Pedestrian Demand Model for Evaluating Pedestrian Risk Exposure

Summary

Prepared by

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1. INTRODUCTION

Planning for the mobility and safety of pedestrians is a major concern for urban and rural areas. One important aspect for developing pedestrian plans is estimating the amount of pedestrian traffic that can be expected in a particular area given the land use, transportation and social context. Pedestrian demand is also an important component for safety analysis. Estimates permit calculation of risk exposure – or crashes per pedestrian, which is a useful metric in directing public resources to the most dangerous locations. The lack of consistent pedestrian volume or count data limit the ability to analyze current and past situations and has hampered the development of more sophisticated tools for estimates and forecasts.

For this reason, the tools available for predicting non-motorized transportation have typically been underdeveloped and less sophisticated than those methodologies for motorized modes. The advances in geographic information systems (GIS) and the availability of detailed spatial data now permit advances in pedestrian modeling techniques that can be used by pedestrian planners to forecast pedestrian volumes in a given area. **The objective of the study described in this paper is to develop a method to estimate pedestrian demand – or pedestrian volumes on a network – in order to evaluate pedestrian risk exposure in Maryland communities.** This paper describes the approach developed to model pedestrian demand using readily available data at the sub-regional scale. A more detailed presentation of the model can be found in the Pedestrian Demand Model and Crash Analysis Protocol (Clifton et al., 2008), an accompanying document for this report.

We present a pedestrian demand model that builds upon the traditional four-stage urban transportation modeling process, used extensively in regional travel demand models. But unlike regional travel models, this model functions at the pedestrian scale (at the neighborhood and street block level), utilizes readily available archived data, and operates entirely within a geographic information systems framework. The model has three components: trip generation, trip distribution and network assignment. Trip generation estimates the numbers of pedestrian trips that originate and end at each street block. Trip distribution connects these trip origins and destinations to estimate pedestrian flows. Finally network assignment predicts routes that pedestrians are likely to take on their journey. The end result is an estimate of the numbers of pedestrians, or pedestrian volumes, which will occur on sidewalks and intersections in the study area over a 24-hr period.

Use of the model requires the following:

- A geographic information system and experience using it, and ArcGIS in particular
- A personal computer
- Access to Maryland Property View data for the study location and times, geo-referenced to the centroid of parcels
- A recent road centerline file (e.g. Census Tiger File)
- The traffic assignment program module – Ped_Assign.exe
- Pedestrian-vehicle crash data (from Maryland Police Accident Reports) geo-referenced.

- Aerial photos, maps or some other visual source of information of the study area

- The Pedestrian Demand Model Protocol

We explain how the model output could be used in conjunction with pedestrian-vehicular crash data for analysis of pedestrian risk exposure. Pedestrian crash data are commonly available at the intersection level but data on the number of pedestrians per intersection are frequently not available or incomplete across a study area. The model addresses this deficiency by providing an estimation of the numbers of pedestrians per intersection in a typical day.

Finally, we outline a plan for implementation and application of this model in the State of Maryland for pedestrian safety and planning purposes. Because the model runs on a GIS platform, most local planners can have the capacity to run the model themselves. This tool will bring a new resource to the issue of pedestrian safety and will assist public agencies in prioritizing and directing investments to mitigate problems.

2. DATA

To estimate pedestrian demand using the four-step method, a trip based database is needed with detailed information about the trip-maker and the trip itself. In this study, we used the 2001 National Household Travel Survey (NHTS) – Baltimore Add On. This dataset contains detailed information about the trip-maker and the household (socio-economic data, vehicle ownership, presence of children, etc.) and the trip itself (mode used, origin and destination locations, purpose of trip, whether it is part of a tour, time

and length of trip, etc.). This dataset was chosen for estimation of pedestrian demand because it has a large sample size in which enough pedestrian trips are captured and thus robust results can be obtained in the trip generation stage. The NHTS Add-on datasets have been compiled by gathering large samples, which include geographic coordinate locations for trip ends, in specific areas in the country.

Parcel level land use data was used for the analysis of pedestrian demand. These data came from the Maryland Property View database and contained spatial referencing so that it could be aggregated to trip ends. The importance of good parcel level land use data is significant in obtaining robust results in the model.

Employment data is also very important in pedestrian demand modeling because the equations for trip production and attraction rely heavily on these data. However, employment data is very difficult to obtain and therefore we estimated employment based on land use information. This method will be discussed in the subsequent section.

For the calculation of pedestrian risk exposure, we have obtained pedestrian-vehicular crashes information from the State of Maryland - Motor Vehicle Accident Reports for two study areas in Baltimore City and in Prince George's County.

3. METHODS

Travel demand modeling has been dominated by the 4-step model (McNally, 2000). This type of model consists of 4 parts as described by McNally (2000):

1. Trip Generation: measures of trip frequency are developed based on the propensity to travel. The origins and destinations of trips are estimated separately as productions and attractions

2. Trip Distribution: trip productions are distributed to match the trip attraction distribution yielding origin-destination (OD) trip tables of person-trip demands.

3. Mode Choice: trip tables are factored to reflect relative proportions of trips by alternative modes (not included in the model presented below).

4. Route Assignment: modal trip tables are assigned to mode-specific networks

The pedestrian demand model presented in this paper differs from the traditional vehicular model in that we need to combine two steps of the process, the trip generation and mode choice steps. This is because we will only consider pedestrian travel and therefore there is no need to segment travel by modes after the trip distribution step. Therefore, the model presented here includes steps 1, 2 and 4 described above. We estimated the home-based trip generation and trip distribution models using data from the 2001 National Household Travel Survey for the Greater Baltimore Region as shown in Figure 1. The route assignment program uses a equilibrium assignment methodology for the shortest (distance) path. The models were applied can calibrated to a smaller study area (about 10 sq. mi.) within the City of Baltimore as shown in Figure 2.

The pedestrian demand model described in this paper is intended to be very user friendly and very transferable to other regions. We have used a geographic information system (GIS) software that is capable to performing network analysis, ESRI's ArcGIS. This

spatial software allows the user to spatially locate all trips, households and land use parcels so that the data can be aggregated spatially to trip ends. Before beginning any analysis, we created a pedestrian network and pedestrian analysis zones (PAZs) using ArcGIS.

4.1. *Pedestrian Network and Pedestrian Analysis Zones*

The first step in this process was to build a spatial pedestrian network. Most jurisdictions do not have a sidewalk network already created for its study area, therefore the user will need to create his or her own sidewalk network based on aerial photographs and road network overlays. We have created a protocol to instruct the user of our model of how to create the pedestrian network based on the U.S. Census tiger roadway layers using GIS.

This protocol also explains how to create PAZs, which are either the block face center point or the street block centroid depending on the type of environment (urban versus suburban). The PAZ represents the basic area unit of the model, similar to a Traffic Analysis Zone used in conventional travel demand modeling. All of the land uses on the block face or block are aggregated to the PAZ using GIS. PAZs are the zonal locations for trip origins and destinations.

In preparation for the trip generation stage, we aggregated land use information to the PAZ level and to a ¼ mile buffer around each PAZ. The land use data (Maryland Property View) stratified by type (example: retail square footage within ¼ mile buffer, number of office jobs within ¼ mile buffer, etc.) were aggregated to the PAZ and ¼

buffers from each PAZ, respectively. In addition, a measure of street connectivity was
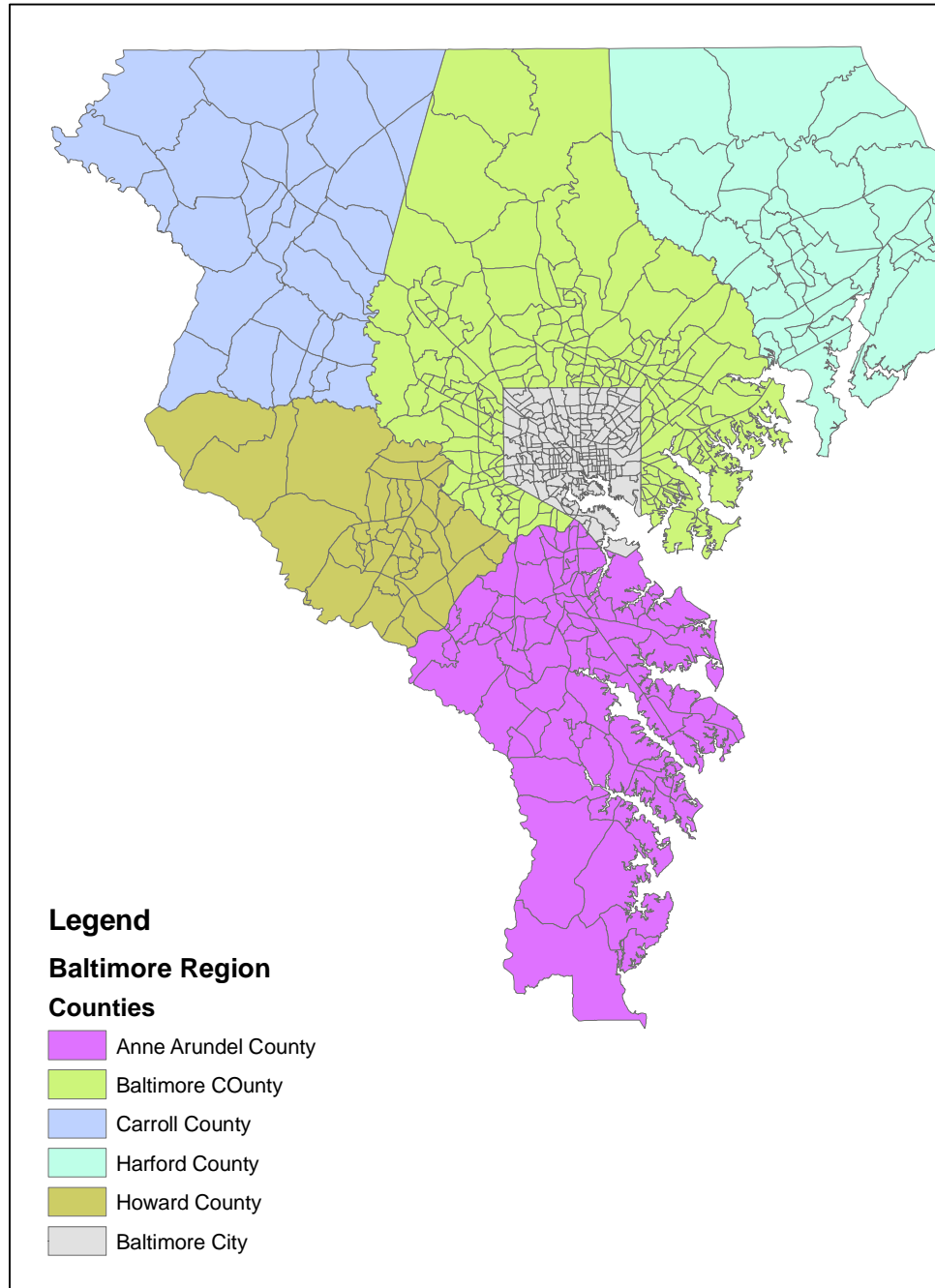calculated from the road centerline file for each of these buffers.

