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ESTIMATION OF TRUCK VOLUMES AND FLOWS

FINAL REPORT
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Submitted by

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16. Abstract

This research presents a statistical approach for estimating truck volumes, based primarily on classification counts and information on roadway functionality, employment, sales volume and number of establishments within the state. Models have been created that may predict truck volumes, flows and percentages at any given location in the state highway network. Profiles of truck traffic are developed for selected roadways, indicating the AADT, truck and passenger car volumes and percentages. The procedure has been modeled into a GIS framework, facilitating data analysis and presentation.

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ABSTRACT

Freight transportation plays a vital role in the development and prosperity of New Jersey. Estimates say that more than 375 million tons of freight is transported each year in New Jersey. Trucks dominate this transportation, carrying 283 million tons. The 1997 CFS survey reported that about 67 percent of the freight tonnage that originates in New Jersey stays in the state, indicating that the truck traffic is mainly regional or local.

Trucks negatively impact the roadway network, primarily because of their massive weight and poor operating characteristics. These factors result in a stronger need for truck traffic estimation. Such an estimate can be helpful in pavement and bridge design and management, reconditioning and reconstruction of highway pavement, planning for freight movements, environmental impact analysis, and investment policies.

This research presents a statistical approach for estimating truck volumes, based primarily on classification counts and information on roadway functionality, employment, sales volume and number of establishments within the state. Models have been created that may predict truck volumes at any given location in the state highway network. Profiles of truck traffic are developed for selected roadways, indicating the AADT, truck and passenger car volumes and percentages. The procedure has been modeled into a GIS framework, facilitating data analysis and presentation.

ESTIMATION OF TRUCK VOLUMES AND FLOWS

In response to the RFP from NJDOT's Project # 2004-27, the following research was carried out. The research aims at providing a tool for the planning division at NJDOT to quickly and accurately estimate truck volumes, flows and percentages on the New Jersey roadways. It analyzes and builds mathematical models for the estimation of trucks using the real observed classification counts collected throughout the state. It does not use any counts from any previous studies and models. The state has developed a traffic data collection program, through which traffic counts are taken at certain locations throughout the state. A limited number of locations are surveyed each year due to budgetary constraints. An effort is made to provide a good coverage through these counts (geographical, temporal, spatial, etc.) The scope of this work is to determine whether these data could be used to develop a profile of traffic (truck volumes and percentages) on roadways where traffic counts are not available.

The objectives of this study can be enlisted as:

- Develop a database of truck classification counts, directly linked to existing NJDOT database systems.
- Develop methodologies for calculating truck volumes, flows and percentages on Interstates/Freeways, and principal arterials where some count information is available, and on lower facilities (principal and minor arterials) where little or no count information is available.
- Apply the methodology to New Jersey roadways to develop a geographic information system (GIS) database of truck volumes, flows and percentages.
- Evaluate the methodology and the database developed using actual data collected through the NJDOT traffic monitoring system.
- Validate the method on a selection of at least twelve highways, including four Interstate/Toll Authority routes, four principal arterials, two urban major arterials, and two rural major arterials.

The proposed method is not intended to "replace" or "compete" with existing methods. It is not built as a freight-forecasting tool. The tool developed here will help planners to obtain truck volume, flow and percentage profiles on NJ roadways for use in their decision making processes, without having to run freight forecasting tools which require more time and effort, a large number of data items and large amount of data, and a big number of assumptions to be made. Furthermore, this kind of activity is typically outsourced to consultants by state DOTs. With this tool available, information will be readily available, in-house, through an easy to use tool.

RESEARCH PROBLEM STATEMENT & BACKGROUND

Freight transportation plays a vital role in the development and prosperity of New Jersey. More than 375 million tons of freight are transported each year in New Jersey. Trucks dominate this movement, accounting for 283 million tons (Wieder, 2001). According to the US Bureau of the Census, about 95 percent of all trips taken by trucks are less than 200 miles in length; so most truck traffic is regional or local. This holds true in New Jersey, where most of the truck trips are intrastate, according to the 1997 Commodity Flow Survey (CFS). The CFS survey reports 67 percent of the freight tonnage that originates in New Jersey stays in the state. Truck trips are more regional and generally longer distance than auto trips; therefore less local. While almost all of the daily passenger auto trips (work and recreation) are less then 40 miles in length, 22.5 percent of truck trips are over 50 miles in length.

Trucks impact the New Jersey roadway network in several ways. First, trucks, because of their weight, cause significant degradation of the highway pavements and bridges. A single tractor-trailer can equal the impact of 1000 or more passenger cars. Second, trucks significantly impact roadway capacity because of their poor operating characteristics, especially on two-lane roads where passing is difficult. As truck volumes have grown dramatically in the past few years, so has the need for better methods to estimate truck volumes, percentages and flows on major truck volume facilities such as interstates and principal arterials, as well as on minor arterials with lower truck volumes. Common uses of truck volume information include the following:

- Pavement and bridge design
- Pavement and bridge management
- Scheduling the resurfacing, reconditioning, and reconstruction of highways based on projected remaining pavement life
- Prediction and planning for freight movements
- Modeling and prediction of traffic flow, capacities, congestion levels and lane needs
- Providing traffic input for the design of the overall highway system
- Development of weight enforcement strategies
- Vehicle crash record analysis
- Environmental impact analysis, including air quality studies
- Analysis of alternative highway regulatory and investment policies

Due to budgetary constraints, classification counts can be conducted on only a small percentage of roadway sections in the state. Estimations of truck volumes for all roads are extrapolated from these counts. Not only is the sample size limited, but also the estimation techniques are generally simplistic.

Truck volumes on a given route may be divided into two categories: through-traffic and local access. Through-traffic refers to trucks traveling to distant destinations; local access refers to trucks traveling to land uses adjacent to the roadway. Each category has unique characteristics. For example, long distance, or through-travel is likely to be subject to different economic motivations than local traffic, and would be sensitive to truck generating facilities such as warehouse and port locations. In addition, local traffic would be sensitive to the placement of retail businesses. Techniques to estimate truck information must account for the unique characteristics of both local and through-truck traffic.

On interstate highways and other higher type facilities, at interchanges (or intersections) with lower volume facilities, truck trips to and from local origin and destinations generally occur at lower truck percentages than the mainline route, except at locations of ports, major industrial, and truck facilities where higher truck percentages occur.

Validation of estimation methodology must be performed on all types of facilities: higher type roadways, principal arterials and local roads. For higher type roadways, such as the Interstate system, most, if not all, truck traffic is through-traffic. For principal arterials, the traffic is split between the two uses. For minor arterials and local roads, most, if not all, truck traffic is local traffic. Local truck traffic is a function of adjacent land uses.

RESEARCH PLAN

Ideally, a State Department of Transportation should be able to provide users with an estimate of the amount of truck traffic by type of truck on each road segment under their jurisdiction. Truck volume and percentage estimates should be made available for the date when data were collected and as annual average daily traffic estimates which have been corrected for seasonal and day-of-week variation. Annual average daily truck volumes, preferably by truck type, is a very useful measure for some analysis such as pavement design, but other average statistics, such as average peak hour truck volume, may be more appropriate for traffic analysis.

For this study, a procedure was developed for estimating truck traffic on all roadways in the state. Eight tasks were identified as in the RFP. Below is table 1 showing the various tasks undertaken in the project.

Table 1: List of Tasks

TASK	DELIVERABLES
Task I.1	Literature Review
Task II.1	Technical Memorandum of the data activities. A GIS database including a line layer for roadways and a point layer for existing traffic counts.
Task II.2	Technical Memorandum of the major truck generators. Additional GIS point layer including route, direction, and milepost, and type of facility.
Task II.3	Technical Memorandum of the criteria or factors that define changes in truck flow and is used in the definition of segments. Additional GIS line layer with the defined roadway segments for twelve sample roadways.
Task II.4	Technical Memorandum of the analysis of the relationships between truck volumes and adjacent land use, population and employment.
Task II.5	Technical Memorandum of the methods developed and the software to perform the calculations.
Task II.6	Technical Memorandum of the validation effort to estimate truck flows on at least four Interstate/Toll Authority routes, four principal arterials, two urban major arterials, and two rural major arterials.
Task II.7	Technical Memorandum describing application of methodology on a statewide basis. List of supplemental counts (if necessary) on a statewide basis.
Task II.8	Quarterly Progress Reports

LITERATURE REVIEW

Knowledge of the truck volumes on the local, state and inter state highways has been important for the highway authorities and the government because of their strong influence on the economy of the state and the nation, and the influence on the pavement design and planning systems. Studies for estimating truck flows and volumes by type and weight of vehicle provide the authorities with good statistics of the freight system to thereby plan for improving the traffic and pavement designs and improve air quality and maintenance.

Freight transportation affects the nation's economy, businesses, industries and the consumer. In general, the freight service providers extend beyond the trucks and include water and air freight carriers, railroads and combinations thereof, but it has been seen that the shipments by truck alone, account for more than half (53%) of the total tonnage, more than two-third (72%) of the shipments by value and nearly one quarter (24%) of the total ton miles in US. (1)

Freight transportation by truck has a major impact on the roadways it uses as it influences the traffic conditions. It has been shown that a single tractor-trailer equal the impact caused by 1000 or more passenger cars. (2) It affects the local roadway capacity because of its poor operating characteristics and its large dimensions. A method for estimating truck traffic is important to determine these impacts. To determine the accuracy of the methods to estimate truck flows of a local, regional or national level, their estimates should be checked against classification counts, conducted by the states or local authorities.

This section of the report reviews existing literature in two main areas, which are of primary interest to this project: *Freight Data Collection* and *Freight Modeling.* Each of these sections is further divided as: in the *Freight Data Collection section*, which discusses about the basic structure for the state traffic monitoring program and the types of counts employed for the data collection procedure. It also reviews various factors causing variations in the traffic and the types of these variations. Lastly, the adjustment procedures used to adjust counts for traffic variations are briefed upon.

In the *Freight modeling section*, the software packages and general tools available are firstly discussed, followed by the different model applications conducted by different States.

Freight Data

<u>Introduction</u>

States and local highway agencies need to comply with the Highway Performance Monitoring System (HPMS) and report the traffic data collected to the Federal Government. A comprehensive data program needs to be built by the highway agencies to meet these defined data collection requirements. Traffic Monitoring Guide (TMG) specifies that a sufficient number of traffic volume counts with vehicle classification data is the foremost requirement for any study. TMG recommends states to improve the quality of reported traffic data by establishing control processes and subjective editing procedures which may identify the missing or invalid data and thereby reduce the bias in the results. An efficient system comprises of a good relationship and network between the different sources, agencies and authorities in the same field of work. This relationship and network helps in adopting common standards in data collection and recording procedures and collecting and summarizing data from various agencies. This way inconsistency in data classification methods is minimized and potentially eliminates the invalid data to get accounted for with utmost economy. “For example, as mentioned in TMG, truck weights and volumes may be monitored at the State’s borders by the agency in charge of collecting or enforcing the collection of truck fuel taxes.” Furthermore, many local authorities in the state install and operate traffic counters, the data from which can be used to supplement the counters operated by the state. These counts may provide more information on seasonal travel patterns in areas where monitoring those patterns is not feasible, but important.

Nevertheless, a well-designed data collection program may also be defined as the one that consists of such traffic monitoring equipment, which can provide with more than one type of the data at a time, such as permanently installed sensors and electronics at a WIM site which can be used for continuous vehicle classification and volume data collection even when weight data are not collected.

Traffic Counts

According to the Traffic Monitoring Guide, the primary data collection plan includes:

- A large number of short duration count collectors
- An appropriate number of permanent and continuously operating sites undertaking a continuous count program

Short Duration Counts

These counts are collected on specific roadway segments to ensure highway agencies of the validity of truck counts on arterial and major collector roads. They give segment-specific traffic count information. TMG recommends collection of short duration counts over a 48-hour period. TMG also recommends states to develop a structured coverage program that provides a geographically diverse set of roadway locations to address most needs of the study. Short duration counts do not account for temporal variations in traffic, such as seasonal and day-if-week variations. Short duration counts need to be factored to adjust the overall traffic data (from short-term monitored sites), to estimate the annual traffic data.

The classification counts at the short duration count stations are taken for a 48-hour period using the standard FHWA 13 vehicle categories. These 13 vehicle categories are tabulated in table 2 and are shown in figure 1.

Table 2: FHWA Vehicle Classification Scheme
(Source: NJDOT, FHWA vehicle classification schème)

Class 1	Motorcycles. All two- or three wheeled motorized vehicles. This category includes motorcycles, motor scooters, mopeds, and all three-wheel motorcycles.
Class 2	Passenger Cars. All sedans, coupes, and station wagons manufactured primarily for purpose of carrying passengers.
Class 3	Other two-axle, four-tire single units. Included in this classification are pickups, vans, campers, and ambulances.
Class 4	Buses. All vehicles manufactured as traditional passenger-carrying buses with two axles and six tires or three or more axles.
Class 5	Two-Axle, Single Unit Trucks. All vehicles on a single frame including trucks, camping and recreation vehicles.
Class 6	Three Axle Single Unit Trucks. All vehicles on a single frame including trucks, camping and recreational vehicles.
Class 7	Four or more Axle Single Unit Trucks. All vehicles on a single frame with four or more axles.
Class 8	Four or Less Axle Single Trailer Trucks. All vehicles with four or less axles consisting of two units, one of which is tractor or straight truck power unit.
Class 9	Five-Axle Single Trailer Trucks. All five-axle vehicles consisting of two units, one of which is a tractor or straight truck power unit.
Class 10	Six or More Axle Single Trailer Trucks. All vehicles with six or more axles consisting of two units, one of which is a tractor or straight truck power unit.
Class 11	Five or Less Axle Multi-Trailer Trucks. All vehicles with five or less axles consisting of three or more units, one of which is a tractor or straight truck power unit.
Class 12	Six Axle Multi-Trailer Trucks. All six-axle vehicles consisting of three or more units, one of which is a tractor or straight truck power unit
Class 13	Seven or More Axle Multi-Trailer Trucks. All vehicles with seven or more axles consisting of three or more units, one of which is a tractor or straight truck power unit

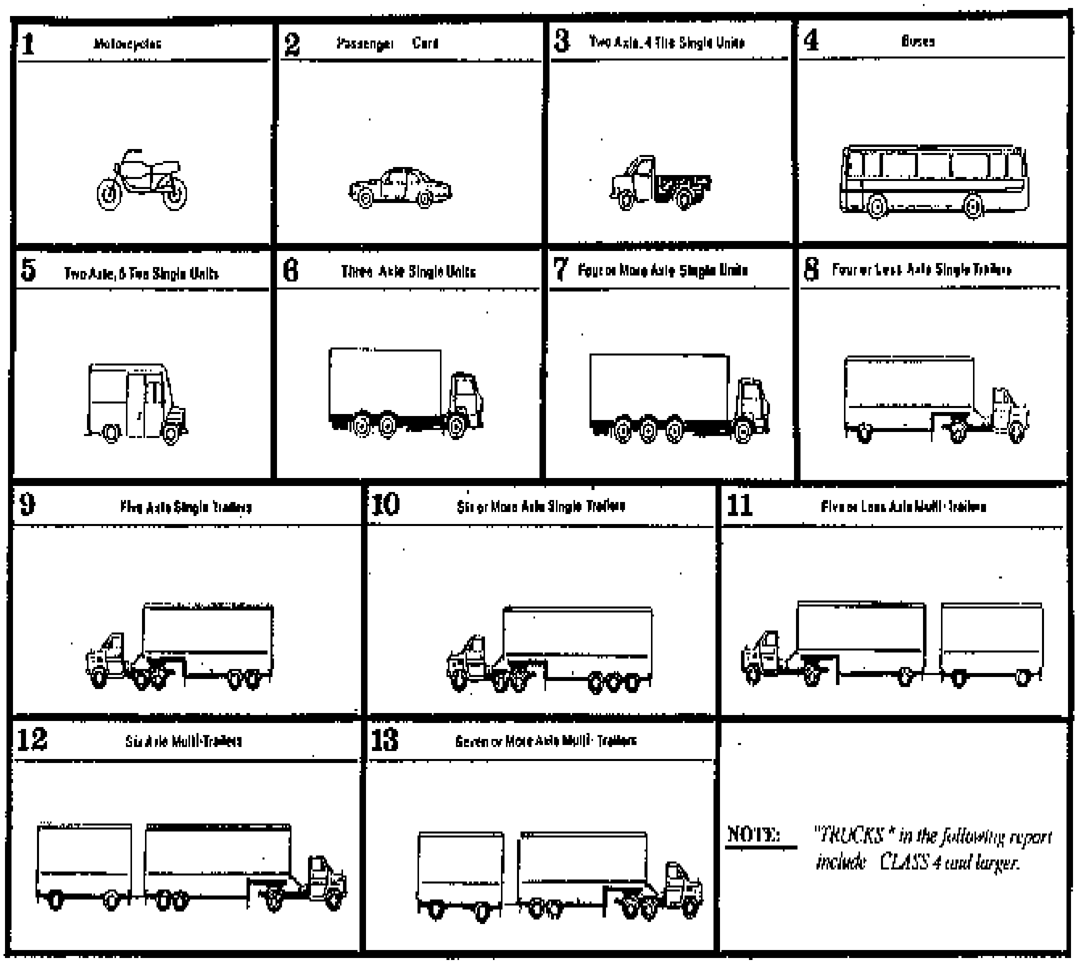

Figure 1: Automatic Vehicle Classification
Source: 2001 Report (Vermont Agency of Transportation)

In some locations, equipment limitations prevent such collections, in which cases highway agencies are encouraged to use a simplified classification scheme suited to their equipment and needs. Many states are found to consistently use fewer vehicle classes in their count collection systems. Figure 2 shows the vehicle classification adopted by the New York State Thruway. In general, the four broad categories of vehicles used are: Passenger Cars, Single-unit Trucks, Combination Trucks, and Multi-Trailer Trucks. The goal for every highway agency is to collect enough data that can provide a valid estimate of the truck counts on each route.

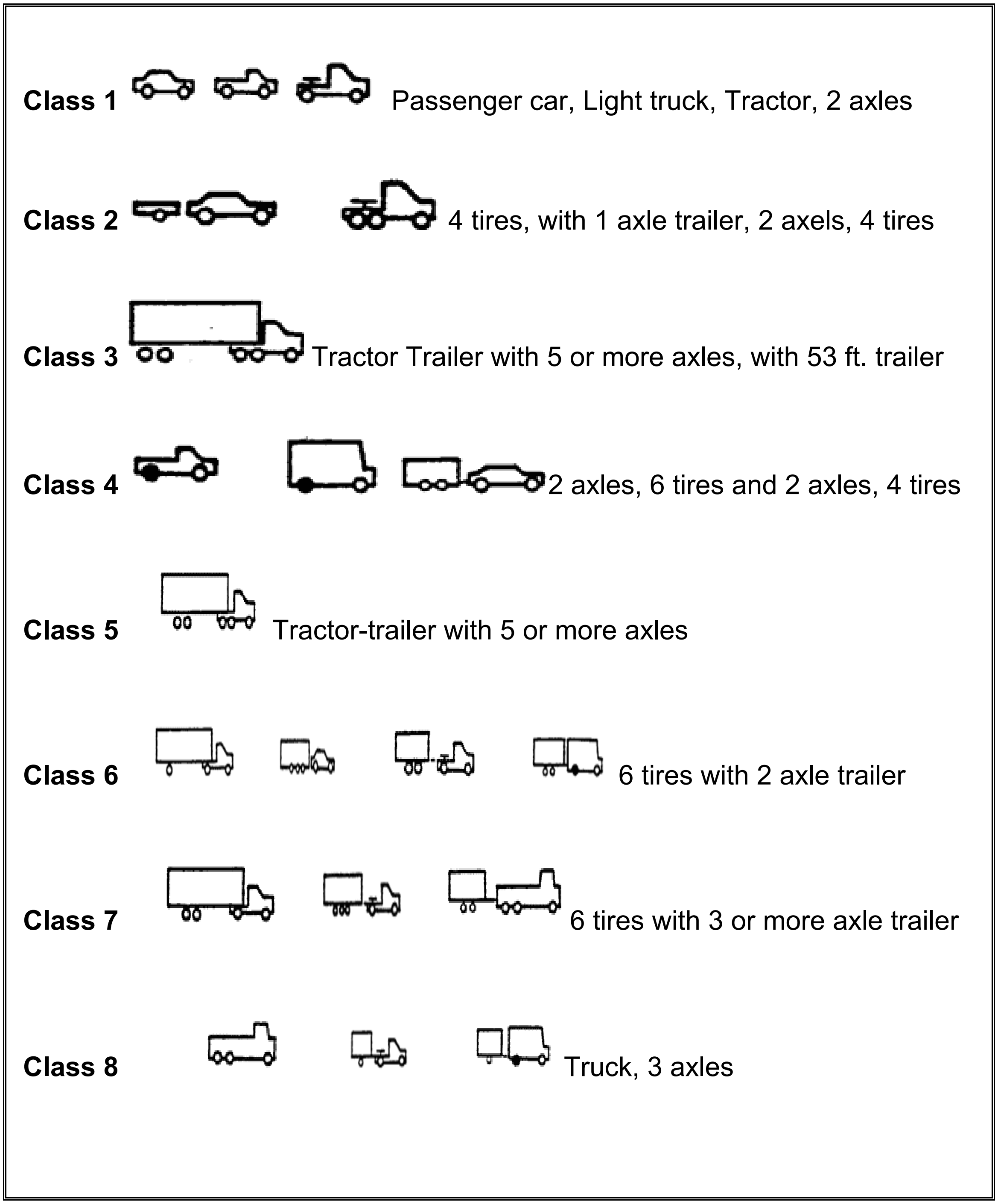

Figure 2: New York State Thruway: Vehicle classes

Unlike the continuous count locations, the short duration counters can be placed at different location depending on the need. They are mobile and can be shifted. Short duration counts providing the geographic coverage can be a part of the statewide monitoring effort or can be site-specific project counts. At times when more extensive data is required for a project, special counters are installed catering to the needs of the project. According to the NJDOT Bureau of Data Development, short duration counts are collected at 3,000 locations throughout the state of New Jersey among which 500 are with the classification counts. On an average, 1,000 locations are covered each year, with a cycle period of three years. (2)

Continuous Count Program:

Data is collected from the continuous counters to understand the temporal changes in traffic volume. The site is composed of sensors cut into the pavement while computer equipment at the centers allows for the continuous recording of traffic data. Data is collected continuously, 24 hours a day all around the year. It provides the basis for determining design hourly traffic factors, fluctuations in traffic on recreational roads, weekend traffic patterns etc. Continuous counters provide the controls for adjusting short-term counts to average daily traffic.

For selecting the continuous count locations, a statewide need is first determined. If a project is in the hands of the state, the specific project locations are prioritized. Then depending on the funds available, more count stations may be placed. For statewide surveys a combination of special and present counters is made to work together. The most commonly used device for the continuous data collection is the Automatic Traffic Recorder (ATR). ATR data collects hourly volumes for a lane. The data collected is periodically sent to the central system where it is evaluated and summarized for calculating the various statistics such as AADT, AAWDT (weekday traffic), and adjustment factors for seasonal variations, lane distribution factors etc.

