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Assignment of estimated average annual daily traffic on all roads in Florida

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Assignment of Estimated Average Annual Daily Traffic Volumes on All Roads in Florida

by

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DEDICATION

This thesis is dedicated to my parents who have support me all the way since the beginning of my studies.

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It is with great pride that I thank the brilliant minds affiliated with the Department of Civil and Environment Engineering at the University of South Florida. I would like to give special thanks to my major professor, Dr. Jian John Lu, for the guidance he has provided. In addition, I would like to thank committee members Dr. Edward Mierzejewski and Dr. Pei-Sung Lin. This thesis would not have been possible without your contributions.

NOTE TO READER

The original of this document contains color that is necessary for understanding the data. The original thesis is on file with the USF library in Tampa, Florida.

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ABSTRACT

In the first part, this thesis performed a study to compile and compare current procedures or methodologies for the estimation of traffic volumes on the roads where traffic counts are not easily available. In the second part, linear regression was practiced as an AADT estimation process, which was primarily based on known or accepted AADT values on the neighboring state and local roadways, population densities and other social/economic data.

To develop AADT prediction models for estimating AADT values, two different types of database were created, including a social economic database and a roadway characteristics database. Ten years social economic data, from 1995 to 2005 were collected for each of the 67 counties in the state of Florida, and a social economic database was created by manually imputing data obtained from different resources into the social economic database. The roadway characteristics database was created by joining different GIS data layers to the Tele Atlas base map provided by Florida Department of Transportation (FDOT).

Stepwise regression method was used to select variables that will be included into the final models. All selected independent variables in the models are statistically

significant with a 90% level of confidence. In total, six linear regression models were built. The adjusted R^2 values of the AADT prediction models vary from 0.166 to 0.418. Model validation results show that the MAPE values of the AADT prediction models vary from 31.99% to 159.49%. The model with the lowest MAPE value is found to be the minor state/county highway model for rural area. The model with the highest MAPE value is found to be the local street model for large metropolitan area. In general, minor state/county highway models provide more reasonable AADT estimates as compared to the local street model in terms of the lower MAPE values.

CHAPTER ONE

INTRODUCTION

1.1 Background Information

On October 1, 2005, Federal Legislation “the Safe, Accountable, Flexible, Efficient Transportation Equity Act: A Legacy for Users (SAFETEA-LU)” created a new Highway safety Improvement Program (HSIP) to reduce traffic fatalities and serious injuries on public roads. In the Section 148(b)(2), states are required to submit an annual report describing on a minimum of 5 percent of the locations with the most hazardous roads. The Federal Highway Administration (FHWA) noted in Title 23, United States Code that the 5 percent report should address locations exhibiting the most severe safety needs on all public roads and the identification of hazardous roads should be based on fatalities and serious injuries. In an effort to meet these SAFETEA-LU requirements the Florida Department of Transportation (FDOT) has purchased a GIS base map from Tele Atlas and is assigning the geographic location of all crashes on all roads for calendar year 2006.

It is believed that different measures used may result in different listings of the locations with the most severe safety needs, a mixture of methods may be appropriate. For example, a low volume road that having one or two fatalities or serious injuries in a year may be involved in the most severe list if rate per 100 million vehicle miles traveled

(MVMT) is used as the measure, but may not be on the list if rate per mile is used. Conversely, a high volume road like an interstate highway could possibly have a high severity ranking based on fatal and serious injury crashes per mile but a relatively low ranking based on such crashes per 100 MVMT. FHWA also required that each state should provide a composite listing based on low volume and high volume roads. As a result, to identify the 5% most hazardous roads, Annual Average Daily Traffic (AADT) information on all roads should be collected and assigned to all roads on the purchased map first. On the other hand, AADT itself is an important measure of crash exposure and also needed to derive other measures like vehicle miles traveled (VMT). For production of these required analyses by traffic safety engineers, the information of AADT on all roads in Florida is extremely important for calculating crash exposure on every specific roadway segment.

In Highway Capacity Manual 2000 (HCM 2000), Annual Average Daily Traffic (AADT) is defined as the total volume passing a point or segment of a highway facility in both directions for one year divided by the number of days in the year. It is one of the most important traffic variables needed for analysis of traffic crash rates and is widely used in almost all transportation fields.

The state road system and many of the major county and local roads have AADT data compiled annually in the Department's Roadway Characteristics Inventory database. Various offices within the FDOT have tools for estimating traffic volumes on some of the primary local collector and connecting roadways.

On state roads or major county or local streets, AADT values are measured by Automatic Traffic Recorders (ATR) installed on the roads. Due to budgetary restraints, AADT counts for some local streets or county roads are often not available and it is not practical to collect data on the 100,000 miles of local roads in Florida. Sometimes, AADT values on such roads can be estimated by using multiple linear regression models or other transportation demand estimating models. Several studies (Q, Xia et al. (1999), F. Zhao et al. (1999) and D. Mohamad et al. (1998)) have developed regression models for estimating the AADT values on off-system roads where traffic counts are not available. For example, in a study conducted by the Florida International University (FIU) in 1999, four linear regression models were developed to estimate ADT values on off-system roads for four different area types in Florida. The FIU ADT prediction models include a state-wide model, a rural model, a small-medium urban area model and a large metropolitan area model. The R^2 values for these models vary from 0.29 to 0.69. Model validation results show that the forecasting error of the FIU models varies from 23.73% to 188.00%.

All the studies mentioned above mainly focused on state maintained roads in state highway system due to the lack of traffic data, especially on local streets. Therefore, FDOT proposed this project to develop new methodologies or procedures to estimate AADT on all roads in Florida, and assign the estimated results to the purchased base map. This project was entitled "Assignment of Estimated Average Annual daily Traffic Volume on All Roads in Florida", and the principal investigator of this project was Dr. Jian Lu, Professor in the Department of Civil and Environmental Engineering at the University of South Florida. This thesis covered the whole process of the project, which focused on the AADT data collection and processing, models development and AADT assignment.

In this thesis, the author completed the following tasks:

1) Collecting road characteristics data such as number of lane, median type, accessibility to freeway, lane use, locale and functional classification for all public roads in Florida, merging and assigning all these information to the GIS base map given by FDOT, which has roadway characteristics for numerous line segments in all the 67 counties in Florida. This phrase was the most important and time consuming part of the project.
2) Collecting ten years social economic data from 1995 to 2005 for all the 67 counties in Florida, and creating social economic database for the further model development. Seven categories of social economic data, including county population, mileage, vehicle, municipality, labor force, income and retail sales, were analyzed in detail.
3) Stepwise regression method was used to select variables that will be included into the final models. All selected independent variables in the models are statistically significant with a 90% level of confidence. Totally six linear regression models were built.
4) Model validation was conducted to test whether or not newly created models provided reasonable for all roads in Florida. Three counties were randomly selected, and all the 1149 traffic count data within these three counties were considered as testing sites, and not involved in model development.
5) Assigning estimated AADT values to the base map. Given the fact that the various FDOT applications should not be producing or using contradictory information, the author provided reasonable estimations of AADT only for those

road segments that did not have reasonable values or estimates from known sources.

1.2 Research Objective and Approaches

The main objective of the study is to develop new procedure/methodology for the estimation of traffic volumes on the roads where traffic counts are not easily available, and validate the results with current count data from GIS base map provided by FDOT. This AADT estimation process is primarily based on known or accepted AADT values on the neighboring state and local roadways, population densities and other social/economic data. More specifically, the research should follow these steps:

1) Identify and compare the existing methods for estimating AADT values on county roads/local streets from any reliable and reputable source.
2) Select the most promising method for a) Adoption into this crash analysis process; b) Modification for use in this specific function; and/or c) Use in the development of a new estimating model.
3) Adopt or develop models for use in this safety analysis process.
4) Validate the models based on AADT values collected from fields.
5) Select the best model for estimating the AADT values on county/local roads which takes into account the volumes on its neighboring state roads and other social/economic data.

1.3 Organization of the Thesis

This thesis consists of five chapters. Chapter 1 provides a brief introduction of the research, including the background of the research, research objectives and past studies conducted in this area. Chapter 2 discusses past studies in this field, along with their study's key findings and limitations. Chapter 3 summarizes the methods used for estimating and assigning the AADT values for different types of road in Florida. Issues related with data collection and databases were discussed in Chapter 4. Chapter 5 presents the calibration and validation of AADT prediction models. Finally, Chapter 6 provides a summary and the conclusions of this research.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

Literature review is conducted to summarize the methods used by previous studies to estimate AADT values on off-system roads and to see whether or not the models or results can be used in Florida. Previous studies in this area have mainly focused on two topics, including: (1) the conversion of daily traffic volume data obtained from traffic counts into AADT, and (2) the estimation of AADT values based on regression models.

2.2 Traffic Count

The most direct and reliable method for obtaining AADT is to install Automatic Traffic Recorders (ATR) on road segments. The ATRs provide continuous traffic volume counts in each day throughout the whole year under ideal conditions. Due to budgetary limitations, it is impractical to install ATRs on all road segments in the State of Florida. As an alternative, Coverage Count is widely used on non-ATR road sections for short period traffic count (SPTC). As a short term AADT estimation method, coverage count usually collects 24 to 48 hour traffic volume data in two success days, 48 consecutive hours in rural areas while 24 hours in urban areas to meet the requirements on minimum count duration in *Traffic Monitoring Guide*. However, it is still labor costly to use coverage count to collect traffic volume on all roads in the network, because personnel is needed to install portable traffic count to get data and then turn to the next point. Another short-period traffic count called control or seasonal count also provides continues traffic volume data. Not like coverage count, seasonal count is only used for seasonal factor estimation and seldom mentioned in documents because there are a lot of alternatives available.

2.3 Traffic Count Program

Due to limitation of budget, in most states, AADT is estimated by multiplying the coverage count data by day of week (DOW) and month of year (MOY) factors, which are estimated from continuous count groups. Even for Coverage count data, because of limitation of personnel resources, some states conduct a traffic count program to collect coverage count data in a three year cycle rather than collect all the data each year. Annual Growth Factor is applied on those segments without current traffic volume data to calculate AADT data based on historical traffic count data.

In Indiana, Indiana department of Transportation (INDOT) sets two Traffic Monitoring Systems to obtain AADT information. 110 ATRs are set on the statewide road network to determine AADT values (these data are collected 24 hours per day, 365 days per year) as well as several adjustment factors such as Axle, Annual Traffic Growth trends and Seasonal Factor. Besides these 110 permanent traffic counters, the statewide coverage count program is applied to collect 48 hour traffic counts on all State Highway system segments. A three year program is conducted to collect the coverage count data, which means one-third of all the segments are counted per year. Average Daily Traffic (ADT) values got from 48 hour traffic coverage count can be converted into AADT by multiplied with corresponding Seasonal Factors. Because only one-third of all the segments are counted in each year, AADT of the rest two/third roads can be calculated from previous data by employing time series model, in which Annual Traffic Growth factor is to be used.

Virginia Department of Transportation (VDOT) conducts a traffic count program in which 100,000 segments of roads and highways are included. 322 of these segments have traffic count station. Over 250 of the continuous traffic counters are installed on the National Highway System to determine adjustment factors.

In the state of Florida, to meet various transportation needs, a solid Traffic Monitoring Program is operated to estimate AADT on state maintained roads. Based on more than 6,000 traffic monitoring locations, the estimated AADT on approximately 12,000 miles of state highways can be done, that is, for every two miles of roadway there lies a traffic monitoring (Desai, 2000). In addition to these 6000 traffic monitoring locations, more than 300 seasonal counters are used to provide continues traffic data on road network. In doing so, a clear picture is given to display traffic seasonal pattern, in which seasonal factor is to be calculated to adjust volume data got discontinuously into AADT.

2.4 AADT Conversion with ATR Data

For Automatic Traffic Recorder (ATR) data, one simple and precise method to estimate AADT is calculating the mean value of all the 365 daily traffic volume collected in one year. However, in practical terms, ATR data may be insufficient or discontinues because of malfunction on recorders, construction nearby or data missing. American Association of State Highway and Transportation Officials (AASHTO) documents describe that most permanent counters retain about 270 of a total of 365 days traffic data, and few permanent counters can keep more than 350 days volume data. As a result, the daily traffic information from device contains some zero data pattern which can be easily found out. These missing data may cause considerable bias in AADT calculation. To solve the problem, AASHTO puts forward a sophisticated algorithm to reduce this kind of bias in *Guidelines for Traffic Data Programs*.

In AASHTO method, the first step is to calculate Monthly Average Days of the Week (MADW), which is the average traffic volume for each day of the week for each month. Thus there are seven MADW values (Monday to Sunday) for each month. These calculated results can be marked with $MADW_{i,j}$, where i (= 1, 2… 12) stands for the twelve months in one year and j (= 1, 2… 7) represents the seven days in one week. For instance, the average daily traffic on Monday in January can be marked with $MADW_{1,1}$. To the end of the whole, there are totally 84 MADW values can be obtained. The second step of the procedure is to calculate the average value of each day across the twelve months, yielding seven Annual Average Days of the Week (AADW) values, and AADT is the arithmetic mean of these seven AADWs, under the potential assumption that the weight of each calendar day is equal. The whole procedure can be expressed as the following equation (1):

$$AADT = \frac{1}{84}\sum_{i=1}^{12}\sum_{j=1}^{7} MADW_{i,j} \qquad (1)$$

Where i = twelve months in a year (i = 1, 2… 12),

j = seven days in a week (j = 1, 2, …, 7), and

MADW = monthly average days of the week traffic.

2.5 AADT Conversion with Coverage Count Data

For coverage count data, methods are also developed to convert the short term traffic counts to AADT. For example, still in AASHTO *Guidelines for Traffic Data Programs*, a standard procedure is provided for converting the coverage count data into AADT.

The first step of the AASHTO method is to summarize the coverage count data as a one-day, 24 hour traffic volume data. The second step is to multiply the 24-hour axle impulses by the axle correction factor for the presence of vehicles with more than two axles. The preferred approach to obtain the axle correction factor is to study the continuous data from corresponding grouped vehicle classification counters for the same days as the short-term traffic count. An average number of axles per vehicle at permanent counts is calculated based on the 13 vehicle classifications used by the Federal Highway Administration (FHWA). A group mean value is summed for all similarly grouped counter sites, and the inverse of the group mean is the axle adjustment factor. The third step is to find out the relationship of days of short-term traffic monitoring to the whole year. To remove the difference between traffic patterns in short period count station and that in long term stations, seasonal factors such as the month-of-year (MOY) and day-of-week (DOW) factors are summarized and calculated from similar grouped ATR or other continues count station like Control/seasonal Count. The whole procedure currently adopted in Florida for summarizing AADT from short term counts can be presented in the following equation.

$$AADT = ADT \times SF \times Axle \tag{2}$$

Where

Axle = axle correlation factor that converts the counted number of axels to the number of vehicles;

ADT = average daily traffic, typically the average value of a 72-hour traffic count collected from Tuesday to Thursday;

SF = seasonal factor that reflects traffic seasonal fluctuation pattern; and

AADT = estimate of typical daily traffic on a road segment for all days of the week, Sunday though Saturday, over the period of one year.

The problem with coverage count is that the method still needs the installation of traffic counters to collect traffic volume data. Thus, it is impractical to cover the whole road network in the State of Florida. Instead of using traffic volume data collected from coverage count to estimate AADT, Wang and Teng (2004) used traffic volume data collected by other agencies such as traffic management centers to estimate AADT. Traffic management center is an important component of intelligent transportation systems (ITS). Traffic volume data collected by traffic management center is originally used for some other purposes such as transportation planning, travel time estimation, congestion detection, pavement management, and/or air quality analysis. Once used for AADT estimation, the method suffers from a major limitation that the ITS data is often not reliable because of insufficient maintenance work. Wang and Teng compared the ITS data based AADT estimation method to the coverage count method. It is observed that with the number of missing days increasing, coverage count based AADT is more likely to have smaller errors than ITS data based AADT.

Several studies (*AASHTO Guidelines for Traffic Data Programs*, 1992, S. Gadda et al. (2007) and *Traffic Monitoring Guide,* (1995)) have also looked at the errors associated with AADT conversion methods.

The first type of error described in *AASHTO Guidelines for Traffic Data Programs* is called sampling error, which is caused by measure instrument during the procedure of data collection. It is found that when traffic volume is near 5000 AADT, short period traffic count typically like pneumatic road tube can provide results with an error less than 10 percent. When traffic volume reaches 10,000 AADT the error increases to more than 10 percent. This is because axles on several vehicles press on the tube at same time.

The short period traffic volume data collected by coverage counts should be transformed to AADT value by multiplied adjustment coefficients. To obtain these coefficients, there lies an assumption that the traffic pattern in the short-period count site should be equal to that in continues counts. It is not necessarily the same case in real world. As a result, the second type of error called factoring error occurs. Generally, seasonal factor, axle correction factor and Day of Week adjustment factor calculated from continues traffic count like ATR or control/seasonal count are adopted in such a conversion.

Error may increase dramatically if the short period volume data is affected by holidays or special events, since these adjustment coefficients cannot correct this kind of error. Because these correction factors cannot help remove atypical volume variation caused by holidays or special events.

Gadda et al. (2007) conducted a study to quantify the uncertainty related with the AADT estimated using coverage count or other short-term AADT estimation methods. Several error types were mentioned in Gadda's study, including:

1) Sampling Errors and factoring error
2) Misclassification Error
3) Spatial Error

As mentioned above, sampling error is the error generated during the data collection procedure, and factoring error is the error resulting from estimating AADT by using coverage count data. Misclassification error occurs when AADT data was assigned to a different site. Spatial error occurs when a road segment is assigned with AADT information obtained from nearby road segments even they are on the same road. In Gadda et al.'s study, variations in AADT estimation errors were investigated for both Minnesota and Florida's ATR sites. It was found that including weekend traffic data will result in large errors in the AADT estimates. In generally, data collected from urban sites suffers from higher error levels as compared to those collected from rural sites. It is also found that classifying the count sites into different categories based on the functional classification, lane count, and area types would help to reduce the estimation error of AADT.