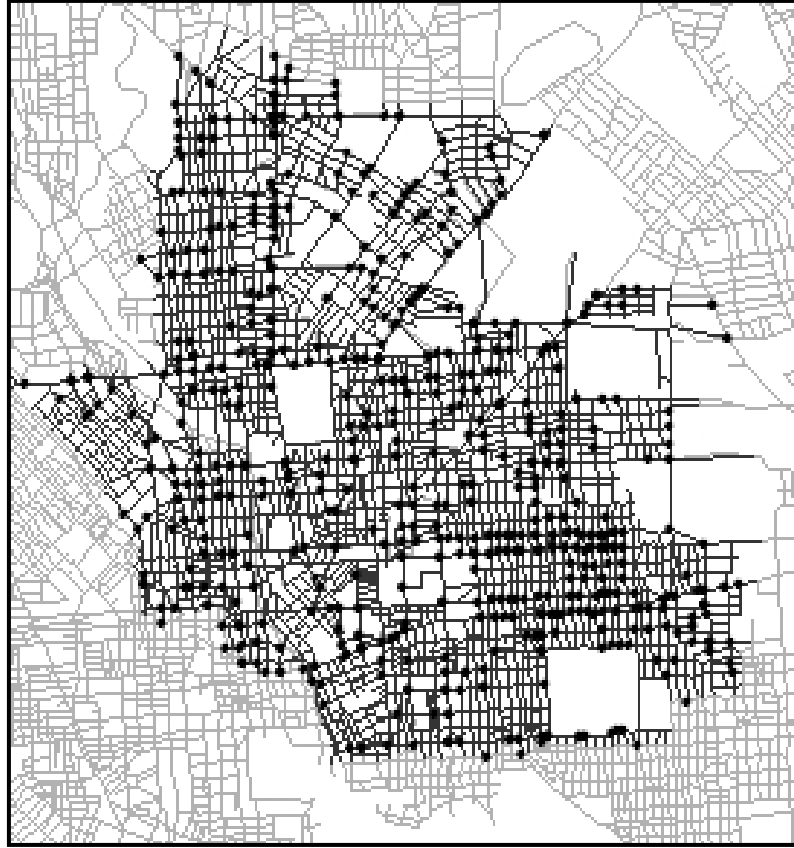*Figure 1: Greater Baltimore Region used for estimation of Trip Generation Models*

Figure 2: Study Area in Baltimore City

4.2. *Trip Generation*

For the estimation of the trip generation equations, the NHTS trip dataset was divided

into two categories: Home Based trips (HB) and Non-Home Based trips (NHB).

For the HB trips, we estimated the trip productions and attractions from the walk trips in

the NHTS – Baltimore Add On dataset as shown by the regression models discussed

below. We assumed that trip productions and attractions for walking trips are equal for

HB trips and therefore used the same estimation equation for both. For the NHB trips, we

used trip production and trip attraction equations from the Travel Demand Models for the

San Francisco Bay Area (BAYCAST-90), (Purvis, 1997) and then estimated the

probability that a given NHB trip would be made by walking using the 2001 NHTS data

for Baltimore.

4.2.1. *Home-based Walk Productions and Attractions*

Home based walk productions and attractions are calculated using the same equation

below:

HB Walk (Walk trips/household) =exp (-1.034232 -0.9455401*vehicle ownership

+2.371351*street connectivity

+0.0070639*percent commercial +

0.0001527*total dwelling units)

Note: vehicle ownership is calculated from the US Census at the nearest tract and all of

the land use variables are calculated at the ¼ mile buffer

We then converted the walk trips per household to walk trips per PAZ with the equation:

HB Walk/ PAZ (walk trips/PAZ) =   HB Walk (walk trips/hh) *

total dwelling units in the PAZ

4.2.2. NHB Walk Trip Productions

NHB Productions (Total trips/PAZ) = 0.798*Other Employment

+2.984*Retail Employment

+0.916*Service Employment

+0.707*Total Households

Note: variables in this model are calculated at the PAZ level

Since we did not have employment information available at the PAZ level, we used conversion factors as shown below to calculate employment based on land use data. These conversion factors were calculated based on the ES 202 employment data and square footage of commercial parcels from the Maryland Property View.

For urban areas:

Retail = 2.49 employees/1000 sq ft of retail

Service = 5.52 employees/1000 sq ft of service

Other = 1.35 employees/1000 sq ft of other jobs

For suburban areas:

Retail = 3.41 employees/1000 sq ft of retail

Service = 18.26 employees/1000 sq ft of service

Other = 0.34 employees/1000 sq ft of other jobs

Since the above trip generation equations are estimated for all trips (all modes), we then we extracted the walk trip rates with the following probability equation:

$$\text{Prob (Walk trip)} = \frac{\exp(U_{Walk})}{(1 + \exp(U_{Walk}))}$$

Where, U_{Walk} = -4.286918 + 3.041807*Connectivity + 0.0051575*Percent Commercial

Note: Variables in this model are calculated at the ¼ mile buffer of the PAZ.

Again, we then converted the walk trips per household to walk trips per PAZ with the equation:

NHB walk trips(walk trips/PAZ) = NHB total trips (Total trips/PAZ) * Prob (Walk trip)

4.2.3. NHB Walk Trip Attractions

NHB Attractions (Total trips/PAZ) = 0.636* Other Employment

+ 3.194* Retail Employment

+ 0.730* Service Employment

+ 0.803* Total Households

Note: variables in this model are calculated at the PAZ level

Again, since the above trip generation equation is estimated for all trips (all modes), we then extracted the walk trip rates with the following probability equation:

$$\text{Prob (Walk trip)} = \frac{\exp(U_{\text{Walk}})}{(1 + \exp(U_{\text{Walk}}))}$$

Where, U_{Walk} = -4.286918 + 3.041807*Connectivity + 0.0051575*Percent Commercial

Note: Variables in this model are calculated at the ¼ mile buffer of the trip end.

Once more, we converted the walk trips per household to walk trips per PAZ with the equation:

NHB walk trips(walk trips/PAZ) = NHB total trips (Total trips/PAZ) * Prob (Walk trip)

4.3. *Trip Distribution*

In this step, we estimate pedestrian trip distribution (walk trips from origin PAZs to destination PAZs) based on (i) the walk trip Productions and Attractions of PAZs obtained in the Trip Generation stage and (ii) the "friction factor" or decay function for walking trips by increasing distance. We used the "Gravity Model" for estimating the pedestrian walk trip distributions, as follow:

$$T_{ij} = P_i \left[\frac{A_j F_{ij} K_{ij}}{\sum_j A_j F_{ij} K_{ij}} \right]$$

Where T_{ij} = Walk trips from i^{th} PAZ to j^{th} PAZ

P_i = Walk trip productions from i^{th} PAZ

A_j = Walk trip attractions to j^{th} PAZ

F_{ij} = Friction factor for walk trips from i^{th} PAZ to j^{th} PAZ

K_{ij} = K factor for balancing trip production and attraction

(we assume K_{ij} = 1 for all i, j pair)

The friction factors, F_{ij} are normally developed using a gamma function that is estimated with trip length and trip length frequency distributions. The general form of the gamma function for the friction factors is shown below:

$$F_{ij} = \alpha \times \left(\frac{1}{d_{ij}}\right)^{\beta} \times \exp(\gamma d_{ij})$$

Where, F_{ij} = Gamma function for Friction factors

d_{ij} = walk trip distance (meter)

α, β, γ are coefficients of the gamma function

The normalized friction factor function used in the Gravity Model is presented in the figure below. This plot also provides a picture of the traveler's sensitivity to travel distance by trip purpose (Home Base Walk and None-Home Base Walk). Note that since there is no big difference in both trip purposes, we estimate one friction factor function for all walk trips. We then apply these friction factors for each potential trip, to the gravity model equation.

The output of the trip distribution step is a trip table (or origin-destination matrix) for each type of trip modeled. In the case presented here, we have two trip tables: one for HB trips and one for NHB trips.
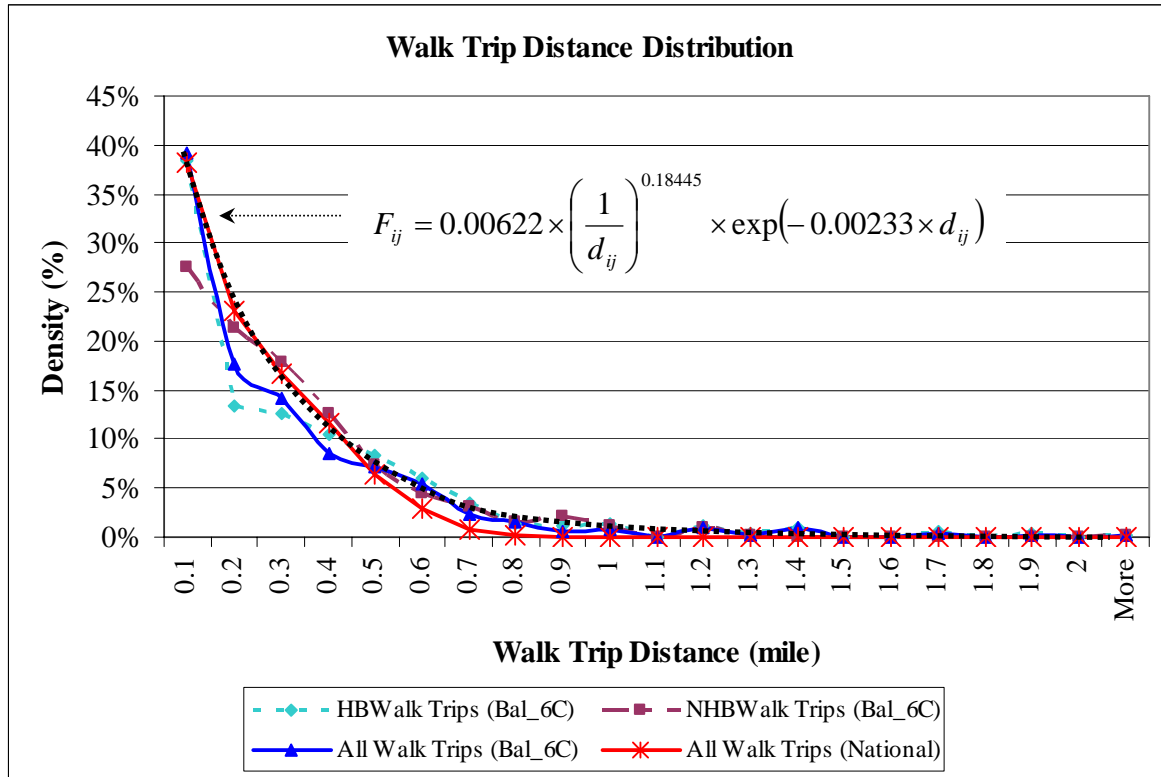
Walk Trip Distance Distribution

$$F_{ij} = 0.00622 \times \left(\frac{1}{d_{ij}} \right)^{0.18445} \times \exp\left(-0.00233 \times d_{ij} \right)$$