Many states are now combining the Automatic Traffic Recorders with the vehicle classifying equipment to study, maintain and develop the pavement and transportation system in a more efficient manner. The data collected by this combination can also be used to determine the seasonal adjustment factors for correcting traffic counts in estimating truck highway studies and in predicting the traffic volumes on roadways. The truck weight data is required for converting truck volumes into the axle load estimates as an input to the pavement design and maintenance procedures. WIM scales along with providing the truck and axle weight information provide the same data as the continuous vehicle classifiers and ATR. WIM scales can be used with a flat terrain, dry conditions and no curvatures on the roadway. The various WIM locations in New Jersey are shown in figure 3. Each WIM location shown in the map is linked with the traffic count table and the user is able to click on the location of the station to view the traffic information associated with that station.

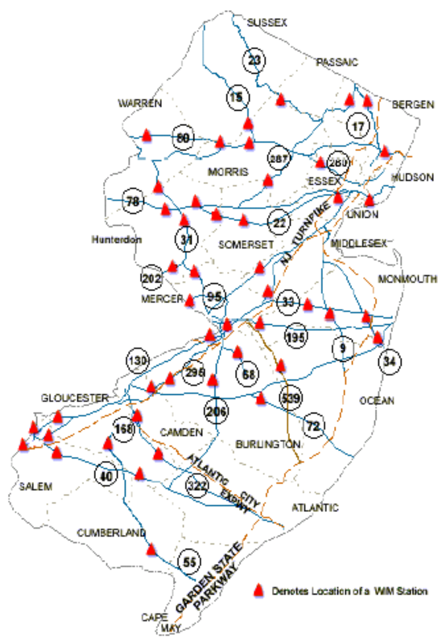

Figure 3: WIM-station Locations in New Jersey
(Source: http://www.state.nj.us/transportation/count/vclass/class_2001.html)

The data collected on each of these WIM stations is tabulated and made available for use at the DOT' s website. The table summarizes the Annual Average Daily traffic for prior years and shows the same by each month and vehicle class for the latest year.

The data from the different counting stations placed throughout the state are all tabulated in the same manner and the user can access these counts on the website: www.state.nj.us/transportaion/count/data/sub/files/99rtmpt.pdf. This site gives data for all seven days of a week, specifying the station and the direction of traffic. TMG recommends that for most truck weight groups, a minimum of six sites should be monitored and one of them is required to work continuously throughout the year to measure temporal changes in the loads carried by the trucks. When the in-ground sensors are used, a one-week count is recommended at all measurement locations that are not operated continuously. For a small state the basic recommendation is for 12 locations and 2-4 continuously operating sites. A large state with varied truck characteristics need to have 60 WIM sites. In general therefore the number of weighing locations in a State falls between 12 to 90 sites.

TRAffic DAta System

TRADAS is a software system used for collecting, editing, summarizing and reporting a wide range of traffic data. TRADAS Version 2 uses C++ and Oracle RDBMS. TRADAS has been inspired by the Chaparral System's traffic monitoring system developed for the New Mexico State Highway and Transportation Department. [4] TRADAS is designed to meet the AASHTO data processing requirements.

It processes all types of traffic data, e.g. roadway volume, speed, vehicle classification and weight, accommodating data from both the short duration and the continuous count stations, producing high quality traffic data. For producing high efficiency results, TRADAS performs services that include automatic detection of device type. Three levels of quality control (device, channel and count), data summarization, standard and ad-hoc reporting and database management are served.

TRADAS also produces the Public databases as an Oracle database, which helps in disseminating traffic data in a simple form. These databases are also developed in Microsoft Excel and Microsoft Access to make Public Databases easily accessible. Chaparral Systems Corporation has marketed TRADAS, which has become an ideal foundation for an excellent traffic data collection and analysis program.

Variations in Traffic Counts

The short duration counts need to be adjusted, so as to get reliable and unbiased estimates of traffic volume and flow. Total traffic volume, size of the vehicle and the loads carried by the trucks vary by month of the year, day of the week and time of the day. Research by Hallenbeck et al. 1997 has shown that the truck volumes vary by time and space. He also found out that the behavior of the truck volume on the roadway is different then those of the car volume. The variations in truck volumes on the roadways were found to be dependent on the following factors: (3)

1. Time of the day
2. Day of the week
3. Season/month of the year
4. Directional variations
5. Geographic variations

Time of the day:

Refers to the use of the road changes during the course of a day. The overall traffic volumes are observed to increase during the day and decrease at night. The truck traffic behavior depends mostly on the type of the truck, i.e. a long hauling inter-state truck or a business-day or typical short-hauling truck. The interstate long-hauling through trucks travel generally at constant rate throughout the 24-hour day, whereas the business-day or typical trucks are found to show a characteristic high or low in the volume during the day rather similar to other vehicles. These variations are shown in the figure 4.

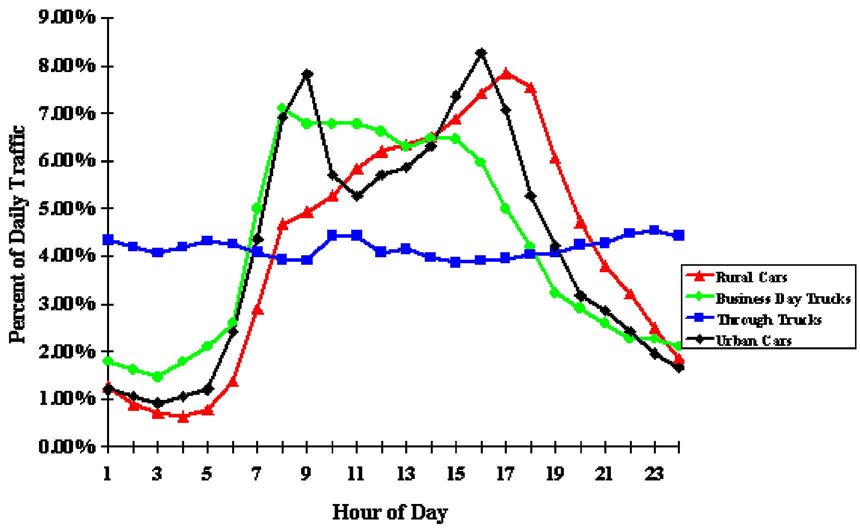

Figure 4: Basic Time of day Pattern.

Variations can also be understood with reference to different vehicle classes. There is a pattern known as the 'business-trucking pattern', which fits most truck classifications. The smaller truck classifications (classes 5-8) usually follow this pattern and start and begin their trucking movements during the normal business hours in a day. Classes 11 and 12 follow the 'through truck' pattern shown in figure 4. The remaining truck classes (9, 10 and 13) switch from one pattern to another, depending on the truck traffic on each road. (5)

<u>Day of the week:</u>

Day of the week also influences the truck flow behavior. Weekday truck volumes are found fairly constant, with a decline on the weekends. Long distance truck travels are not influenced by the day of the week, i.e. by a business day or a weekend and volumes do not show significant variations throughout a week. Therefore the roads with a high traffic of through trucks maintain high truck volumes during the weekends, even though the local truck traffic declines. In case of local or typical business-day trucks, the truck flow is higher on the weekdays with a decline at the weekends. These variations are shown in figure 5.

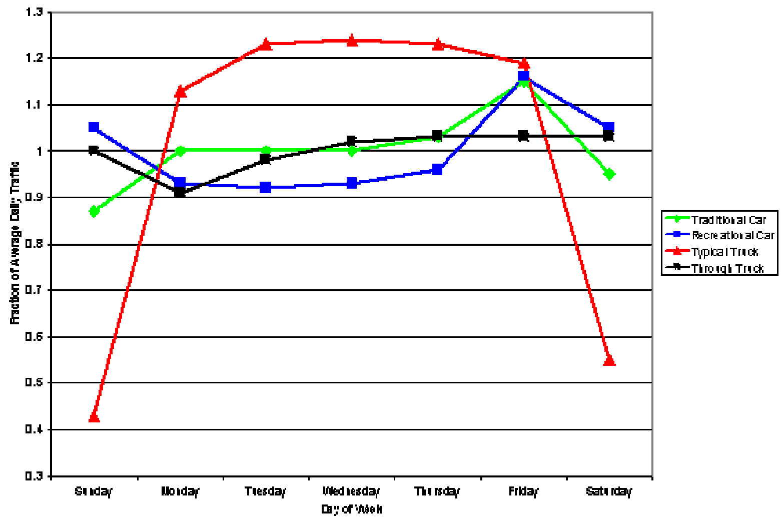

Figure 5: Typical Day-of-Week Traffic Pattern
(Source: TMG, 2001)

Local conditions prevailing in the area also affect the day-of-week pattern of specific vehicle classes. Recreational activities by car are important part of the local conditions, but freight movements can also create unusual day-of-week conditions.

Seasonal changes:

This refers to truck traffic changes over the course of the year. Some truck movements are found to be constant all around the year. Other truck travels and movements might be different, for example in case of agricultural areas where the weights carried by trucks vary by the season. Roads carrying primarily through trucks tend to have significant changes in their travel pattern due to the changing seasons, than the roads carrying local freight traffic. Figure 6 shows the seasonal variations in the traffic due to the season or month of the year. Truck volumes are generally significantly higher in the summer than the winter.

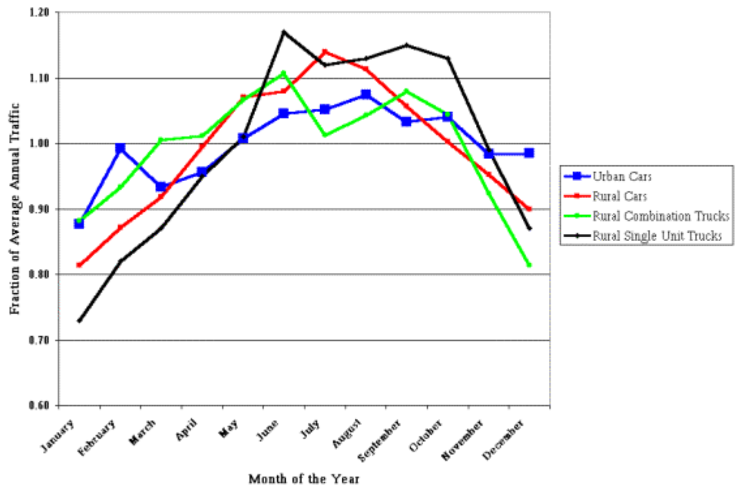

Figure 6: Typical Monthly Volume Patterns

<u>Directional variation:</u>

Directional characteristics are site-specific. These geographical differences depend on the level of commercial developments, other traffic generators in the study area, the nature of the traffic using the road etc. (5) Most of the roads are found to show variations in the traffic volume by direction. The traditional urban commute shows a heavy inbound movement in the morning and an outbound movement in the afternoon. In areas with high recreational traffic flows, travelers arrive in the area late Thursday night and depart on Sunday. In areas with mineral resources, a directional difference in the trucks is the movement of loaded trucks in one direction with a return movement of the empty trucks. Tracking these directional movements are important in estimating the impacts of the new developments on a rural land, along with the planning, design and operation of existing roadways.

<u>Geographic variation:</u>

This factor stresses upon the fact that the truck travel might vary from route-to-route and region-to-region. Example, California ski areas have different travel patterns than California beach highways.

"The distribution of vehicles among vehicle classes changes dramatically by geography and, to a lesser extent, by functional class of roadway. In particular, the presence or lack of multi-trailer trucks tends to be geographically based. These large trucks seem to be uncommon in eastern or southern states and much more common in the western states." [5]

Interstate and major intercity routes tend to have lower overall volume away from urban areas, but tend to carry greater percentage of trucks (as a higher percentage of truck trips are intercity trips).

Adjustment for the Variables

The variations described above need to be accounted for while collecting data, proposing designs and further in the implementation phases. To remedy the effects of variations, a large count sample is very important. At times, states are expected to review their respective data collection programs and refine their monitoring system. [3]

To monitor the traffic at the statewide level the recommended plan by TMG consists of:

- A modest number of continuously operating data, from the continuous count taking sites.
- A large number of short duration data collection efforts.

Most states have installed continuous counters to study the traffic volume patterns and to account for the variations in seasonal, day of week and time of day factors, so as to improve the accuracy of traffic estimates. Over the passage of time and with the improvements in the data collection equipment, continuous traffic monitoring data collection programs in use today include the automatic traffic recorders (ATR), automatic continuous vehicle classifiers (AVC), continuously operating weigh-in-motion sites (WIM) etc [3].

Truck volumes follow different patterns in the roadway than auto trips and overall traffic. Truck trips tend to be longer than auto trips as auto travel tends to be more local. As a result on higher level facilities, such as interstates, overall volumes are less, away from large urban areas, and truck percent is higher. The truck traffic often follows different seasonal and day-of-week trends than do total volumes by automobiles. Therefore, if truck movement patterns are to be accounted for, then traffic monitoring by vehicle classification becomes of utmost importance. Continuous operating vehicle classifiers most commonly use two types of classifiers, the axle classifier and the length classifier. The number and location of axles for each vehicle define the vehicle classification categories.

Factoring Traffic Counts:

Adjustments to traffic counts volumes are need to be made to account for variability in the traffic stream. A short duration count takes observations for the time it was in-use. [3] To use the data from the short duration counters to estimate the average conditions in the traffic stream, adjustments need to be made. The most common adjustments include the following:

1. Time of day adjustments for data collected for less than 24 hours. (TMG recommends a minimum period for data collection as 48 hours)
2. Day-of-week adjustments for data not collected for all seven days of a week.
3. Seasonal adjustments for data collected over a few days within a year.
4. Axle-correction adjustments for axle counts that do no convert the axle pulses to vehicle counts by vehicle classification

Creation of Factor Groups:

Factor groups may be defined as the groups of individual data records that may exhibit similar characteristics within them. These groups are generally used for data-mining and statistical analyses.

To create the factor groups for roadway systems, a group of roads is defined based on the traffic variation and the characteristics of the roadway. [3] All roads within the group are assumed to behave similarly. The mean value for the group is calculated and is used as the base measure to know how the roads within a group behave. The three mainly used techniques for the purpose of creating the factor groups are:

1. Cluster analysis
2. Geographical/functional assignment of roads to groups
3. Same road factor application

In the *cluster analysis*, a statistical analysis program, which uses a least-squares minimum distance algorithm, is used to determine the stations most similar. The similar stations are then further grouped and the next closest station is found thereafter. The output of the cluster program helps in knowing which stations have most similar traffic adjustment patterns as it gives a sequential list of the counters based on the similarities between them. In order to terminate the grouping process, the mathematical distances between the groups are considered. Too large changes in the distances between the groups indicate a logical point to stop. In another way, a predetermined number of groups can be set and the cluster process can be terminated at the point. It has been found difficult though in this process to exactly know which road fits in which cluster group. For this reason the cluster process is often modified by the use of secondary procedures to develop the final factor groups.

In the *geographical/Functional classification of the roads factor groups*, the procedure of allocating roads to factor groups is based on the available knowledge on the traffic patterns to the professional analyst. The knowledge is gathered from the combination of data summaries and professional experience with traffic patterns. The initial factor groups include:

1. Urban interstates and expressways
2. Other urban roads

3. Rural interstates
4. Other rural roads in the eastern portion of the state
5. Other rural roads in the western portion of the state
6. Recreational routes.

This characterization of the roadways makes it easy to assign roads to the factor groups. Once the factor groups are identified, the continuous counts data is examined. The mean and the standard deviation of the factor group is computed. These statistics help the analyst determine the size of the error for the defined set of roadways. This process helps in reducing the bias in short counts to produce reasonable annualized estimates of traffic.

Same Roads Application of Factor: In this process the factors are assigned from a single continuous counter to all road segments within the influence of that counter site. One thing important here is that the short count in question should be taken on the same road as the continuous counter. The boundary of the influence zone is marked on an intersection or a point where the nature of the traffic volume changes. This approach requires a large number of continuous counters on a network and a small number of roads against which the single-use factors can be applied.

Weinblatt and Margiotta have worked on the seven factoring strategies for adjusting the short duration counts. They have proposed different aggregations for each factor and at times have combined two factors into one. (3) Table 3 below summarizes the work done by Weinblatt and Margiotta for AADT estimates. They have found relatively similar results in terms of reduction in bias and the expected errors remaining.

Finally, it is important to stress here that these analyses hold good for the case specifics. States need to be aware of the differences in the total volume factors and the traffic volume generated by trucks alone. Trucks have different patterns and thus need to be treated with different factoring procedures.

Table 3: Effects of Alternative Current Year Factoring Procedures on AADT

	Mean Absolute Percentage of Error	Average Percentage of Error	Percent of Observations with Error > 20%	Number of Weekday Counts Required	Number of Weekday and Weekend Counts Required
Unfactored	12.4%	-0.6%	18.2%		
Separate Month and Day-of-Week	7.5%	-0.5%	6.2%	17	19
Combined Month and Average Weekday	7.6%	0.4%	5.9%	12	24
Separate Week and Day-of-Week	7.5%	-0.9%	6.0%	57	59
Combined Month and Day-of-Week	7.4%	-0.2%	5.8%	60	84
Combined Week and Average Weekday	7.3%	0.5%	5.1%	52	104
Specific Day	7.1%	0.2%	5.1%	261	365
Specific Day with Noon-to-Noon Factors	7.0%	0.3%	4.8%	261	365

<u>Computing AADT (Annual Average Daily Traffic)</u>

1. By vehicle classes
2. By simple average of all days
3. By average of all the averages, known as the AASHTO method

FHWA classifies vehicles into 13 categories based on their number of axles, length, weight etc. In the first method of computing AADT, a set of short duration classification counts on a road segment are obtained and without factoring it by any adjustment factors, the estimate of AADT by VC is obtained by dividing the counts by two. In other methods, a factored total traffic count is taken for the whole roadway section and short duration classification counts are used to distribute the estimate of total AADT across VC.

The second method was found easy to program. A simple average is made in this method for all 365 days in a year. In cases of missing data, the denominator is adjusted accordingly by subtracting the number of missing days from 365. This does cause some bias in the program because of the unequal number of weekday or weekend days get removed from the database.

The third method known as, AASHTO method accounted for the missing data. In this method the average monthly days of the week are first computed. Finally, the eighty-four values (84 = 12 months / 7 days) are averaged to yield the seven average annual days of the week.

<u>Denominator for monthly factor</u>
Here the only days that are included in the computation of denominator are the days that actually include in the data collection effort. Thus, the factor computed here applies directly to the count against which it is being applied.

<u>Denominator for weekly factor</u>
For a weekly factor, the denominator is simply the average of the seven days for the appropriate week.

<u>Errors in Calculating AADT</u>
To compute the error in the estimated values of Truck Annual Average Daily Traffic (TAADT) obtained from sample classification counts, University of Regina

studied two scenarios and finally a research note was published from where this abstract of the findings is made. [6] The first scenario revealed an improper factoring procedure that may be used by highway agencies. It found a substantial over estimate of truck traffic when truck counts were estimated using adjustment factors obtained from total traffic volume. In the second scenario, adjustment factors were obtained from the permanent automatic vehicle classifiers (PAVC) and here better estimates for the truck traffic were found.

Only PAVC are found to provide an accurate estimate of TAADT. However due to the budgetary and resource constraints, short-period counts are more commonly used by the agencies. The data from the short duration counters are factored thereafter, to estimate TAADT.

Weinblatt (1996) in his studies on the procedures, for estimating AADT and vehicle miles traveled (VMT) has made several recommendations to reduce truck AADT and VMT estimation errors through the categorization of highway sections and use of appropriate seasonal and day-of-week adjustment factors.

The study undertaken by the Regina University, studied on the eight PAVC sites representing a variety of highway types and traffic volumes. The trucks were grouped into three classes: single-unit, single-trailer and multi-trailer. Numerous observations regarding the temporal variations in truck type and volume were made by the use of 48-hour period sample count.

Two scenarios were studied for calculation of the adjustment factors. Scenario 1 assumed the adjustment factors are obtained from the permanent traffic counter reflecting the total traffic variations, rather than truck traffic variations. Scenario 2 assumed that the adjustment factors were obtained from a PAVC that has a truck traffic pattern similar to the short-duration count site present nearby. Estimation errors were calculated as

Error = [(Estimated TAADT – Actual TAADT)/ Actual TAADT] * 100

The statistical results of the report showed substantial overestimates of TAADT, when truck counts were estimated using factors obtained from the total traffic volume, because of large differences between the traffic variation patterns for the total vehicular traffic and the truck traffic. The width of the error interval varied from 50 –125 percent. In the case two, where appropriate adjustment factors are used, the expected width of the error interval got reduced to a large extent.

Results of the study also indicated a large margin of error while estimating the truck-type distribution from a single 48-hour count site. But at the same time, it was also found that increasing the frequency of the counts to two or three in a year reduces the error interval.

<u>Estimate of truck vehicle-miles traveled by use of seasonal & day-of-week factoring</u>

Classification count data needs to be adjusted for seasonal and day-of-week variations. Estimating truck vehicle miles traveled using unadjusted counts may produce wrong results. Several studies dealing with this issue are described next.

In a study by Herbert Weinblatt, an improved effort to estimate the truck Vehicle Miles Traveled (VMT) and Annual Average Daily Traffic (AADT) for combination trucks was made. The procedure uses the seasonal and day-of-week factoring recommended by the FHWA, to reduce the errors in truck AADT estimates and eliminate the upward bias in truck VMT estimates that result from un-factored weekday classification counts. [(7)]

When estimating the truck VMT, which were derived using the traditional count-based estimation techniques, Mingo and Wolff found out that there were large differences in the estimates, [(8)] reported by the VM-1, Table of Highway Statistics and the one from the Truck Inventory and Use Survey (TIUS). [9] They concluded the differences were due to two main sources:

- The derivation of truck VMT estimates is based primarily on the weekday classification counts, which may cause bias in the results.
- The seasonal and day-of-week factoring procedure distinguished four categories of the highway section and used different procedures for each category. The four categories were:
  - Sections that contain Permanent Automatic Vehicle Classifiers (PAVC)
  - Sections on which short-duration classification counts are collected periodically
  - Nearby sections on the same road as Category 1 or 2
  - All other sections of road

To develop the seasonal and day of week factors, the highway system is divided into at least three factor groups: urban, rural interstate and rural other. Permanent AVC's are established on a representative sample of five to eight sections in each factor group. AADT by vehicle class is estimated by applying the standard AASHTO process. Initially, an average for seven days of the week for each month is obtained for each vehicle class. These are further averaged across all 12 months to produce a single set of annual average days of the week (AADW). These seven AADW values are then averaged to produce estimated AADT for each vehicle class.

Short duration traffic counts obtained with AVC are collected for at least one 48-hour period at least once in 3 years. At locations where AVC cannot be used because of non-uniform speed, classification counts can be taken manually. If manual classification counts collected during part of a day are used at some sites, time of day factors should be used to convert these counts and estimate total traffic by vehicle class for that day. The raw 48 hr. counts do not provide good estimates of AADT by vehicle class.

Sections on the same roadway located a few miles apart are also considered for estimating AADT along the roadway. It has been observed that a section, which resembles the section containing the AVC, can produce better results and estimates of AADT by vehicle class rather than those obtained from the short duration count section of the roadway.