2.6 AADT Estimation Models

On roadways where traffic counts are not available, AADT data is often estimated using AADT prediction models. There are two major types of AADT prediction models, including time series models and linear regression models. Time series models estimate the AADT growth factors based on historical AADT data. The growth factors were used to predict AADT values in forecasting years. Linear regression models estimate the relationships between AADT and various explanatory variables. The explanatory variables used in this AADT prediction models often include the roadway characteristics such as median type, number of lanes, land use, and/or the functional classification of the road, and social-economic variables such as the county population, taxable sales, county lane mileage, and vehicle registration.

A study conducted by Mohamad et al. (1998) in Indiana developed a multiple linear regression model to estimate the AADT on the county roads where traffic counts are not available. The initially considered independent variables include the following:

1) County Population
2) County Households
3) County Vehicle Registration
4) County Employment
5) County Per Capita Income
6) County Mileage, which includes State Highway Mileage, Arterial Mileage, and Collector Mileage.
7) Location: rural or urban
8) Presence of Interstate Highway
9) Accessibility, which is defined as the accessibility to freeways for each road.

Stepwise regression method was used to determine which independent variables should be included in the model. Four independent variables were selected. The final AADT prediction model is given as follows:

$$Log(AADT) = 4.82 + 0.82X_1 + 0.84X_2 + 0.24Log(X_3) - 0.46Log(X_4) \quad (3)$$

Where

X_1= Locale (1 = urban; 0 = rural)

X_2= Access (1 = easy access or close to the state highway; 0=otherwise)

X_3= County Population

X_4= Total Arterial Mileage of a county

The R^2 value of the model is 0.77 which is reasonably high. The major limitation of the study is that the AADT prediction model is developed based on a relatively small database. The model was developed based on 89 traffic counts collected from 40 counties, which means that an average of only 2 traffic counts was available for each county.

The most relevant study regarding this topic was conducted by Zhao et al. in 1999. In that study, 67 counties in Florida were classified into three categories based on the population in each county. For each category, a linear regression model was developed for estimating ADT values on off-system roads where traffic counts are not available. The counties with population less than or equal to 100,000 were defined as rural area. 27 traffic counts obtained from eight rural-area counties were used to build the rural area model. The counties with the population greater than 100,000, but are not located in major metropolitan areas were defined as small-medium urban area. 270 traffic counts were randomly selected to develop ADT prediction model for the small-medium urban area. Counties located in major metropolitan areas such as the Broward County were defined as large urban area. 443 traffic counts were used to develop ADT prediction model for the large urban area. Researchers of that study also developed a state-wide model based on 107 county level data obtained from 1995 county profile provided by FDOT.

In Zhao et al.'s study, the independent variables initially considered in the statewide and the rural area models include:

1) Population (POP): the total population in a county.
2) Municipality Population (MUNICI): the total population in incorporated areas.
3) Labor Force (LABOR): the total labor within a county.
4) Per Capita Income (INCOME): the per capita income of a county.
5) Taxable Sales (TAXABLE): the taxable sales of a county.
6) Lane Mile (LANEMILE): the total lane miles of state roads in a county.

A total of 14 variables were initially considered in the small-medium urban area model development. These variables include:

1) DU_SF: the total single family dwelling units in a Traffic Analysis Zone (TAZ).
2) POP_SF: single family population in a TAZ.
3) SAUTO: total single family automobile ownership in a TAZ.
4) DU_MF: total multi-family dwelling units in a TAZ.
5) POP_MF: multi-family population in the TAZ.
6) MAUTO: total multi-family population in the TAZ.
7) HOT_OCC: population in hotel/motels in a TAZ.
8) IND_EMP: industrial employment in a TAZ.
9) COM_EMP: commercial employment in a TAZ.
10) SER_EMP: Service employment in a TAZ.
11) SCH_ENR: school enrollment in a TAZ.

12) LANES: number of lanes at the count station location in two directions.

13) ATYPE: area type of the count station location.

14) FTYPE: facility type of the road located the count station.

The following variables were initially considered in the large urban area model:

1) Number of Lane (NUMBEROFLANE): the number of lanes on a roadway.

2) Area Type (AREATYPE): land use types includes: Central Business District (CBD), Fringe Area, Residential Area, Outlying Business District, and Rural Area.

3) Functional Classification (FCC): state minor arterial, county minor arterial, county collector, city collector, local and unclassified.

4) Facility type (FACI): divided arterial, undivided arterial, collector and centroid collector.

5) Population (POP): the total population within a certain distance of a count station.

6) Single-family Population (SFPOP): the total single-family population within a certain distance of a count station.

7) Single-family dwelling units (SFDUS): the total occupied single-family housing units within a certain distance of a count station.

8) Multi-family dwelling units (MFDUS): the total occupied multi-family housing units within a certain distance of a count station.

9) Auto Ownership (AUTO): the estimated total number of automobiles within a certain distance of a count station.

10) Industrial Employment (INDEMP): the total industrial employment number within a certain distance of a count station.

11) Commercial Employment (COMMEMP): the total commercial employment number within a certain distance of a count station.

12) Service Employment (SEREMP): the total commercial employment number within a certain distance of a count station.

13) School Enrollment (SEREMP): the total service employment number within a certain distance of a count station.

14) Hotel Occupancy (HTL): the total hotel occupants within a certain distance of a count station.

15) Accessibility to State Roads (ACCESS1): this variable will assume a value of 1 when there are state roads nearby, and 0 otherwise.

16) Accessibility to Off-system Road (ACCESS2): this variable will be 1 when there are other county roads nearby, and 0 otherwise.

The final model equations in Zhao et al.'s study are given as follows:

1) State-wide model:

$$ADT = 9562.60 + 0.0057 \times POP - 0.1077 \times INCOME \tag{4}$$

Adjusted $R^2 = 0.1128$

2) Rural area model:

$$\begin{aligned} ADT = {} & 4853.489444 + 0.122587 \times POP + 0.261858 \times LABOR - 18.930235 \times LANEMILE \\ & - 0.003238 \times VEHICLE \end{aligned}$$

Adjusted $R^2 = 0.4488$ (5)

3) Small-medium urban model:

$$\begin{aligned} ADT = {} & -13418 + 6770.23 \times LANES + 1580.14 \times ATYPE + 2.85 \times COMMERCIAL \\ & + 1.78 \times OCCUPATION \end{aligned}$$

Adjusted $R^2 = 0.7206$ (6)

4) Large metropolitan model:

$$ADT = -12886 + 4689.86 \times NUMBEROFLANE + 5227.57 \times FCC + 1388.27 \times AREATYPE + 0.15 \times AUTO - 1224.06 ACCESSIBILITY$$

Adjusted R^2 = 0.6069 (7)

The authors of that study also validated the ADT prediction models based on a relatively limited number of traffic counts. The mean absolute percentage errors of the ADT prediction models range from 22.66% to 188.00%. The small-medium urban area model has the best performance in terms of the lowest mean absolute percentage error (22.66%).

In summary, Zhao et al.'s study provided very useful information about the ADT estimation methods in the State of Florida. However, the models developed in that study cannot be directly used in our project because of the following two reasons: (1) Zhao et al.'s study was focused on estimating the ADT of off-system roads in Florida while the objective of our study is to estimate AADT values of off-system roads; and (2) The models in Zhao et al.'s study were developed and validated based on a limited number of traffic counts. It is generally believed that the forecasting capability of AADT prediction model will increase if it is based on a large sample of traffic volume counts.

In a study conducted by J.K. EOM et al. (2006) in the North Carolina State University, a spatial regression model was developed for estimating the AADT values on county roads where traffic counts were often not available. It was the first time that AADT was estimated from a spatial regression model, which takes into account the spatial correlation between AADT at one location and those at its neighboring locations. The thinking behind this method is that traffic volume at one monitoring station is correlated with the volume at its neighboring stations. 200 traffic counts were selected randomly out of all the 1154 available counts in Wake County, North Carolina. In the process of sampling data, traffic counts on freeways like I-40, I-440, and US-1 were excluded from the entire database because the high percentage of through traffic on freeway hurts the spatial relationship with traffic volume on surrounding roads. It was found that spatial regression models provided better AADT estimates as compared to ordinary linear regression models if spatial correlation between AADT at one location and those at its neighbor exists. However, the conclusion needs further validation because of the small sample size and ignorance of freeways. Since only 200 samples were selected in the study for model developing, there lies a question that how representative these sample stations are and whether or not the model is biased towards the selected samples.

2.7 Other AADT Estimation Methods

Tang et al. (2003) used historical and current-year volume data from Hong Kong core traffic count station to compare four different forecasting models for traffic flow estimation. The four models included:

1) Autoregressive Integrated moving Average (ARIMA) Model
2) Neural Network Model (NN)
3) Nonparametric Regression (NPR)
4) Gaussian Maximum Likelihood (GML) Model

ARIMA model is used to forecast both non-seasonal and seasonal data an can only be applied to stationary time series. Neural network model (NN) applies the idea of writing software based on the structure of the human brain and consist of many simple processing elements called neurons. Nonparametric regression (NPR) models perform in a sense that is more dynamic than the time series and neural network models. Nonparametric regression performs prediction based on a group of similar past cases defined around the current input state at the time of prediction. GML models explicitly make use of historical traffic information and real time information in an integrated way The two key random variables considered in the GML model were flow and flow increments with a time interval of five minutes.

In that research, data within a period from January 1994 to December 1998 was chosen as historical data for the model development while January to December 1999 was chosen as current-year for the model validation. Two measures of performance, the mean absolute error (MAE) and the mean square error (MSE), were selected for comparing the results of the four models.

It was pointed out that the ARIMA and NN models require extensive data calibration, but the NPR and GML models do not require data calibration and can be implemented easily. The GML model was found to be more promising and robust for extensive application in AADT estimation.

M. McCord et al (2002) conducted a project to estimate AADT information by analyzing high resolution satellite imagery. However, it seemed not an easy task to achieve because the "noise" associated with inferring average traffic conditions from satellite imagery should be small enough and the quantity of images should be great enough that the information can be combined with ground-based data to improve estimation performance.

Although the result given in that project show that high resolution satellite image-based estimation method works as reinforcement of ground-based AADT estimation, satellite image analysis still cannot be used widely because of the cost of obtaining and processing image data.

2.8 Summary

Traffic volume collection strategies currently adopted cannot cover all the road segments in the whole network, especially limited data resources are available for off system roads. Although some attempts have been made to set up models or procedures of AADT estimation in the past few years, most of them focused on state highways due to the limitation of traffic data. Results or models in those past studies seemed not suitable for this research, and new methodologies or models are needed for the AADT estimation on all roads in the state of Florida. Grounded on the achievements of previous researches, multiple linear regression is proved to be a promising and dependable method to estimate AADT, which is strict in methodology and easy in practice.

CHAPTER THREE

METHDOLOGY

3.1 Introduction

The objective of this study is to develop a method/procedure for estimating the AADT values on off-system roads where traffic counts are not available, and validate the estimated results with current count data from the Tele Atlas digital map provided by the FDOT. The Tele Atlas digital map is a GIS based map which contains almost all roadway segments in the State of Florida. Each roadway segment in the digital map is assigned with a unique variable called Dynamap_ID.

The FDOT also provided an AADT database which included the AADT values for about 2.35% roadway segments in the State of Florida. The AADT database was joined to the Tele Atlas base map based on the same Dynamap_ID of each road segment. The Tele Atlas digital map also provides the functional classification codes for the roadways.

In order to achieve the research objectives, the streets provided by the Tele Atlas digital map were divided into three different types based on the number of traffic counts available to each street as well as the functional classification codes provided by the base map. The descriptive statistics for traffic counts in Hillsborough County, Citrus County and Nassau County were given in Table A-1 through A-3. The Type I streets include all freeways and major state highways where each road has at least one traffic count in each county. In total, the Type I streets account for about 10-15% of the streets in the Tele Atlas digital map. Given the fact that the various FDOT applications should not be producing or using contradictory information the author need to provide reasonable estimations of AADT only for those road segments that do not have reasonable values or estimates from known sources. Due to this reason, AADT values on Type I streets should not be estimated using AADT prediction models because each Type I street has at least one traffic count in each county. In this study, AADT values for Type I streets were assigned manually. Each roadway segment was assigned with the traffic counts collected from the closest roadway segment. The method used for assigning AADT values to Type I streets was described in the next subsection.

The Type II streets include minor state and county highways, and local streets. Less than 10% of these streets have traffic counts. In total, the Type II streets account for about 80-85% of the streets in the Tele Atlas digital map. AADT values on Type II streets were estimated based on AADT prediction models developed in this study.

About 5% of the streets were defined as Type III streets. The Type III streets include: vehicle trails, freeway ramps, cul-de-sacs, traffic circles, service drives, driveways, roads in parking area, and alleys. Traffic counts on Type III streets are extremely limited, and the samples available to this study are too small to build an AADT prediction model. Due to this reason, we feel that it is very hard to estimate the AADT values on these streets without large-scale field data collection. Several aero photos of Type III streets are given in Figure 3.1 through 3.3.

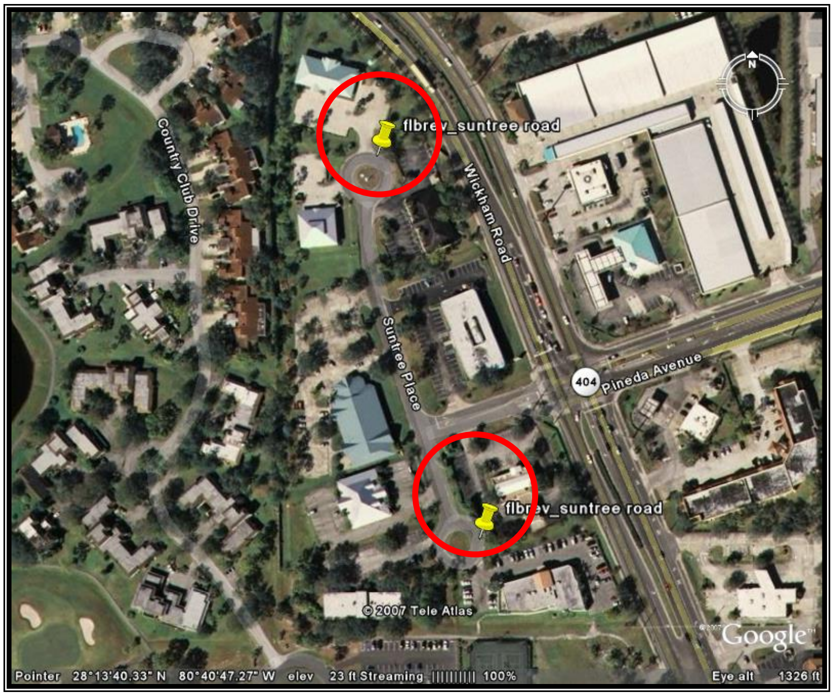

Figure 3.1: Suntree Road in Brevard County

Figure 3.2: Driveway in Alachua County

Figure 3.3: Bismark Road in Nassau County

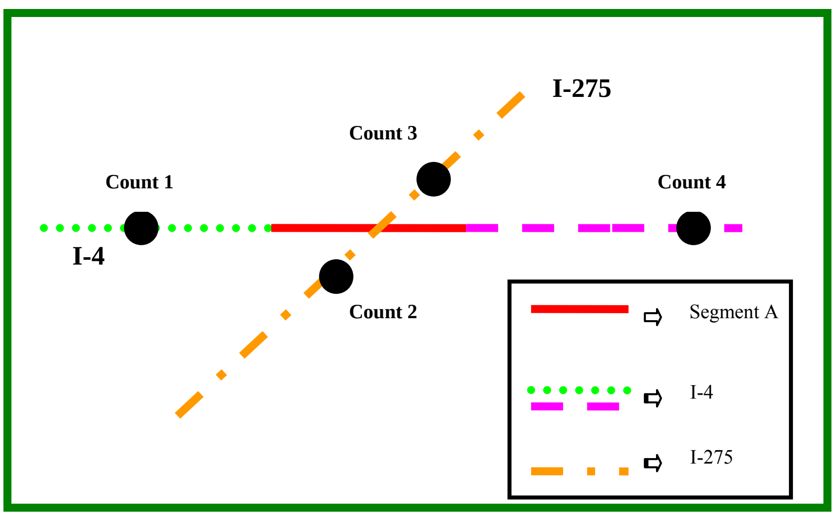

Figure 3.4: Assigning AADT Values to Type I Streets

3.2 Methods for Assigning AADT Values to Type I Streets

Type I streets include freeways and major state highways where sufficient traffic counts are available. The task for AADT assignment on Type I streets is to assign the traffic counts obtained from traffic count locations to all the segments on the same street. When assigning the AADT values on Type I streets, the following principles were followed: (1) Traffic count obtained from a particular road segment was only assigned to the roadway segments on the same street; and (2) If a street in a county has more than one traffic count station, road segments on the same street were assigned with the AADT values obtained from the nearest traffic count station. The logic is illustrated by the example given in Figure 3.4. The purpose of the example is to assign AADT value to the segment A. AADT value collected from traffic count station 2 and 3 will not be considered because they are not on the same street with segment A. Both count station 1 and 4 are on the same street with segment "A". In this case, AADT value collected from count station 1 will be assigned to segment "A" because it is the nearest traffic count station on the same street.

In this study, AADT values for Type I streets were assigned manually. It is extremely time consuming and labor intensive to do so for 67 counties in the State of Florida. Using Flagler County as an example, the general procedures for assigning AADT values for Type I streets were illustrated in Figure B-1 through B-5 and briefly described as follows:

1) Step 1: In the Tele Atlas digital map, select the Type I streets and traffic counts on these streets.
2) Step 2: Separate the Type I streets from other streets in the digital map.

3) Step 3: There are three Type I streets in Flagler County. Each street was selected by attribute query based on the street name. The selected street was exported into a new shape file. Traffic counts on the same street were also selected by using spatial query method provided by ArcGIS.
4) Step 4: Assign the AADT values to all sections on the same street based on the spatial distance.

3.3 Methods for Assigning AADT Values to Type II Streets

Previous studies have demonstrated that linear regression models can provide reasonable AADT estimates for off-system roads where traffic counts are not available (Q, Xia (1999), F. Zhao (1999) and D. Mohamad (1998)). In this study, multiple linear regression models were developed for estimating AADT values for Type II streets. The linear regression model takes on the following functional form:

$$AADT = \beta_0 + \beta_1 X_1 + ... + \beta_j X_j + \varepsilon \quad (8)$$

Where

AADT = the dependent variable;

X_i = the value of i^{th} independent variable, i=1, 2, 3 …n;

β_0 = constant term;

β_j = regression coefficient for the i^{th} independent variable;

ε = error term;

n = number of independent variables.