Figure 3: Walk Trip Distribution and Friction Factor Equations

Data source: 2001 NHTS

4.4. *Network Assignment*

The last step in the Travel Demand Model is to assign the route of the trips on the network based upon the shortest path between the origin and destination. The assignment method assumes an all-or-nothing assignment (all demand is assigned to the shortest path) and it is assumed that no capacity constraints exist on the pedestrian network. To

accomplish this task, we first create a script that calculates the shortest path for each pair of PAZs based on the Origin-Destination Matrix from the trip distribution step. Then we build a shape file using GIS that contains a network of all shortest paths between PAZs. This network than records all walk trips at each intersection (node points) and outputs the total pedestrian volume at each intersection. A final database is then generated containing the ID of each intersection on the pedestrian network and its corresponding pedestrian volume

4.5.   *Pedestrian Risk Exposure Analysis*

After we have obtained pedestrian volumes for all intersection on the network from the pedestrian demand model, we can use these pedestrian volume data along with disaggregate pedestrian crash data (geo-referenced to a block or intersection) to analyze the number of crashes per pedestrian. For this step we compute risk exposure based on the number of pedestrian-vehicular crashes and the pedestrian volumes obtained from the travel demand model. The equation used to obtain risk exposure for any spatial unit is as follows:

$$\text{Risk Exposure} = \frac{\#\text{ of pedestrian crashes}}{\text{pedestrian volume}}$$

5. RESULTS

This section will use two case studies to demonstrate the functionality of the pedestrian demand model presented in this protocol. Two case study locations were selected as the prototypes for testing of the pedestrian model methodology and application of the model

results to safety analysis: an urban area in Baltimore City, MD and a suburban area in Prince George's County.

5.1. *The Baltimore City Case Study*

The Baltimore City case study encompassed a large portion of the city, approximately 10 square miles, including the neighborhoods of Mount Vernon, Bolton Hill, Charles Village, Patterson Park and Johns Hopkins Hospital. The road network of the study area is shown in the figure below.
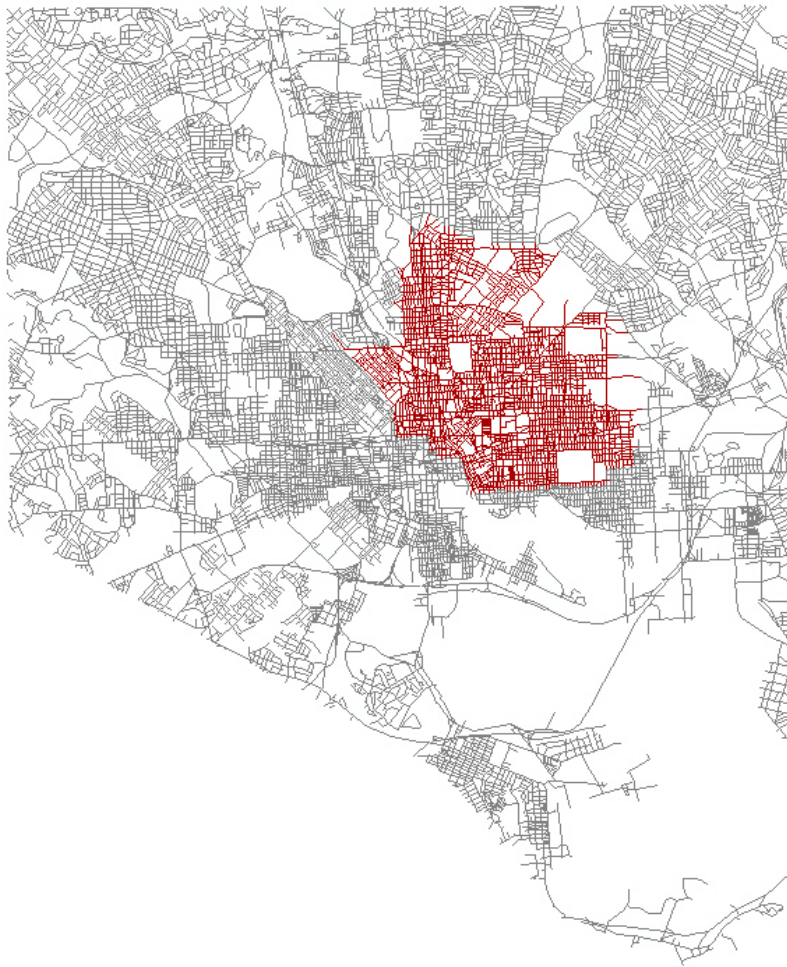

Figure 4: Baltimore, MD case study location

5.1.1. *Pedestrian Volume Estimation*

Because of the traditional street network pattern in this section of Baltimore City, the first step in this case study was to create Pedestrian Analysis Zones (PAZs) where the PAZ was represented by the centroid of the street block. For this study area 1709 PAZs were created.
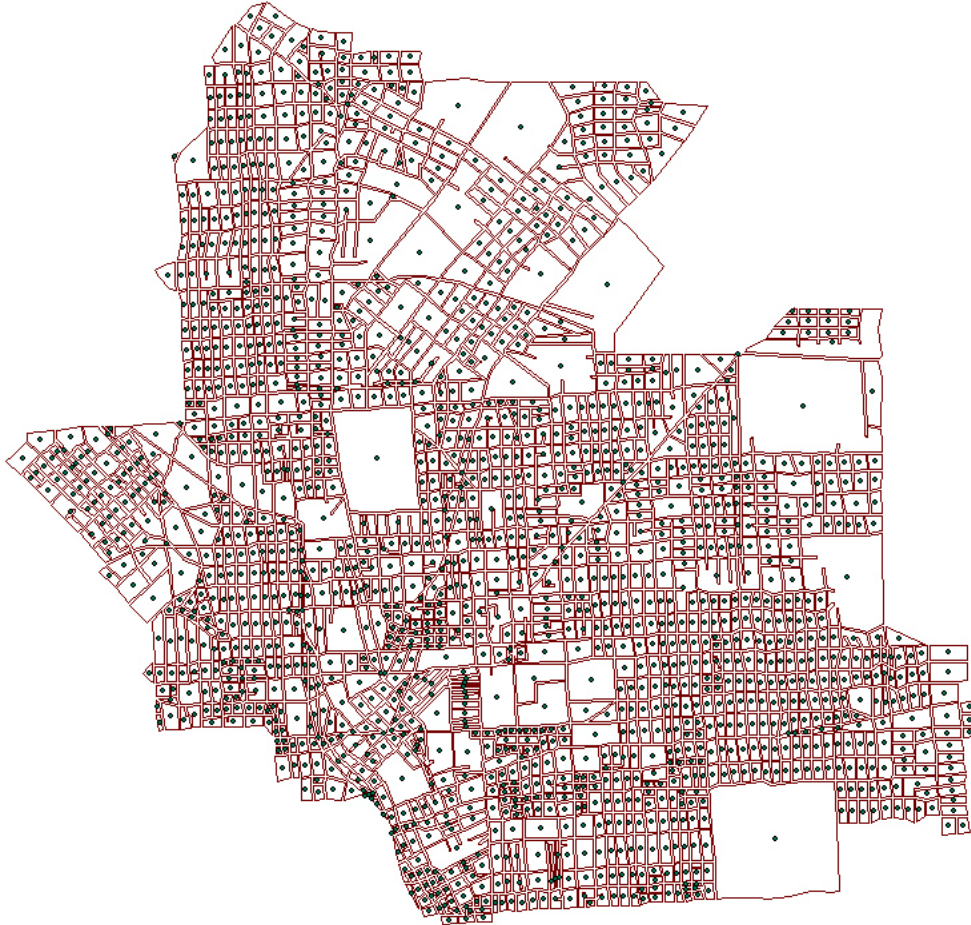