Highway sections in each functional system should be grouped on the basis of their traffic volumes using volume groupings given in the Highway performance monitoring system field manual. For each functional class and corresponding traffic-volume groups, a set of distribution factors is developed by aggregating the AADT by vehicle class estimates obtained from the AVC sites and short duration count site, and dividing these results by total AADT for these sections.

These factoring procedures are designed to eliminate the bias in the estimates of truck AADT and VMT that are generally due to the weekday classification counts. The seasonal and day-of-week factoring procedures to estimate the VMT and AADT for combination trucks has been used by the California Department of Transportation (CalTrans) since 1993 and by the Virginia Department of Transportation (VDOT), since 1996.

In another study, VDOT used the Seasonal and Day-of-Week factoring to estimate the truck AADT and VMT. The AADT values for single and combination units were taken from various sources in the State of Virginia along with estimates from conventional truck counts. The unfactored and distributed estimates obtained from the 48-hour weekday counts were derived. The unfactored estimates were derived by extracting the data from 30 sets of 48-hour weekday classification counts obtained at each site, as the average of all estimates for single unit and combination trucks. The distributed AADT estimates were derived by using each set of unfactored 48-hour classification counts as the basis for distributing total AADT across vehicle classes.

The differences between each of the two estimates and the data obtained through various sources in Virginia represented estimates of the average error introduced by the two procedures for estimating truck AADT from 48-hour classification count.

Transportation Demand and Freight Models

Transportation demand models are used to simulate the traffic flow on highways (and on transit routes). They are based on trips being generated through the transportation network from zonal locations as a function of population, employment, and other demographic data. Freight movements by truck and other modes can be simulated based on commodity flows and truck trip generation based on land use.

A Model can be defined as an abstraction or a simplification of the 'real world' system. Planners and Engineers use these models of the transportation system and their relationship to socio-economic activities to analyze the consequences of changes in the system. Transportation planning relies on the use of models to assess the impacts of the proposed alternatives. Future transportation supply and demand is studied with the help of network and demand models.

Prior to World War II, information on urban traffic was obtained using roadside interviews. Later, statistical surveys, such as home interviews, license plate surveys and roadside surveys were employed to obtain O-D trip tables. The increased need for studying small urban areas in detail, with cheaper and quicker-response theories and methods for solving trip tables more conveniently began the invention of more advanced models, since the year 1970. These models were modified and adopted to the study of freight movements.

Specifically, when discussing freight transportation and it's modeling, it is foremost important to know the different types of activities that generate freight movement, as a base for further study. So some of the activities that can be listed here are: [(10)]

1. Goods transported from the producers to the consumers
2. Multi-channel distribution chains, involving wholesalers and warehousing operations that transport goods
3. Trans-shipments or intermodal movements, etc

This classification of activities helps in defining the trip purposes in freight models. Generally two main approaches exist that most of the freight models pursue: (I) Commodity-based approach and (II) Vehicle-based approach. The commodity based approach for freight models concentrates on the producers and consumers of the goods, whereas vehicle-based models generate truck trips directly as a function of different land-uses existing in the region.

In simple words, it can be said that while the vehicle-based approach develops truck trip generation rates using land-use as a function of the socio-economic data, the commodity based approach estimates commodity flows using socio-economic data, economic production or consumption and shipper-carrier surveys.

In the study undertaken here, the vehicle-based approach is considered and truck volumes and flows are produced primarily as a function of the land-use activities for the New Jersey region.

For the commodity-based approach, economic data and input-output tables are used to estimate the quantity of each commodity that is produced and consumed in each geographic unit. Generally, models start with a known region-to-region flow table and disaggregate inbound and outbound flows to the zonal level depending on the economic data. [(10)] For the vehicle-based approach, data is collected through travel diaries or shipper surveys. Once trips are generated in a vehicle-based model, they are distributed through the determination of the destination choice. Trip table synthesis technique is used to estimate the origin-destination matrices for the vehicle-based models.

The New York Metropolitan Transportation Council (NYMTC) has developed such a model, which is based on linear programming algorithms. This approach uses O-D data as well as truck counts to develop a trip table, which most fits to the actual traffic volume on the network. The procedure for a vehicle-based approach has been shown in the figure 7 below. Figure 8 shows the model components for a commodity-based approach. [11]

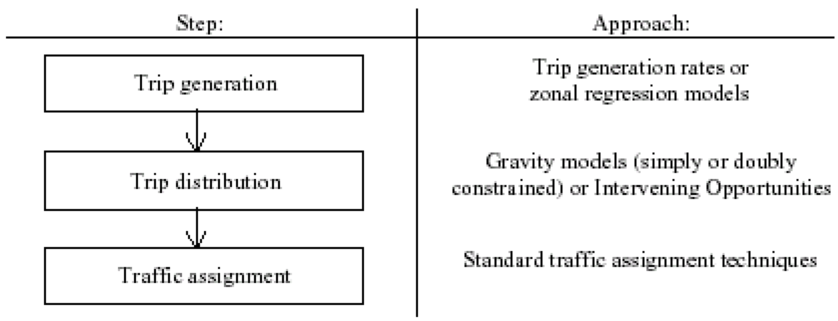

Figure 7: Model Components of a Trip-based Approach
(after Holguín-Veras and Thorson, 2000a) [11]

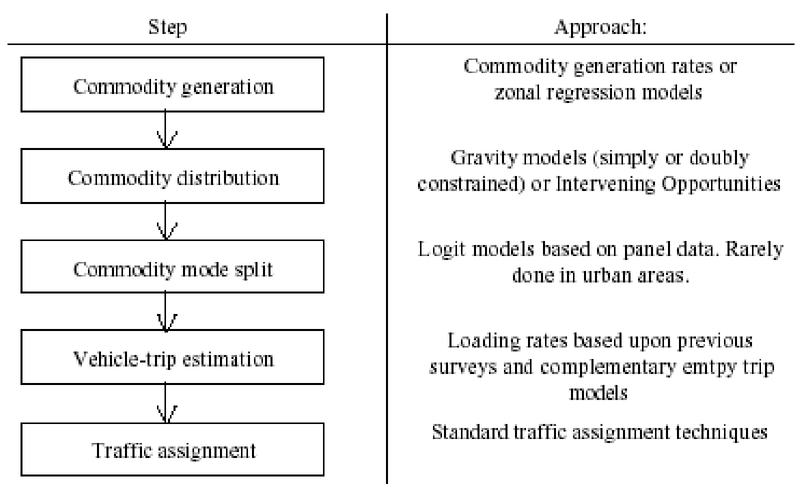

Figure 8: Model Components of Commodity-based Models
(After Holguín-Veras and Thorson, 2000a) [11]

Freight transportation models involve the movement of goods along with some other movements that are not strictly speaking associated with the goods (For e.g. construction, repair and maintenance truck trips, etc.). The non-good truck trip models also use the vehicle-based approach for their calibration, as commodity flows fail to have any relevance for these trips.

Freight models and software packages

Based on the purpose for which a model is used, transportation demand and freight models are classified into various subgroups. These subgroups can be enlisted as; National Cooperative Highway Research Program (NCHRP), Simplified Techniques, Traffic Count-Based Models, Self-Calibrating Gravity Models, Partial Matrix Techniques, GIS-based Models, Heuristic Models and Facility Forecasting Techniques. There are also some special application models, such as, the freeway trip distribution, pedestrian trip distribution and special purpose trip-distribution models. Examples of special purpose trip-distribution models include choice models (employing individual travelers instead of the zones as the observation unit), continuous models (that ignores the zones altogether with small changes in the land-use activities) and simultaneous models (that simultaneously analyze trip distribution and other planning steps).

Traffic Count-Based Models base their working on the data collected through the traffic counts at the different sections of roadways and highways. In order to achieve O-D trip tables from count-based information, traffic flow is considered static, i.e. time independent. It has been seen that among all types of easily derived data, traffic counts gives the most important information about O-D distribution. Based on this principle or hypothesis, many models fall and work under this subgroup.

Gravity Models are the Self-Calibrating Models and represent the original idea of establishing trip distributions. Here the entries of the O-D matrix are assumed to be a function of traffic counts and other parameters. Regression techniques and the flow conservation law are applied to calibrate the parameters, to minimize the difference between the observed and the established readings. This subgroup divides further into Linear and Non-Linear Regression Models. Among the Linear Regression Models, except the Holmes Model, all adopt a proportional all-or-nothing assignment. Among the Non-Linear models, some models use the proportional assignment technique and some use the all-or-nothing approach. None of the models are found to use the user-equilibrium assignment principle. Gravity and Intervening Opportunity Models are generally used under the context of Urban Transportation Modeling System (UTMS).

Equilibrium Models base on the principle of user optimization of traffic flow. This principle was originally used to guide the traffic flow assignment process. This principle mainly states that, all the routes having positive flows between any O-D pair should have equal traffic cost and also should not exceed the cost from any other unused route between this O-D pair. This model helps in producing the observed O-D travel times and as the equilibrium link flow and equilibrium O-D travel times for a standard problem is 'one-to-one', it consequently reproduces the observed link flows.

Statistical Models estimate trip tables directly from the prior information using statistical techniques by taking into account the inaccuracies on the observed O-D flows, row and column sums and traffic counts. This group includes the Constrained Generalized Lease Square Model (CGLS), Constrained Maximum Likelihood Model (CML), and the Matrix Estimation Using Structure Explicitly (MEUSE), which uses both the historic data and the parking data as inputs.

Now, the basic models, which were first developed in the early stages of freight modeling, are discussed in the following section and the more advanced models and some resulting software packages that were developed based on the simple and basic models are reviewed later. A brief review of the model applications is also given after discussing the various Models.

Urban Transportation Modeling System (UTMS)

In the very early stages of transportation demand model development, a model, now commonly known as the 'Four-Step Model' was most popular. It was originally developed during the 1950s and 1960s as the basic modeling framework for the comprehensive, long-range transportation modeling. It embodied the basic approach to urban travel demand modeling. This model, named UTMS, i.e. Urban Transportation Modeling System, helped in predicting the number of trips made within an area by type (work, non-work); time of day (peak period, daily); zonal O-D pair; mode of travel used to make the trip; the routes taken etc. [12] UTMS consisted of four major stages: Trip generation, Trip distribution, Modal split and Trip assignment. These four stages correspond to a sequential decision process in which people decide to make a trip (generation), where to go (distribution), which mode to take (modal split) and what route to use (assignment). Various models and techniques are used in each of these steps. Although initially UTMS had been developed to forecast person trips, the four-step process has been adjusted and used in freight modeling.
The four stages of UTMS are shown in figure 9 below. [12]

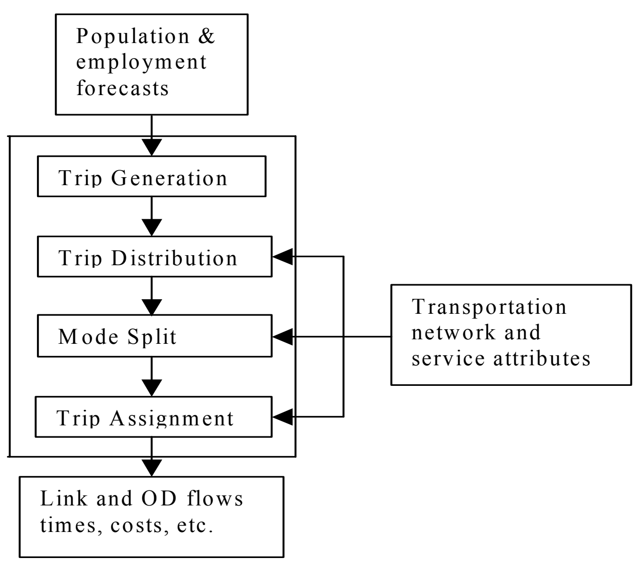

Figure 9: Urban Transportation Modeling System

Followed by this invention and model development, came the Input-Output models. These I-O models helped in understanding the economic interrelationships. They provided a view of the regional production and its multipliers helping to understand the relationships between accessibility, jobs gained and lost, and their values. They provided insights to labor force, basic and secondary employment and the impacts of employment shifts on regional economies.

Mathematical Models

Mathematical models are used to forecast freight traffic over specific network links and nodes. They express results in volumes per unit of time. In the strategic freight network modeling, the network models are expressed in closed mathematical forms as optimization and game theoretic problems. As these models are very big in size and complexity, adaptations of powerful linear and non-linear programming algorithms are used to simplify the calculations. (14)

The demand for freight transportation services is derived from the zonal separated production and consumption activities associated with individual commodities. The Computable General Equilibrium (CGE) models determine the cost, consumption and production activities for the whole economy. Researchers have found out a common synthesis between the two, i.e. the freight models and the general equilibrium model, and have come out with a new synthesis "Spatial CGE model" (14)

A number of freight network models have been developed in the past. The first significant strategic freight network model stating that the interactions of freight infrastructure and the decision making agents active on a freight network can be analyzed using mathematical programming was developed by Kresge and Roberts (1971). It is referred to as the Harvard Brooking model and has influenced the development of the subsequent models.

Another important freight model has been developed by Bronzini. [15] Here, a non-linear programming formulation is used based on non-linear cost and delay functions, considering different railway and waterway operating environments. This model, called the CACI model, has been extensively used by many states in the US.

Another notable freight model is the 'Freight Network Equilibrium Model' (FNEM), which was developed at the George Mason University. [16] It is based on the game theoretic model of shipper and carrier interactions. Shippers and carriers are the decision-making agents, where a shipper desires a commodity and the carrier actually effect the transportation of commodities, satisfying the transportation demands of the shippers.

A distinguished work on freight models by Friesz describes the typologies of the models and the various compromises involved in constructing and applying an actual model. [17] A list defining the research issues in predictive freight-network modeling was also developed.

The following section presents a brief description of newer models, which were derived primarily from the earlier transportation models described above.

<u>Quick Response Freight Model</u>

The US DOT's, The Quick Response Freight Manual (QRFM), uses simple techniques and transferable parameters to help in developing commercial truck movements. It gives urban areas a simple transportation-modeling tool for the development of urban freight planning. [18] QRFM follows the three-step process, which includes trip generation, distribution and assignment of the traffic. It is similar to the TranPlan model, based on the four-step model that develops, assigns and analyzes commercial truck trips in small and medium sized areas. Here, truck trips are broken into three types: four tired, single unit trucks with six or more tires and combination trucks.

The existing model structure according to the 1996 released QRFM, assumes an urban area with a 4-step planning model without a transit model, and with a separate truck purpose. (19) The truck purpose can be home based work, home based non work, non home based, internal to internal trips, internal to external, and finally external to external.

Model application: The model application includes mainly building of a truck network, finding out the minimum time paths and thus skimming-off the minimum paths to find the shortest possible way.

Trip Generation: Demographic data are organized into employment categories. For the Quick-Response (Q-R) trip generation, these employment categories are broken for each Traffic Analysis Zone (TAZ). The initial attractions and productions are developed by the existing employment categories. Trip generation rates are applied to both the employment and dwelling units by traffic analysis zone. For the places where no local data/rates exist, trip generation rates are taken from Phoenix, which are set as the default generation rates by the QRFM. Phoenix trip generation rates are found to be close to the median value for all available generation studies, and thus are considered as the default values.

In order to compute truck productions and attractions simple spreadsheets are used. It is recommended to have the spreadsheets for all three-truck categories separately, because each class is found to have its own trip length frequency. Finally, the trip generation balancing process is executed by setting the destinations and attractions equal to the origins and productions.

Trip Distribution: Trips are distributed using the gravity model. The process of distribution combines three passes: non-commercial, light trucks and the medium to heavy trucks. The first pass computes standard distributions for the three possible work purposes, i.e. HB Work, Non-Work and Non Home-based. Second pass uses the normal updated free-flow skim paths, computing the trip tables for internal to internal four tired trucks, external to internal non commercial vehicles and the external-internal four tired trucks. Lastly, the third pass uses the special updated free-flow truck skim paths to compute trip tables for internal-internal and external-internal, six tired and combination trucks

Assigning trucks to networks: Two approaches are generally found to exist for the purpose of determining the number of commercial vehicles in a network. They can be bulleted as:

- Existing networks are edited by removing most of the arterials and minor collectors, leaving only an optimum number of arterials and minor collectors in the network.
- Another approach establishes a truck network by weight limits, restrictions and signed truck routes in an urban area.

The trips generated and distributed (as explained above), are assigned to the networks, using user equilibrium techniques, all-or-nothing assignment techniques or by assigning the truck trips to special truck networks.

These three processes are used as:

- Medium/heavy trucks to a special truck network
- Other non-commercial, light trucks and medium/heavy truck trips to the full network using equilibrium assignment techniques.
- Medium/heavy truck trips and remaining light trucks to full network by the all or nothing assignment technique.

Model Calibration: After the traffic has been assigned to the networks, estimated truck traffic is compared to known counts. QRFM suggests comparing the total VMT by the control total VMT. The model is calibrated when the total model VMT is within the 5% of the total control VMT. Control VMT is calculated as the sum of products of truck counts and link lengths. Hourly volumes are converted to AADT for calibration and analysis, by multiplying the total link volume by 10. After the model output was converted into AADT, truck volumes on the links are multiplied by the link lengths and summed to estimate the total VMT of the model.

Strategic Planning of Freight Transportation, using STAN

STAN is defined as the interactive graphic, multimode, multi-product method, which is used for the strategic planning and analysis of freight transportation. It is used extensively for comparing and evaluating different planning alternatives. Planning issues may include, evaluation of impacts when changes are made in the transportation infrastructure, for regulatory environment, to evaluate the demand patterns based on cost, time, and other performance measures, etc. Existing and future situations are described and a simulation of freight flows is carried out on the scenarios. STAN offers a comprehensive and flexible modeling framework with updated algorithmic techniques and powerful computing capabilities. It permits the planner to visualize; the input data, results of the computations and information from the data bank in a graphic or list form. [20]

STAN is composed of a series of modules to input, modify, and display information related to the transportation network. The data is entered in the form of matrices, networks or functions. The matrices handled in STAN may be full matrices, origin or destination vectors or scalars. It has the capability of containing various data related to the zone subdivision of the area under study, such as O-D demands, productions by origin and the attractions by destinations. STAN allows a variety of functions for links and transfers.

STAN provides a multimode multi-product assignment method, which minimizes the cost of shipping products from origin to destination. It requires data describing the components of the network and data quantifying the transportation demand that is to be shipped, from each origin to each destination. It permits the results to come in comparison between the flows and costs for the specified scenarios. STAN allows marking a demarcation line on a graphical output, which may identify geographical characteristics of the area such as rivers, mountains or certain regions of the country such as states etc. A logbook, created by the user keeps the record of the identities and the elements of the data bank.

STAN is an open system where the new developments and enhancements may be added to its methodological core and to its functionality. It assumes that the demand for transport has been specified for each product by a number of O-D matrices. It allows the evaluation of the maximal flow amounts of certain commodities that can be transported with the existing infrastructure, thus being useful when considering major changes in demand.

Applications of the Models and the Software Packages

Analyzing Highway Capacity for Freight Transportation

An analysis examining the sufficiency of capacity of the transportation system in meeting forecasted freight demand has been done by Edward Fekpe [(21)] Using the TransCAD, Geographic Information System (GIS) framework a base network for the freight transportation demand analysis was established. [(22)] While establishing the freight network, logical consistency, network connectivity for all links, county centroid connections and identification of key intermodal connections were made. The freight demand analysis was carried out only after the network was established. Traffic flow maps showing the actual volumes of traffic were made from the state provided traffic count data. These freight flows were then converted into truck trips using knowledge of truck payload characteristics (by commodity type), i.e. commodities were converted into truck types and then each type was configured to convert the commodity into truck trips. Empty truck percentage was derived in order to account for the total capacity of the highways.

Traffic assignment models were used to estimate the traffic flow on the network. Both the Capacity Constrained and Capacity Unconstrained scenarios were considered for the traffic assignment. The network was calibrated further to ensure that the assigned truck trips were as closely as possible matching the actual truck volumes in the network. Truck peak hours were considered for the analysis. After the trips were assigned on the highway in the network, performance measures such as traffic volume, travel time, link delay, average speed etc. were measured to determine the network deficiencies, and thus the capacity of the highway.

Input-Output Model in the State Of Wisconsin

The study by Sorratini, deals with the statewide truck trip estimation using Commodity Flow Surveys and the Input-Output coefficients. [(23)] This model was used for the state of Wisconsin. Production and attraction rates were derived at the county level in terms of tons of each commodity. TRANSEARCH, the private database developed as a joint product of many agencies, was used for the State to derive the trip production rates. Economic based I-O software (it was believed that the demand for freight is better explained when derived from economic activities rather than from traffic counts and projections) was used to derive the I-O coefficients and develop the trip attraction rates. Annual tons were converted into daily truck trips using an average-tons-per-vehicle, and a days-per-year factor. The resulting trips were disaggregated to the Traffic Analysis Zones (TAZ), based on zonal population.

Vehicle and commodity flow data rather than traffic counts and frequency alone were fed as input. Freight traffic projections were based on the economic activity instead of trend extrapolation. The commodity and employment data together with the I-O coefficients were used to improve the truck trip generation process. The procedure was used in the four-step model. The overall algorithm for the freight productions and attractions is shown below in figure 10.

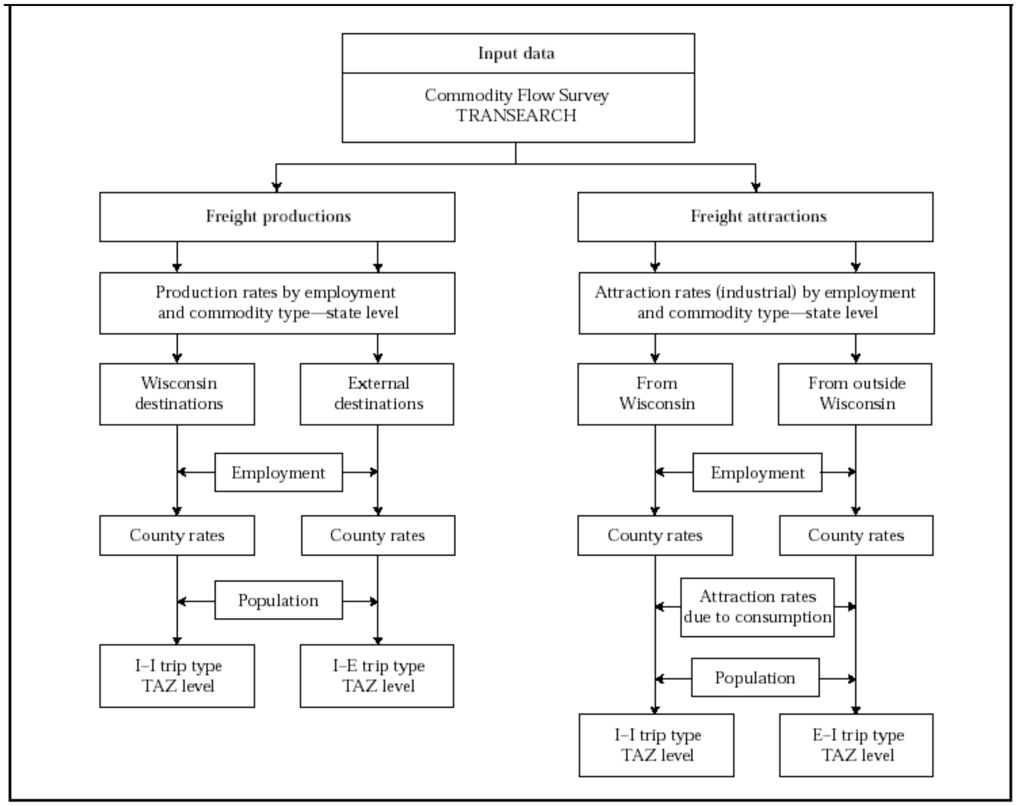

Figure 10: Production and Attraction rates
(A report on Estimating State-wide Truck Trips by Input-Output Coefficients, by Jose A. Sorratini)

The production and attraction rates in tons are stratified by commodity type and by all modes of transportation, including trucks, rail, air, water and pipeline. The truck share from the Commodity Flow Survey data is applied to derive the truck tons. Truck trips for four trip types: Internal-to-Internal, Internal-to-External, External-to-Internal and External-to-External was derived. IMPLAN Professional, which has been described in a previous section, was also used for the state of Wisconsin, with 528 sectors to be aggregated.