In this study, 67 counties in the State of Florida were divided into three area types based on the county population in 2005. The area types considered in this study include:

1) Large Metropolitan Area Group (population > 400,000)

2) Small-Medium Urban Area Group (100,000 < population < 400,000)

3) Rural Area Group (population < 100,000)

Figure 3.5 present the county grouping information as well as the population data in each county. 12 counties were included in the large metropolitan area group. Population in these counties accounts for 67.43% of total population in the State of Florida. The small-medium urban group includes 22 counties. The population in these counties accounts for about 26.40% of total population in the State of Florida. A total of 33 counties were included in the rural area group and the total population in these counties accounts for 6.17% of total population in the State of Florida. The spatial distribution of the county groups is given in Figure 3.6.

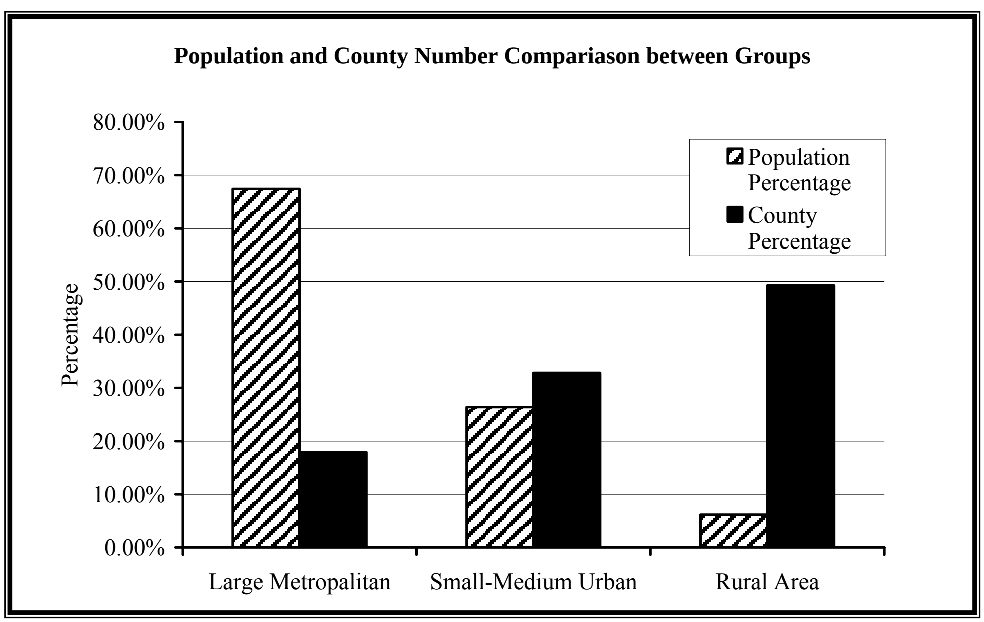

Figure 3.5: County Group based on Population

Figure 3.6: Distribution of County Groups in the State of Florida

CHAPTER FOUR

DATA COLLECTION

4.1 Introduction

The major purpose of data collection work in this study was to collect data used for developing AADT prediction models. The AADT prediction models were used for estimating AADT values on Type II streets which, as mentioned above, account for about 80-85% of the streets in the Tele Atlas digital map. Extensive data collection is conducted to cover most possible potential factors that have significant impacts on AADT and great efforts are also made to compile and process these data. Two different types of data were collected from different resources, including social-economic data and roadway characteristics data.

4.2 Roadway Characteristics Database

Most of the roadway characteristics information used in this study is provided by the digital maps provided by the Tele Atlas. Tele Atlas provides a GIS based digital map in which roadway networks are composed of line segments. The base map includes almost all street segments in the State of Florida. More specifically, the information provided by the base map includes:

1) Dynamap_ID: it is the key variable that was used as a unique identification of each road segment and traffic count in the whole street network;
2) Name: names of road segments. Segments on the same road share the same name.

3) FCC (Feature Classification Codes): it is a very important variable which defines the functional type of roadways.

A roadway characteristics database was created by joining different data resources to the vector based, geography base map provided by the Tele Atlas. An example of the roadway characteristics database is given in Table 4.1. Most of the GIS data layers were obtained from the FDOT website except the land use data layer, which was obtained from the website of the Florida Geographic Data Library (FGDL). More specifically, the GIS data layers which need to be joined to the Tele Atlas digital map include:

1) Urban/rural data layer;
2) Number of lanes data layer; and
3) Land use data layer.

These GIS data layers were joined to the Tele Atlas digital map based on their spatial relationships. It is important to note that the data collection work in this study is very time consuming and labor intensive because each data layer has a different geographic coordinate system and cannot be directly joined to the Tele Atlas digital map. Table 4.2 describes the coordination system of each GIS data layer. The author have developed procedures to join different data layers to the Tele Atlas digital map using ArcGIS but it is very time consuming to do so for 67 counties. The most difficult part the author found was to join the land use data layer to the base map. It takes about 20 hours for the computer to join the land use data to the digital map for the county like Hillsborough.

4.3 Social Economic Database

Ten years social economic data, from 1995 to 2005 was collected for each of the 67 counties in the State of Florida. Social economic data was collected from different data resources such as the website of state and county governments and the US census bureau. Social economic data in some years was not available. Social economic data in these years was extrapolated from the data in other years. A social economic database was then created by manually imputing data obtained from different resources into the social economic database. A picture of the social economic database is given in Figure 4.1. The social economic database includes aggregated data in county level including county population, total lane mileage, vehicle registration, municipality, labor force, average income, and retail sales.

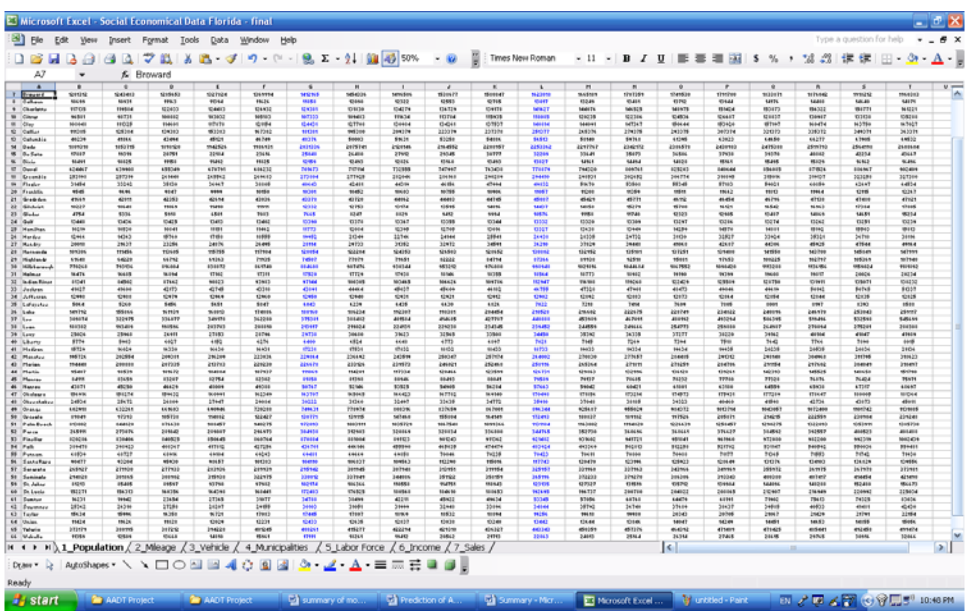

Figure 4.1: The Social Economic Database for Florida Counties (1995-2005)

Table 4.1: Road Characteristics Database

Dynamap_ID	Street Name	FCC	Land Use	Road Side	Locale	Lane Count	Access 0_5mile	Access 1mile	Access 1_5mile
386,914,608	**CR581**	**A35**	**12**	**R**	**1**	**2**	**0**	**1**	1
386,914,608	**Bruce B Downs**	**A35**	**12**	**R**	**1**	**2**	**0**	**1**	1
386,914,633	**CR581**	**A35**	**12**	**R**	**1**	**2**	**0**	**1**	1
386,914,633	**Bruce B Downs**	**A35**	**12**	**R**	**1**	**2**	**0**	**1**	1
386,914,636	**County Hwy 581**	**A35**	**12**	**R**	**1**	**2**	**0**	**1**	1
386,914,636	**Bruce B Downs**	**A35**	**12**	**R**	**1**	**2**	**0**	**1**	1
386,914,684	**Veterans**	**A15**	**8**	**L**	**1**	**2**	**0**	**0**	0
386,914,712	**Debuel**	**A41**	**2**		**1**		**0**	**0**	0
386,914,718	**I-75**	**A15**	**13**		**1**		**0**	**0**	0
386,914,723	**County Hwy 685A**	**A41**	**2**	**C**	**1**	**2**	**0**	**0**	1
386,914,723	**Van Dyke**	**A41**	**2**	**C**	**1**	**2**	**0**	**0**	1
386,914,724	**CR685A**	**A41**	**11**		**1**		**0**	**0**	0
386,914,724	**Simmons**	**A41**	**11**		**1**		**0**	**0**	0
386,914,725	**Juanita**	**A41**	**11**		**1**		**0**	**0**	0
386,914,727	**County Hwy 685A**	**A41**	**11**	**L**	**1**	**1**	**0**	**0**	0
386,914,727	**Van Dyke**	**A41**	**11**	**L**	**1**	**1**	**0**	**0**	0
386,914,737	**Veterans**	**A15**	**8**	**L**	**1**	**2**	**0**	**0**	0
386,914,741	**Cypress**	**A41**	**2**		**1**		**0**	**0**	0
386,914,744	**Debuel**	**A41**	**1**	**L**	**1**	**4**	**0**	**0**	0
386,914,746	**Debuel**	**A41**	**12**	**L**	**1**	**4**	**0**	**0**	0
386,914,753	Cypress	A41	11		1		0	0	0

Table 4.2: GIS Layer Metadata

Data Layer	Geometry Type	XY Coordinate System	Datum	Units
Street	Line	Lat Long WGS84	D_WGS_1984	Degree
Traffic Count	Point	GCS_WGS_1984	D_WGS_1984	Degree
Urban Boundary	Polygon	NAD_1983_UTM_ZONE_17N	D_North_American_1983	Meter
Number of Lane	Line	NAD_1983_UTM_ZONE_17N	D_North_American_1983	Meter
Land Use	Polygon	Albers Conical Equal Area (Florida Geographic Data Library)	D_North_American_1983_HARN	Meter
County Boundary	Polygon	Lat Long WGS84	D_WGS_1984	Degree

CHAPTER FIVE

MODEL CALIBRATION AND VALIDATION

5.1 Model Calibration

5.1.1 Introduction

In this study, the counties in Florida were divided into three groups based on the population in each county. The counties with the population less than 100,000 were classified into the rural area group. The counties with the population between 100,000 and 400,000 were classified into the small-medium urban area group. The counties with the population greater than 400,000 were classified into the large metropolitan area group. In each group, two models were developed for estimating the AADT values on Type II streets, including a state/county highway model and a local street model. The dependent variable of the state/county highway model is the AADT values on minor state/county highways. In Tele Atlas base map, these roads have the functional classification codes of A3X. The dependent variable of the local street model is the AADT values on local streets which have the functional classification codes of A4X.

5.1.2 Variable Description

The dependent variable of the AADT model is the AADT value on a particular street segment. The initially considered independent variables are grouped into two types, social economic variable and roadway characteristics variable.

There are totally seven initial social economic variables included in the model development.

1) Population. The total population in a county. Population is taken as independent variable based on the assumption that population within one area have a significant impact on traffic volume.
2) Total Lane Mileage of Highways. The Total lane mileage of highways in a county.
3) Vehicle Registration. The total number of registered vehicles in one county. There lies an assumption that the more vehicles registered in a county, the more traffic volume will be loaded on the roadway network in the same county.
4) Personal Income. The per capita income of a county. Accounting to trip generation theory, daily traffic will increase with personal income.
5) Retail Sales. Yearly retail sales in each county. Similar to personal income, it is believed that daily traffic increase with the development of social economy.
6) Municipalities. Population within incorporated area.
7) Labor Force. Labor force within one county. It is reasonable that more labor attracts more traffic volume within a county.

In addition of these seven social economic variables, there are five initial roadway characteristics variables included in the model development.

1) Divided/not. A binary variable to indicate the type of median: divided or undivided.
2) Number of lanes in both sides. The total number of lanes in both sides of roadways.

3) Location (rural or urban). A binary variable indicating the type of location: urban or rural. The variable is assumed to have a significant relationship with AADT. Roads within urban areas will carry more daily traffic as compared to those within rural areas.
4) Land use. The abutting land use type of a road segment. It is believed that there lies a strong relationship between AADT and land use, with which volume distribution varies dramatically. In this study, land use data was originally collected from the FGDL website as GIS shape files and joined to the Tele Atlas GIS base map based on the spatial relationship. The original land use shape files provided by FGDL contain 15 land use types. They were reclassified into 8 similar categories, including public-semipublic, agriculture, commercial, institutional, residential, recreation, industrial and others. The reclassification of land use data is described in Table 5.1. Eight binary variables are defined for the eight land use types.
5) Accessibility to Freeways. Unlike other variables, accessibility will be added into roadway characteristics database as a new variable. It is adapted to judge whether roadway segments fall into areas affected by freeways or major state highway, that is, Type I roads. Based on literature review and small sample tests, three buffer sizes are finally selected. They are 0.5 mile, 1 mile and 1.5 miles. It means road segments fall in a distance of 0.5 mile, 1 mile and 1.5 mile from freeways or state highways will be highlighted and marked separately. Figure 5.1 is the sketch map of the three buffer ranges, in which the central heavy line stands for State Highway 20, shaded pattern for 0.5 mile buffer area, striped area for 1.0 mile and

dotted area for 1.5 mile. Road segments within different buffer areas are marked with different colors.

Table 5.1: Land Use Reclassification

Land Use	Description	Land Use	Description
Public-Semipublic	• **Public Schools** • **Public Hospital** • **Gov. Owned Leased by Non-Gov. Lessee** • **Utilities**	**Industrial**	• Manufacturing • Lumber Yard • Fruit, Meat Packing • Canneries • Warehouse • Industrial Storage
Commercial	• **Stores** • **Shops** • **Office** • **Supermarket** • **Shopping Malls and Centers** • **Airports, Marinas and Bus Terminals** • **Restaurants** • **Financial Institution** • **Theater and Stadium** • **Night Club and Bar** • **Hotel and Motel**	**Agriculture**	• Timberland • Cropland • Grazing Land
		Institutional	• Churches • Private School • Private Hospital • Colleges
		Other	• Mining and Gas • Rivers and lakes • Undefined
Residential	• Family • Mobile Homes • Condo	Recreation	• Forest, Park • Golf

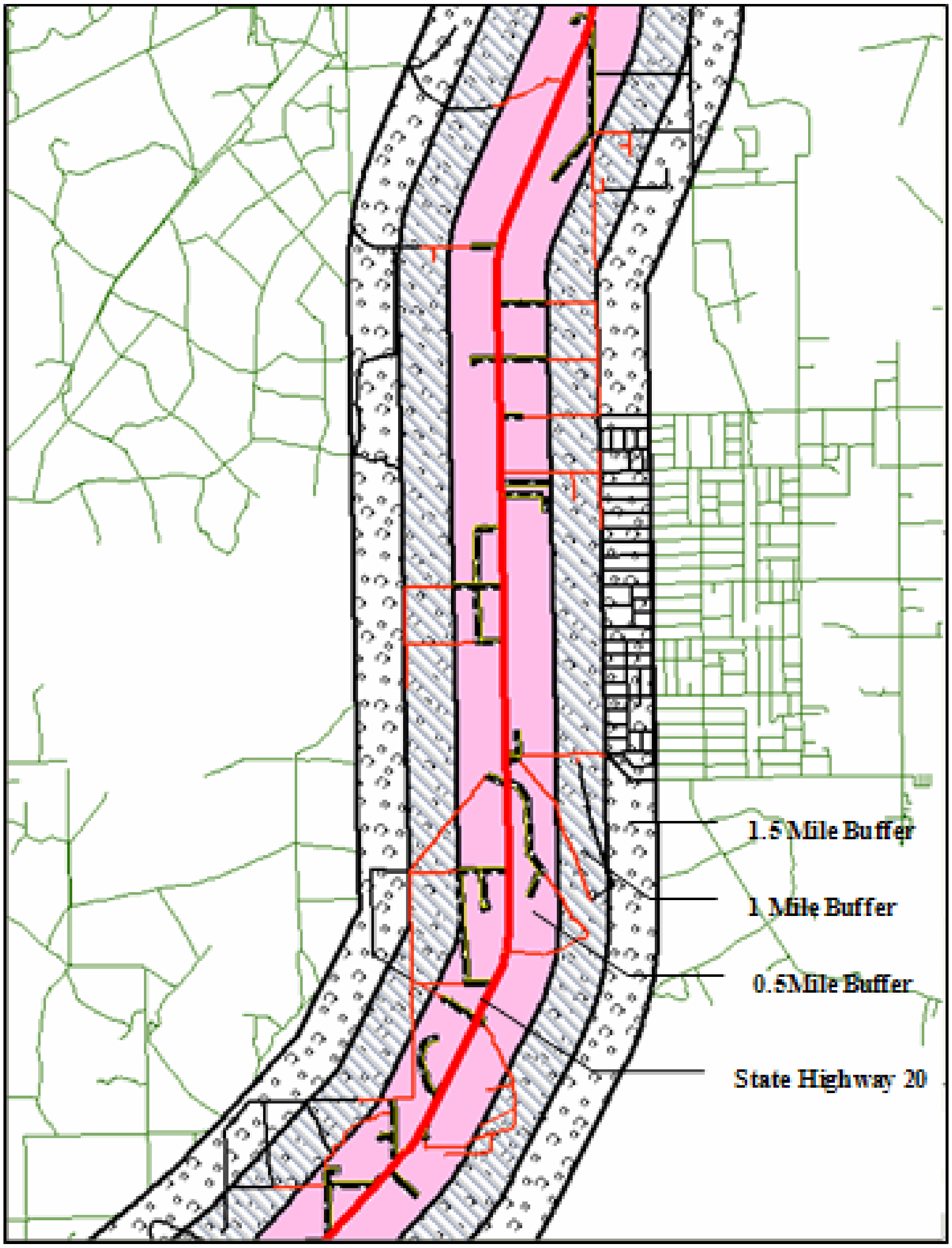

Figure 5.1: Accessibility to Freeway or State Highway

5.2 Model Development

The dependent variable of the AADT model is the AADT value on a particular street segment. A total of 26721 traffic counts provided by the FDOT were used to build six AADT prediction models. The initially considered independent variables include seven social economic variables and fourteen independent variables. The definition of independent variables is given in Table 5.2. Stepwise regression method was used to select variables that will be included into the final models. In total, six linear regression models were built.