Figure 5: Pedestrian Analysis Zones in Baltimore, MD case study location

Parcel level land use data was added to study area and land use variables were calculated for each PAZ. Following the methodology provided in this protocol, Home-Based (HB) and Non-Home Based (NHB) walk trip productions and attractions were generated for each PAZ in the study area. The distribution of production and attractions for HB and NHB walk trips are shown below.
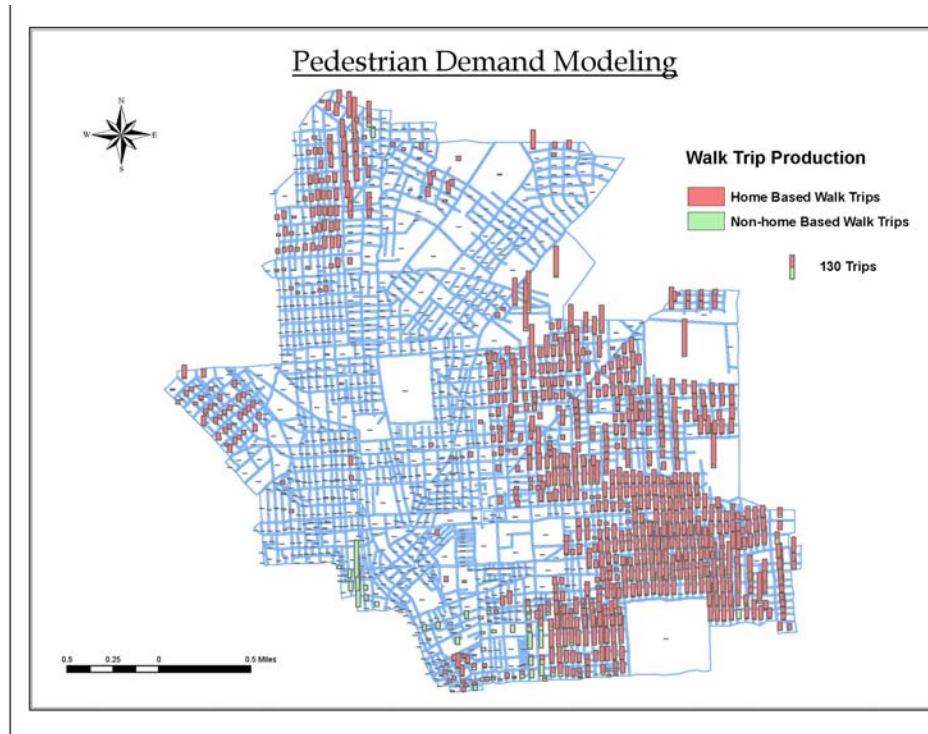
Figure 6: Distribution of Home-based and Non-home-base Walk Trip Productions in Baltimore, MD case study location
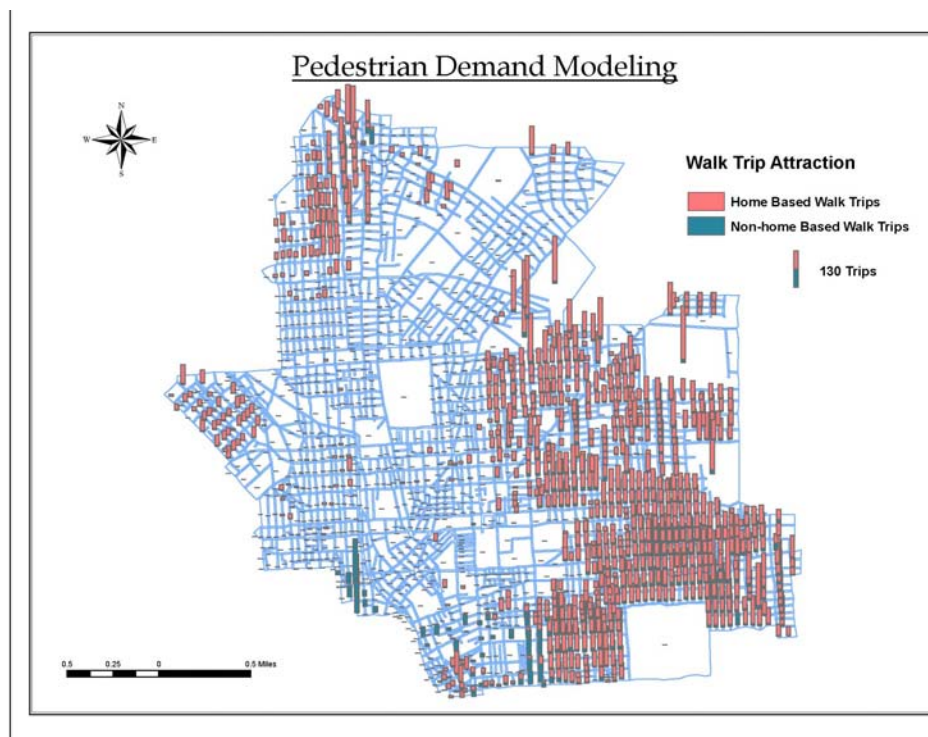

Figure 7: Distribution of Home-based and Non-home-base Walk Trip Attractions in Baltimore, MD case study location

Next, based on the trip productions and attractions for each PAZ, trips were distributed among the study area. Sample diagrams of trip distribution for HB and NHB trips are shown in the figures below.
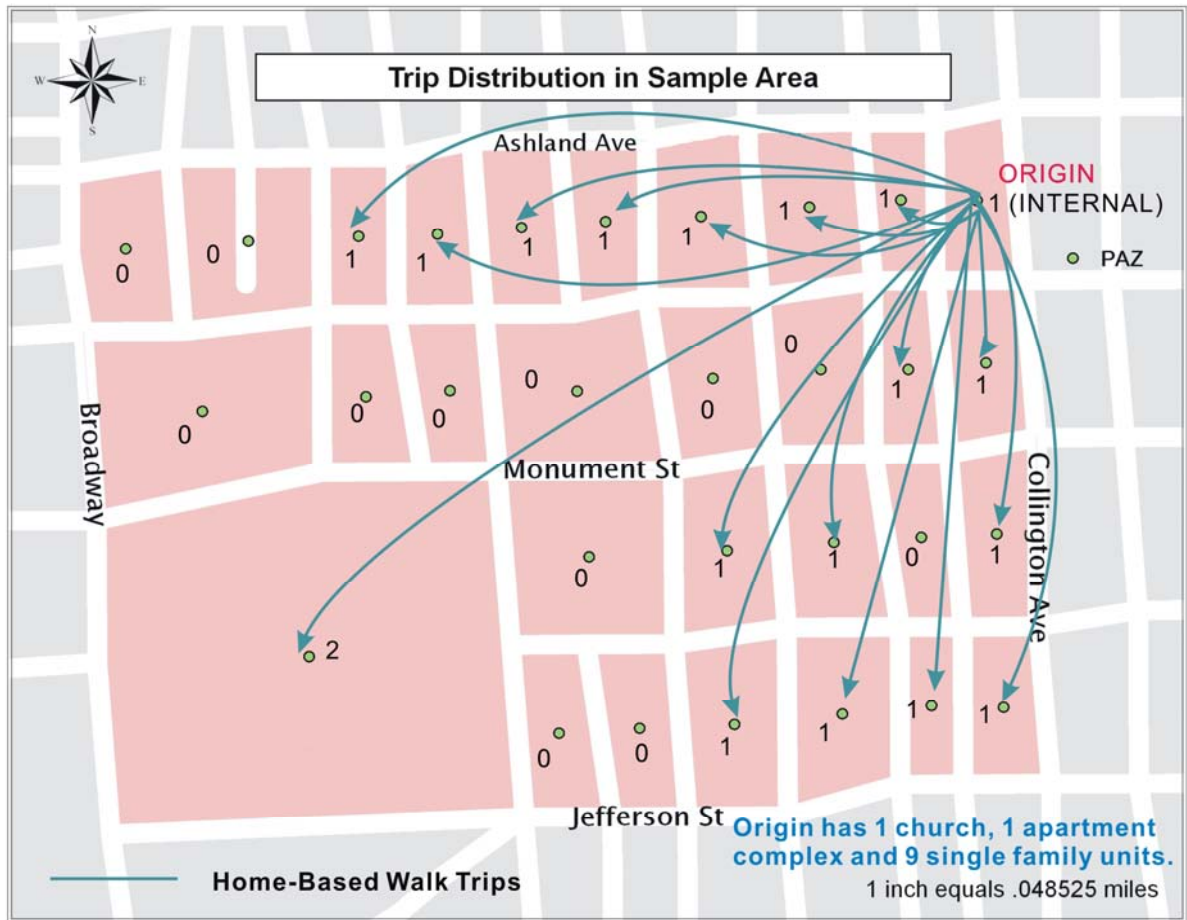

Figure 8: Example of Distribution of Home-based Walk Trips in Baltimore, MD case study location
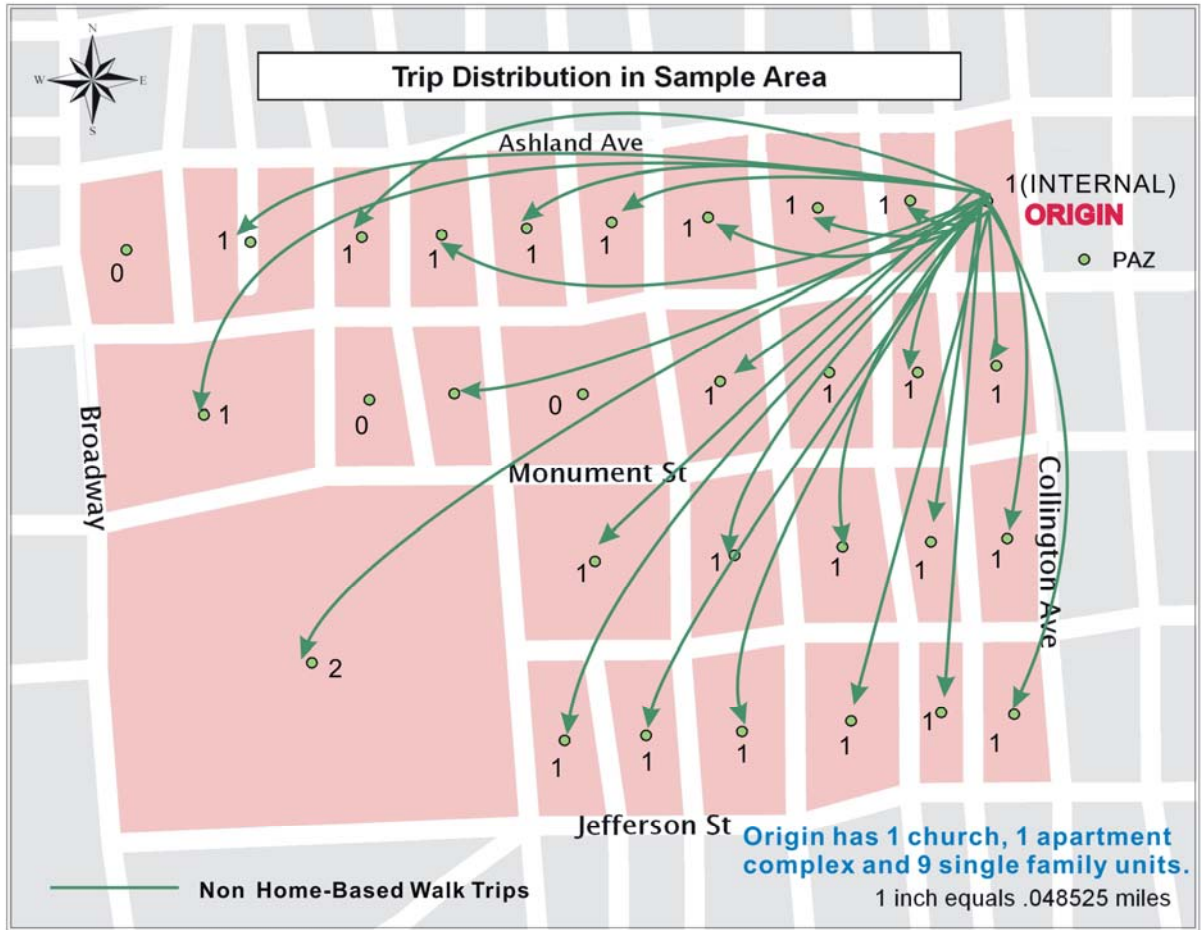
Figure 9: Example of Distribution of Non-Home-based Walk Trips in Baltimore, MD case study location