<u>Truck-Travel Demand Model for the State of Wisconsin</u>

A simple statewide truck-travel demand model for Wisconsin was developed using only readily available data, including a small amount of data from O-D travel surveys and fairly extensive truck-classification count data. [(24)] Trucks in this study were defined as two-axle heavy trucks or larger. The conventional three-step process (trip generation, distribution and assignment) was used with the addition of selected link-loop analysis (SELINK). This was required because of the inefficiency of the available O-D survey data, for calibrating statewide trip generation model at the zonal level. Data for SELINK analysis is obtained from the traffic assignment programs. “ For each specified one-way link, the assignment program creates an O-D trip table that is composed of all the trips that are assigned to the specific selected link. In the adjustment procedure, the actual truck-traffic volumes were compared with the estimated truck-traffic volume for each selected link”.

Initial internal trip generation model was based on the population data and measures of economy activity for trip attractions and productions in the zone. For external stations, direct estimates of truck-trip productions and attractions were available from the vehicle classification counts. Trip distribution was carried out using the Gravity models. For the statewide traffic assignment, All-or-Nothing Approach was used, as very few links were found congested in the zones. The resulting link volumes were compared with truck volumes from the classification counts.

The over-all performance of the truck-travel demand model was measured by the Root-Mean-Square Error method, when the model generated link volumes were compared with ground counts. Screen-lines were also identified for potential regional biases.

O-D Estimation Models and Freight Modeling in Bronx (NY City)

To synthesize the truck flow pattern from the fragmentary data / observation, List and Turnquist (1994) proposed an O-D estimation method. This method was based on a linear programming model that would minimize an objective function, given the user-defined choice of variables for the truck classes and network zone structure. This model used data in different forms and combinations, including link volumes, classification counts, cordon counts for the trucks entering and leaving the study area etc. The link-use coefficients for each O-D pair were calculated with the help of a probabilistic path assignment algorithm.

Unlike past models, this model incorporates multiple vehicle classes. It employees a three-tier classification scheme in the form of commercial vans, medium trucks (two axle, six tire and three-axle single unit), and heavy trucks (trucks with four or more axles, and all tractor trailers). This model also provides the control parameters to allow introduction of varying degrees of confidence in different observations of link volumes and classification counts. This new method was found to have a more general formulation, designed to accept data in forms other than link counts. (11)

The model was tested in a network in Bronx, New York City. Data for the flows to and from the specified zones were collected for three different times in a day (a.m., p.m. and midday) and three truck classes (light, medium and heavy). The developed model generated nine O-D matrices and link flows for the test network.

Truck Flow Estimation by use of O-D matrix

To estimate the O-D flows for a given region, a trip matrix matching a set of field observations is of great interest and importance. List and Turnquist used data from various sources and in varied forms with multiple vehicle classes for the OD estimation, for the City of New York. Varying degrees of estimation with asymmetric error functions for overestimation and underestimation of observed values were provided with controlled parameters to allow for their specification. (11)

Vectors for estimated O-D flows and flow observations were found. They called these vectors '*x*' and '*b*' respectively. A set of estimates for the observations derived from '*x*' was named as '*v*'. Target matrix was '*t*'. List and Turnquist have given two models in the same study; in the earlier model the objective was specified as:

$$\text{Minimize: } \gamma_1 D_1(x, t) + \gamma_2 D_2(v, b)$$

Where, $D_1(x, t)$ and $D_2(v, b)$ are the penalty functions and, γ_1 and γ_2 are the weights that control relative degree of importance placed on matching either '*t*' or '*b*'.

Once all these parameters are specified, O-D flows '*x*' are matched with '*t*', subject to $v = Ax$ and $v >= 0$ and $x >= 0$. A gradient-based optimization technique to create the trip matrix fitting the set of input data was used.

The model accepted three types of field observations: arc volumes, area-to-area flows and total originating/terminating trips for a given zone or set of zones. The analysis network consisted of arcs and nodes. Non-overlapping zones were established with each zone having a node known as the centroid. Truck flows were divided based on the FHWA truck classes.

Another model by List and Turnquist addressed a larger population adding new types of observations to the original observation set, screen line counts, and the distribution of trip lengths. The new model accounted for small deviations of 'v_n' from 'b_n'. It developed a high tolerance for inconsistent observations and helped in easily detecting and fixing of data errors. Also it produced a trip matrix that matched the field observations very well.

Statewide Models from different States across the Country

Virginia

Application of a Statewide Intermodal Freight Planning Methodology [28]

The state of Virginia developed a Statewide Intermodal Freight Transportation Planning Methodology to identify problems and evaluate alternative improvements for Virginia's freight transportation infrastructure. In order to have all the freight movements across Virginia analyzed, commodity flows by both weight and value were considered. A geographic information system (GIS) database was created to show freight volumes, county-level population, and the employment information. The various factors influencing generation and attraction of freight in a given area of Virginia were studied and using statistical analysis techniques, relationships were defined among freight origins; attractions, or destinations of freight traffic; and publicly available socioeconomic data. These relationships were used to predict the generations and attractions of each key commodity for each Virginia county and independent city.

Florida

Florida Intermodal Statewide Highway Freight Model [28]

With the growing importance of the freight transportation and in response to some legal legislatives, the Florida department of transportation (FDOT) developed an Intermodal Statewide Highway Freight Model in the year 2000. This model identifies and measures the truck activity in the state, also providing an adequate in-sight into highway connection for other modes of transportation and regional freight hubs. This model was created compatible with other planning databases and tools supported by the Department, so that a framework could be provided for modeling statewide truck freight activity, consistent with ongoing enhancements in the state. This model was made supportive to the freight modeling activities within urban areas of the state.

Indiana

Commodity Flow Survey in Indiana [28]

In the year 2000, the Indiana state authorities created a database of commodity flows within the State using the Commodity Flow Survey from the year 1997, so as to forecast the freight movement for the whole state. Commodity flow survey was done as a partnership program between the Bureau of the Census, U.S. Department of Commerce and the Bureau of Transportation Statistics, U.S. Department of Transportation, providing information on commodities shipped, their value, weight, mode of transportation, and their origins and destinations. Indiana created the database for the state and assigned these flows to the Indiana highway network, which would help them know the freight demand. (28)

<u>Iowa</u>

<u>Statewide Transportation Planning Model</u> (28)

The state of Iowa has been active in freight transportation modeling efforts since the early 1970s, focusing primarily into the grain forecasting models. In the year 1996, the Iowa DOT developed a multi-modal and tactical model capable of modeling movements of several commodities. The department wanted to simulate the impacts of changes in service variables on freight movements and investigate the rational behind the commodity movements. To identify and develop tools that may support freight planning and modeling for the DOT, a matrix was developed in 1997, to help the authorities. Dimensions of the matrix included selected freight planning issues and scenarios, and a prioritized list of commodity types for Iowa, using GIS and Internet technologies. (29)

<u>Kentucky</u>

<u>Freight Commodity and Intermodal Access in Kentucky - Freight Movement and Intermodal Access in Kentucky</u> (28)

In order to understand the freight flows in the state of Kentucky, and also to know the potential of commodity data as an input for the statewide transportation-planning model, the Kentucky DOT conducted a project in the year 1999. It used its data from the Reebie Associates, developed with the Federal Highway Administration, and checked for its consistency with other sources of aggregate freight data for Kentucky (except for airports). Later in the project, it was found that the modeled truck volumes do not match with the 1996 KyTC classification counts particularly for non-freeway routes and these errors were attributed to the large zone size used in the model as well as the representation of Tennessee as a single zone. Specific recommendations were also made for KyTC's consideration for future freight transportation planning efforts.

Minnesota

Minnesota Statewide Freight Flows Study [28]

In the March of 2000, the state of Minnesota undertook a study, to identify and understand the movement of goods in the State and also locate the key corridors where improvements were needed. The study aimed at identifying the volume, density, and character of major freight flows in the State by mode and corridor; the origins and destinations of freight flows; study the infrastructure and policy issues. It compiled and evaluated data with freight system performance measures and made recommendations to support and compliment the Interregional Corridors study.

Oklahoma

Freight Movement Model Development for Oklahoma [28]

The state of Oklahoma developed a prototype software system to run its Freight Movement Model for the state. This model, named as the 'Freight Movement Model Development' for the state aimed to help the Oklahoma DOT in planning & executing projects related to improving freight movement in the state.

Oregon

Oregon Freight Truck Commodity Flows [28]

The Oregon DOT in 1998 initiated a study to know the information gaps of commodity movements by truck in the state. The 'Oregon Freight Truck Commodity Flows' study would help authorities in knowing the goods movement in terms of truck volume, payload weight, economic value, time of day travel, and fleet ownership attributes, given by key commodity groups.

Texas

A Comprehensive Commodity/Freight Movement Model for Texas [28]

To better estimate and forecast movement of passengers, freight and commodity into and within the state of Texas, the Texas DOT developed a Statewide Analysis Model (SAM). The freight and commodity modeling results of the SAM were then integrated into the urban area travel demand models. The models were developed to predict intra-urban area movements of freight and commodities by mode and the additional movements generated by state, regional, and national movements of freight and commodities into urban areas. These models were tested and applied to a major urban area within Texas to demonstrate their application.

New Jersey Statewide Existing Models

MPO Regional Models

The state of New Jersey has three metropolitan planning organizations (MPO), namely the North Jersey Transportation Planning Agency (NJTPA), the Delaware Valley Regional Planning Commission (DVRPC) and the South Jersey Transportation Planning Organization (SJTPO). [26] These three agencies divide the twenty-one counties of New Jersey with NJTPA catering to thirteen counties, DVRPC with four New Jersey and five Pennsylvania counties and lastly SJTPO with the remaining four counties including Atlantic City. Three transportation demand models, corresponding to each of these MPO have been developed jointly by NJDOT and the MPO.

The Statewide Model:

A statewide model including all 21 counties has been developed. To lower the cost, time and complexity of the model, the three regional models along with the Port Authority of NJ/NY and the New Castle County Model from Delaware DOT were combined. The main benefit of this approach was that a need for an all-together new four-step model was eliminated, which would save both the time and the money. The North Jersey model, which included the largest portion of the NJ zones, was considered as the base for the statewide model.

None of the existing old models had the ability to separately evaluate truck and goods movement, therefore development of a truck model as part of the statewide model was found important. The Statewide Model developed the networks that were expanded to include the coding for truck and non-truck routes. Truck restrictions were placed on the network. The external zones and the trip tables from the five models were connected to create a single network for the statewide model, by the use of the FORTRAN based Trip Table Weaving Technique. The truck trip tables, considering four truck classes, were developed using a standard gravity model, based on the commodity flows for the region.

This network merging and Trip Table Weaving Technique provided a cost-effective method to create a statewide model which allows NJDOT and other outside agencies to evaluate significant projects that cross MPO boundaries, which otherwise could not be accomplished alone by any of the three existing regional models.

Furthermore, a model for assigning multi-commodity, multi-class truck trips between various origin and destination points has been developed for the state of New Jersey. [27] The model takes into account the impacts of congestion on truck route choice and is implemented as a Geographic Information System (GIS) within the TransCAD software package and Microsoft Access. It is used to ascertain impacts of proposed capital improvements on the transportation network performance.

DATA COLLECTION

The data collection effort was separated into two areas: traffic counts and roadway information.

Traffic Counts

A majority of the traffic counts have been obtained through New Jersey Department of Transportation's (NJDOT) Bureau of Data Development. NJDOT maintains numerous vehicle count stations throughout the state through their Traffic Monitoring System (TMS). As a part of this system, certain stations collect information pertaining to vehicle size, weight, and classification for selected roadways throughout the state.

The traffic counts are divided into two categories: long and short duration counts. Long duration counts are collected from permanent facilities that record vehicle counts year-round. Short duration counts are temporary vehicle count stations situated at various locations around the state. These counts are primarily 48-hour vehicle classification counts that provide added geographic coverage but do not account for the temporal variations in traffic such as seasonal (monthly) and day-of-week variations. Upon recommendations of NJDOT personnel, all short duration vehicle classification counts compiled for this task have been adjusted using axle correction and pattern factors from the year 2000.

A number of supplemental traffic counts were also collected from toll authorities such as the New Jersey Turnpike Authority and the Delaware River Joint Bridge Commission as well as from NJDOT's non-classified Automated Traffic Recorder (ATR) locations.

The following is a summary of the long and short durations count sources identified and collected as part of Task 2.1.

Long Duration Counts

1. Source: New Jersey Department of Transportation WIM Stations

NJDOT maintained 46 permanent weight-in-motion (WIM) locations between 1998 and 2001. These stations report average daily vehicle classification counts for both directions of travel throughout the year. The table 4 below shows the vehicle classification scheme and the locations are shown in figure 11.

Table 4: Vehicle Classification scheme

Class 0	Unclassified vehicles which do not fit into any other classification.
	Vehicles which do not activate the system sensors are also unclassified.
Class 1	Motorcycles. All two- or three wheeled motorized vehicles. This category includes motorcycles, motor scooters, mopeds, and all three-wheel motorcycles.
Class 2	Passenger Cars. All sedans, coupes, and station wagons manufactured primarily for purpose of carrying passengers.
Class 3	Other two-axle, four-tire single units. Included in this classification are pickups, vans, campers, and ambulances.
Class 4	Buses. All vehicles manufactured as traditional passenger-carrying buses with two axles and six tires or three or more axles.
Class 5	Two-Axle, Single Unit Trucks. All vehicles on a single frame including trucks, camping and recreation vehicles.
Class 6	Three Axle Single Unit Trucks. All vehicles on a single frame including trucks, camping and recreational vehicles.
Class 7	Four or more Axle Single Unit Trucks. All vehicles on a single frame with four or more axles.
Class 8	Four or Less Axle Single Trailer Trucks. All vehicles with four or less axles consisting of two units, one of which is tractor or straight truck power unit.
Class 9	Five-Axle Single Trailer Trucks. All five-axle vehicles consisting of two units, one of which is a tractor or straight truck power unit.
Class 10	Six or More Axle Single Trailer Trucks, consisting of two units, one of which is a tractor or straight truck power unit.

Class 11	Five or Less Axle Multi-Trailer Trucks, consisting of three or more units, one of which is a tractor or straight truck power unit.
Class 12	Six Axle Multi-Trailer Trucks. All six-axle vehicles consisting of three or more units, one of which is a tractor or straight truck power unit
Class 13	Seven or More Axle Multi-Trailer Trucks. All vehicles with seven or more axles consisting of three or more units, one of which is a tractor or straight truck power unit

2. Source: New Jersey Turnpike Authority

The New Jersey Turnpike Authority (NJTA) collected vehicle classification counts between each exit along the Turnpike (i.e. a counter was placed at a mid-way point between exits 5 and 6 on the New Jersey Turnpike) for each month from 1998 through 2001. There were a total of twenty-five locations that vehicle counts were collected from. Dividing each month's count by the number of days in that month provides the average daily vehicle count for that month.

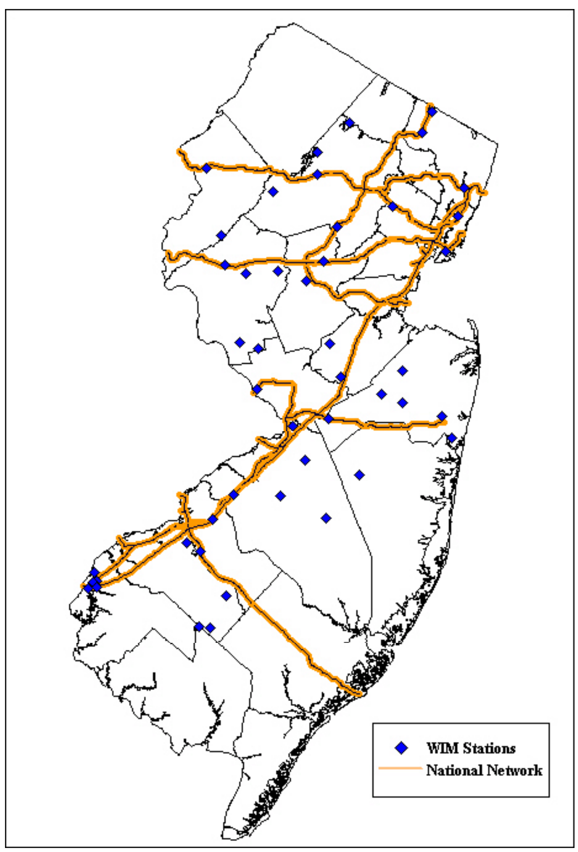

Figure 11: NJDOT's WIM Locations

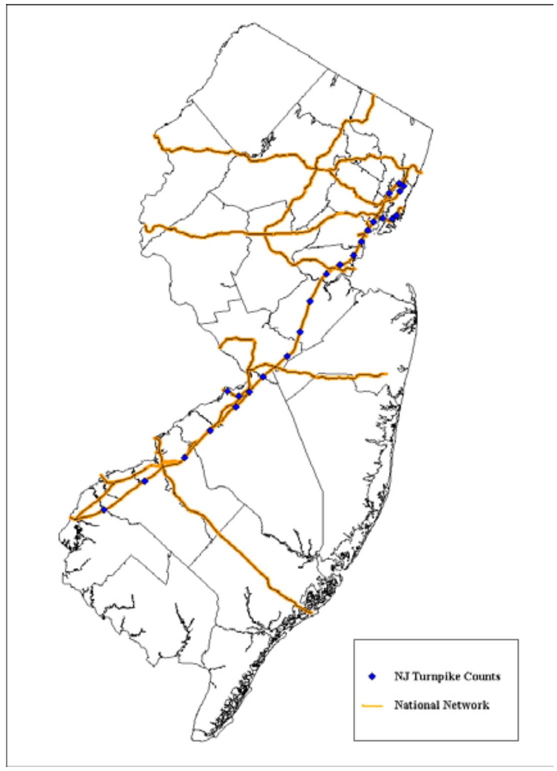

Figure 12: NJTA Vehicle Classification Counts

3. <u>Source: Delaware River Joint Toll Bridge Commission Classification Counts</u>

The Delaware River Joint Toll Bridge Commission (DRJTBC) maintains seven facilities that record the total number of vehicles by class for the years 1998 through 2001. The locations of these facilities are shown in figure 13. The totals can be divided by the number of days in a year (365) to get an average annual daily traffic count. Each December, the total number of vehicles by class is recorded each day for each toll facility. Once again, this value can be divided by the number of days in December (31) to obtain average daily traffic.

Short Duration Counts

4. Source: NJDOT Vehicle Classification Counts (Division of Transportation and Data Technology / Division of Traffic Engineering and Safety)

   From NJDOT, vehicle classification counts are available for a variety of roadways between 1996 and 2002. For particular locations, truck percentages have been calculated for heavy, single-trailer, and double-trailer trucks. In addition, single and double-trailer truck percentages are divided into peak and off-peak percentages. The count locations for this dataset, which includes 296 24-hour surveys, 34 8-hour surveys, and a 1-hour survey, are shown in figure 14.

5. Source: NJDOT Vehicle Classification Counts (Division of Transportation Systems Planning

   Bi-directional vehicle classification counts and truck percentages are available for download from the NJDOT website as PDF files for interstate, state, county, and toll facilities for the year 2000. There were a total of 36 locations throughout the State that contained count information; all 36 locations provided truck percentages and 30 locations provided vehicle classifications counts, as shown in figure 15. The count time periods ranged from eight hours to 29 days. Locations were identified using latitude-longitude coordinates obtained from the downloadable files.

6. Source: NJDOT ATR, Classification, and Turning Movement Counts

   Automatic Traffic Recorders (ATR), vehicle classification, and turning movement counts for various areas in Union, Essex and Hudson counties are available in hard copy format. The majority of these locations have been identified and geo-coded, as shown in figure 16.