The regression results of the AADT prediction models were given in Table 5.3 through 5.8. The final equations of the AADT prediction models and the adjusted-R^2 values of the models were given as follows:

Large Metropolitan Area, State/County Highway Model: (9)

$$\begin{aligned}
&\mathrm{AADT} = -848.8 + 13.541\times \mathrm{VEHICLE} + 1273.347\times \mathrm{DIVIDED} + 2983.442 \\
&\times \mathrm{COMMERCIAL} + 6259.677\times \mathrm{LOCATION} - 8.845\times \mathrm{LABORFORCE} \\
&- 2839.185\times \mathrm{AGRICULYTURE} + 421.252\times \mathrm{NUMBEROFLANE} \\
&+ 1311.231\times \mathrm{INSTITUTIONAL} + 129.069\times \mathrm{INCOME} + 796.601\times 0.5\mathrm{MILE} \\
&- 782.648\times \mathrm{RESIDENTIAL} - 585.47\times \mathrm{SEMIPUBLIC} \qquad R^2_{adj} = 0.186
\end{aligned}$$

Large Metropolitan Area, Local Street Model: (10)

$$\begin{aligned}
&\mathrm{AADT} = -2738.443 + 3.806\times \mathrm{MUNICIPALITIES} + 1349.659\times \mathrm{DIVIDED} \\
&- 452.459\times \mathrm{RESIDENTIAL} - 567.182\times 1.5\mathrm{MILE} + 2745.195\times \mathrm{LOCATION} \\
&+ 259.492\times \mathrm{MUNBEROFLANE} + 1040.226\times \mathrm{SEMIPUBLIC} + 769.194 \\
&\times \mathrm{COMMERCIAL} - 19.545\times \mathrm{LABORFORCE} + 17.369\times \mathrm{POPULATION} \\
&- 4.345\times \mathrm{VEHICLE} \qquad R^2_{adj} = 0.242
\end{aligned}$$

Small-Medium Urban Area, State/County Highway Model: (11)

$$\begin{aligned}\text{AADT} &= 770.374 + 5566.145 \times \text{LOCATION} + 122.079 \times \text{LABORFORCE} \\ &+ 2760.767 \times \text{COMMERCIAL} + 960.82 \times \text{NUMBEROFLANE} + 27.673 \\ &\times \text{VEHICLE} - 70.869 \times \text{POPULATION} + 0.994 \times \text{SALES} - 13.311 \\ &\times \text{MUNICIPALITIES} + 952.963 \times 1.5\text{MILE} - 431.282 \times \text{RESIDENTIAL} \\ &+ 765.103 \times \text{SEMIPUBLIC} - 0.43 \times \text{MILEAGE} + 1072.666 \times \text{INDUSTRIAL}\end{aligned}$$

$$R^2_{adj} = 0.259$$

Small-Medium Urban Area, Local Street Model: (12)

$$\begin{aligned}\text{AADT} &= 1533.94 + 2482.69 \times \text{DIVIDED} - 679.405 \times \text{RESIDENTIAL} \\ &+ 2107.874 \times 1.5\text{MILE} + 2707.119 \times \text{LOCATION} + 18.468 \times \text{VEHICLE} \\ &- 14.468 \times \text{POPULATION} + 0.9437 \times \text{MUNICIPALITIES} + 3320.091 \\ &\times \text{INDUSTRIAL} + 1491.556 \times \text{COMMERICAL} + 1464.231 \times \text{INSTITUTIONAL} \\ &+ 2011.814 \times \text{RECREATION} \qquad R^2_{adj} = 0.166\end{aligned}$$

Rural Area, State/County Highway Model: (13)

$$\begin{aligned}\text{AADT} &= 3015.747 + 3878.551 \times \text{LOCATION} + 17.722 \times \text{VEHICLE} \\ &+ 57.072 \times \text{MUNICIPALITIES} - 1656.733 \times \text{AGRICULTURE} + 22.293 \times \\ &\text{LABORFORCE} - 1.931 \times \text{SALES} - 3312.919 \times \text{RECEATION} - 2324.493 \\ &\times \text{INDUSTRIAL} + 33.239 \times \text{POPULATION} - 748.708 \times \text{RESIDENTIAL}\end{aligned}$$

$$R^2_{adj} = 0.378$$

Rural Area, Local Street Model: (14)

$$\begin{aligned}\text{AADT} &= 1225.505 + 62.168 \times \text{POPULATION} + 1458.501 \times \text{LOCATION} \\ &- 1445.085 \times \text{AGRICULTURE} - 1017.873 \times \text{RESIDENTIAL}\end{aligned}$$

$$R^2_{adj} = 0.418$$

The adjusted R^2 values of the models vary from 0.186 to 0.418. The R^2 values are not un-acceptable considering the fact that the AADT prediction models are, in fact, disaggregate models for which the dependent variables are AADT values for a particular road segment. All independent variables are statistically significantly with a 90% level of confidence. The author also tested possible multicollinearity between independent variables. It was found that the multicollinearity does exit between several independent variables and, as a result, some of the coefficients in the model do not have the expected signs. These correlated independent variables were still included in the models because: (1) later conducted model validation work shows that keeping these variables in the model helps reducing prediction errors; and (2) the objective of AADT models are to estimate the AADT values, not to identify the impacts of various independent variables.

Table 5.2: Definition of Independent Variables in AADT Prediction Models

Social economic Variables	
Population = population in thousands	
Mileage = total mileage of highways in a county	
Vehicle Registration = the total number of registered vehicles in thousands	
Personal Income = the per capita income in thousands	
Retail Sales = yearly retail sales in million	
Municipalities = population within incorporated area in million	
Labor Force = labor force within one county in thousands	
Road Characteristics Variables	
Variable Name	Assigned Value
Divided/not	Divided = 1, and 0 otherwise
Number of lane	Number of lanes in both directions
Location	Urban = 1, and 0 otherwise
0.5 Mile	Roads within 0.5 mile from freeways = 1, and 0 otherwise
1.0 Mile	Roads within 1.0 mile from freeways = 1, and 0 otherwise
1.5 Mile	Roads within 1.5 mile from freeways = 1, and 0 otherwise
Public-Semipublic	Land use type is Public-Semipublic =1, and 0 otherwise
Commercial	Land use type is Commercial =1, and 0 otherwise
Agriculture	Land use type is Agriculture =1, and 0 otherwise
Institutional	Land use type is Institutional =1, and 0 otherwise
Residential	Land use type is Residential =1, and 0 otherwise
Recreation	Land use type is Recreation =1, and 0 otherwise
Industrial	Land use type is Industrial =1, and 0 otherwise

Table 5.3: Regression Results for Large Metropolitan Area, State/County Highway Model

Parameters	Coefficients	Standard Error	t-statistic	Significance Level
Constant	-848.800	766.550	-1.107	0.268
Vehicle	13.541	0.443	30.572	0.000
Divided	1273.347	204.053	6.240	0.000
Commercial	2983.442	227.294	13.126	0.000
Location	6259.677	529.653	11.818	0.000
Laborforce	-8.845	0.716	-12.355	0.000
Agriculture	-2839.185	389.819	-7.283	0.000
Numberoflane	421.252	69.617	6.051	0.000
Institutional	1311.231	383.175	3.422	0.001
Income	129.069	26.513	4.868	0.000
0_5mile	796.601	196.480	4.054	0.000
Residential	-782.648	248.232	-3.153	0.002
Semipublic	-585.470	279.777	-2.093	0.036
$R^2 = 0.186$, $R^2_{adj} = 0.186$				

Table 5.4: Regression Analysis for Large Metropolitan Area, Local Street Model

Parameters	Coefficients	Standard Error	t-statistic	Significance Level
Constant	-2738.443	437.939	-6.253	0.000
Municipalities	3.806	0.726	5.238	0.000
Divided	1349.659	212.907	6.339	0.000
residential	-452.459	183.301	-2.468	0.014
1_5mile	-567.182	184.731	-3.070	0.002
location	2745.195	393.557	6.975	0.000
Numberoflane	249.492	86.614	2.880	0.004
semipublic	1040.226	249.959	4.162	0.000
Commercial	769.194	218.337	3.523	0.000
Laborforce	-19.545	1.238	-15.782	0.000
Population	17.369	1.055	16.457	0.000
Vehicle	-4.345	0.816	-5.323	0.000
$R^2 = 0.244$, $R^2_{adj} = 0.242$				

Table 5.5: Regression Results for Small-Medium Urban Area, State/County Highway Model

Parameters	Coefficients	Standard Error	t-statistic	Significance Level
Constant	770.374	404.301	1.905	0.057
location	5566.145	247.125	22.524	0.000
Laborforce	122.079	7.972	15.313	0.000
Commercial	2760.767	207.855	13.282	0.000
Numberoflane	960.820	88.258	10.887	0.000
Vehicle	27.673	1.831	15.114	0.000
Population	-70.896	4.366	-16.237	0.000
Sales	0.994	0.195	5.107	0.000
Municipalities	-13.311	2.365	-5.628	0.000
1_5mile	952.963	196.098	4.860	0.000
Residential	-431.282	219.761	-1.963	0.050
Semipublic	765.103	288.482	2.652	0.008
Mileage	-0.430	0.186	-2.309	0.021
Industrial	1072.666	508.713	2.109	0.035
$R^2 = 0.261$, $R^2_{adj} = 0.259$				

Table 5.6: Regression Analysis for Small-Medium Urban Area, Local Street Model

Parameters	Coefficients	Standard Error	t-statistic	Significance Level
Constant	1533.940	647.179	2.370	0.018
Divided	2482.690	350.562	7.082	0.000
Residential	-679.405	294.645	-2.306	0.021
1_5mile	2107.874	337.002	6.255	0.000
Location	2707.119	476.108	5.686	0.000
Vehicle2	18.468	2.430	7.600	0.000
Population	-14.468	2.597	-5.570	0.000
Municipalities	9.437	3.141	3.004	0.003
Industrial	3320.091	919.746	3.610	0.000
Commercial	1491.556	379.700	3.928	0.000
Institutional	1464.231	585.513	2.501	0.012
Recreation	2011.814	828.079	2.429	0.015
$R^2 = 0.172$, $R^2adj = 0.166$				

Table 5.7: Regression Analysis for Rural Area, State/County Highway Model

Parameters	Coefficients	Standard Error	t-statistic	Significance Level
Constant	3015.747	249.065	12.108	0.000
Location	3878.551	262.420	14.780	0.000
Vehicle	17.722	11.007	1.610	0.108
Municipalities	57.072	14.166	4.029	0.000
Agriculture	-1656.733	224.269	-7.387	0.000
Laborforce	22.293	6.018	3.704	0.000
Sales	-1.931	0.886	-2.180	0.029
Recreation	-3312.919	712.132	-4.652	0.000
Industrial	-2324.493	822.165	-2.827	0.005
Population	33.239	14.270	2.329	0.020
Residential	-748.708	267.852	-2.795	0.005
$R^2 = 0.382$, $R^2adj = 0.378$				

Table 5.8: Regression Analysis for Rural Area, Local Street Model

Parameters	Coefficients	Standard Error	t-statistic	Significance Level
Constant	1225.505	384.195	3.190	0.002
Population	62.168	9.365	6.639	0.000
Location	1458.501	503.887	2.894	0.004
Agriculture	-1445.085	483.470	-2.989	0.003
Residential	-1017.873	471.691	-2.158	0.032
$R^2 = 0.432$, $R^2adj = 0.418$				

5.3 Model Validation

The purpose of model validation is to test if the developed AADT prediction models can provide reasonable AADT estimates for Type II streets in the State of Florida. Traffic counts from three randomly selected counties were used for validating AADT prediction models. These traffic counts were not used for model calibration described in the previous section. The Mean Absolute Percentage Error (MAPE) is used to evaluate the forecasting capability of the AADT prediction models. The MAPE value measures the prediction error between the AADT values estimated using AADT prediction models and those obtained from traffic count stations. The definition of MAPE is given as follows:

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\mathrm{AADT}_{Mi} - \mathrm{AADT}_{Fi}}{\mathrm{AADT}_{Fi}}\right|. \tag{15}$$

Where

$AADT_{Fi}$ = the i^{th} field measured AADT value, i=1, 2, 3 …n;

$AADT_{Mi}$ = the ith AADT value estimated by AADT prediction model, i=1, 2 …n;

n = sample size

In total, 1149 traffic counts from three counties were used for AADT model validation. Model validation results are given in Table 4.9. The MAPE values for six AADT prediction models vary from 31.99% to 159.49%. The model with the lowest MAPE value is found to be the minor state/county highway model for rural area. The model with the highest MAPE value is found to be the local street model for large metropolitan area. In general, minor state/county highway models provide more reasonable AADT estimates as compared to the local street model in terms of the lower MAPE values. In this study, the local streets were defined as the Type II streets with FFC of A4X. It is not a surprise that local street models provide relatively poor AADT estimates since these roads have much fewer traffic counts available as compared to minor state/county highways.

5.3.1 Model Validation for Large Metropolitan Area

The frequency distributions of MAPE values for the large metropolitan area models are given in Figure 5.2 and 5.3. The models were tested against the AADT data collected in Miami-Dade County. As shown in Figure 5.2 and 5.3, the vast majority of the MAPE values for both minor state/county highway model and local street model are less than 50%. The spatial distribution of forecasting errors in Miami-Dade County is also given in Figure 5.4.

Table 5.9: Model Validation for Six Models

County Group	Functional Classification	N	MAPE	Min	Max	Standard Deviation
Large Metropolitan (Miami-Dade County)	County Highway	870	46.81%	12.90%	809.30%	0.664
	Local Street	123	159.49%	2.51%	974.72%	1.820
Small-Medium Urban (Citrus County)	County Highway	112	65.01%	1.05%	609.88%	0.963
	Local Street	20	65.35%	3.36%	213.24%	0.569
Rural (Sumter County)	County Highway	22	31.99%	0.19%	93.87%	0.252
	Local Street	2	46.79%	46.27%	47.325%	0.007

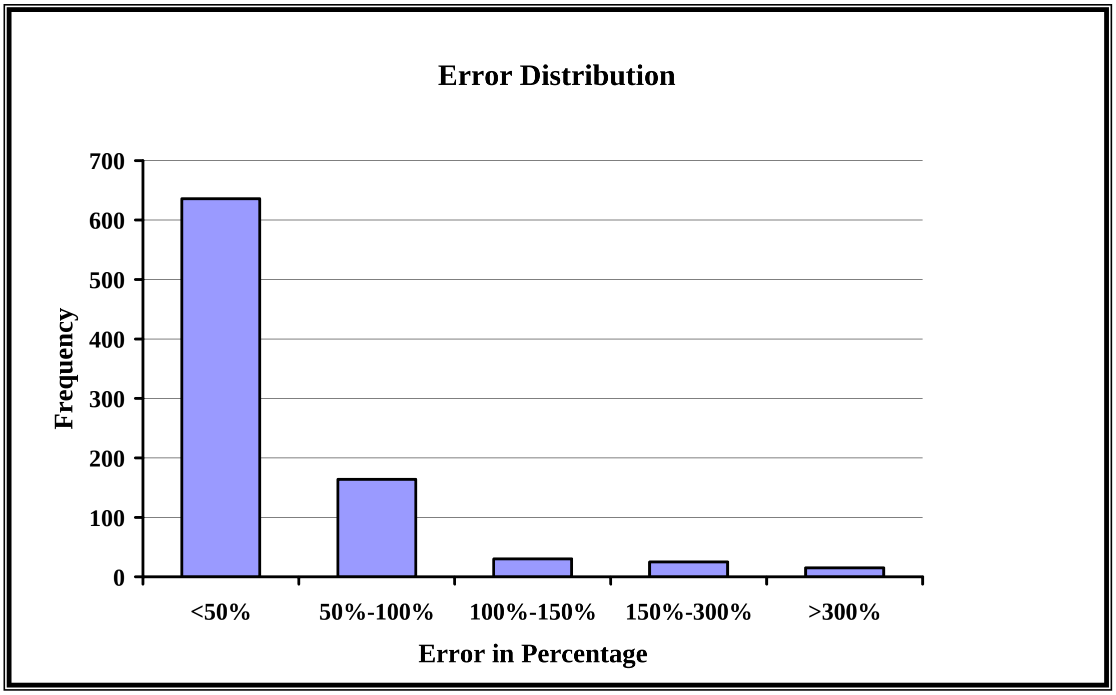

Figure 5.2: Error Distribution of County Highway Testing Counts in Miami-Dade County

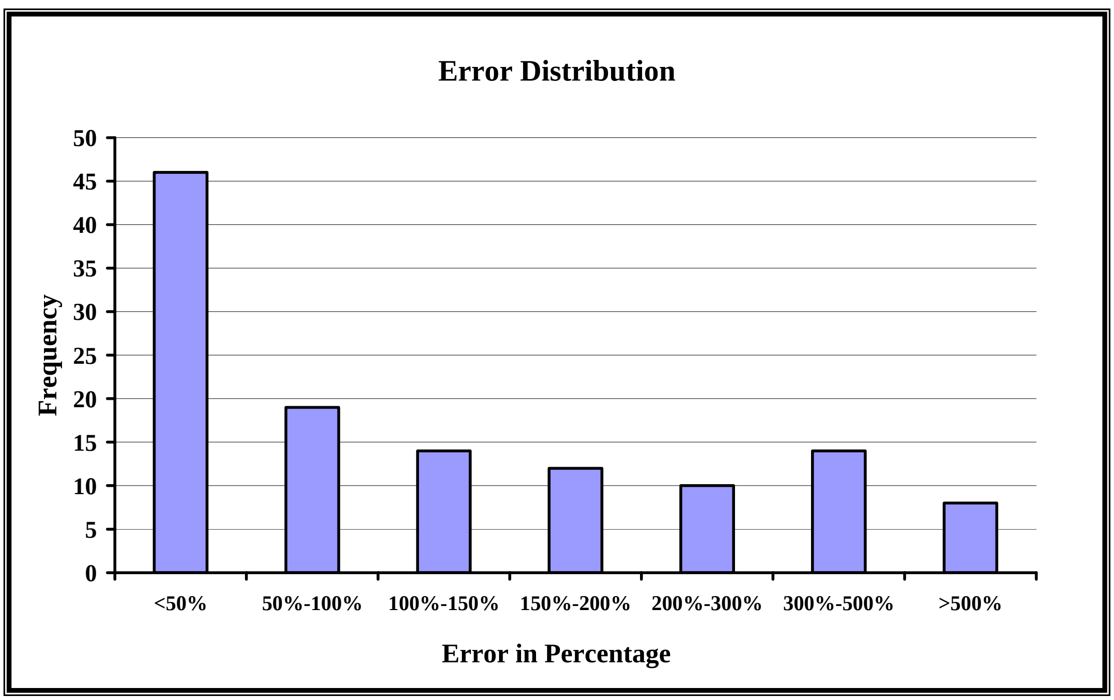

Figure 5.3: Error Distribution of Local Street Testing Counts in Miami-Dade County

5.3.2 Model Validation for Small-Medium Urban Group

The frequency distributions of MAPE values for the small-medium area models are given in Figure 5.5 and 5.6. The models were tested against the AADT data collected in Citrus County. As shown in Figure 5.5 and 5.6, the vast majority of the MAPE values for both minor state/county highway model and local street model are less than 100%. The spatial distribution of forecasting errors in Citrus County is also given in Figure 5.7.