The output of the trip distribution stage was used as an input to the trip assignment program. The trip assignment program output shows volumes for the four sidewalk corners of the intersection. The output of the assignment program for this case study is shown in the figure below.
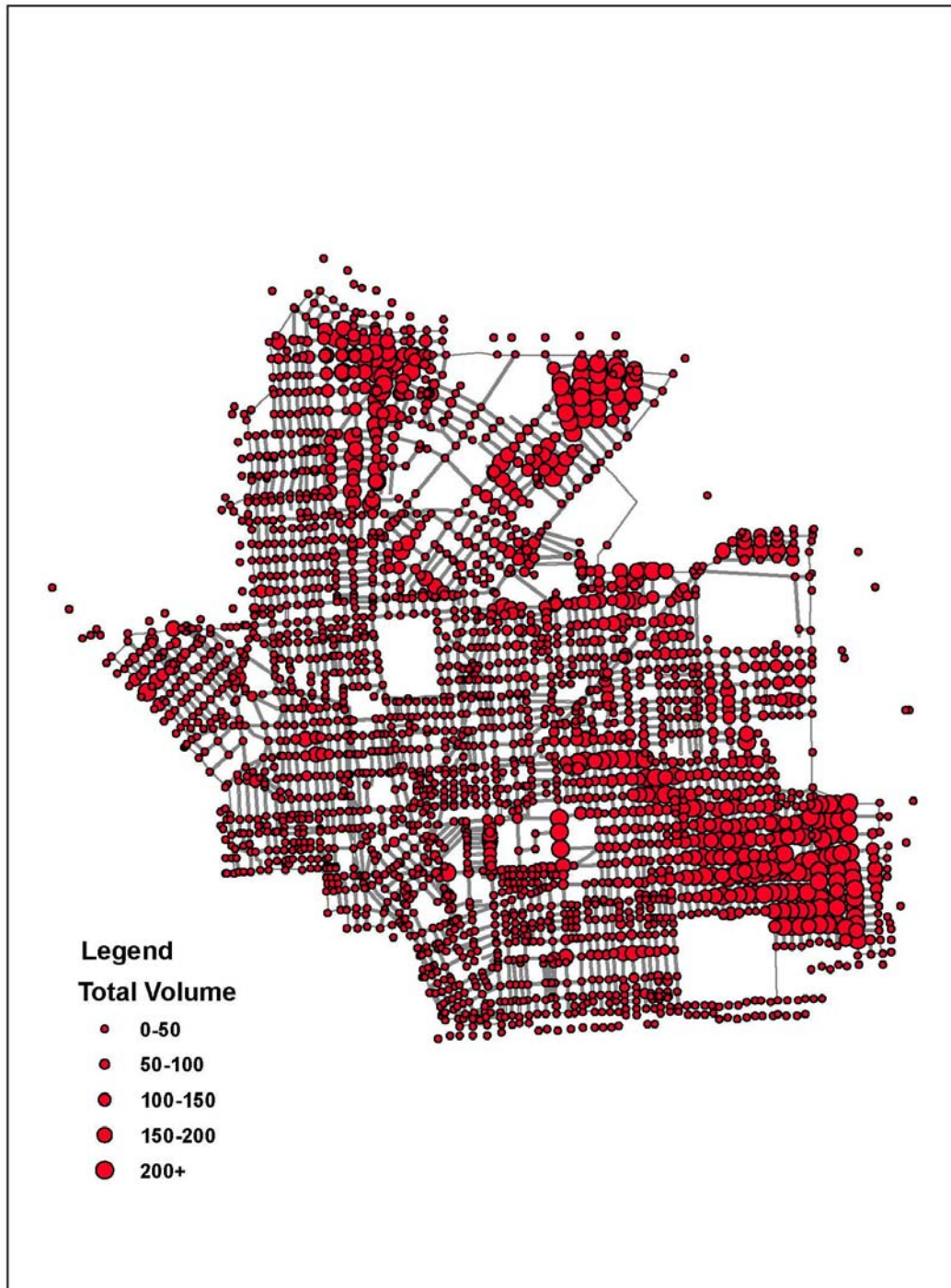
Figure 9: Pedestrian Volumes (per 24 hr. period) for Intersections in Baltimore, MD case study location

However, due to boundary effects, the estimated volumes around the edge may not be accurate. We recommend that the user exclude the volumes locate in the outer edge of the study area.

Pedestrian Crash Analysis

In the Baltimore City case study area, approximately 900 crashes involving pedestrians were reported between the years of 2000 to 2003. These crashes occurred in over 500 intersections. A distribution of these crashes is shown in the figure below.
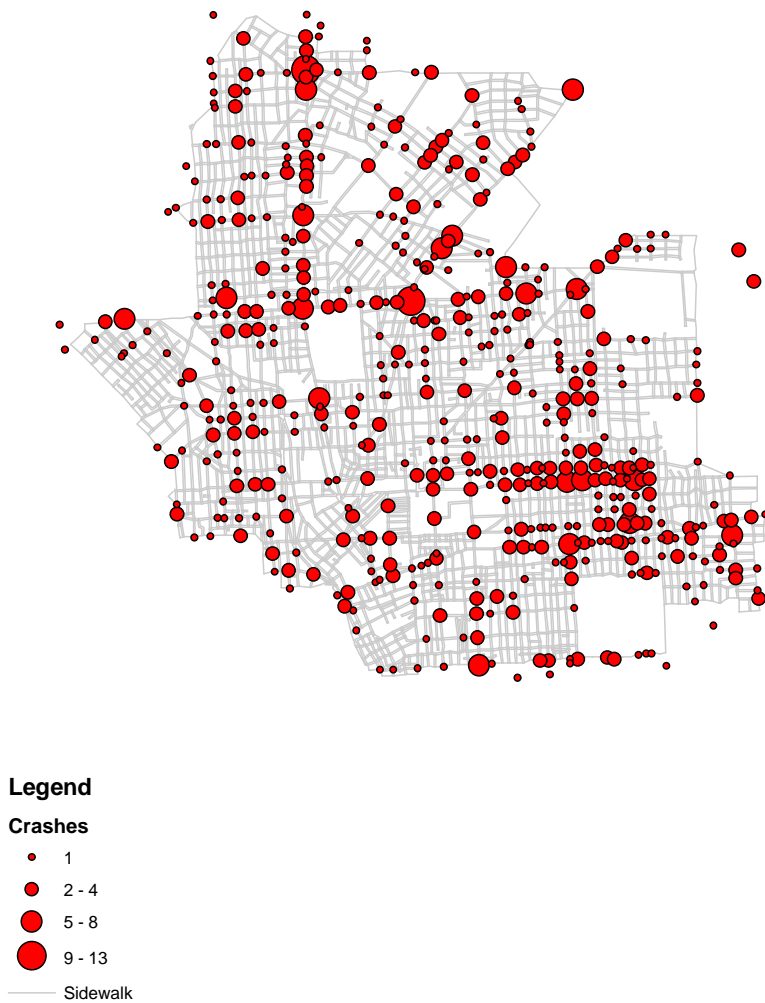
Legend

Crashes

- 1
- 2 - 4
- 5 - 8
- 9 - 13
- Sidewalk

Figure 11: Pedestrian crashes in Baltimore, MD case study location from 2000-2003

A table with the ranking of the top 10 intersections based on number of crashes is provided

Rank	Address	Daily Pedestrian Volume	Crashes	Crash Rate per Million Pedestrians
1	Harford & North	82	13	145
2	Greenmount & 33rd	184	10	50
3	Greenmount & 25th	59	8	125
4	North & Greenmount	1	8	5556
5	Greenmount & Merryman	336	7	19
6	Charles & 20th	7	7	946
7	25th & Harford	17	6	328
8	Sinclair & St Lo	119	6	46
9	Chester & North	198	6	28
10	North & Gay	141	6	39

Table 1 Intersections with most crashes in Baltimore, MD case study location

The pedestrian volumes generated by the methodology presented in this protocol are then used to control the number of crashes at each intersection and thus provide pedestrian risk exposure. Pedestrian risk exposure is obtained with the equation below:

$$\text{Pedestrian Risk Exposure}_i = \frac{\text{Number of Crashes}_i}{\text{Volume of pedestrians}_i}, \text{ where } i = \text{intersection}$$

Since the crash data used in this analysis represents 3 years of data, daily pedestrian volumes obtained by the model, are expanded to reflect 3 years by multiplying the total volume at each intersection by 365 days * 3 years.