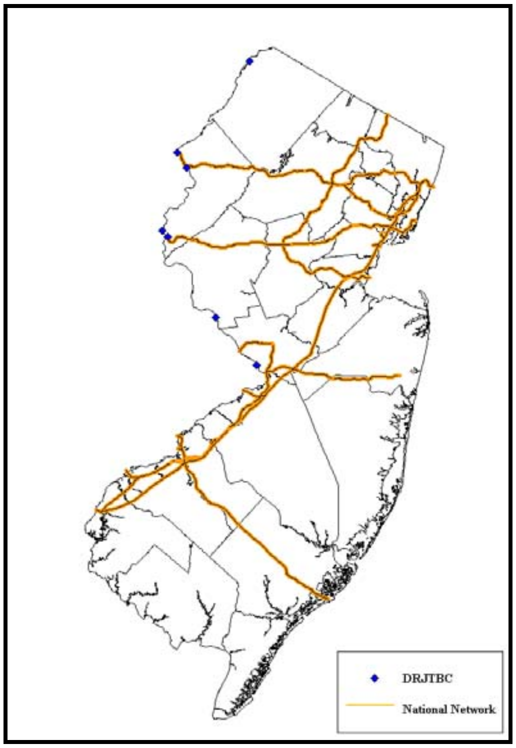

Figure 13: DRJTBC Classification Count Locations

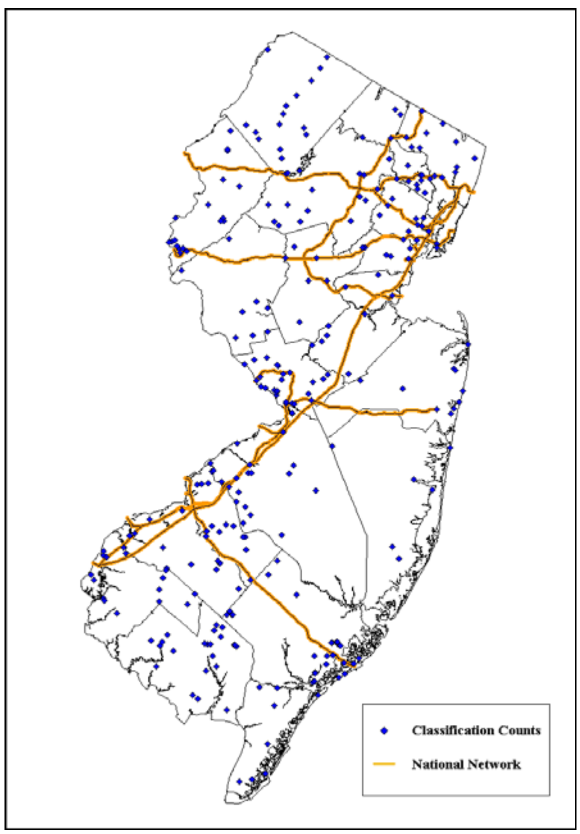

Figure 14: NJDOT Vehicle Classification Locations

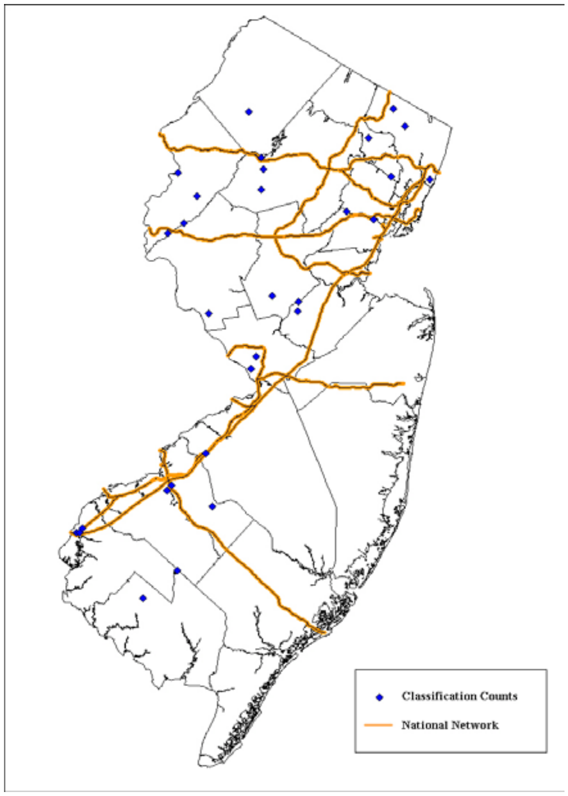

Figure 15: NJDOT Vehicle Classification Counts in 2000

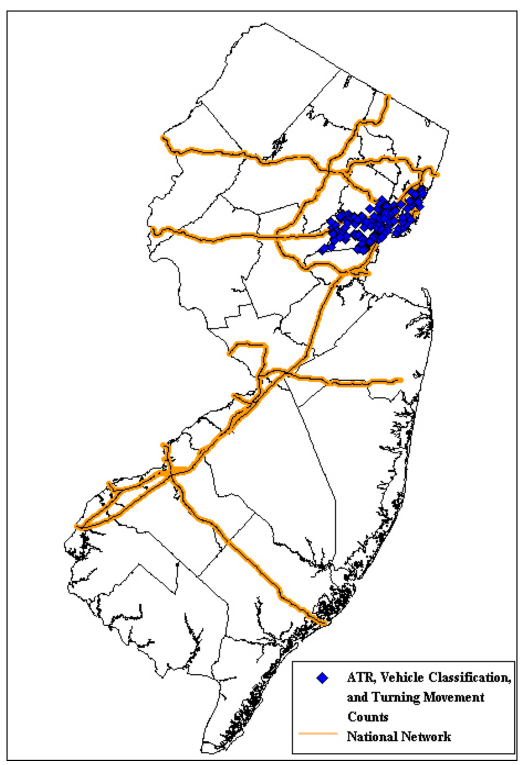

Figure 16: NJDOT ATR, Vehicle Classification, and Turning Movement Counts

The ATR's contain hourly vehicle counts (at least 48 hours), which are used to calculate average weekday vehicle totals. The weekday averages are multiplied by pattern and axle-correction factors to get AADT estimates for both directions of travel.

Vehicle classification counts were collected for all FHWA classes for a minimum of six hours. Percentage totals were calculated for each class for various time periods. Each direction was calculated separately. There were some data sheets that calculated total AADT estimates using pattern and axle correction factors. This data also contained truck percentages for single and multi-unit trucks for the peak hour and a 24-hour average, as well as k-factors, d- factors, and t-factors. (*K = peak-hour factor*; the proportion of vehicles traveling during the peak hour, expressed as a decimal, *D = directional split factor*; the proportion of vehicles traveling in the peak direction during the peak hour, expressed as a decimal and *T = curb lane truck factor*; proportion of large trucks traveling in the curb lane, expressed as a decimal).

Turning movement counts were conducted for each approach of an intersection in 15-minute intervals. The time period for the surveys varied from 8 – 36 hours. Traffic flow diagrams were drawn to show total turning movement traffic for times specified on each sheet. In addition to the turning movement counts and flow diagrams, a few locations calculated 24-hour volumes, AADT estimates, and directional split and "K" factors, for each direction.

7. <u>Source: NJDOT Average Annual Daily Traffic Counts</u>

NJDOT collected short duration counts at various locations throughout the year and subsequently converted them into average annual daily traffic (AADT) estimates. This data, consisting of 1,804 locations, was gathered for geocoded counts collected between 1996 and 2000, are shown in figure 17.

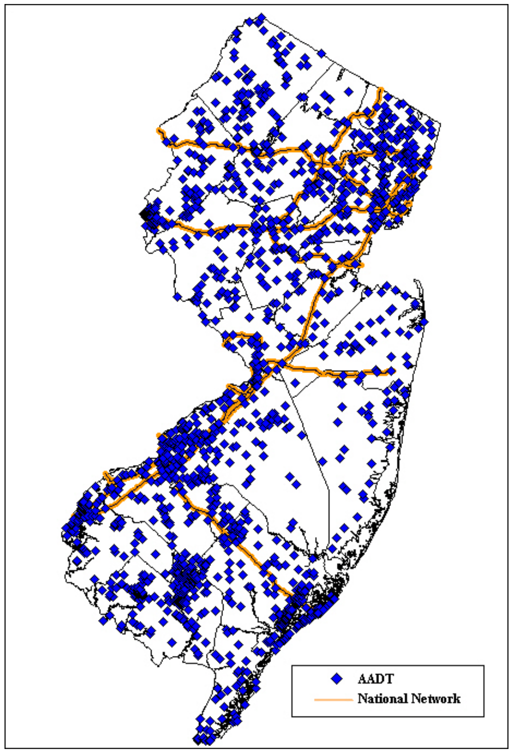

Figure 17: NJDOT AADT Count Locations

Vehicle Count Location Map

All counts that have been geo-coded were mapped and are displayed, by county. Some counts are more relevant to the purposes of this study than others. In an attempt to illustrate the relevancy of each count dataset, a color code scheme was developed and is shown in figure 18. Long duration counts, received the highest relevancy ranking (red), while short duration counts, received the lowest ranking (blue). Figure 19 to 39 show the vehicle count locations by county.