5.3.3 Model Validation for Rural Area Group

A limited number of traffic counts were provided by the Sumter County. The data was used to validate the AADT prediction models for rural area. The frequency distribution of MAPE values for the minor state/county highway model is given in Figure 5.8. The frequency distribution of MAPE values for the local street model cannot be developed because the number of traffic counts is too few. As shown in Figure 5.8, the vast majority of the MAPE values for minor state/county highway model is rural area is less than 50%. The spatial distribution of forecasting errors in Sumter County is given in Figure 5.9.

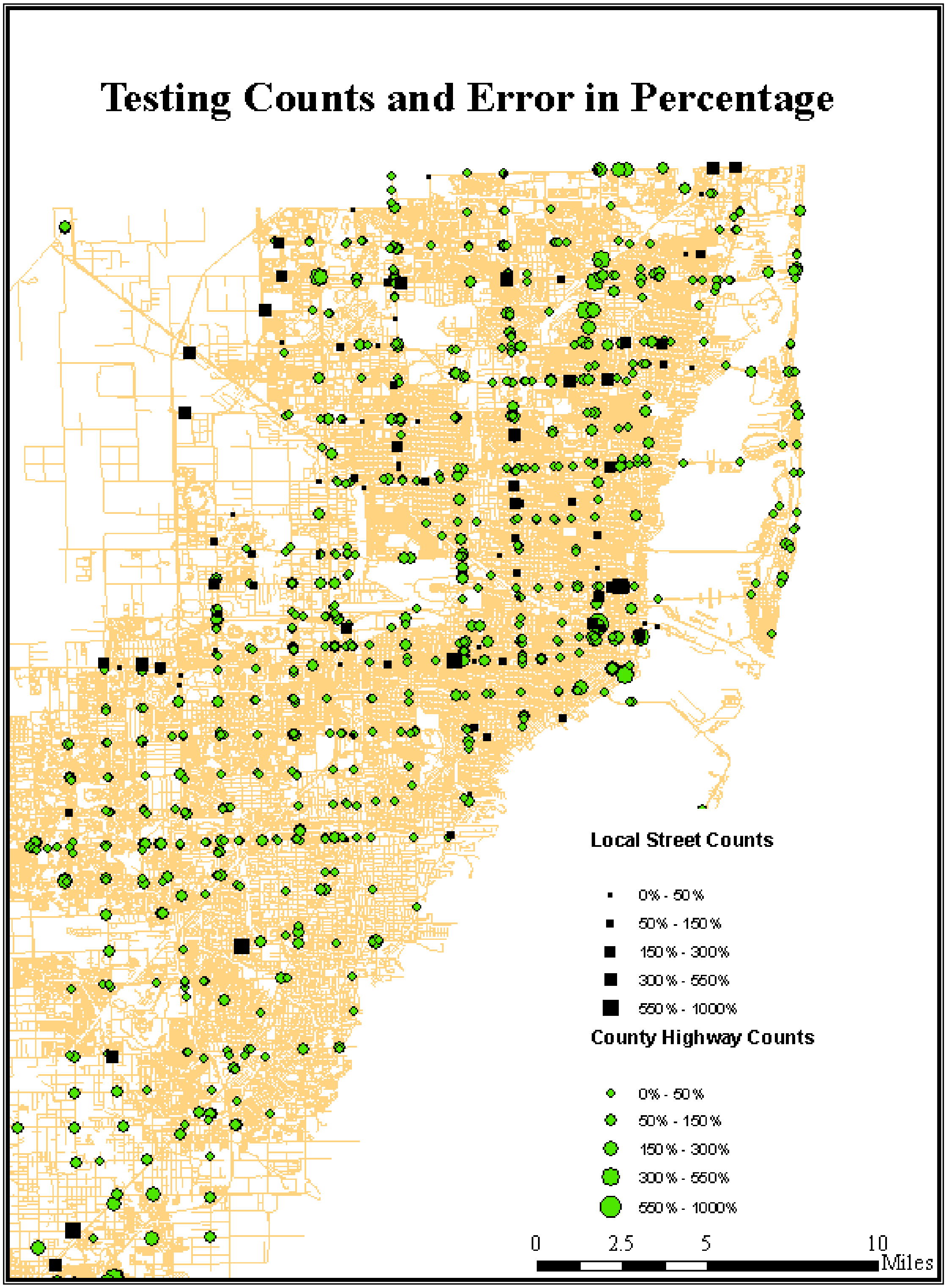

Figure 5.4: Spatial Distribution of Error Percentage of Testing Counts in Miami-Dade County

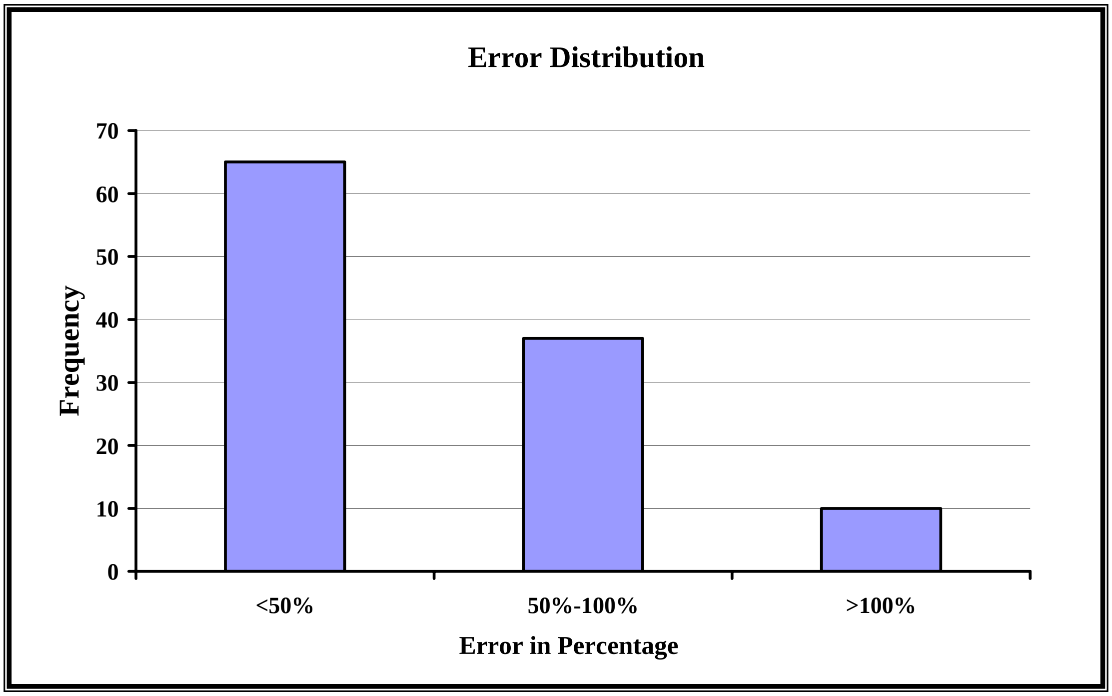

Figure 5.5: Error Distribution of County Highway Testing Counts in Citrus County

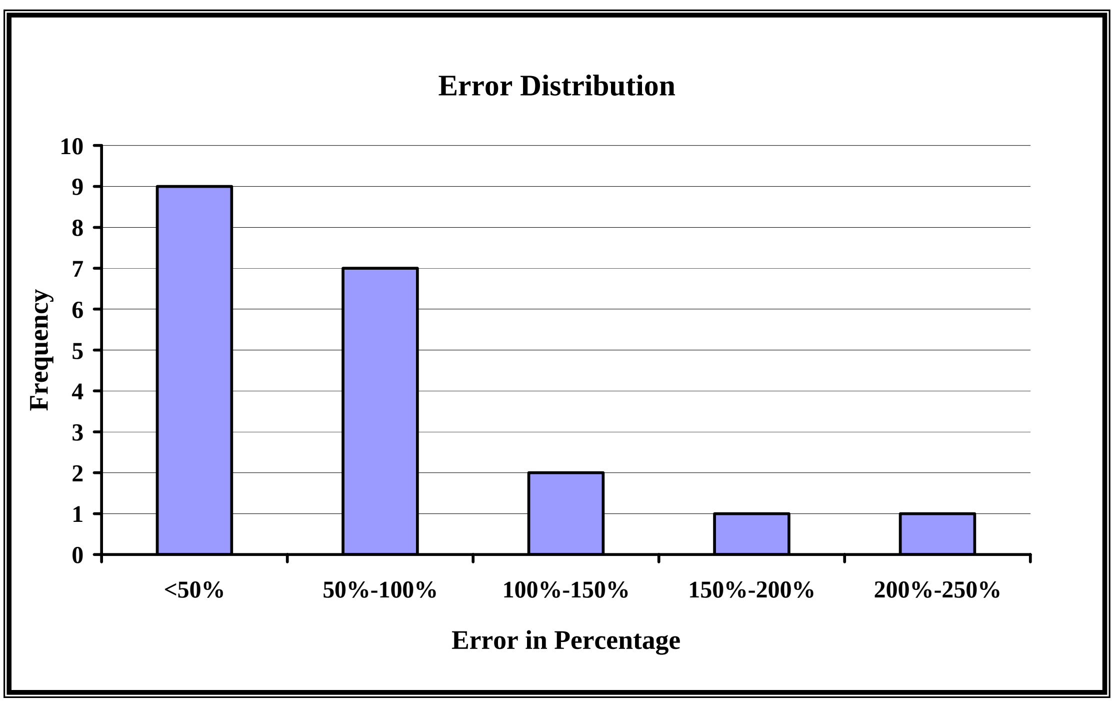

Figure 5.6: Error Distribution of Local Street Testing Counts in Citrus County

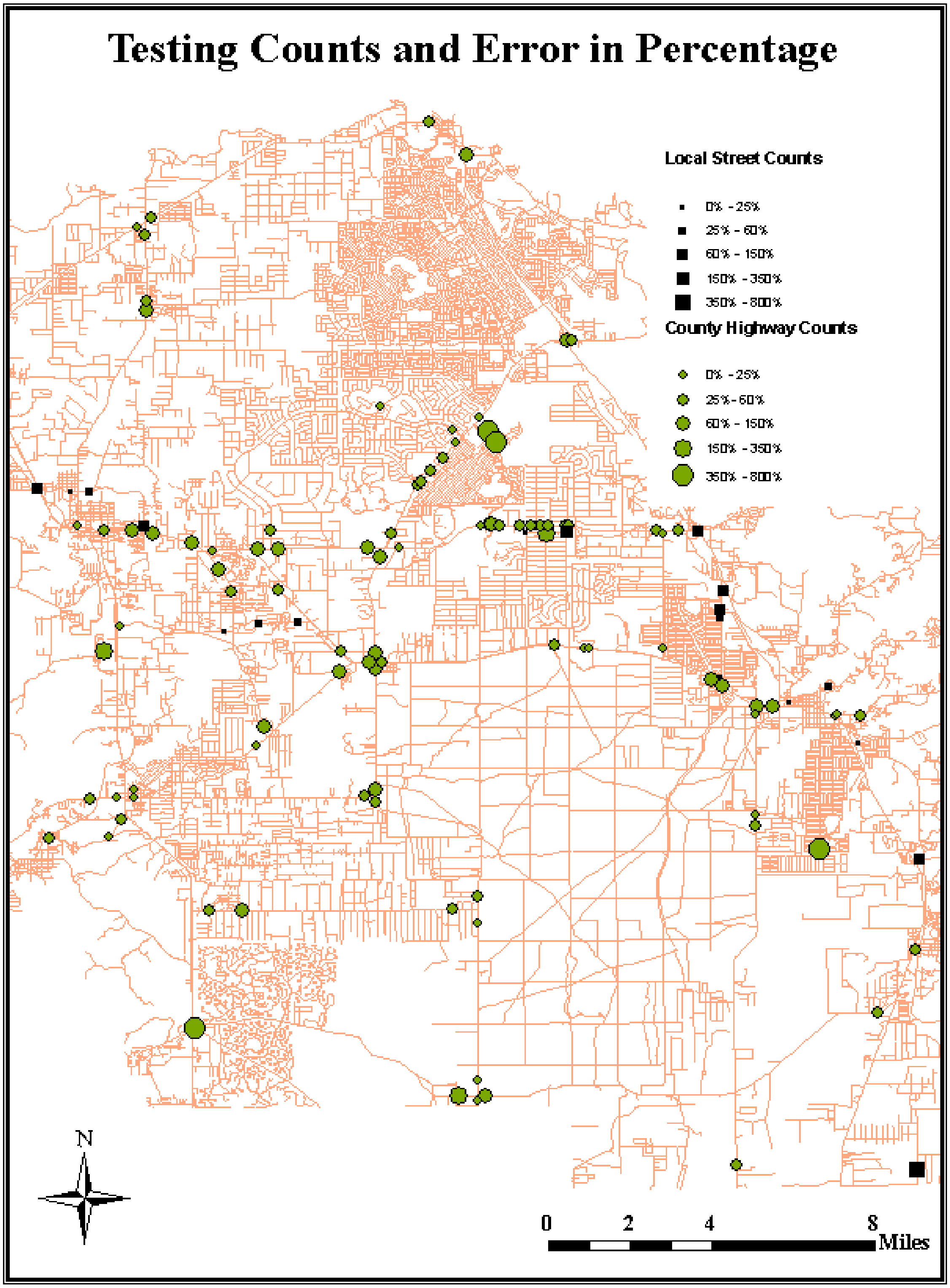

Figure 5.7: Spatial Distribution of Error Percentage of Testing Counts in Citrus County

