as stop locations and service frequency, at these locations. Moreover, the flexibility of this model and the association to travel surveys support the gradual update of the utilized data and the estimated results whenever improved data sources emerge for application.

A major deterrence to the full utilization of the conceptual approach to this study is limited data and incompatibility between data compiled from different sources. These limitations, especially with the travel survey data, forced the use of an existing mode choice model from PSRC which does not necessarily resemble the actual travel behaviors and demographics of households in Knox County. The model was used for the purpose of application and illustration of the outcome probabilities until proper data are collected for future application. Moreover, the limitations associated with the incompatibility of parcel data from different sources forced the application of parcel-scaled TAZ data for some variables.

The estimated values of other variables such as travel times can be easily replaced with more accurate estimates once a comprehensive and more representative household travel survey is conducted and utilized for such analysis. Such data can also be used to estimate the utility of other alternative modes to update the zero utility assumption with more accurate estimated values to produce a more comprehensive probability function.

Moreover, connecting each parcel to the nearest bus stop does not account for route competition and system redundancy. Therefore, recommended future work should include the effect of the existence of multiple transit routes within a certain distance threshold.

The assumption of half headway for waiting times excludes passengers who would attempt to plan their arrival times to minimize waiting times for long service headways. The high sensitivity of estimated probabilities when different values are applied support the use of a modified approach to estimate the approximate waiting times for those passengers which is recommended for future applications of this model.

The analysis in the previous sections included home-based work trips generated from residential households as trip origins. To extend this method, the estimation of different mode

choice models for other trip purposes and the inclusion of commercial parcels and businesses as trip origins and/or destinations can be identified in future work.

Ultimately, this model was capable of applying the results from the estimated mode choice model as walk to transit trips for the purpose of identifying locations with higher potential total trips to the nearest bus stops. Identifying these locations supports the prioritization of pedestrian infrastructure investments at these locations while eliminating a confined buffer service area and including the significant household, system and trip characteristics.

Other applications to this method include transit network development and stop placement. Connecting the estimated demand for transit to stops and stations can be used in optimizing stop locations where high demand is expected. Moreover, a comparison between the option of building a sidewalk at certain locations and modifying stop locations to account for high demand would be useful in selecting the most cost effective approach in providing accessibility.

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VITA

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