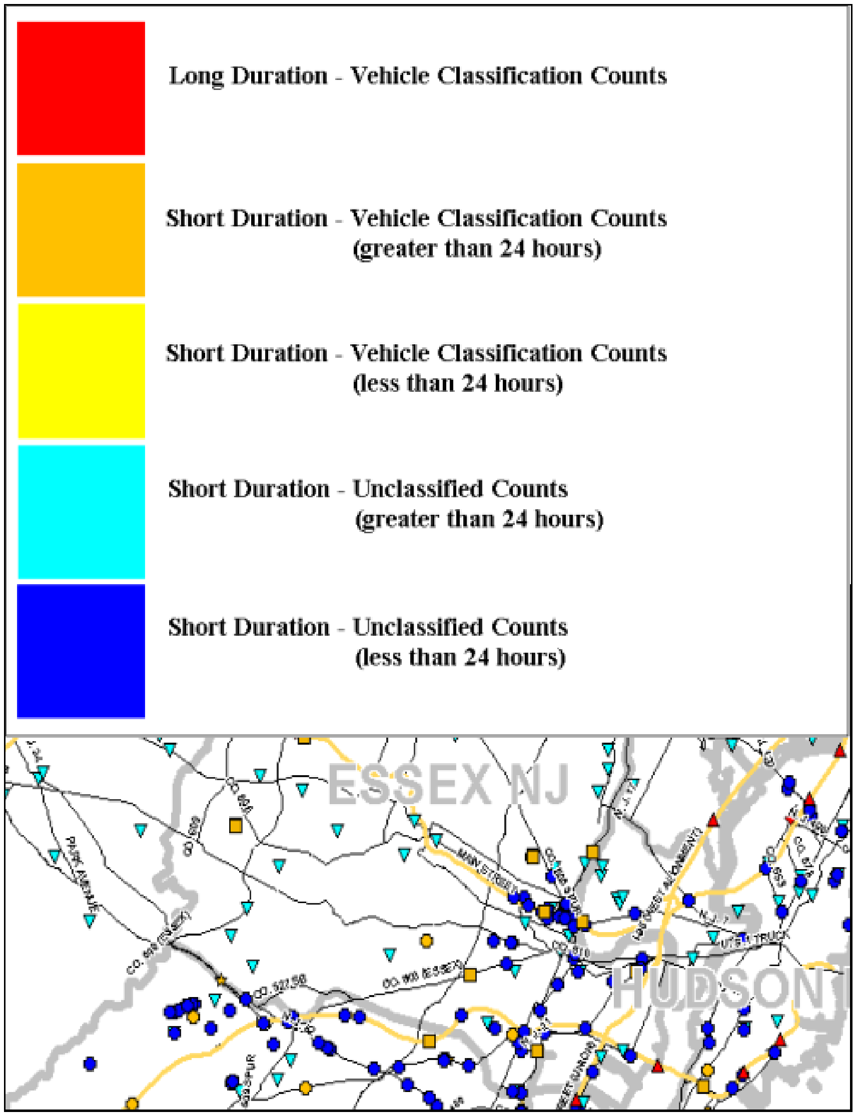

Figure 18: Relevancy Coding

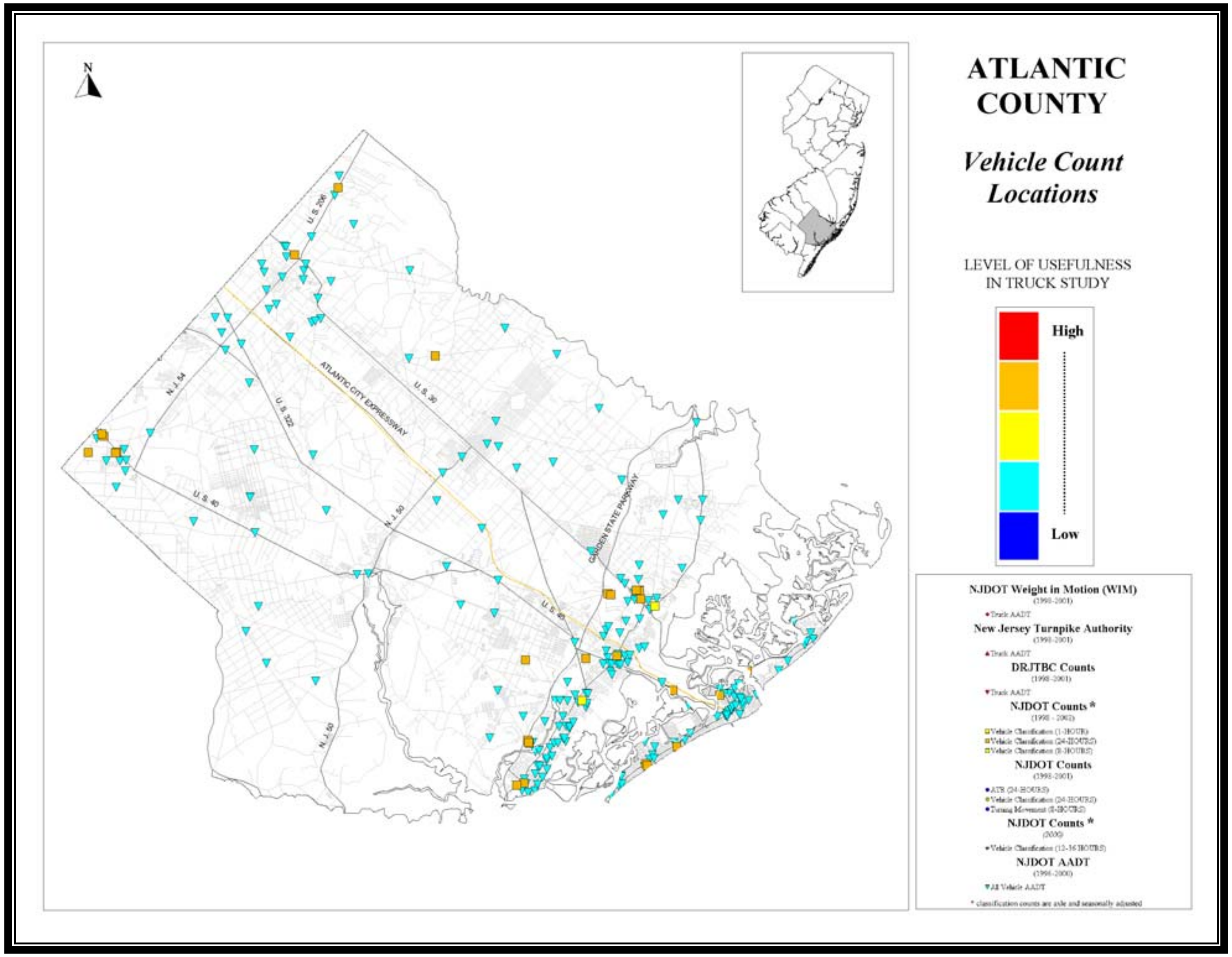

Figure 19: Vehicle count locations for Atlantic County

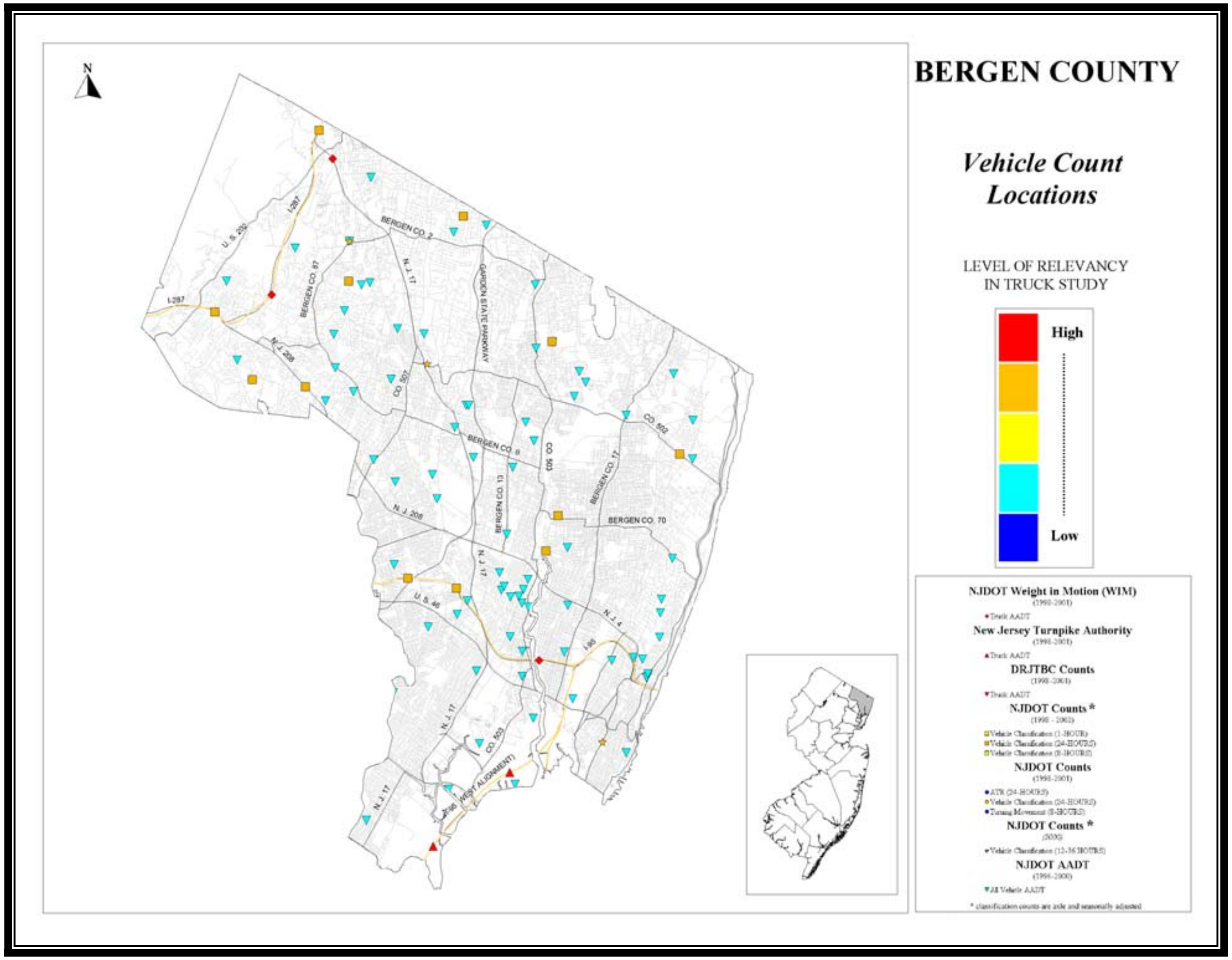

Figure 20: Vehicle count locations for Bergen County

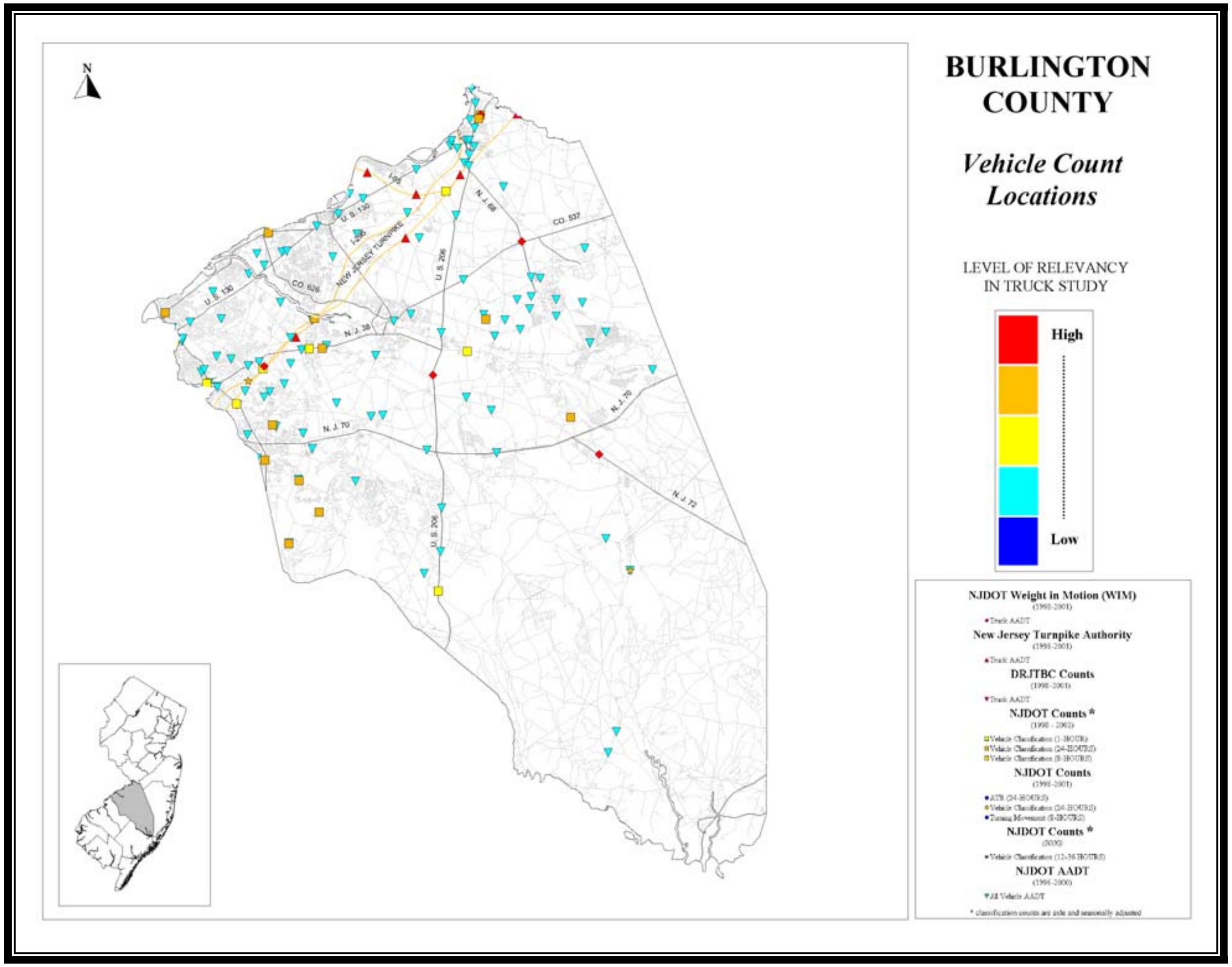

Figure 21: Vehicle count locations for Burlington County

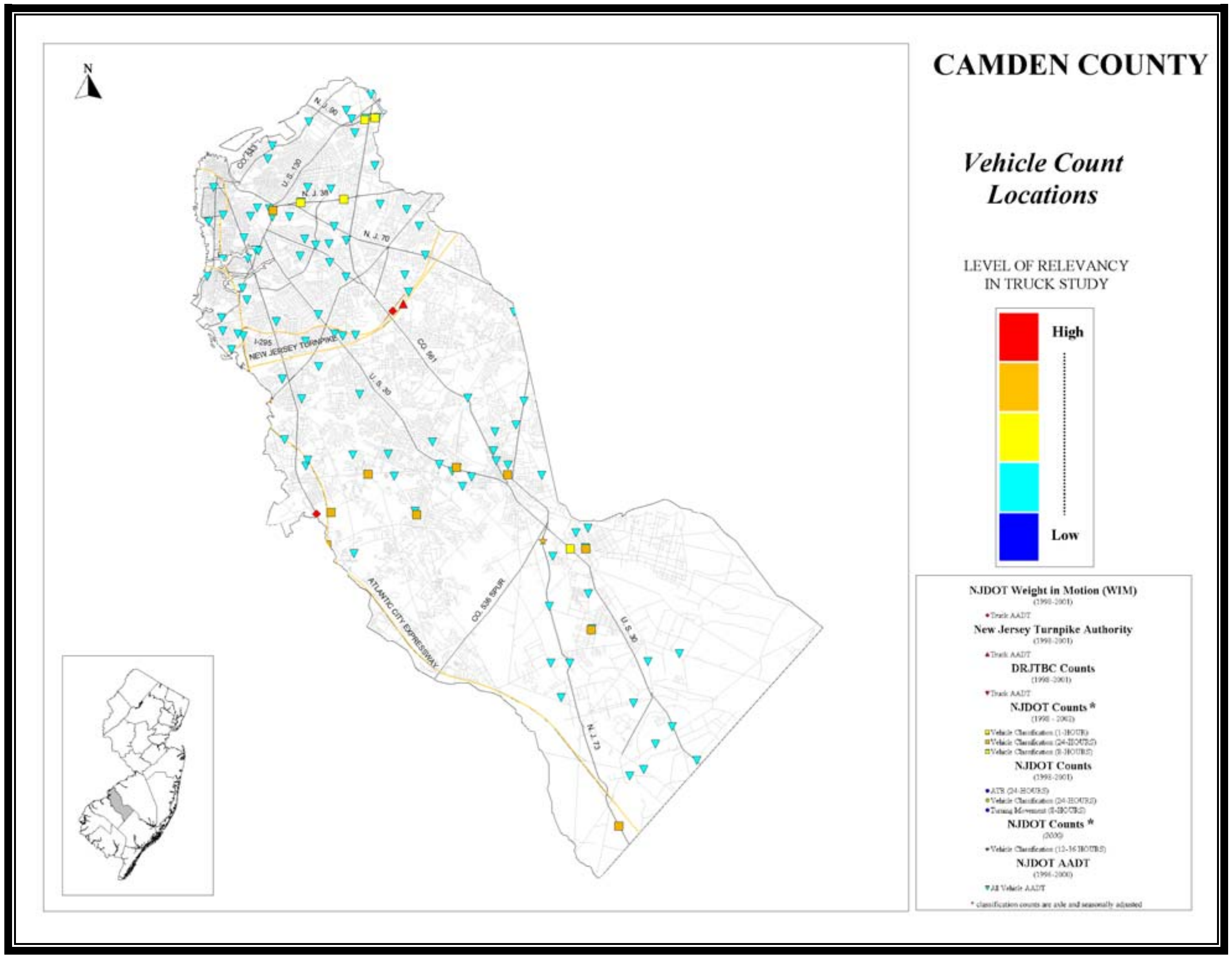

Figure 22: Vehicle count locations for Camden County

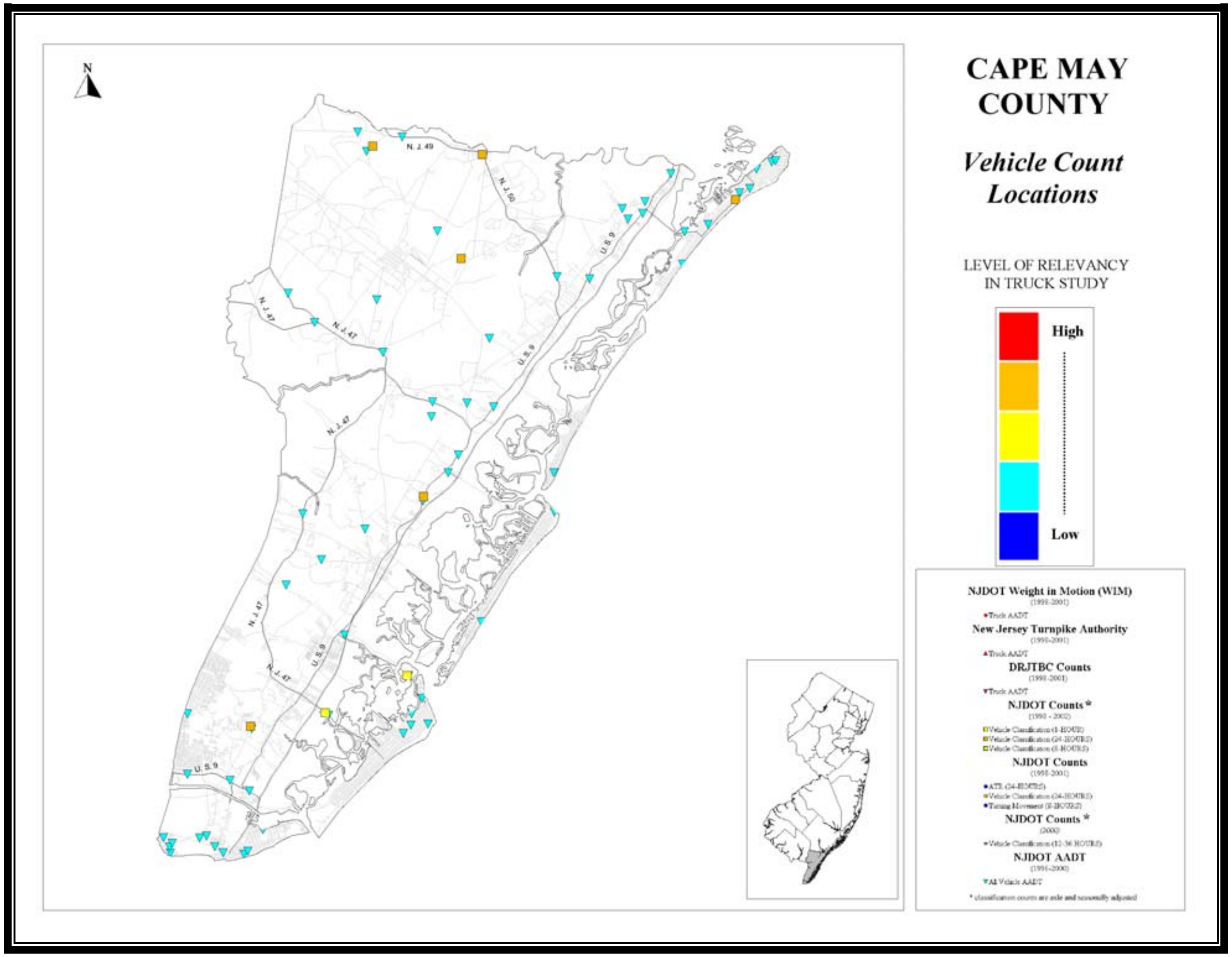

Figure 23: Vehicle count locations for Cape May County

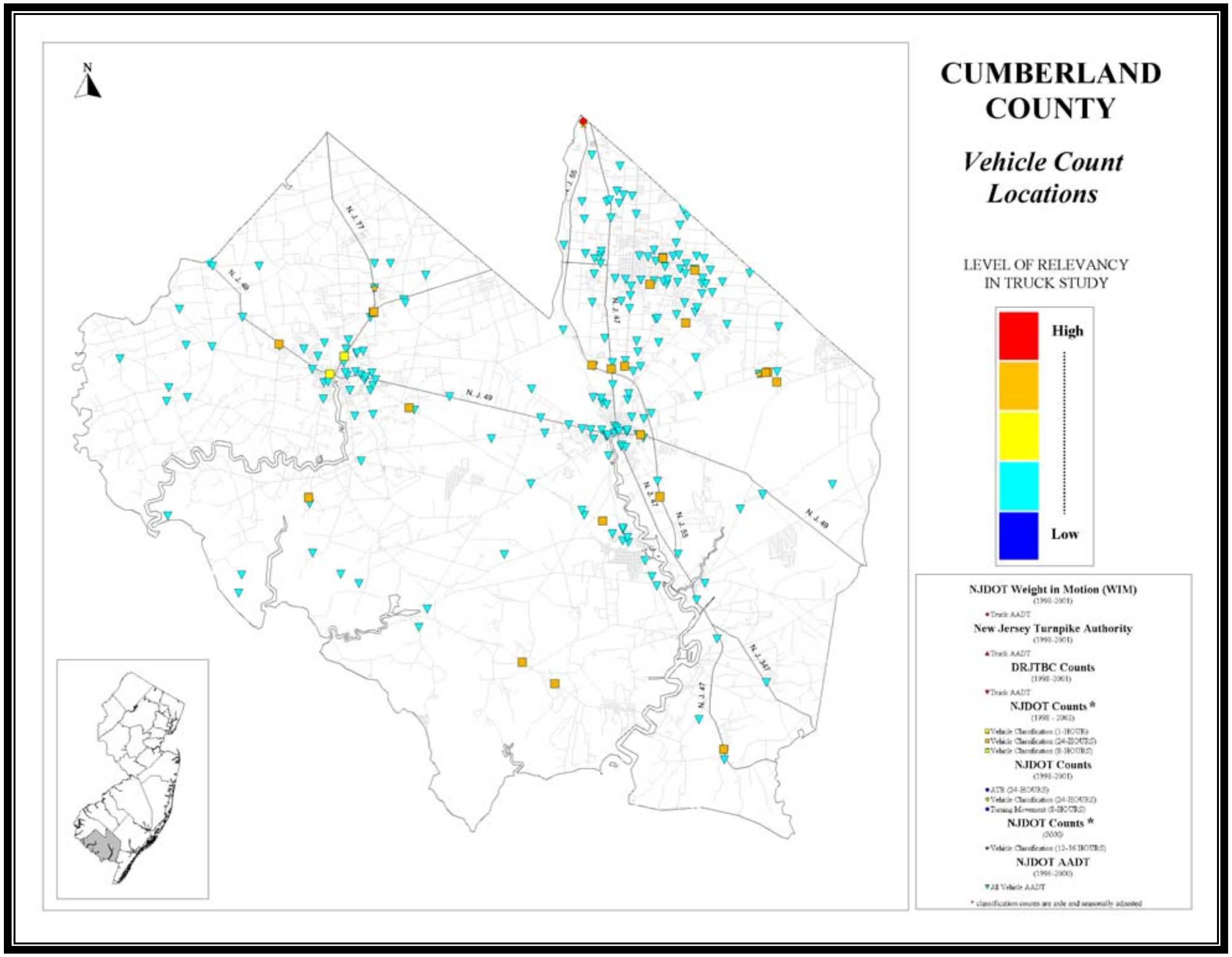

Figure 24: Vehicle count locations for Cumberland County

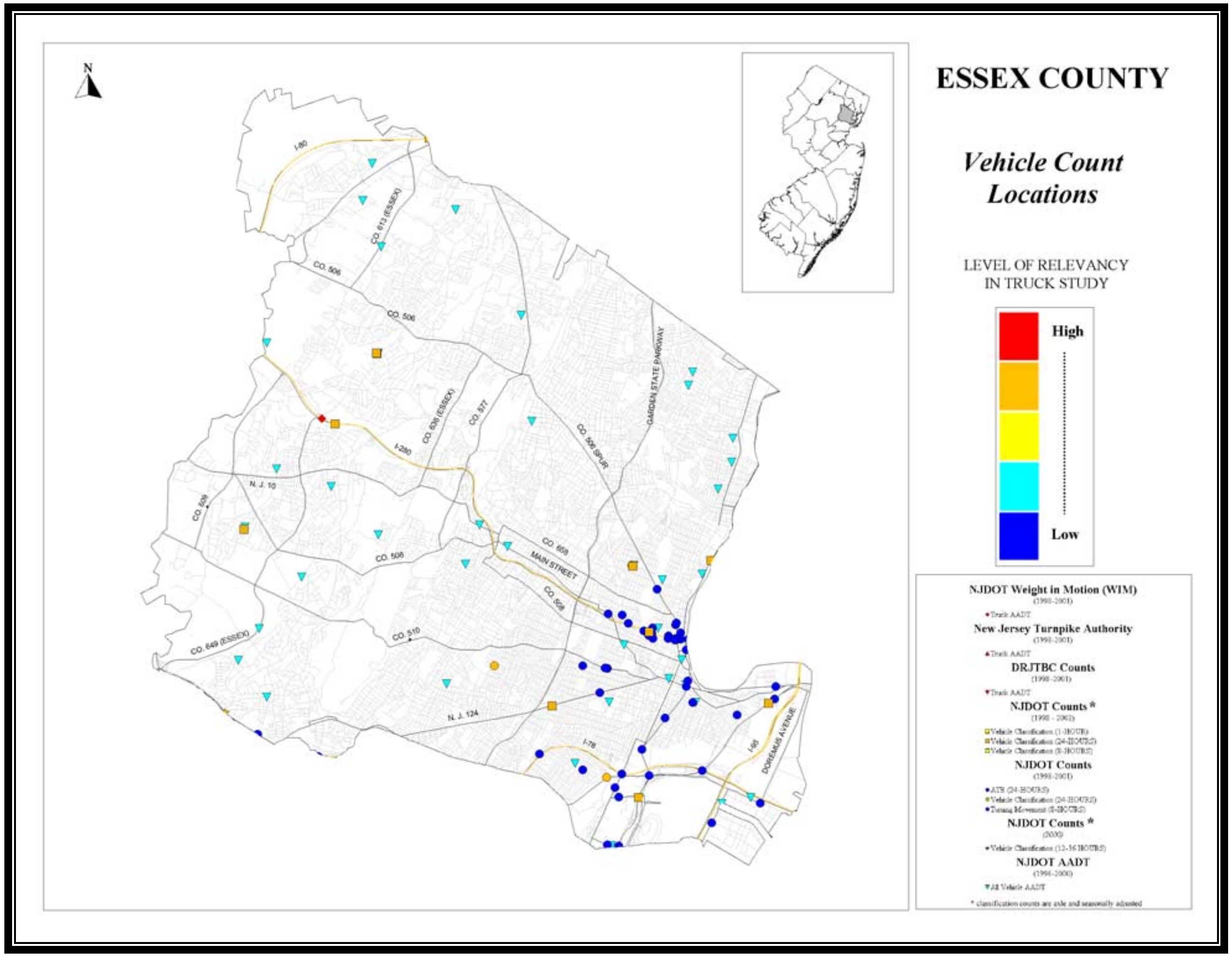

Figure 25: Vehicle count locations for Essex County

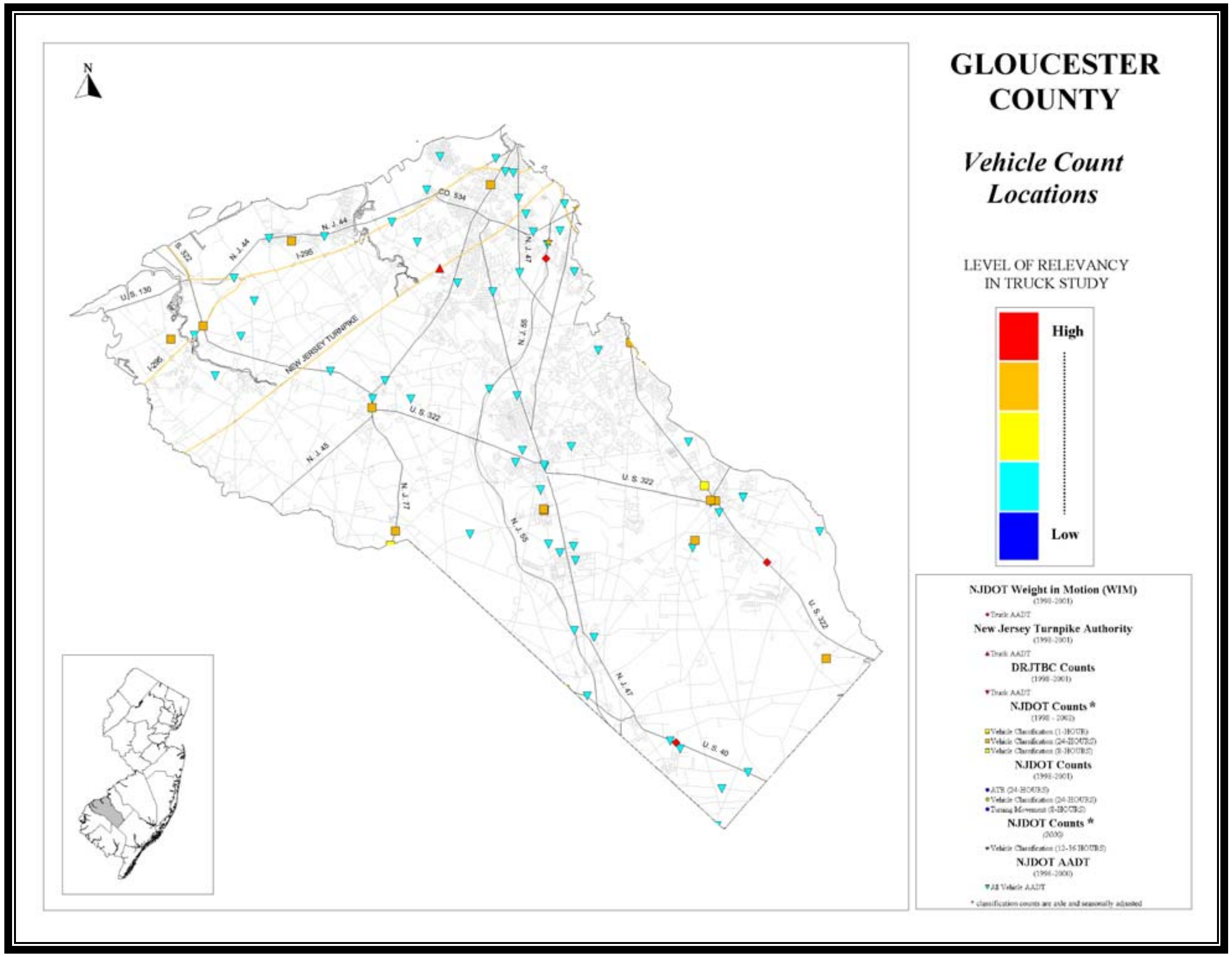

Figure 26: Vehicle count locations for Gloucester County

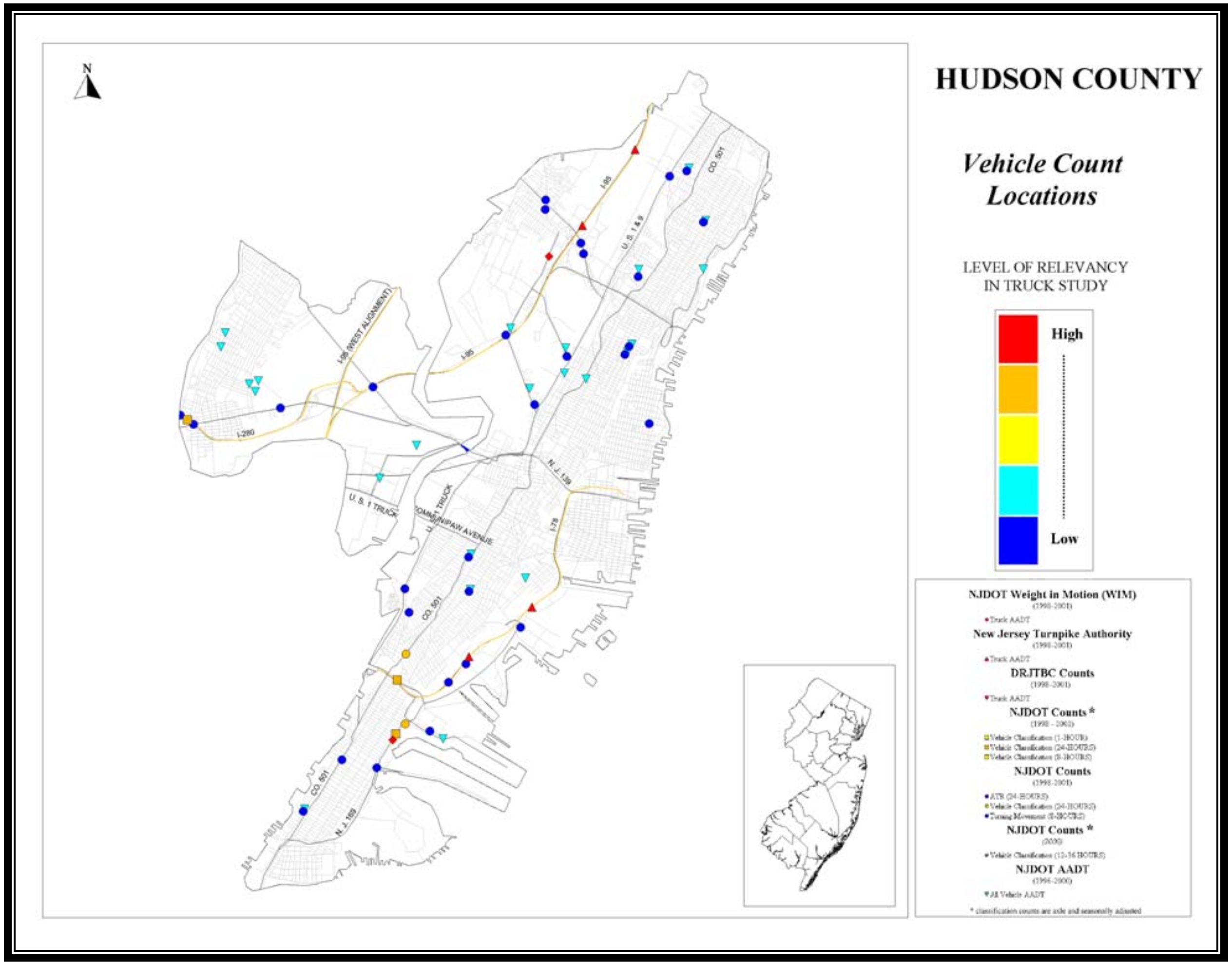

Figure 27: Vehicle count locations for Hudson County

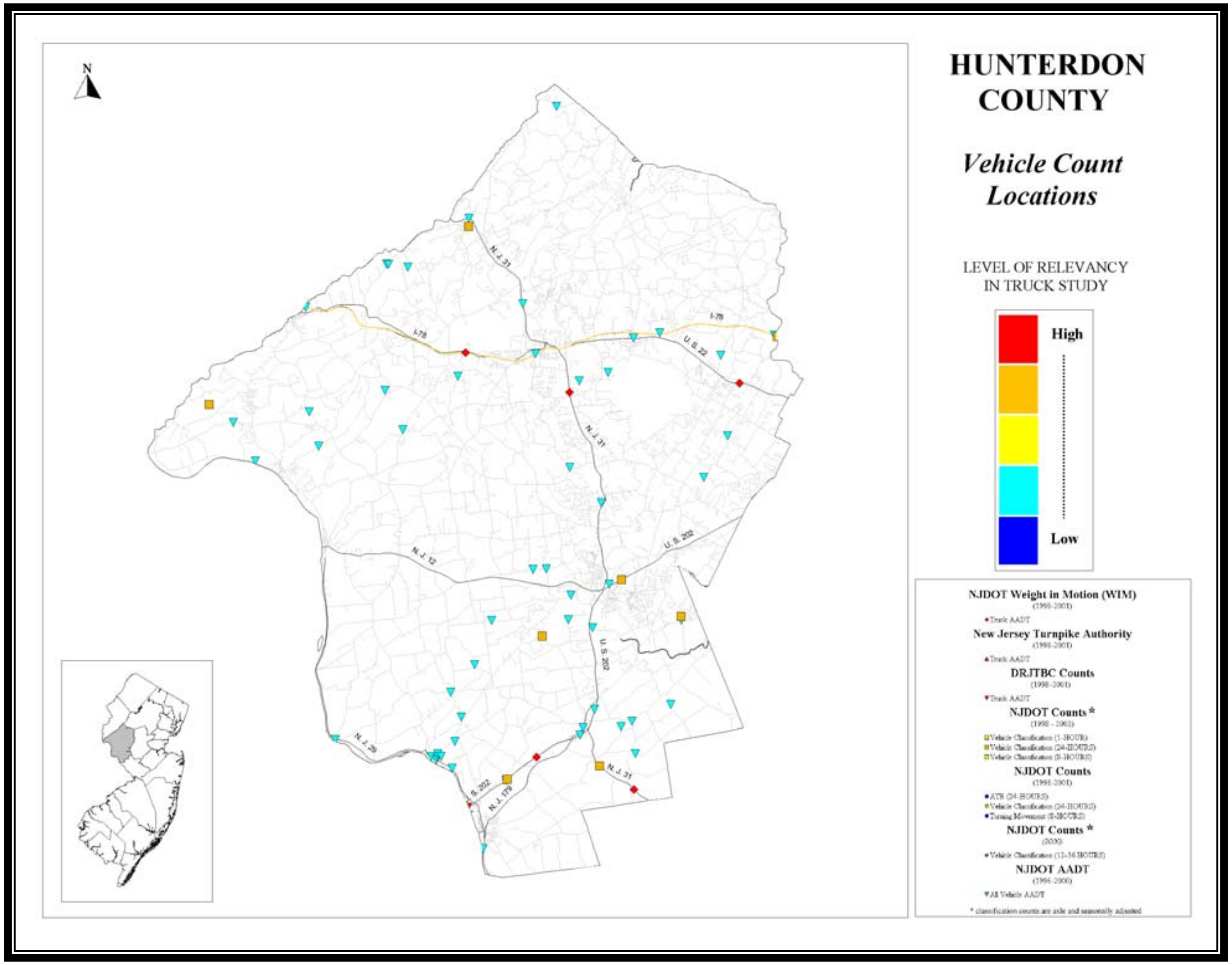

Figure 28: Vehicle count locations for Hunterdon County

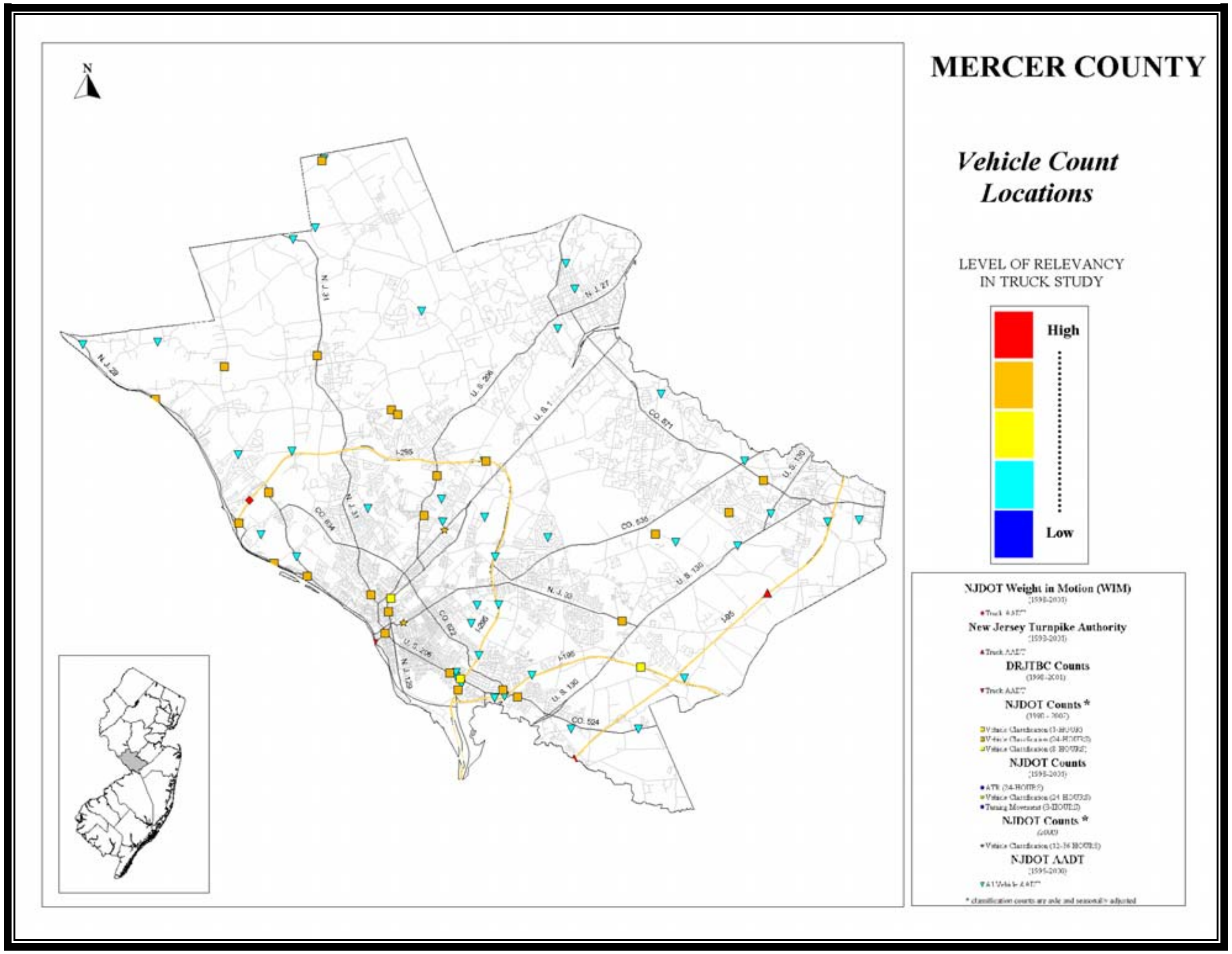

Figure 29: Vehicle count locations for Mercer County

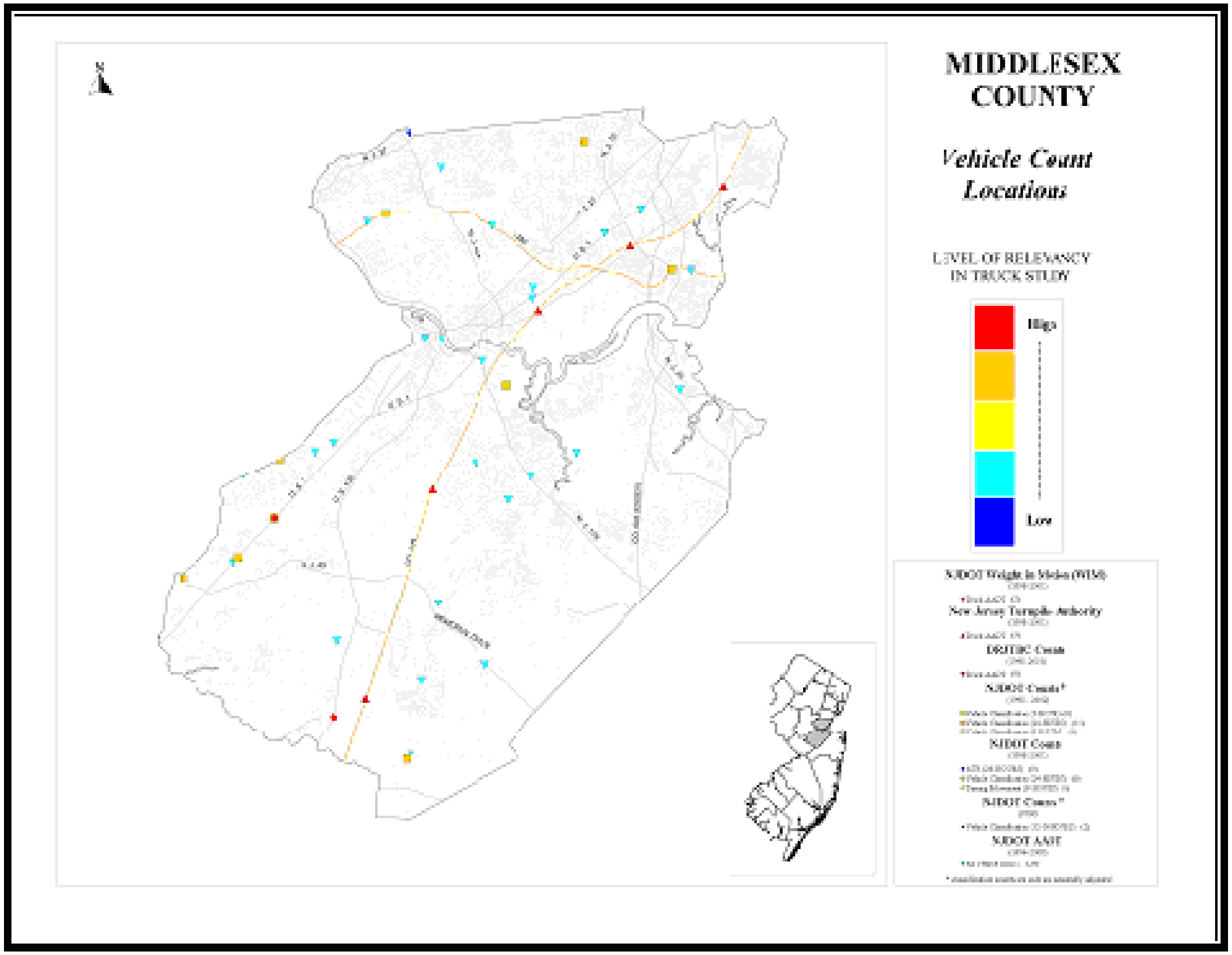