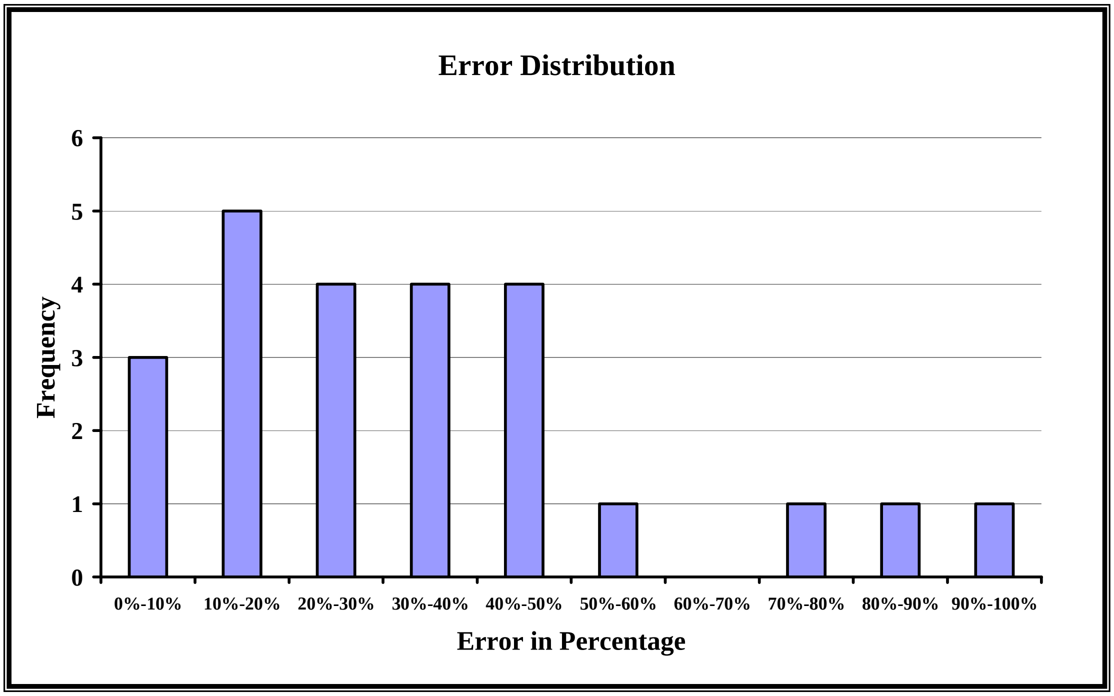

Figure 5.8: Error Distribution of Testing Counts in Sumter County

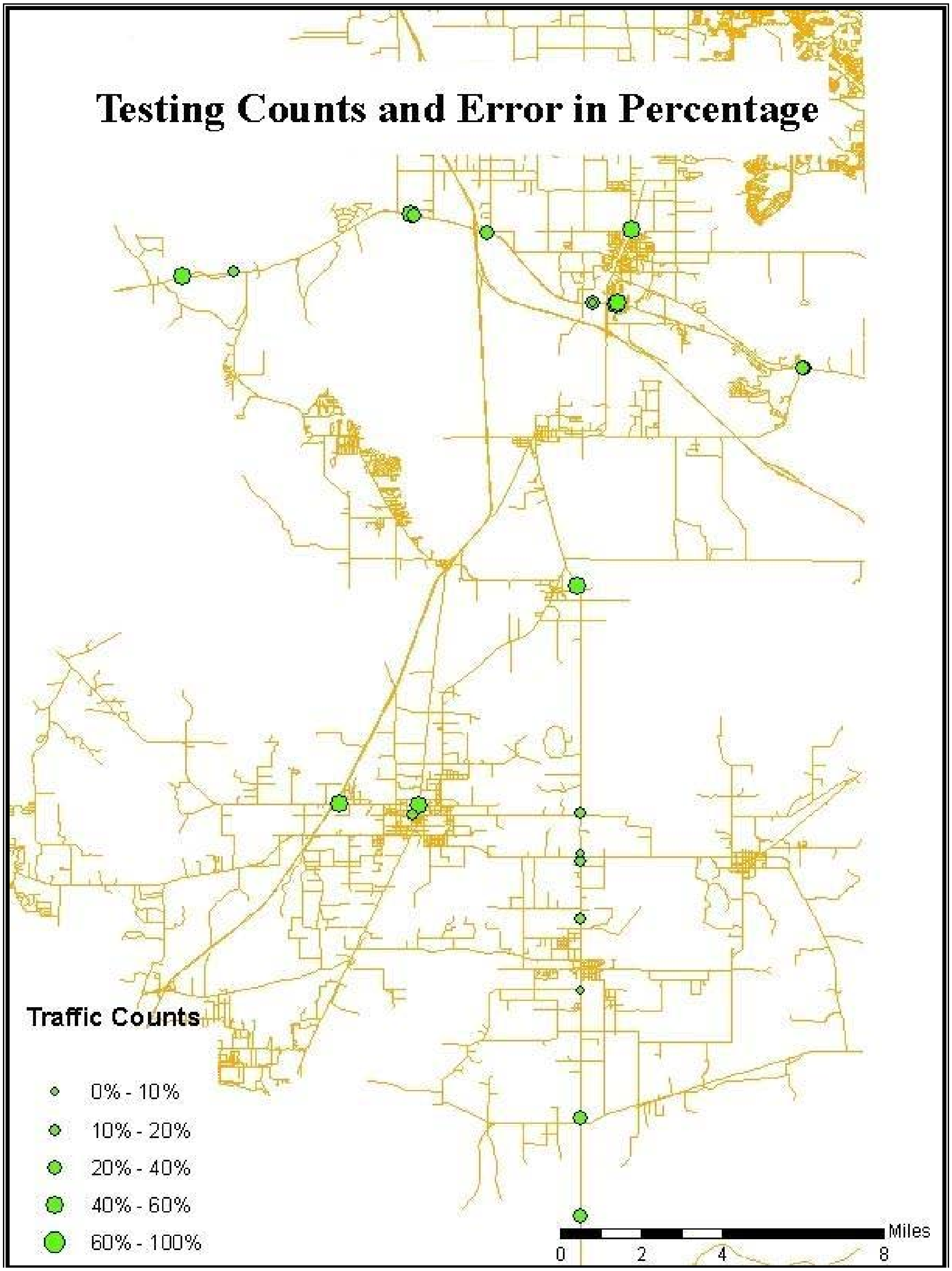

Figure 5.9: Spatial Distribution of Error Percentage of Testing Counts in Sumter County

CHAPTER SIX

SUMMARY AND FINAL RESULT

6.1 Summary

The main objective of the study is to develop new procedure/methodology for the estimation of traffic volumes on the roads where traffic counts are not easily available. This AADT estimation process is primarily based on two categories of data. One is known or accepted AADT values on the neighboring state and local roadways, ArcGIS was applied to merge and create road characteristics database from various data resources; the other type of data is social/economic data like population densities, total lane mile and retail sales.

To achieve the research objectives of this study, the street segments provided by the Tele Atlas GIS base map were divided into three different types based on the number of traffic counts available to each street. The Type I streets include all freeways and major state highways where each road has at least one traffic count in each county. That means there are sufficient traffic counts available on Type I roads and AADT values on Type I streets were assigned manually by assigning AADT values measured from several traffic count stations to all other segments of the same road. In total, the Type I streets account for about 10-15% of the streets in the Tele Atlas base map.

The Type II streets include minor state and county highways and local streets. Less than 10% of these streets have traffic counts available. AADT values on Type II streets were estimated based on six linear regression models developed in this study. In total, the Type II streets account for about 80-85% of the streets in the Tele Atlas base map.

About 5% of the streets were defined as Types III streets. The Type III streets include vehicle trails, freeway ramps, cul-de-sac, traffic circles, serve drives, driveways, roads in parking area, and alleys. Traffic counts on these Type III streets are extremely limited, and the samples available to this study are too small to build an AADT prediction model. Due to this reason, we feel that it is very hard to estimate the AADT values on these streets without large-scale field data collection.

To develop AADT prediction models for estimating AADT values on Type II streets, two different types of database were created, including a social economic database and a roadway characteristics database. Ten years social economic data, from 1995 to 2005 were collected for each of the 67 counties in the state of Florida, and a social economic database was created by manually imputing data obtained from different resources into the social economic database. The roadway characteristics database was created by joining different GIS data layers to the Tele Atlas base map.

Based on literature review, in this study, the counties in Florida were divided into three groups based on the population in each county. The counties with the population less than 100,000 were classified into the rural area group. The counties with the population between 100,000 and 400,000 were classified into the small-medium urban area group. The counties with the population greater than 400,000 were classified into the large metropolitan area group. In each group, two models were developed for estimating the AADT values on Type II streets, one for state/county highways and one for local streets.

Stepwise regression method was used to select variables that will be included into the final models. All selected independent variables in the models are statistically significant with a 90% level of confidence. In total, six linear regression models were built. The adjusted R^2 values of the AADT prediction models vary from 0.166 to 0.418. Model validation results show that the MAPE values of the AADT prediction models vary from 31.99% to 159.49%. The author studied specific locations with large error. Some special urban facilities with more than two lanes were found to load traffic volume less than one thousand per day. That's why some large error caused. This problem may be caused by misclassification of road function or missing other potential important variables. The model with the lowest MAPE value is found to be the minor state/county highway model for rural area. The model with the highest MAPE value is found to be the local street model for large metropolitan area. In general, minor state/county highway models provide more reasonable AADT estimates as compared to the local street model in terms of the lower MAPE values.

6.2 Final Result

The major result of this study is the AADT values assigned to the street segments in Florida counties where traffic counts are not available. The linear regression models developed in this study were used to estimate AADT values on Type II streets. So far, we have finished assigning AADT values to all Type I and Type II streets for 67 counties in Florida, which account for about 93% of the streets in those counties. The estimated AADT values were merged to the Tele Atlas GIS base map based on the Dynamip_ID.

A .dbf file which contains all the information provided by the Tele Atlas base map plus the AADT values assigned to each street segment was created for each of the 67 counties. A picture for the final DBF file for Palm Beach County is given in Figure 6.1.

Attributes of flpalm

HWY_NUM	SEG_LEN	SPEED	ONE_WAY	F_ZLEV	T_ZLEV	FT_COST	TF_COST	FT_DIR	TF_DIR	NAME_FLAG	STATUS	OID_	DYNAMAP__1	VOLUME	YEAR
	0.0133	25		0	0	0.03199	0.03199			1		26590	29742244	7001	2005
27	0.1389	55	FT	0	0	0.15153	-1			1		118386	29743898	7600	2003
25	0.1389	55	FT	-9	-9	-1	-1			0		118386	29743898	7600	2003
80	0.1389	55	FT	-9	-9	-1	-1			0		118386	29743898	7600	2003
	0.0239	25		0	0	0.05747	0.05747			3		26591	29750544	9659	2005
	0.0239	25		-9	-9	-1	-1			0		26591	29750544	9659	2005
	0.0239	25		-9	-9	-1	-1			0		26591	29750544	9659	2005
	0.105	25		0	0	0.25207	0.25207			1		26594	307221848	9659	2005
	0.107	25		0	0	0.25687	0.25687			1		26595	307221849	9659	2005
	0.1156	25		0	0	0.27759	0.27759			1		26596	307221852	9659	2005
	0.0531	25		0	0	0.12765	0.12765			3		26597	326643065	8831	2005
	0.0531	25		-9	-9	-1	-1			0		26597	326643065	8831	2005
	0.0798	25		0	0	0.19156	0.19156			3		26599	326705413	10564	2005
	0.0341	25		0	0	0.08196	0.08196			1		26600	326705418	10564	2005
	0.0207	25		0	0	0.04977	0.04977			3		26601	326708285	9330	2005
	0.006	25		0	0	0.01447	0.01447			3		26602	326712107	9330	2005
	0.0063	25		0	0	0.01521	0.01521			3		26603	326712123	9659	2005
	0.0128	25		0	0	0.03086	0.03086			3		26604	327571686	9659	2005
1	0.0652	35		0	0	0.11185	0.11185			3		120612	327850485	13500	2003
1	0.0652	35		-9	-9	-1	-1			2		120612	327850485	13500	2003
5	0.0652	35		-9	-9	-1	-1			0		120612	327850485	13500	2003
	0.0652	35		-9	-9	-1	-1			0		120612	327850485	13500	2003
1	0.0637	35		0	0	0.10936	0.10936			3		120616	327850487	13500	2003
1	0.0637	35		-9	-9	-1	-1			2		120616	327850487	13500	2003
5	0.0637	35		-9	-9	-1	-1			0		120616	327850487	13500	2003
	0.0637	35		-9	-9	-1	-1			0		120616	327850487	13500	2003
1	0.0635	35		0	0	0.10892	0.10892			3		120620	327850516	13500	2003
1	0.0635	35		-9	-9	-1	-1			2		120620	327850516	13500	2003
5	0.0635	35		-9	-9	-1	-1			0		120620	327850516	13500	2003
	0.0635	35		-9	-9	-1	-1			0		120620	327850516	13500	2003
	0.0876	15		0	0	0.35079	0.35079			1		0	0	0	0
	0.036	25		0	0	0.08642	0.08642			3		26605	327851456	8831	2005
95	0.1049	65	TF	1	0	-1	0.09688		N	1		123003	327851464	57500	2003
95	0.4029	65	TF	0	1	-1	0.37191		N	1		123004	327851467	57500	2003
95	0.0223	65	TF	0	0	-1	0.02059		S	1		123005	327851474	57500	2003
95	0.113	65	TF	0	0	-1	0.10432		S	1		123006	327851475	57500	2003
95	0.0331	65	TF	0	1	-1	0.0306		S	1		123007	327851478	57500	2003
95	0.4035	65	TF	1	0	-1	0.3725		S	1		123008	327851479	57500	2003
95	0.1041	65	TF	0	1	-1	0.09615		S	1		123009	327851482	57500	2003
811	0.0533	35	TF	0	0	-1	0.09138			1		1856	327851584	17601	2005

Record: 1 Show: All Selected Records (0 out of 135820 Selected) Options

Figure 6.1: The DBF File for Palm Beach County

As mentioned before, traffic counts on Type III roads are extremely limited, and the samples available to this study are too small to build AADT prediction models with acceptable precision level. The linear regression models developed in this study provided tools for estimating AADT values on Type II streets. However, some of the models suffer from large prediction errors in terms of the large MAPE values. It was found that minor state/county highway models provide more reasonable AADT estimates as compared to the local street model because local streets have much fewer traffic counts available. A possible solution to these problems is to conduct large-scale field data collection on Type

II and Type III roads to gather more AADT data. The collected AADT data can be used to develop AADT prediction models for Type III roads and re-calibrate the local street model for Type II roads. The authors recommend that future study could focus on these issues.

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APPENDICES

APPENDIX A. Descriptive Statistics for Traffic Counts

Table A.1: Descriptive Statistics for Traffic Counts in Hillsborough County

Type	Road Type	FCC*	Frequency	Traffic Counts	Percentage
I	Freeway	A15	3595	309	8.60%
	Major US and State Highway	A21	1971	217	11.00%
		A25	7699	560	7.30%
II	State and County Highways	A30	155	9	5.80%
		A31	11067	891	8.10%
		A35	12573	832	6.60%
		A37	3	0	0.00%
	Local Streets	A40	484	5	1.00%
		A41	75826	454	0.60%
		A43	2	0	0.00%
		A45	2922	85	2.90%
III	Vehicle Trail	A50	12	0	0.00%
		A51	41	0	0.00%
	Ramp, Cul-de-sac, Traffic circle, Serve drive	A60	2757	1	0.00%
		A61	1933	0	0.00%
		A62	217	0	0.00%
		A63	1306	8	0.60%
		A64	19	0	0.00%
	Driveway, Road in parking area, Alley	A70	463	0	0.00%
		A71	138	0	0.00%
		A73	20	0	0.00%
		A74	1223	0	0.00%
		A75	508	0	0.00%
Note: FCC: the functional classification code provided by the Tele Atlas digital map					

APPENDIX A. (Continued)

Table A.2: Descriptive Statistics for Different Types of Streets in Citrus County

Type	Road Type	FCC*	Frequency	Traffic Counts	Percentage
I	Major US and State Highway	A21	902	131	14.5%
		A25	1252	180	14.3%
II	State and County Highways	A30	3378	198	5.86%
		A31	163	8	4.91%
		A35	1251	36	2.88%
	Local Streets	A40	8513	21	0.25%
		A41	17019	5	0.00%
		A45	172	0	0.00%
III	Vehicle Trail	A50	3	0	0.00%
		A51	2	0	0.00%
	Ramp, Cul-de-sac, Traffic circle, Serve drive	A60	133	0	0.00%
		A61	572	0	0.00%
	Driveway, Road in parking area, Alley	A70	7	0	0.00%
		A71	1	0	0.00%
		A74	1223	0	0.00%
Note: FCC: the functional classification code provided by the Tele Atlas base map					

APPENDIX A. (Continued)

Table A.3: Descriptive Statistics for Different Types of Streets in Nassau County

Type	Road Type	FCC*	Frequency	Traffic Counts	Percentage
I	Freeway	A15	105	4	3.81%
I	Major US and State Highway	A21	441	20	4.54%
I	Major US and State Highway	A25	1618	66	4.08%
II	State and County Highways	A30	71	0	0.00%
II	State and County Highways	A31	2325	51	2.19%
II	State and County Highways	A35	1264	38	3.01%
II	Local Streets	A40	1523	0	0.00%
II	Local Streets	A41	7057	0	0.00%
II	Local Streets	A45	8	0	0.00%
III	Vehicle Trail	A51	30	0	0.00%
III	Ramp, Cul-de-sac, Traffic circle, Serve drive	A60	144	0	0.00%
III	Ramp, Cul-de-sac, Traffic circle, Serve drive	A61	96	0	0.00%
III	Ramp, Cul-de-sac, Traffic circle, Serve drive	A63	26	0	0.00%
III	Ramp, Cul-de-sac, Traffic circle, Serve drive	A64	21	1	4.76%
III	Driveway, Road in parking area, Alley	A70	1135	0	0.00%
III	Driveway, Road in parking area, Alley	A73	2	0	0.00%
III	Driveway, Road in parking area, Alley	A74	122	0	0.00%
III	Driveway, Road in parking area, Alley	A75	1	0	0.00%

Note: FCC: the functional classification code provided by the Tele Atlas base map

APPENDIX B. Type I Road Assignment

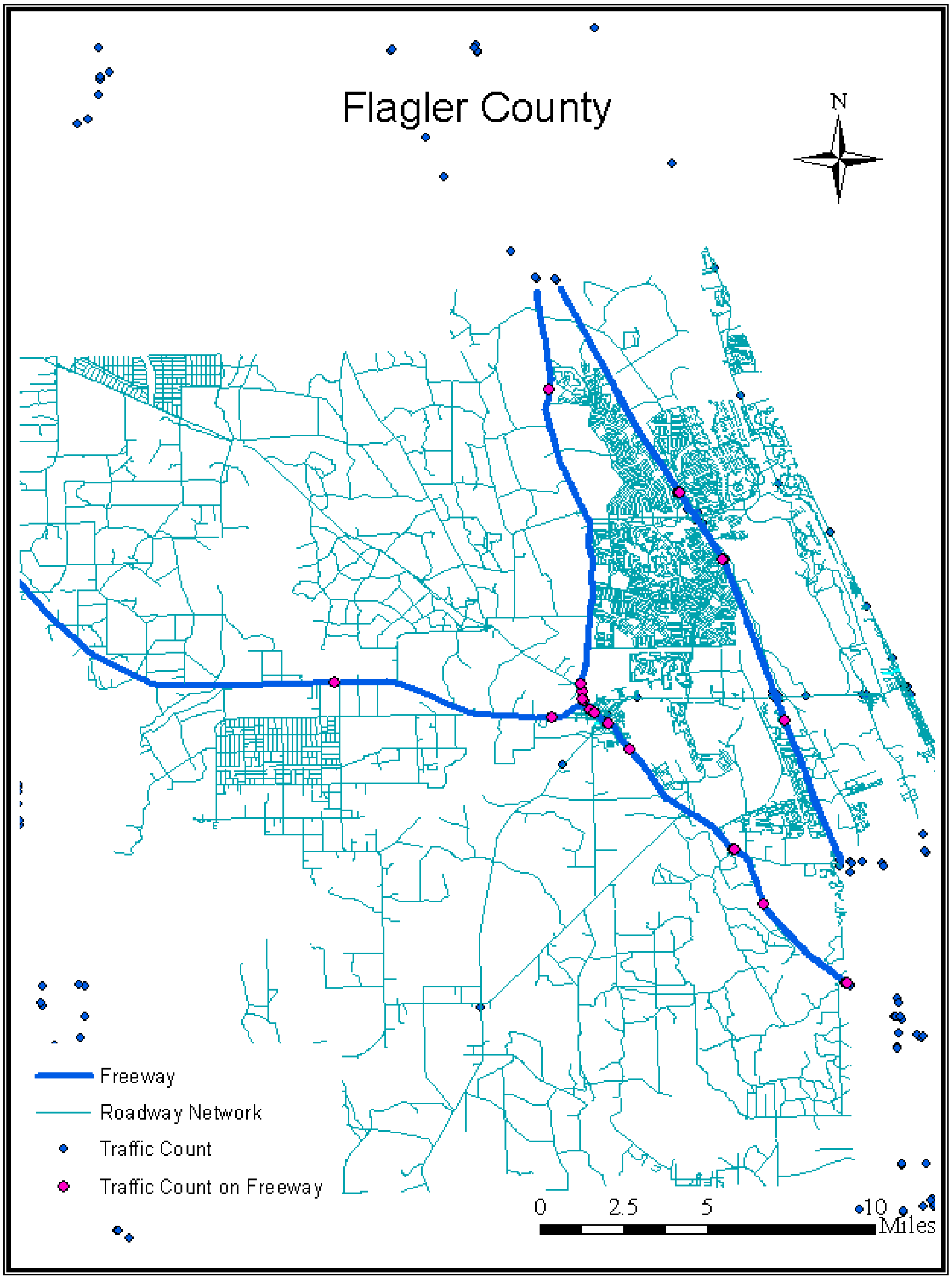

Figure B.1: The First Step of Type I Roads AADT Assignment in Flagler County

APPENDIX B. (Continued)