The next figure shows the distribution of pedestrian risk exposure rates per million of pedestrians.
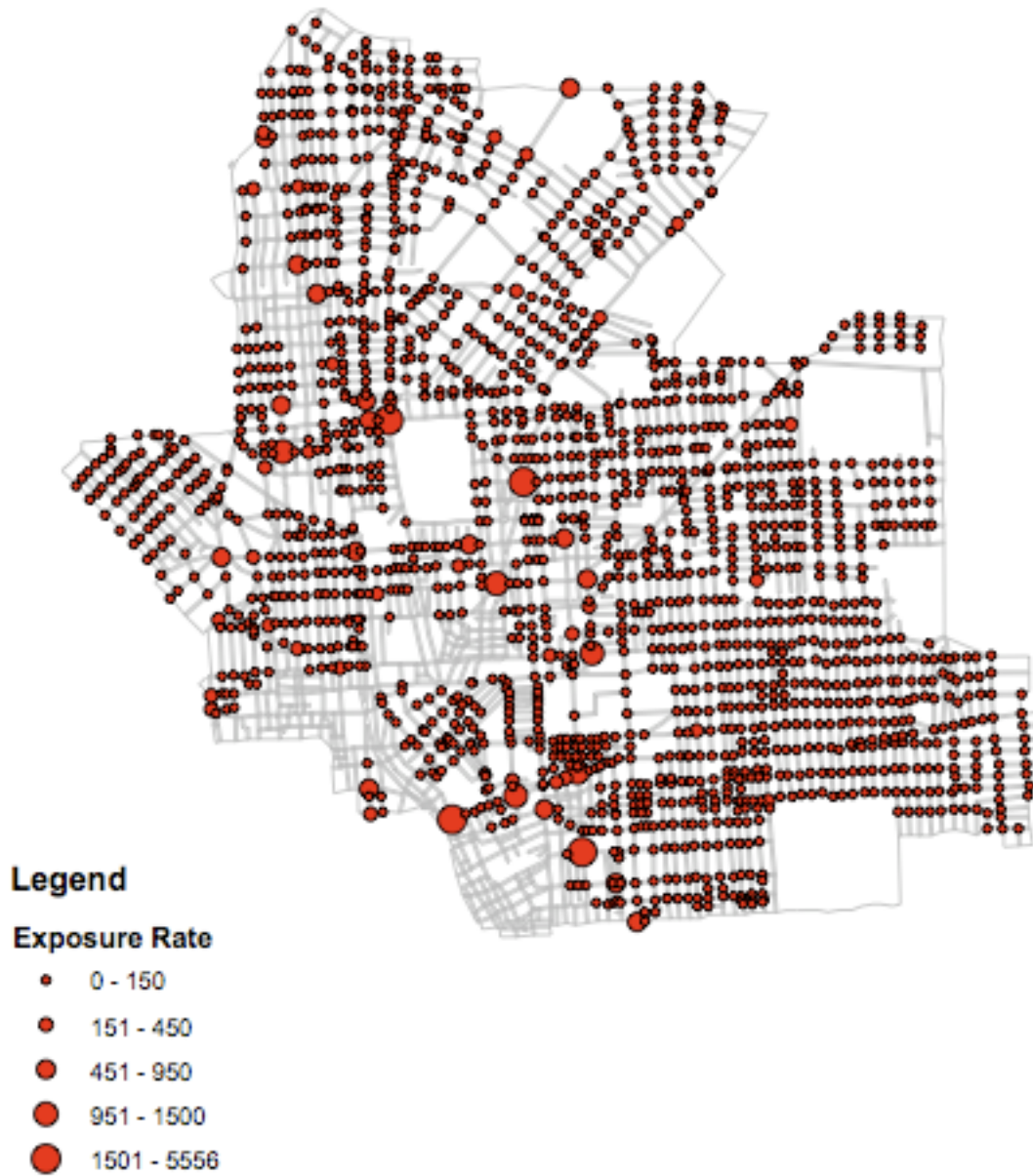

Legend

Exposure Rate
- • 0 - 150
- ● 151 - 450
- ● 451 - 950
- ● 951 - 1500
- ● 1501 - 5556

Figure 12: Pedestrian risk exposure in Baltimore, MD case study location from 2000-2003

A table with the ranking of the top 10 intersections based on crash exposure is also provided:

Rank	Address	Daily Pedestrian Volume	Crashes	Crash Rate per Million Pedestrians
1	North & Greenmount	1	8	5556
2	Front & Fayette	1	3	2083
3	Pratt & Caroline	1	3	2083
4	Harford & Federal	2	3	1563
5	Fayette & Aisquith	3	4	1389
6	Madison & Bond	2	2	1042
7	Charles & Lafayette	3	3	1042
8	Chase & Harford	3	3	1042
9	Fayette & Caroline	4	4	1042
10	Charles & 20th	7	7	946

Table 2 Intersections with most pedestrian risk exposure Baltimore, MD case study location 2000-2003

These rankings of intersections with high pedestrian crashes and risk exposure can be used by local planners to direct safety resources. The model complements data from local crashes by providing a means to normalize crashes by estimates of the amount of pedestrian demand.

5.2. *The Prince Georges County Case Study*

The Prince George's County case study encompassed approximately 3.8 square miles, including the neighborhoods of Marlow Heights and Temple Hills. The road network of the study area is shown in the figure below.
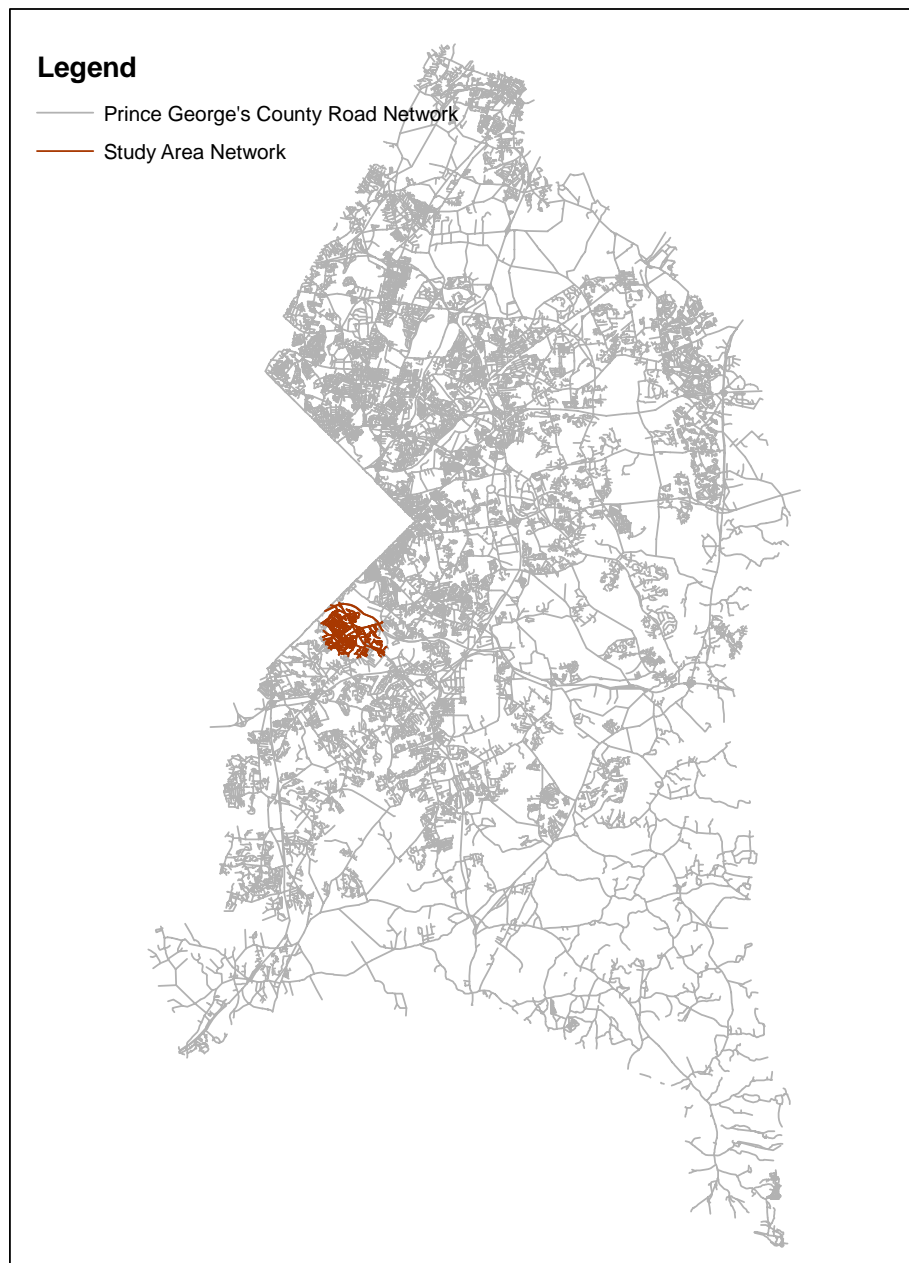

Figure 13: Baltimore, MD case study location

5.2.1. _Pedestrian Volume Estimation_

Because of the suburban street network pattern on Prince George's County, the first step in this case study was to create Pedestrian Analysis Zones (PAZs) where the PAZ was represented by the centroid of the block face. For this study area 806 PAZs were created as shown in Figure 13.
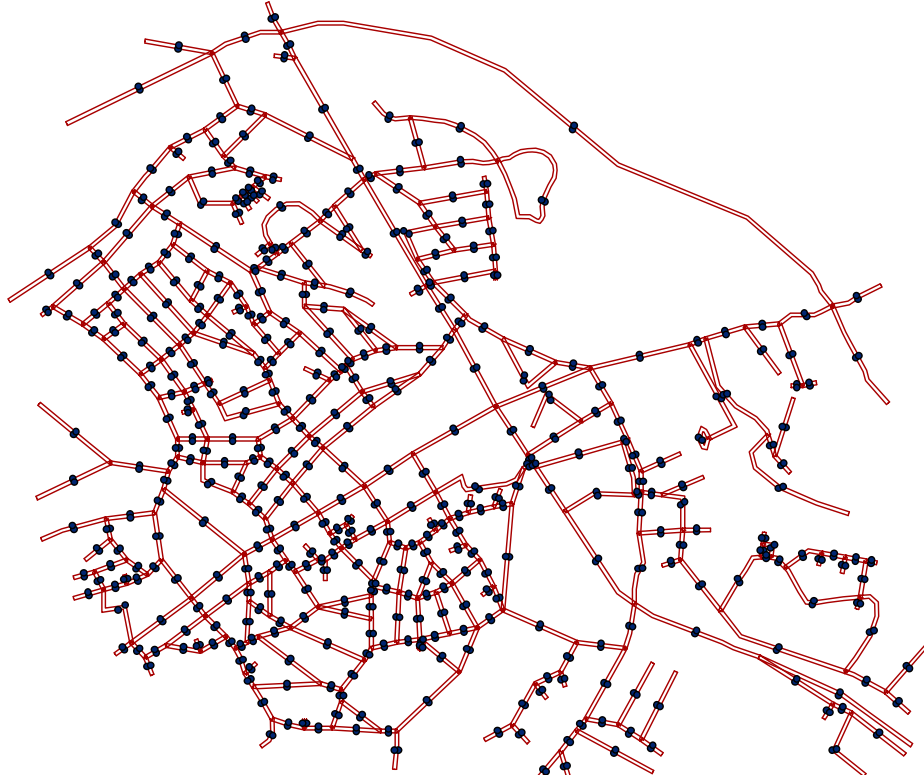

Figure 14: Pedestrian Analysis Zones in Prince George's County case study location