Figure 30: Vehicle count locations for Middlesex County

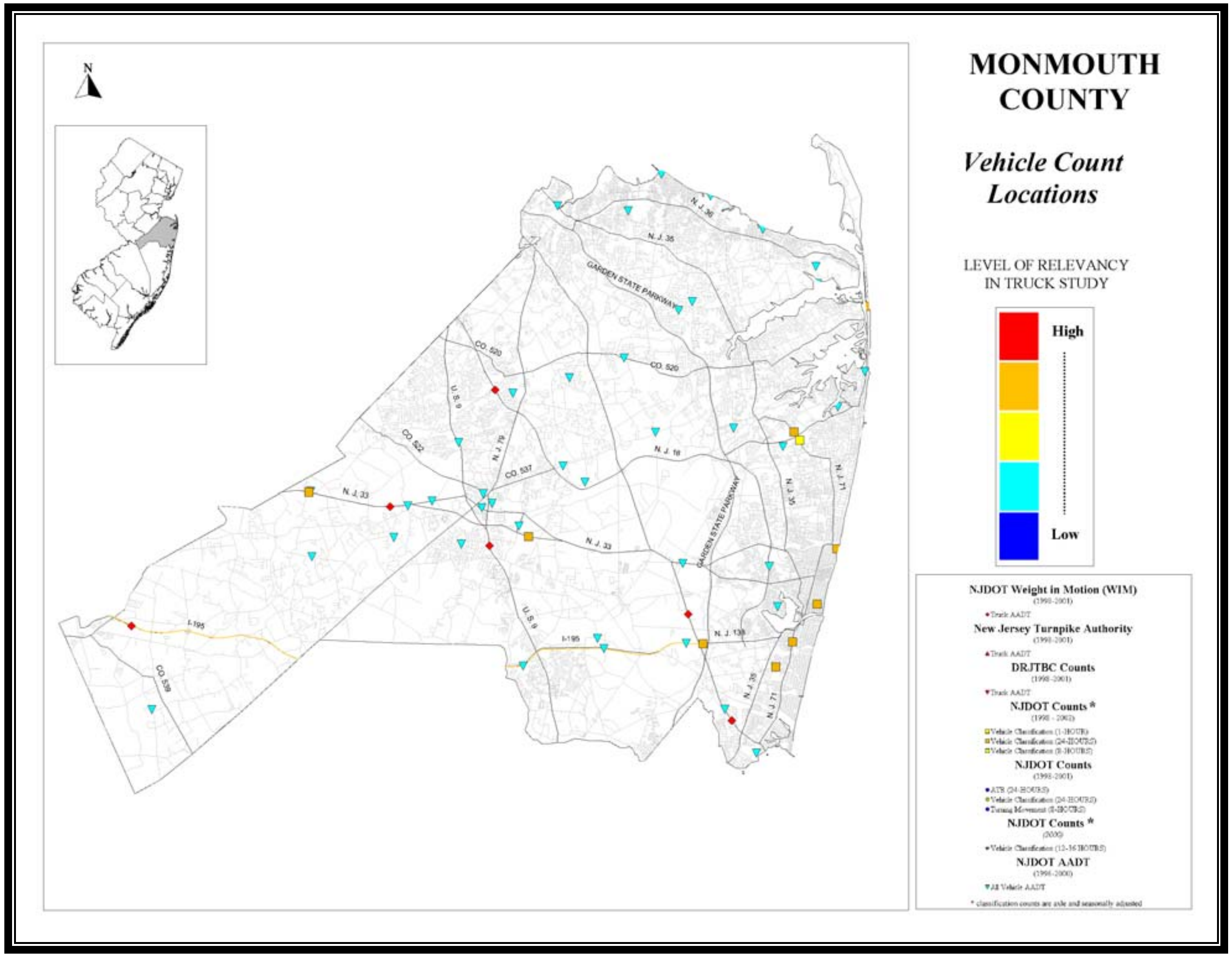

Figure 31: Vehicle count locations for Monmouth County

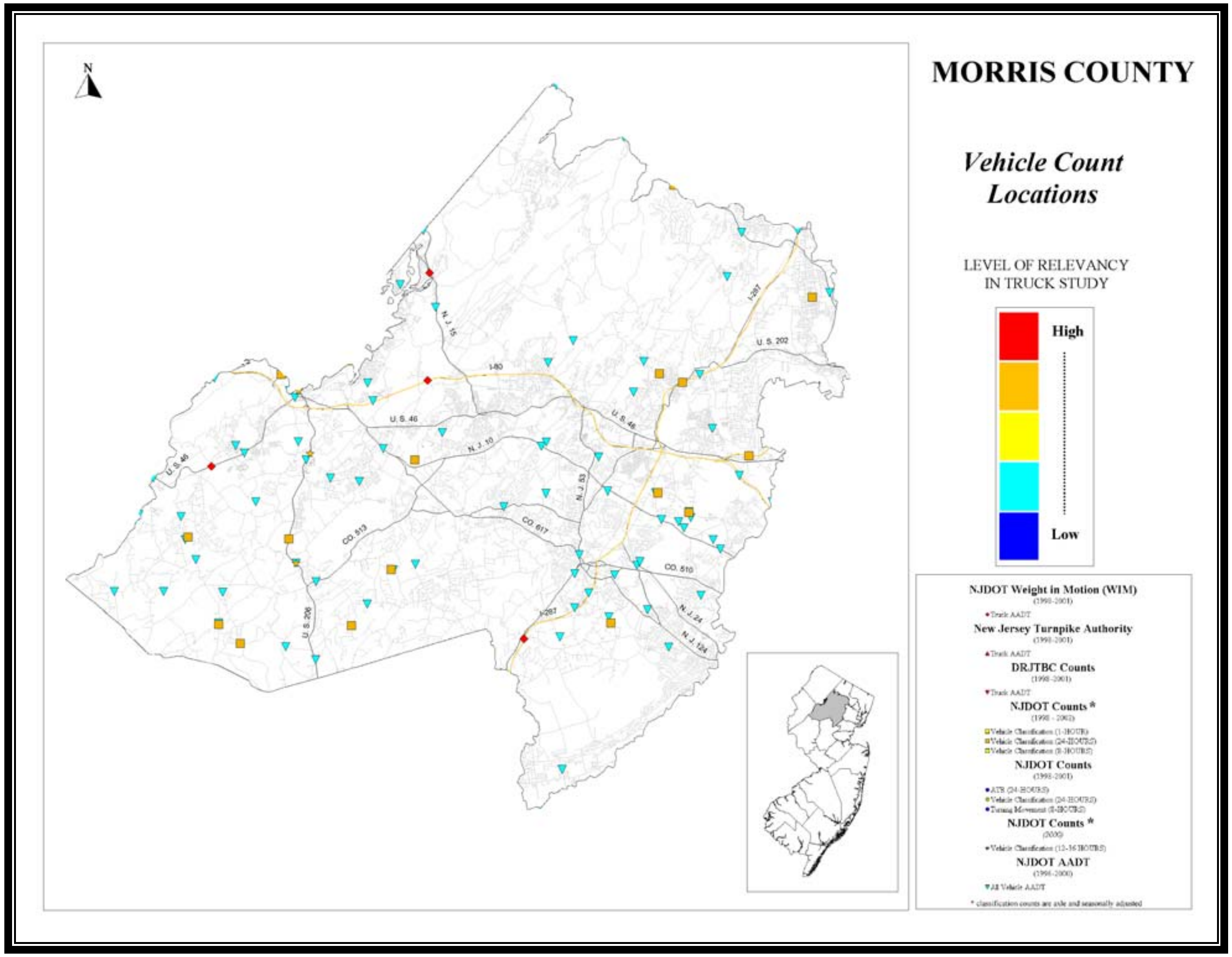

Figure 32: Vehicle count locations for Morris County

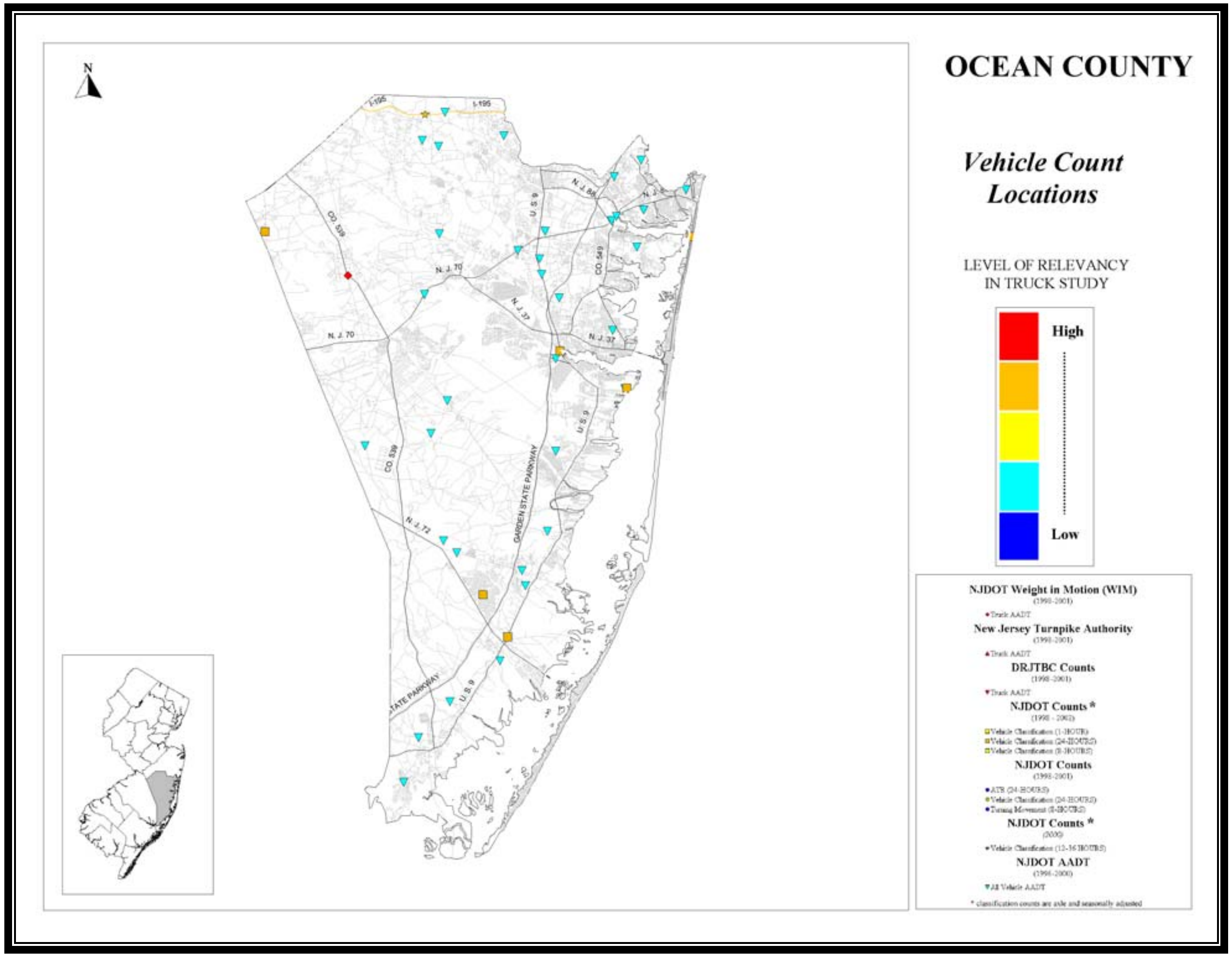

Figure 33: Vehicle count locations for Ocean County

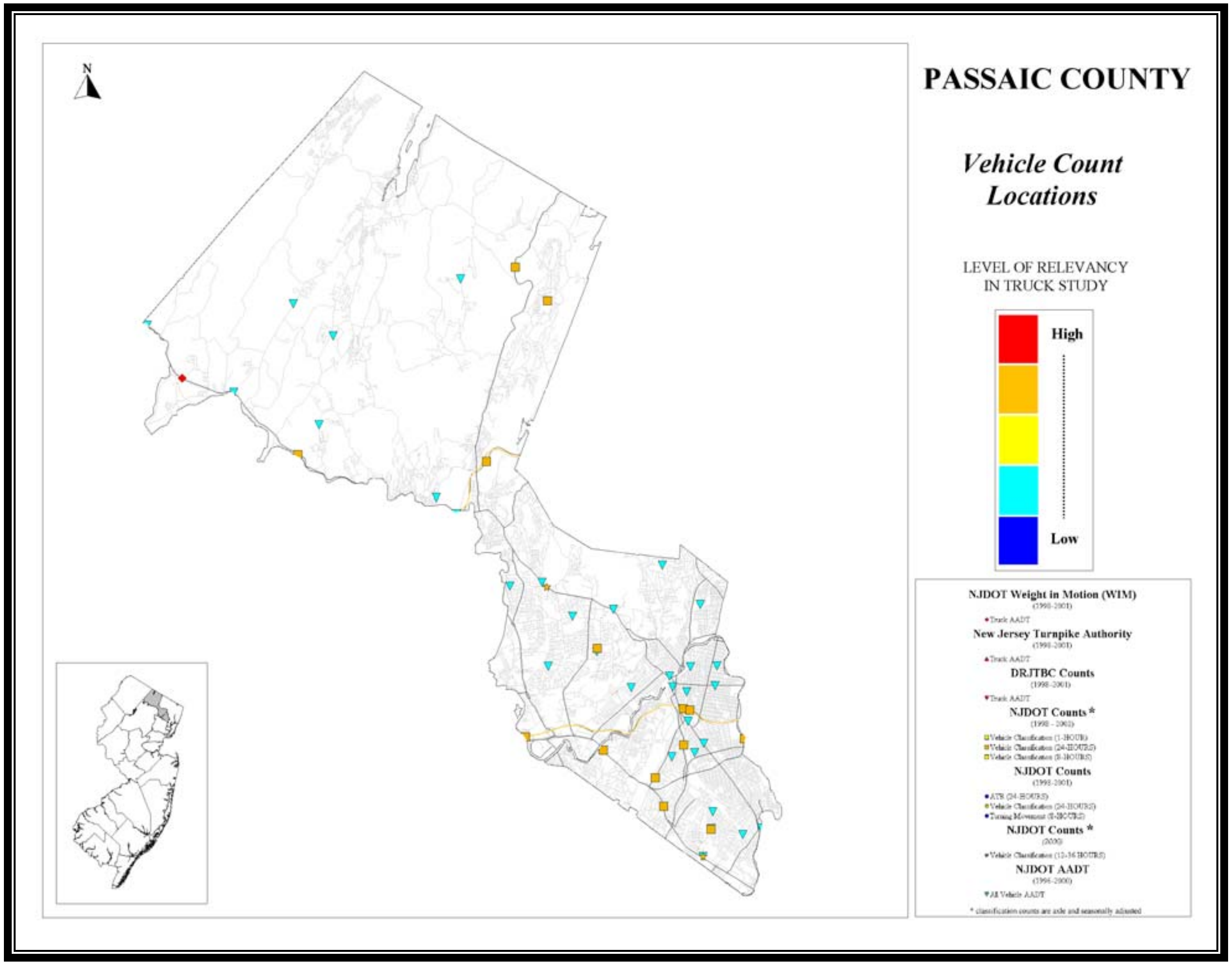

Figure 34: Vehicle count locations for Passaic County

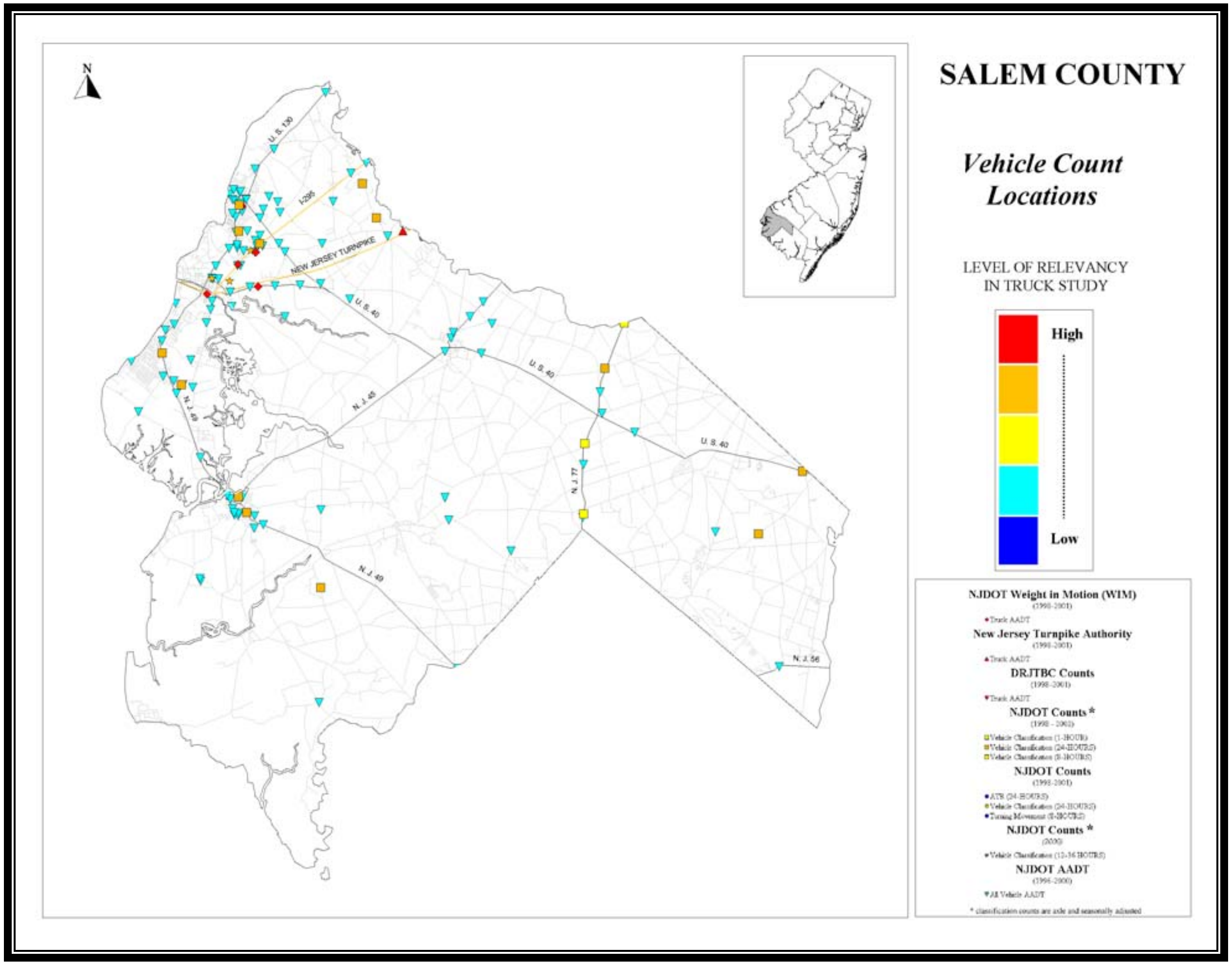

Figure 35: Vehicle count locations for Salem County

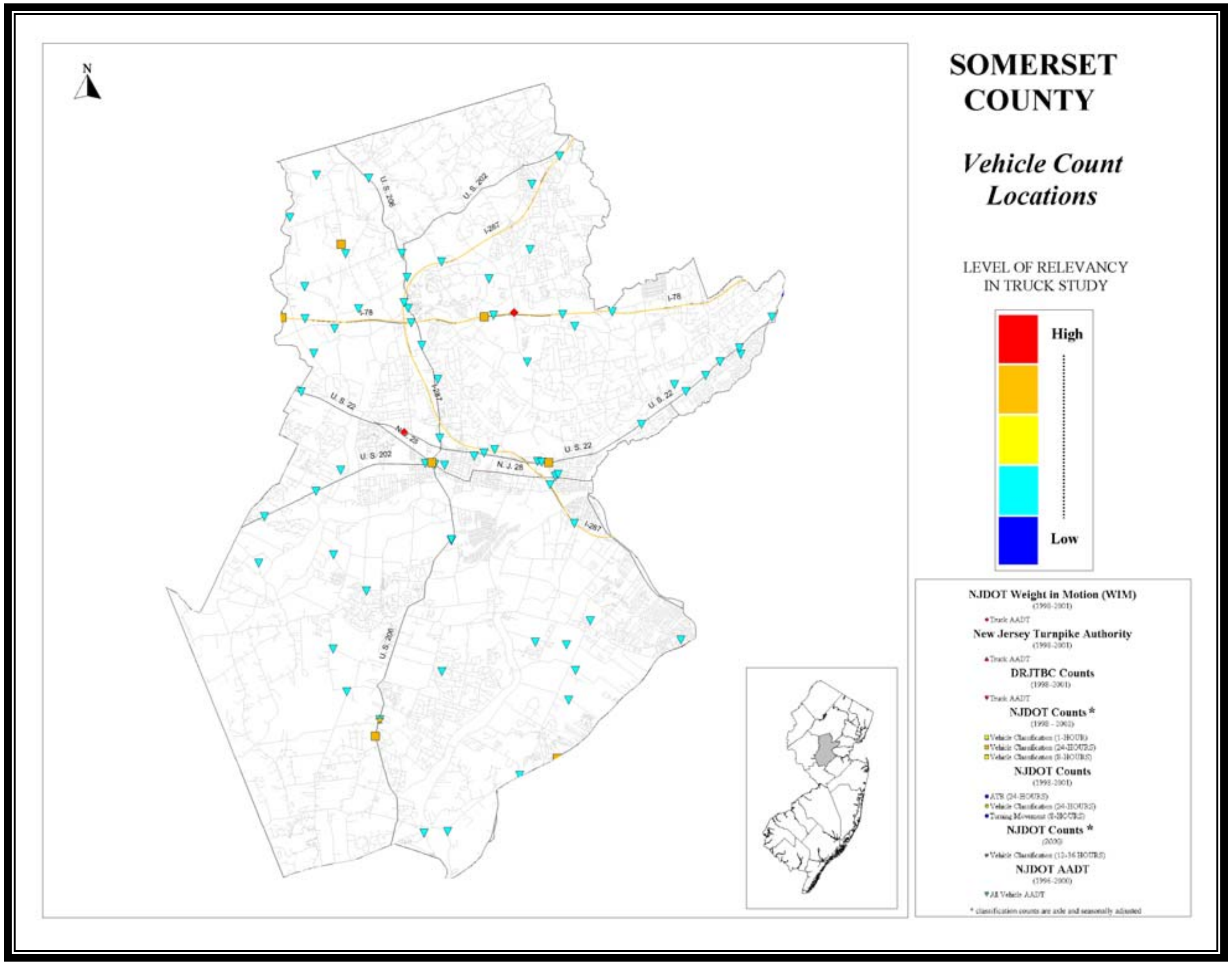

Figure 36: Vehicle count locations for Somerset County

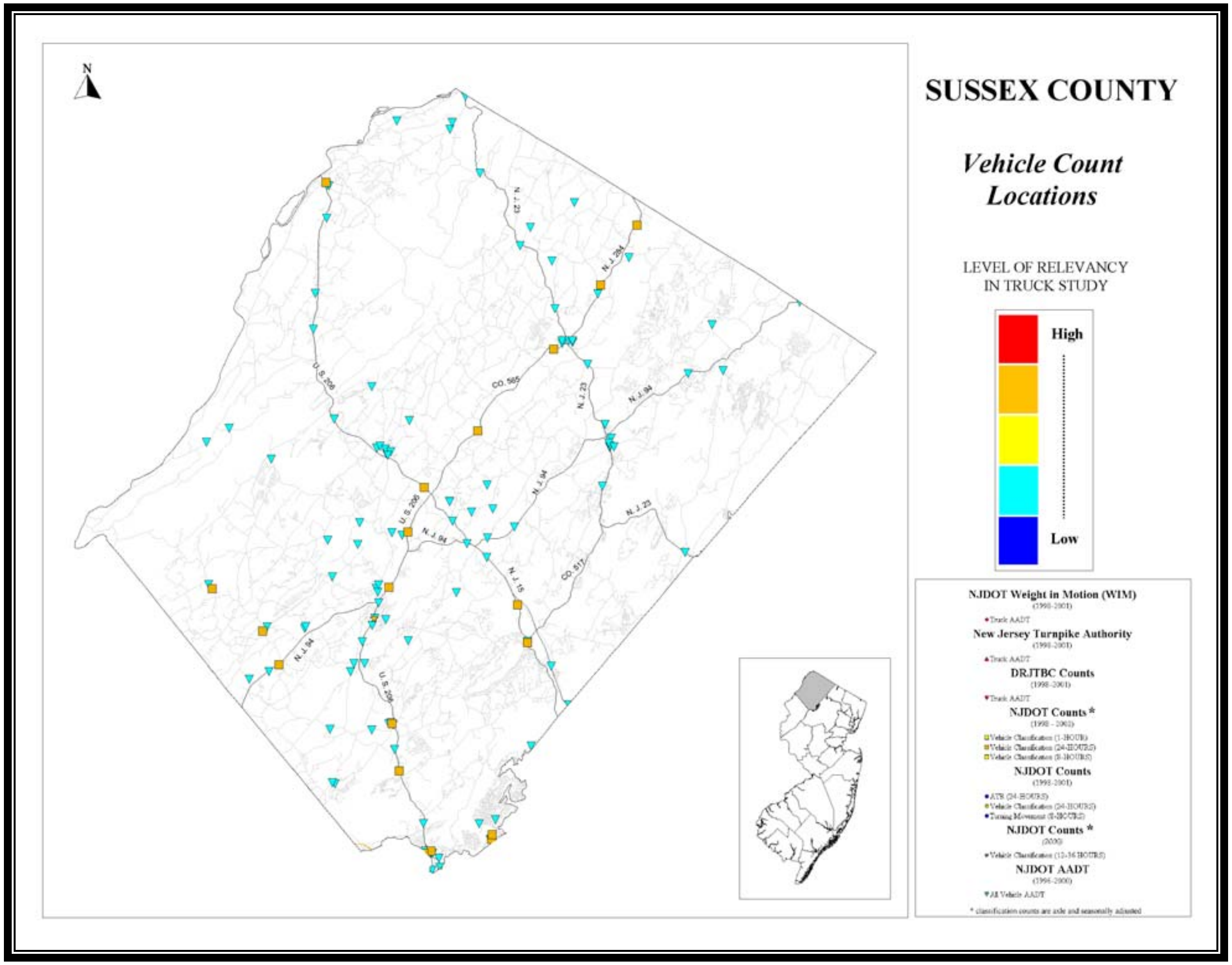

Figure 37: Vehicle count locations for Sussex County

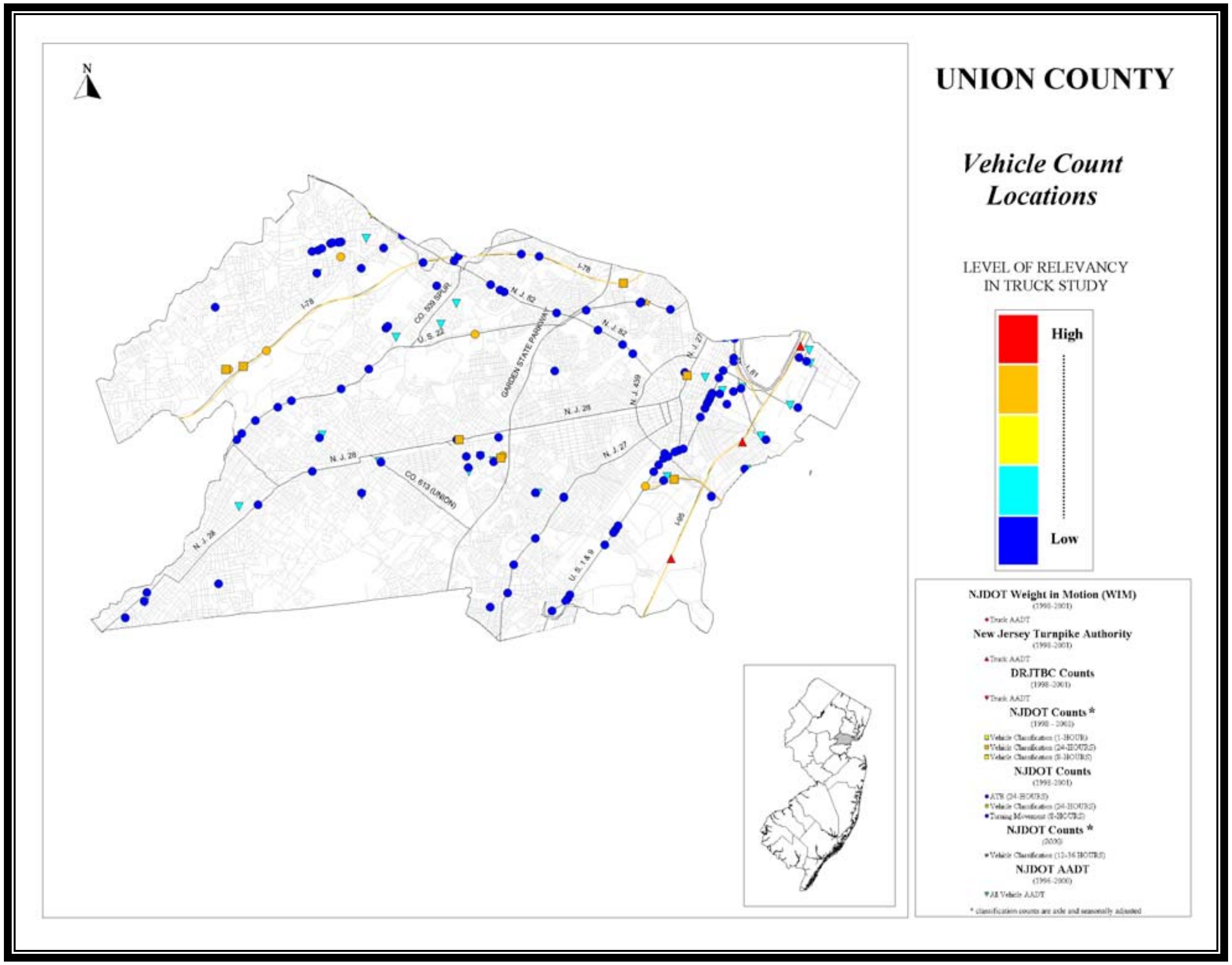

Figure 38: Vehicle count locations for Union County

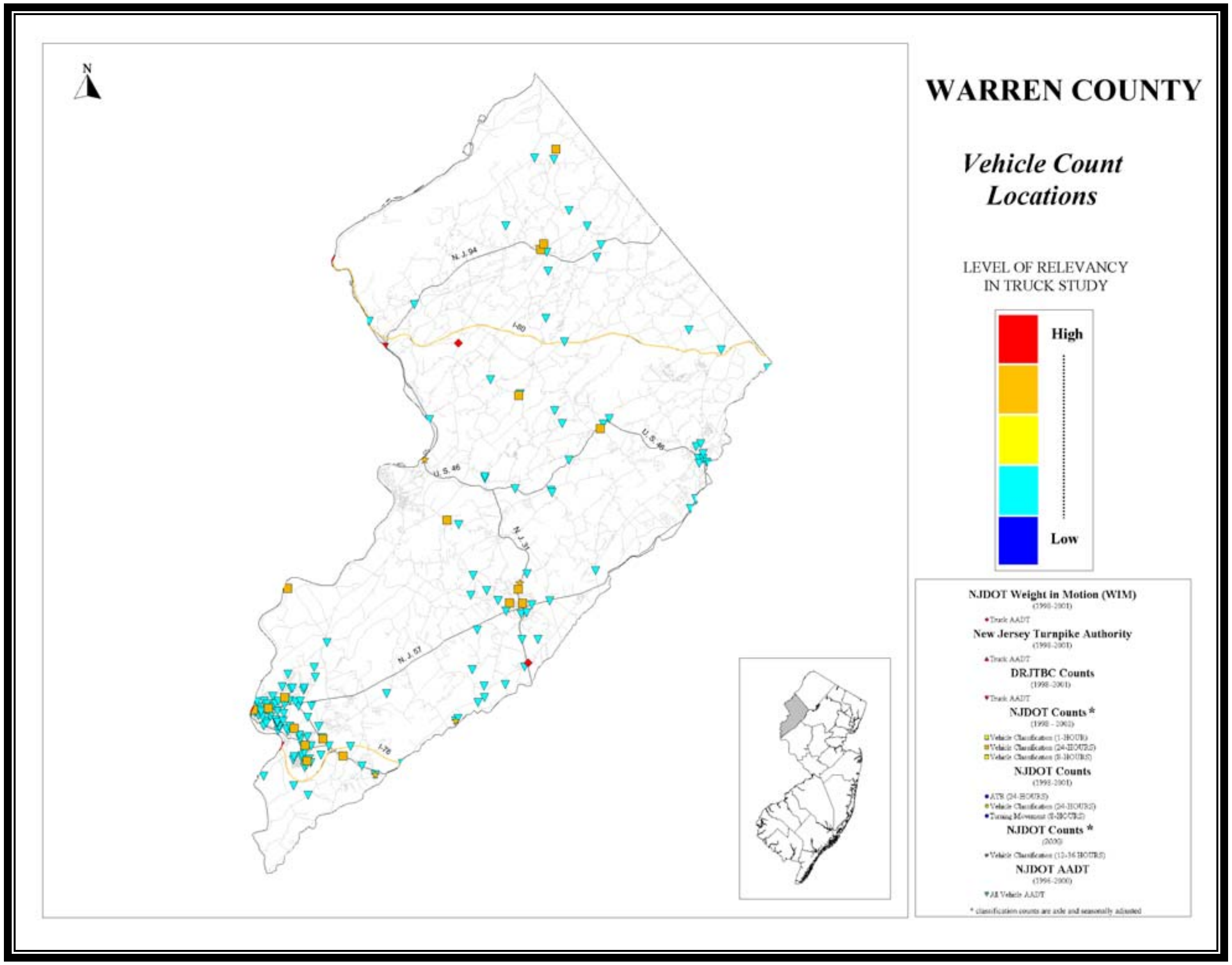

Figure 39: Vehicle count locations for Warren County

In total, a dataset consisting of 270 locations was created and used for the analysis. At the beginning of the project, it was expected that the analysis will have traffic counts available from thousands of locations through-out the state, by various different