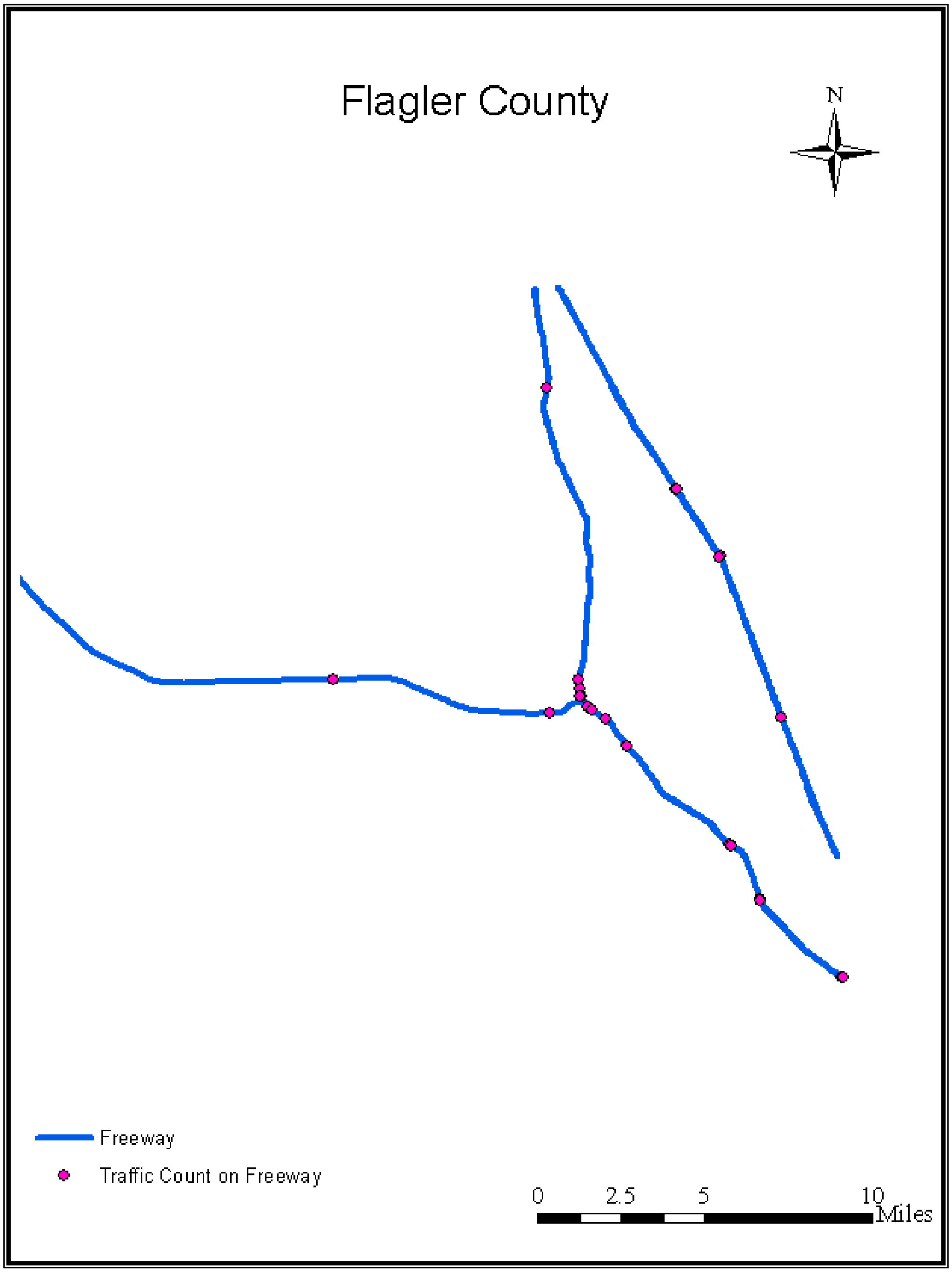

Figure B.2: The Second Step of Type I Roads AADT Assignment in Flagler County

APPENDIX B. (Continued)

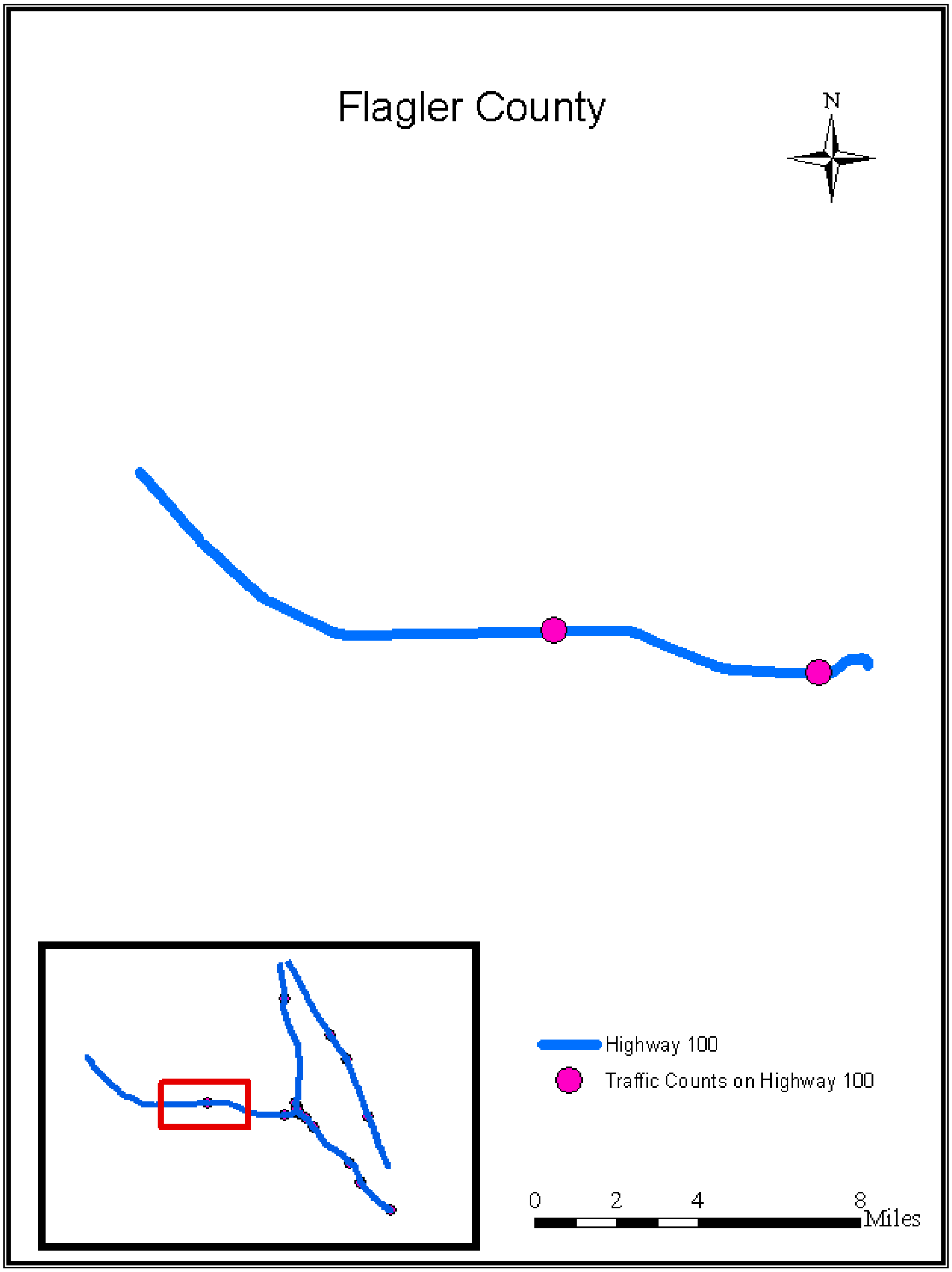

Figure B.3: AADT Assignment on Highway 100

APPENDIX B. (Continued)

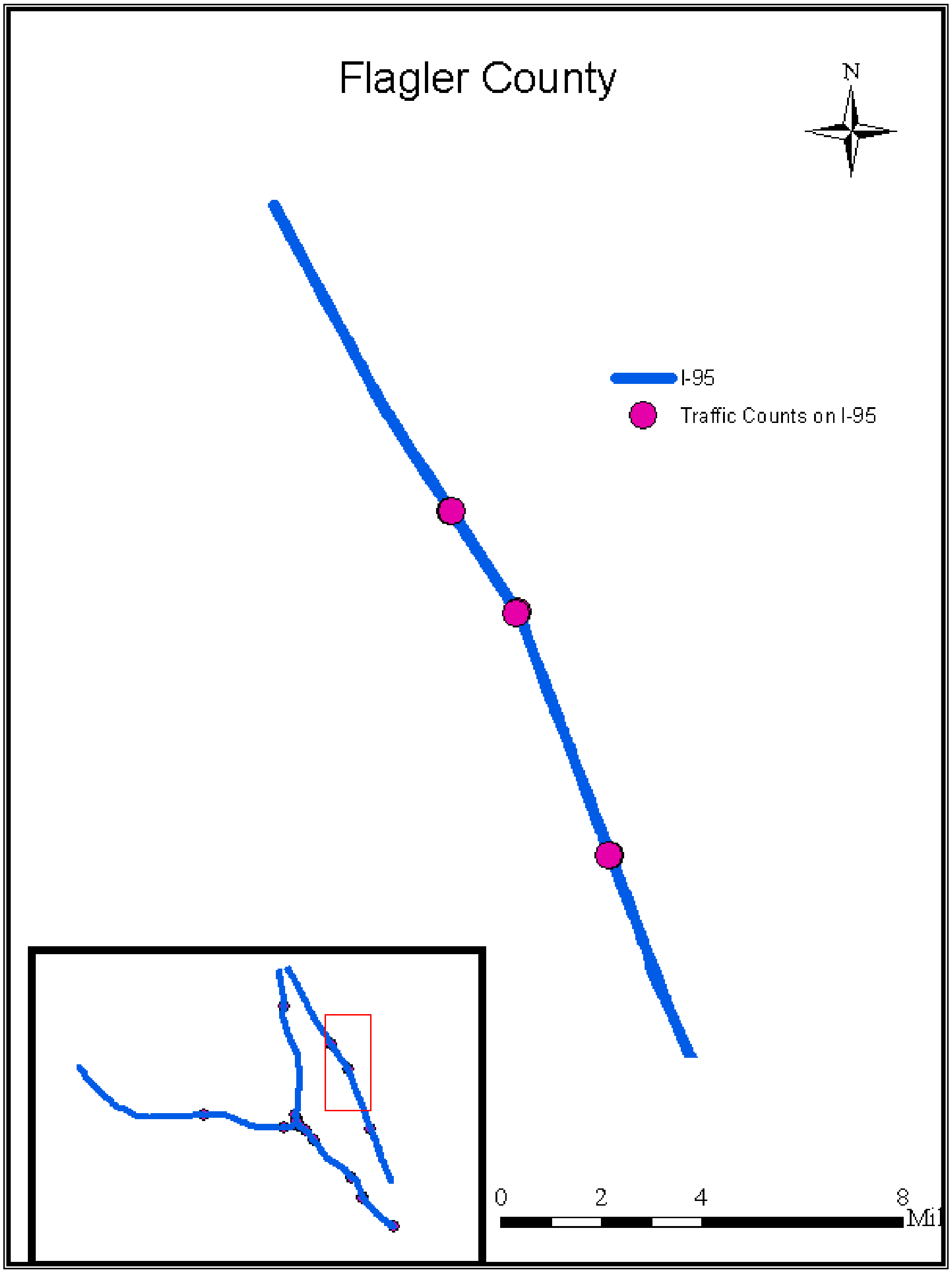

Figure B.4: AADT Assignment on I-95

APPENDIX B. (Continued)

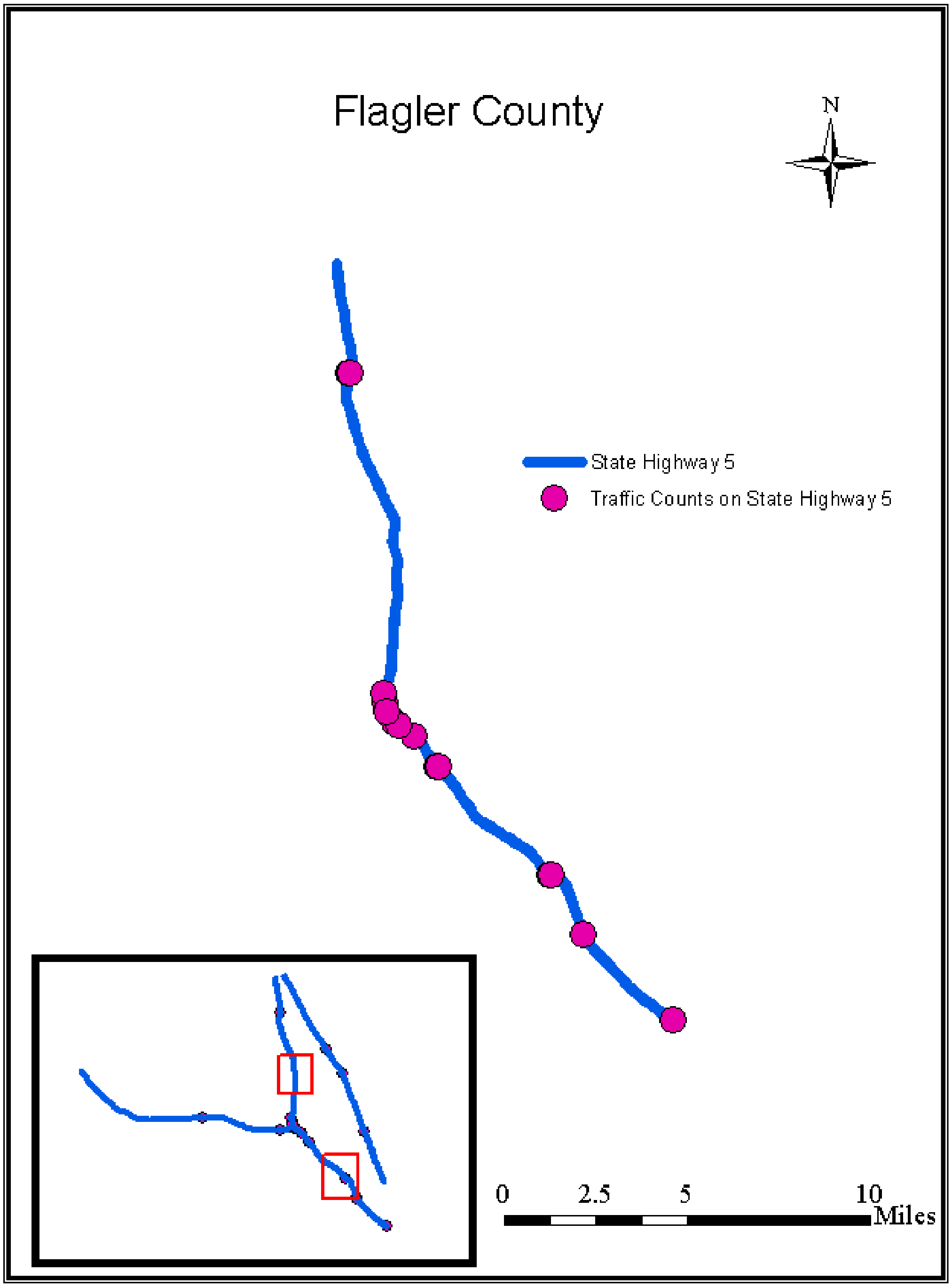

Figure B.5: AADT Assignment on State Highway 5

APPENDIX C. Type III Roads

The Type III streets only account for 5% in the whole network. They mainly include: Vehicle Trail, Ramp, Cul-de-sac, Traffic circle, Serve drive, Driveway, Road in parking area, and Alley. Traffic counts on these types of roads are extremely limited, and the samples available in this study are too small to build an AADT prediction model. Due to this reason, we feel that it is very hard to estimate the AADT values on these streets without large-scale field data collection. To demonstrate the conclusion we made on the Type III streets, great efforts have been made to take a large number of field aero photos from GOOGLE EARTH.

Based on large scale observation, it is found that Type III roads are composed of various assistant streets. It is improper to apply linear regression to predict AADT for these roads for the following reasons.

1) Too limited traffic count stations are available on these roads. That means sample size for regression analysis is insufficient.
2) Type III roads vary dramatically on road characteristics and function, and traffic volumes carried on Type III roads are incomparable between each other. That means the error term is not identically distributed.
3) Traffic volume on Type III roads strongly relies on utilities nearby, rather than roadway parameters or social economic factors. That means there is no strong linear relationship between AADT on Type II roads and the independent variables we have selected in this study.