Parcel level land use data was added to study area and land use variables were calculated for each PAZ. Following the methodology provided in this protocol, Home-Based (HB) and Non-Home Based (NHB) walk trip productions and attractions were generated for each PAZ in the study area. The distribution of production and attractions for HB and NHB walk trips are shown below.
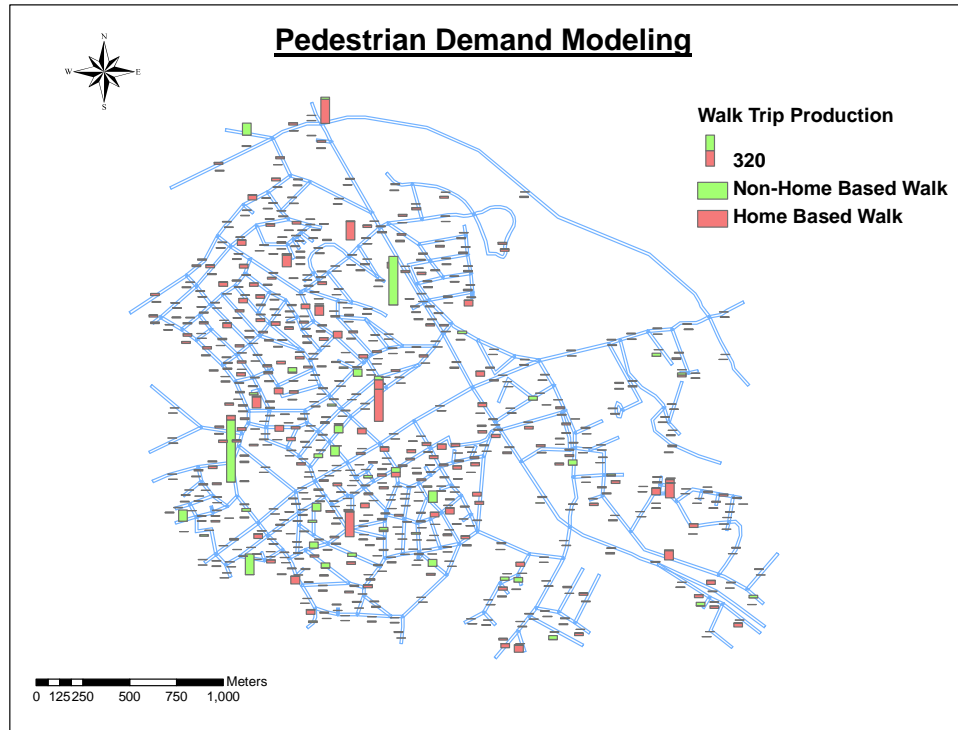
Figure 15: Distribution of Home-based and Non-home-base Walk Trip Productions in Prince George's County, MD case study location
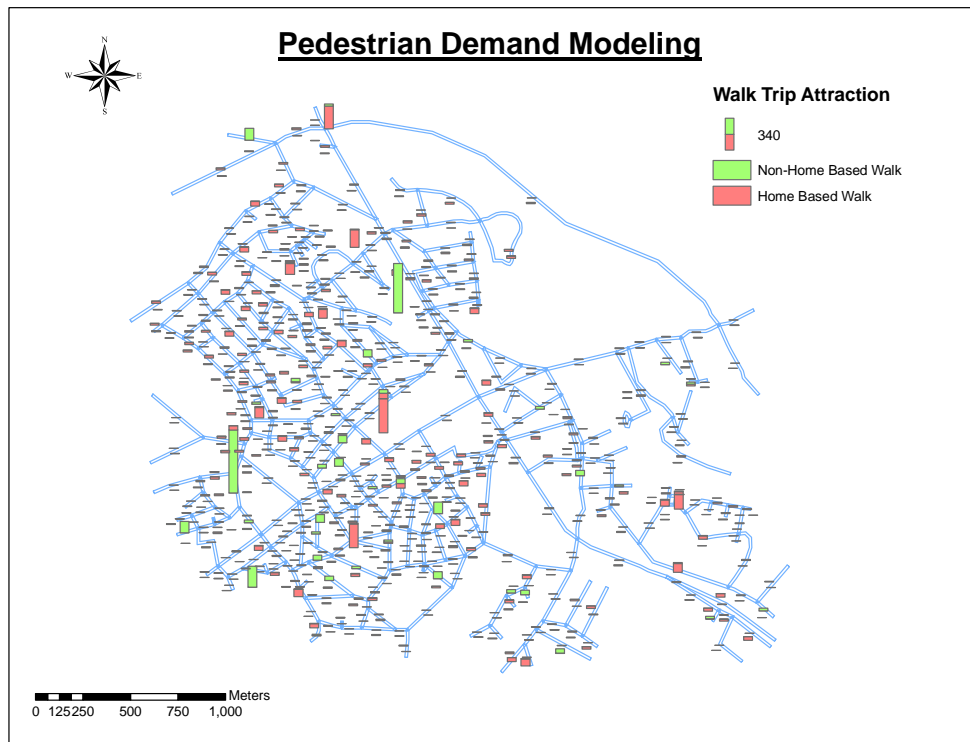

Figure 16: Distribution of Home-based and Non-home-base Walk Trip Attractions in Prince George's County, MD case study location

Next, based on the trip productions and attractions for each PAZ, trips were distributed among the study area as shown in the Prince George's County Case Study. Again, the output of the trip distribution stage was used as an input to the trip assignment program. The trip assignment program output shows volumes for the each intersection. The output of the assignment program for this case study is shown in the figure below.
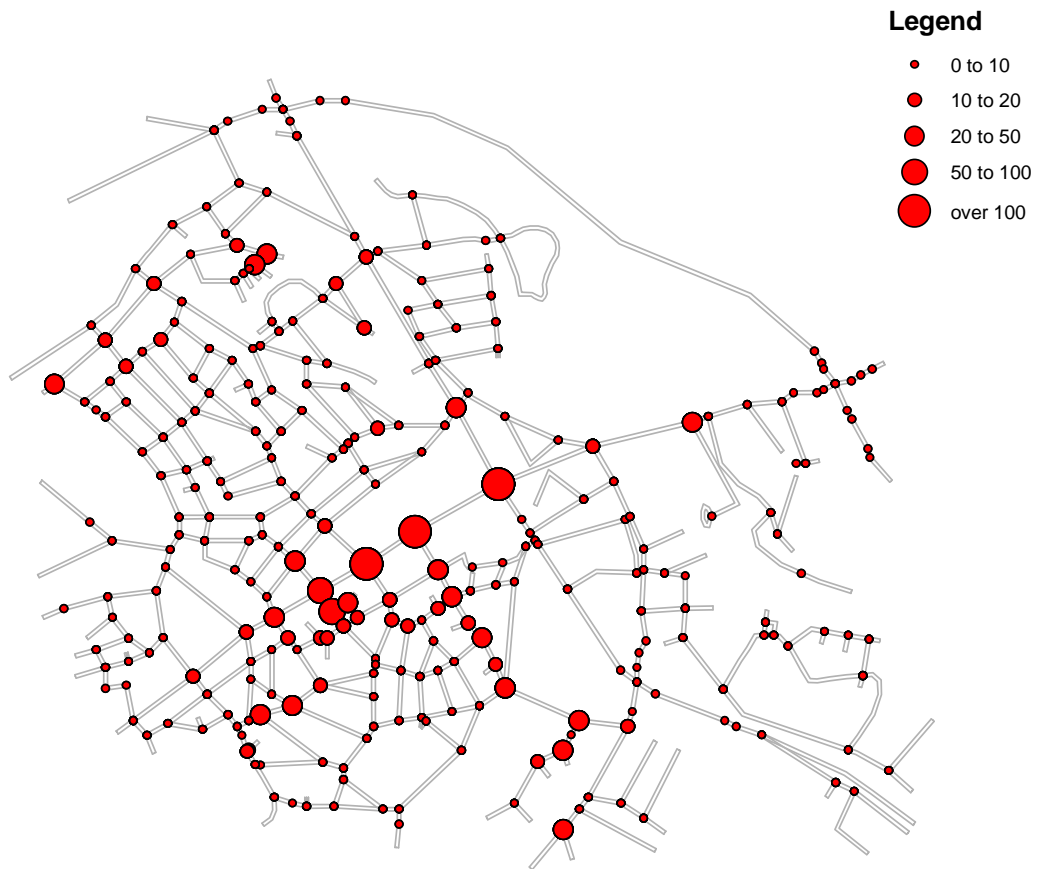

Figure17: Pedestrian Volumes (per 24 hr. period) for Intersections in Prince George's County, MD case study location

Here again, a valid study area was selected and is shown in the figure below:
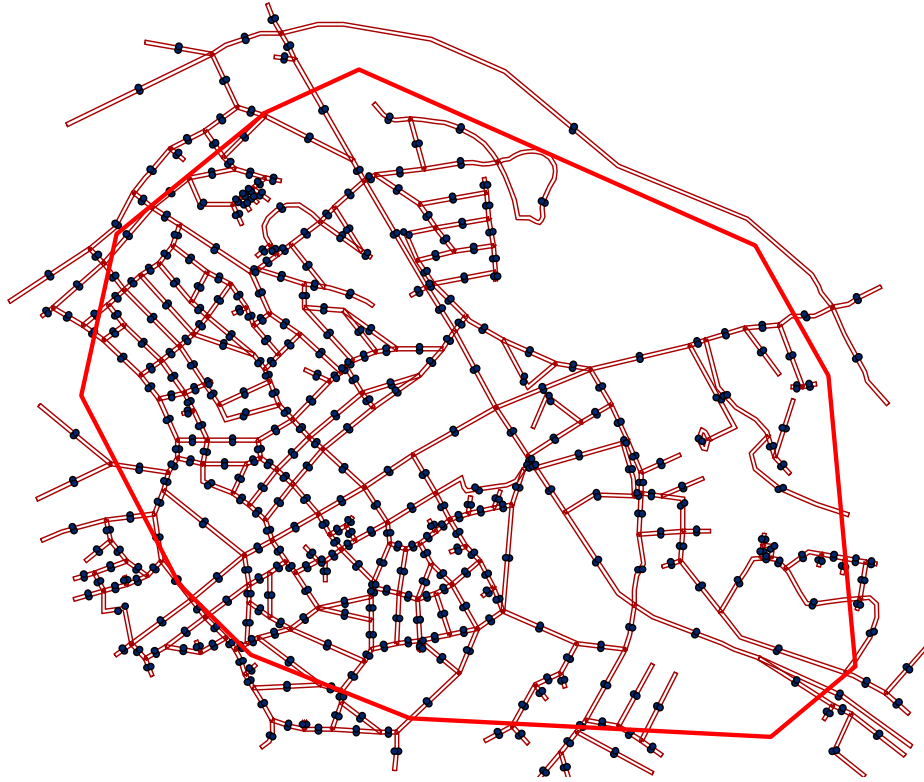
Figure18: Valid Area for the Prince George's County study location

5.2.2. *Pedestrian Crash Analysis*

In the Prince George's County case study area, approximately 65 crashes involving

pedestrians were reported between the years of 2003 to 2005. These crashes occurred in

32 intersections. A distribution of these crashes is shown in the figure below.