APPENDIX C. (Continued)

Table C.1: Local Street

FCC	Description
A40	Local, neighborhood, rural road, city street, major category
A41	Local, neighborhood, rural road, city street, unseparated
A42	Local, neighborhood, rural road, city street, unseparated, in tunnel
A43	Local, neighborhood, rural road, city street, unseparated, underpassing
A44	Local, neighborhood, rural road, city street, unseparated, with rail line
A45	Local, neighborhood, rural road, city street, separated
A46	Local, neighborhood, rural road, city street, separated, in tunnel
A47	Local, neighborhood, rural road, city street, separated, underpassing
A48	Local, neighborhood, rural road, city street, separated, with rail line

Table C.2: Vehicular Trail

FCC	Description
A50	Vehicular trail, road (4WD) vehicle, major category
A51	Vehicular trail, road (4WD) vehicle, unseparated
A52	Vehicular trail, road (4WD) vehicle, unseparated, in tunnel
A53	Vehicular trail, road (4WD) vehicle, unseparated, underpassing

Table C.3: Ramp and Circle

FCC	Description
A60	Access ramp, not associated with a limited-access highway
A61	Cul-de-sac, the closed end of a road that forms a loop or turn around
A62	Traffic circle, the portion of a road that forms a roundabout
A63	Access ramp, cloverleaf or limited-access interchange
A64	Service drive, provides access to businesses and rest areas

APPENDIX C. (Continued)

Table C.4: Other Facility

FCC	Description
A70	Other thoroughfare, major category
A71	Walkway, nearly level road for pedestrians, usually unnamed
A72	Stairway, stepped road for pedestrians, usually unnamed
A73	Alley, road for service vehicles, located at the rear of buildings
A74	Driveway
A75	Road, parking area

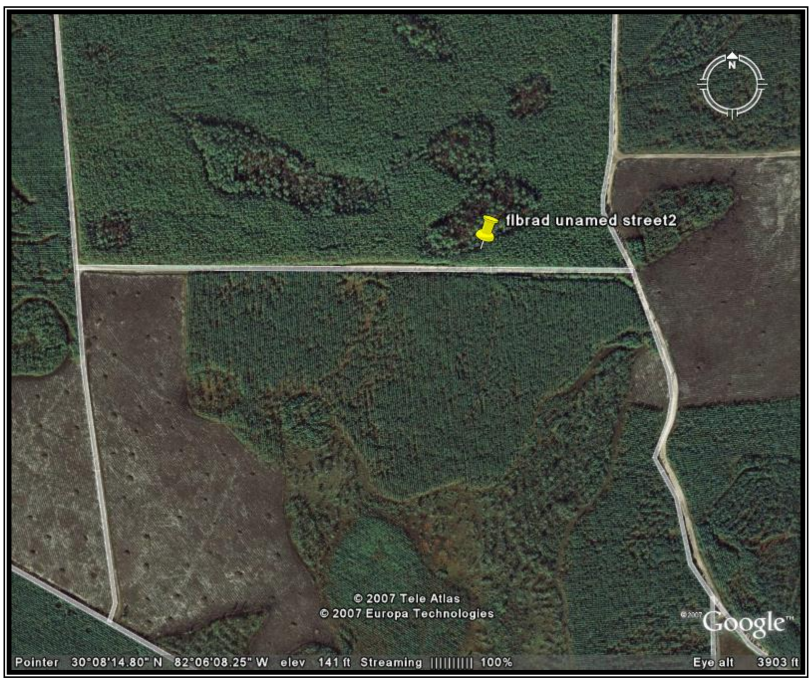

Figure C.1: A40 Unnamed Street in Brad County (Local Street)

APPENDIX C. (Continued)

Figure C.2: Bismark Road (Local Street)

Figure C.3: 4wd Road (Vehicular Trail)

APPENDIX C. (Continued)

Figure C.4: Trail (Vehicular Trail)

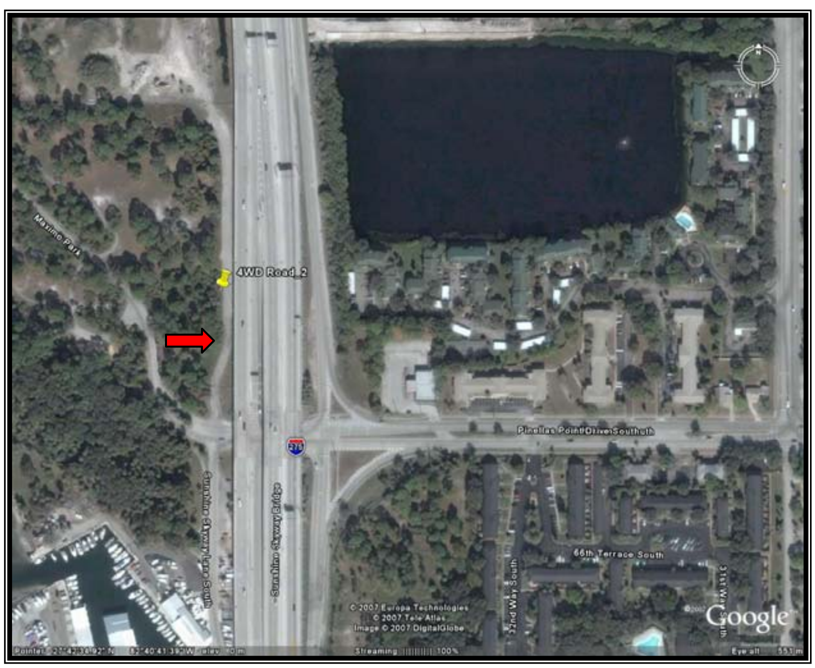

Figure C.5: Trail 2 (Vehicular Trail)

APPENDIX C. (Continued)

Figure C.6: Ramp (Ramp)

Figure C.7: Connecting Road (Ramp)

APPENDIX C. (Continued)

Figure C.8: Minnesota Road (Circle)

Figure C.9: Suntree Road (Circle)

APPENDIX C. (Continued)

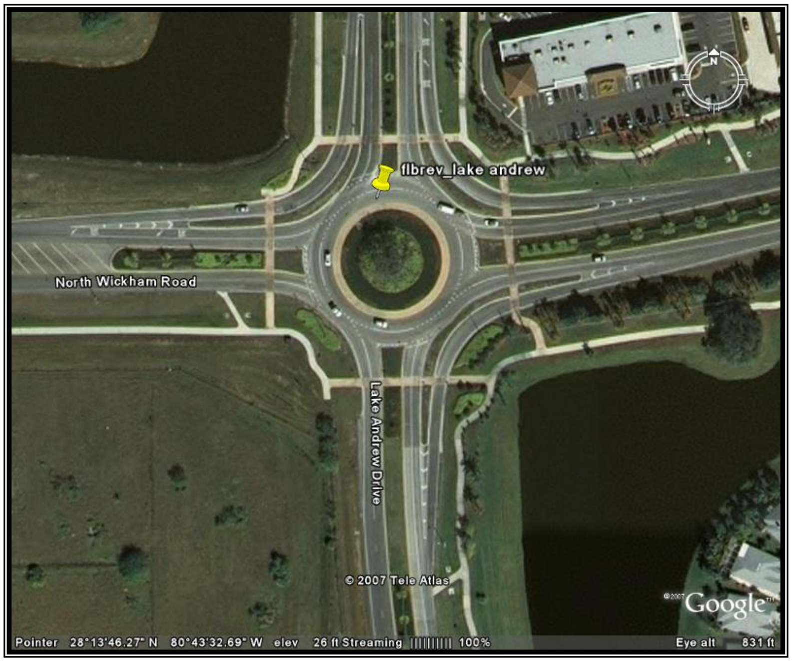

Figure C.10: Lake Andrew (Roundabout)

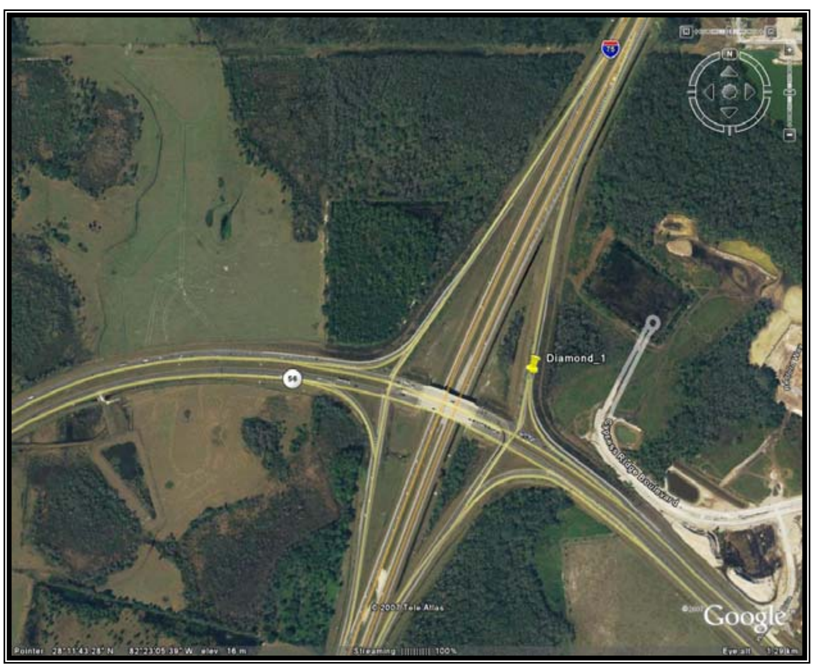

Figure C.11: Diamond Ramp (Ramp)

APPENDIX C. (Continued)

Figure C.12: Service Road (Service Drive)

Figure C.13: Driveway

APPENDIX C. (Continued)

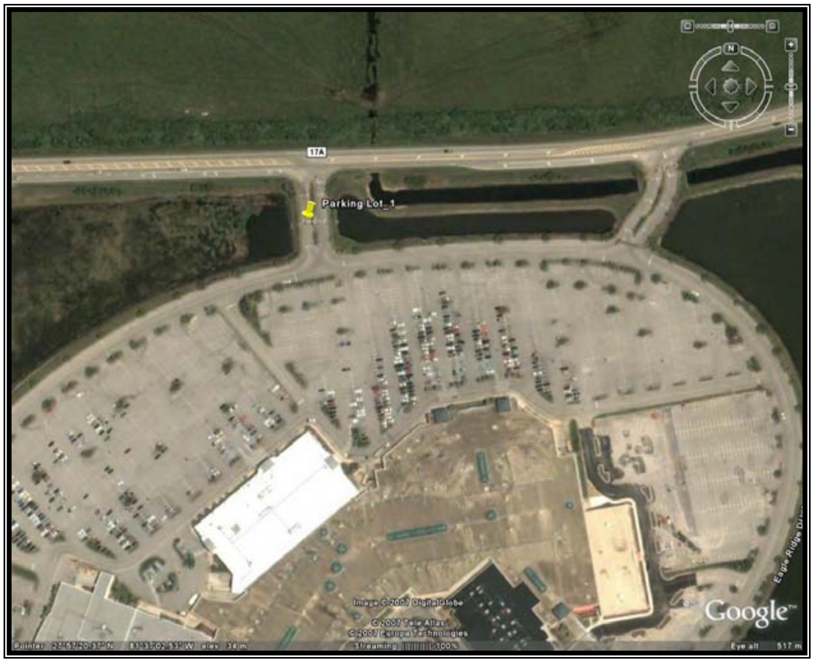

Figure C.14: Park Area

APPENDIX D. County Group

Table D.1: County Group based on Population

ID	Group	County Name	Population
1	Large Metropolitan	Miami-Dade	2475388
2		Broward	1833871
3		Palm Beach	1290275
4		Hillsborough	1113288
5		Orange	1043057
6		Pinellas	972080
7		Duval	856085
8		Polk	531147
9		Lee	506395
10		Brevard	501814
11		Volusia	478425
12		Seminole	400380
13	Small-Medium Urban	Pasco	384592
14		Sarasota	355972
15		Collier	321373
16		Escambia	315016
17		Manatee	298140
18		Marion	291154
19		Leon	264987
20		Lake	240896
21		Alachua	239804
22		Osceola	214215
23		St. Lucie	212907
24		Okaloosa	177289
25		Clay	157197
26		Charlotte	153873
27		Bay	153744
28		St. Johns	144096
29		Martin	142393
30		Hernando	141550
31		Santa Rosa	131376
32		Citrus	128837
33		Indian River	128750
34		Highlands	100225

APPENDIX D. (Continued)

Table D.1 (Continued)

ID	Group	County Name	Population
35	Rural Area	Monroe	77328
36		Sumter	71902
37		Putnam	71365
38		Columbia	64650
39		Nassau	64559
40		Flagler	59021
41		Jackson	49619
42		Walton	47587
43		Gadsden	46796
44		Hendry	44306
45		Okeechobee	41598
46		Suwannee	39585
47		Desoto	39370
48		Levy	39162
49		Hardee	33924
50		Wakulla	28615
51		Bradford	27994
52		Baker	24365
53		Washington	23323
54		Taylor	21067
55		Madison	20235
56		Holmes	19608
57		Gilchrist	16542
58		Dixie	15495
59		Hamilton	14881
60		Union	14451
61		Calhoun	14176
62		Glades	13487
63		Gulf	13274
64		Jefferson	12854
65		Franklin	11813
66		Lafayette	8001
67		Liberty	7642

APPENDIX E. The Social Economic Database for Florida Counties

Table E.1: The Social Economic Database for Florida Counties (2005)

County	Population	Mileage	Vehicle	Municipality	Labor Force	Income	Retail sales
Alachua	18527	1480	193498	119964	123350	18527	2627159800
Baker	16673	837	24849	5399	10859	16673	150177200
Bay	21472	1395	171698	102720	83838	21472	2085346000
Bradford	15992	404	26984	7557	11581	15992	140709800
Brevard	25338	3162	503902	344638	256536	25338	6032675600
Broward	22165	5115	1333056	2216047	946775	22165	24431648800
Calhoun	13263	547	13527	3045	5200	13263	82358600
Charlotte	27497	2486	166855	17478	62267	27497	1657418600
Citrus	128837	2617	163775	10064	52328	23520	1401444200
Clay	157197	1120	167949	16561	83887	24969	1796073800
Collier	321373	1292	283778	48096	147722	34132	5138781400
Columbia	64650	1184	66556	10480	28510	14667	591838000
Dade	2475388	8798	1560708	1297192	1151712	17344	26876917400
De Soto	39370	471	32104	6840	13952	12436	271248600
Dixie	15495	457	18352	1939	5562	18397	44554800
Duval	856085	3791	677061	849435	433512	22153	11476711200
Escambia	315016	2371	252673	55281	136817	21254	3620050200
Flagler	59021	813	76656	59239	29448	32430	401300400
Franklin	11813	368	12935	3339	5055	18663	95141400
Gilchrist	16542	557	42465	15836	20162	15680	299095400
Glades	13487	224	19830	3399	7055	16030	43645400
Gadsden	46796	867	10118	1732	4286	15700	2340000
Gulf	13274	317	16687	4958	6444	14400	63694800
Hamilton	14881	612	12376	3280	4626	8591	53086800
Hardee	33924	609	24286	10361	11721	7878	171138000
Hendry	44306	443	39574	11847	17202	8397	353976000
Hernando	141550	1833	159449	6912	57643	22926	1213458000
Highlands	100225	1640	104669	20962	40280	18244	808460800
Hillsborough	1113288	5338	970179	383109	596028	25837	15696675600
Holmes	19608	840	19487	4079	8284	16804	53215800

APPENDIX E. (Continued)

Table E.1 (Continued)

County	Population	Mileage	Vehicle	Municipality	Labor Force	Income	Retail sales
Lake	240896	2064	294639	119337	117393	24510	2337504000
Lee	506395	4619	569830	255654	272784	29995	7565003200
Leon	264987	1321	226763	166943	139602	24441	2949617600
Levy	39162	1193	52175	9208	16001	17272	290598200
Liberty	7642	464	7884	903	3405	21764	17384800
Madison	20235	771	19465	4029	7266	10780	84085400
Manatee	298140	1279	305062	74477	149758	24457	3041818400
Marion	291154	3543	329312	55218	127360	20662	3243623000
Martin	142393	542	143251	19156	64498	28576	2201889800
Monroe	77328	507	105021	55036	44651	29882	1345789400
Nassau	64559	984	76563	16123	31979	27434	477384000
Okaloosa	177289	1379	182484	77150	97865	24992	2909015800
Okeechobee	41598	426	47804	5634	16810	15042	375502200
Orange	1043057	4034	938702	356124	573640	22880	13574486000
Osceola	214215	1230	198032	83475	114591	19487	1992096800
Palm Beach	1290275	3622	979450	863186	617272	23658	19330602000
Pasco	384592	2012	406426	41504	177748	21834	3570871800
Pinellas	972080	4060	784051	749006	475340	24546	13151777600
Polk	531147	4020	558005	220014	262336	20468	4929128600
Putnam	71365	2012	84820	14332	30526	18050	558579600
Santa Rosa	131376	1772	142945	13074	64378	25389	952465800
Sarasota	355972	2418	360041	103623	178463	27674	4930959200
Seminole	400380	1574	403673	227760	226608	30209	6002229400
St. Johns	144096	925	162811	19410	81144	34490	1628020000
St. Lucie	212907	1618	223133	147983	110016	23316	2186050200
Sumter	71902	658	68446	8222	27297	21143	284887800
Suwannee	39585	1405	49610	7111	16389	15178	309790400
Taylor	21067	859	24955	6603	8612	17668	186670000
Union	14451	294	12339	2098	90187	15236	29972600
Volusia	478425	3044	471475	438886	239707	23674	5210287000

APPENDIX E. (Continued)

Table E.1 (Continued)

County	Population	Mileage	Vehicle	Municipality	Labor Force	Income	Retail sales
Washington	23323	1246	24827	5024	12429	21297	130457800
Jefferson	12854	615	15374	2379	6631	20653	73796200
Lafayette	8001	468	7873	1055	2715	13071	42899600
Indian River	128750	997	130766	46924	58055	27238	1752925000
Jackson	49619	1528	48248	17797	21124	12339	410321000
Wakulla	28615	871	32470	684	13677	21971	95548000
Walton	47587	1291	56730	7022	29664	24303	330914800