Figure 19: Pedestrian crashes in Baltimore, MD case study location from 2000-2003

A table with the ranking of the top intersections based on number of crashes is provided

Rank	Address	Daily Pedestrian Volume	Crashes	Crash Rate per Million Pedestrians
1	Branch Ave & Curtis Dr	10	9	437
2	Branch Ave & Silver Hill Rd	285	6	10
3	Silver Hill Rd & Silver Park Dr	0	5	27397
4	26th Ave & Iverson St	101	3	18
5	Terrace Dr & Silver Hill Rd	0	3	18265
6	23rd Pl & Iverson St	18	2	101
7	Iverson St & 24th Ave	29	2	64
8	Branch Ave & Naylor Rd	9	2	98
9	St Barnabas Rd & Silver Hill Rd	18	2	52
10	28th Pky & Curtis Dr	0	1	3196

Table 3 Intersections with most crashes in Prince George's County case study location

The pedestrian volumes generated by the methodology presented in this protocol are then used to control the number of crashes at each intersection and thus provide pedestrian risk exposure. Pedestrian risk exposure is obtained with the equation below:

$$\text{Pedestrian Risk Exposure}_i = \frac{\text{Number of Crashes}_i}{\text{Volume of pedestrians}_i}, \text{ where } i = \text{intersection}$$

Since the crash data used in this analysis represents 3 years of data, daily pedestrian volumes obtained by the model, are expanded to reflect 3 years by multiplying the total volume at each intersection by 365 days * 3 years.

The next figure shows the distribution of pedestrian risk exposure rates per million of pedestrians.
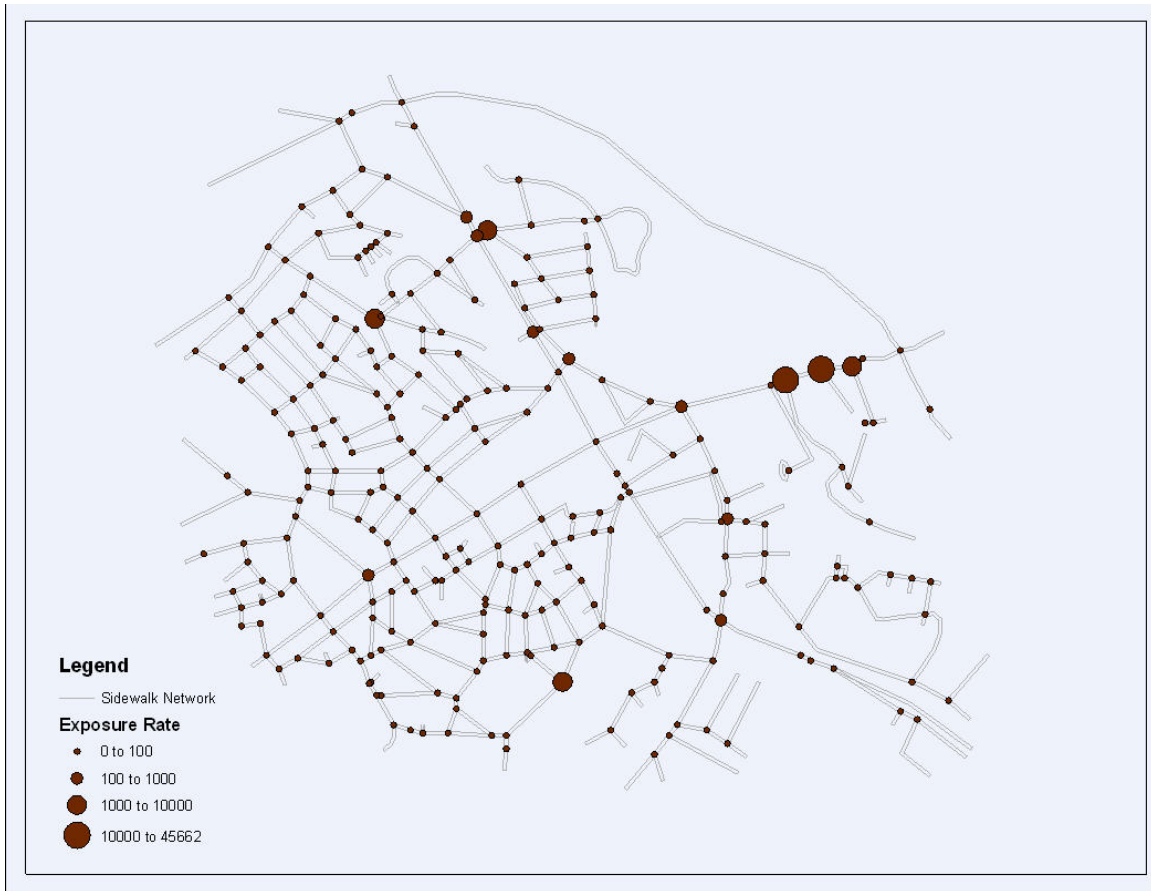
Figure 20: Pedestrian risk exposure in Baltimore, MD case study location from 2000-2003

A table with the ranking of the top intersections based on crash exposure is also provided:

Rank	Address	Daily Pedestrian Volume	Crashes	Crash Rate per Million Pedestrians
1	Scottish Ave & Curtis Dr	0	5	45662
2	Maywood Ln & Silver Hill Rd	0	3	27397
3	Branch Ave & Bonita St	0	1	9132
4	23rd Pl & Iverson St	0	1	9132
5	Olson St & School Dr	0	1	9132
6	Branch Ave & Naylor Rd	0	1	3196
7	Silver Hill Rd & Silver Park Dr	10	9	787
8	23rd Pky & Iverson St	1	1	747
9	Iverson St & 24th Ave	3	1	357
10	Branch Ave & Curtis Dr	9	2	197

Table 3 Intersections with most pedestrian risk exposure Baltimore, MD case study location 2000-2003

6. VALIDATION

To validate the results of the model, pedestrian counts from Baltimore City and Maryland State Highway Administration were used. The average pedestrian volumes estimated with the model were compared against volumes counted at various locations within the study area to get a sense of how well the model performs overall.. Although the model could still be improved upon, the pedestrian count data are not without limitations.

These pedestrian count data are collected for motorized intersection counts and not for the purposes of pedestrian analysis. It is also important to note that counts were only available at 43 intersections but not the entire study area. In addition, the counts were made for specific time periods and not 24 hours as the model predicts. For example, in the Baltimore case, Baltimore City provided counts for the morning, midday and evening peak periods. Therefore a conversion factor was used to bring the volume estimates and

the count volumes to the same temporal scale. For this task, the National Household

Travel Survey was used. We obtained the percentages of walk trips that occurred in each

of these peak periods and applied these percentages to the 24 hour volume estimates.

Although the overall absolute percent mean error was higher that we would have liked at

82%, the model does give reasonable results. The graph below shows the percent error

difference at individual intersections.
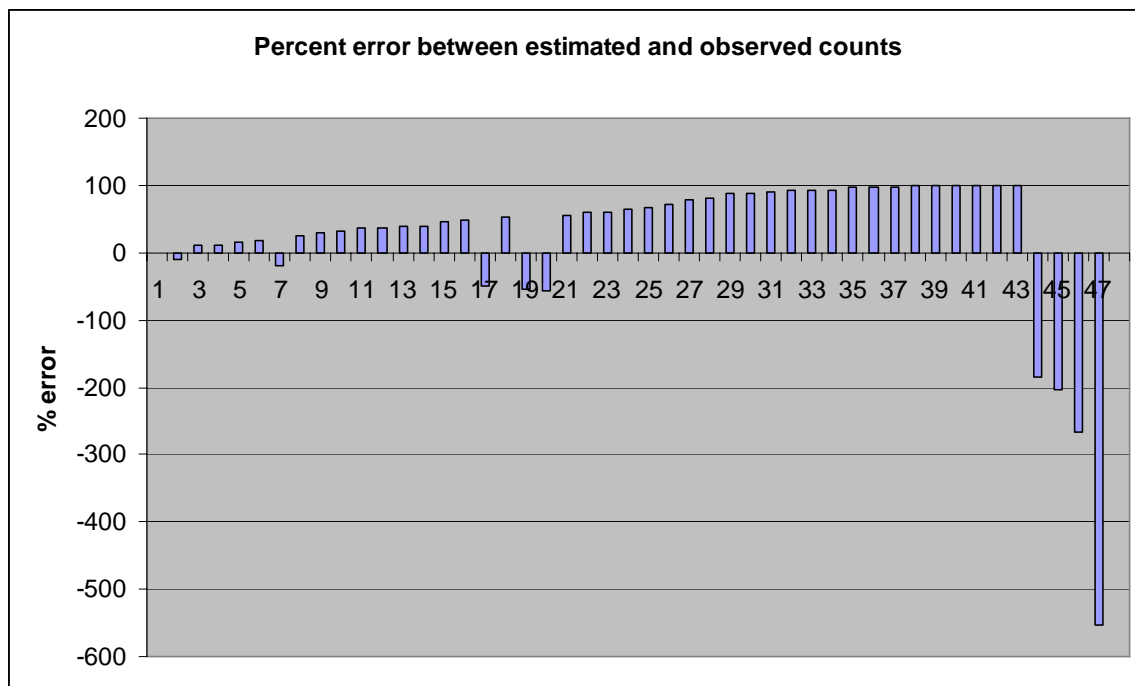
Overall the ratio of total estimated volumes to observed counts is 63%, showing that for

the locations where counts were available, the overall pedestrian volume estimated by the

model was 37% lower than the sum of the counts at these locations. Although the error of

the model fairly high, the model does give reasonable results in an urban context.

Suburban locations were more difficult to evaluate because very few pedestrian counts

are available. In addition, these counts were obtained only for major intersections. These suburban locations are usually not very conducive to walking and therefore results of the model must be interpreted with caution.

Another limitation to the model is that walk trips to access transit were not included in the model. This is a limitation that may be addressed as part of future work.

7. IMPLEMENTATION

The model presented here can be used to provide estimates of pedestrian demand for use along with crash data to evaluate pedestrian risk exposure. In addition, the model can be used as a pedestrian planning tool to estimate future demand for a given area, if the future land use and pedestrian network are known. The tool can be used in a variety of environments, including urban and suburban areas, and operates primarily from a GIS platform. The model utilizes readily available data in the State of Maryland. For this reason, it should be of broad interest and utility to pedestrian and safety planners across the state.

To maximize the dissemination and use of this resource in Maryland, we propose the following:

- Development of a website where users can download the protocol, assignment program and other materials related to the use of the model and analysis of pedestrian demand

- Training workshops that show planners how to use the model in their communities

- Future refinements to the model that facilitates its use and reduces the time needed for the model to run.

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