sources, but later due to the different classification systems adopted and adjustments made on the traffic counts, it was not possible to have and use a huge dependent dataset. Figure 40 below shows the location of the 270 counting sites, which provided data used in the analysis.

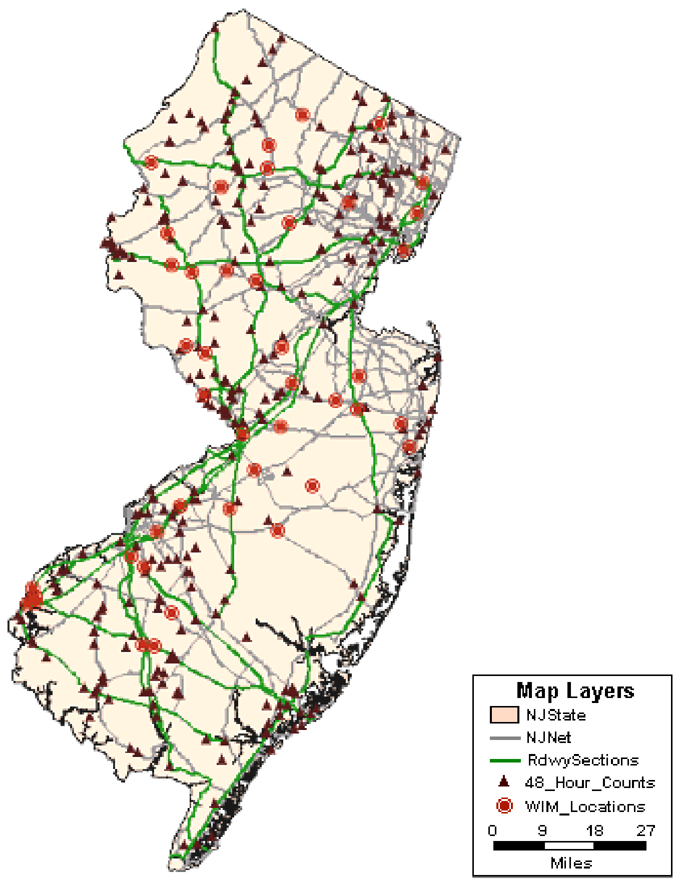

Figure 40: Data locations

Roadway Information

There are several primary sources of data for the roadway network in New Jersey.

1. Source: NJDOT Statewide Truck Model
   The Statewide Truck Model (STM), the network topology of which is shown in figure 41, includes all primary truck routes in the State of New Jersey and surrounding counties of New York, Pennsylvania, and Delaware. The model's base year 2000 contains information for autos, light trucks and heavy trucks in the form of estimated volumes, capacities, and speed/time for both directions of travel. In cases where actual truck volumes are limited or not available, the assigned volumes generated by the base model can be used to support, supplement, or substitute for reliable truck counts.

2. Source: NJDOT – New Jersey Congestion Management System
   The New Jersey Congestion Management System (NJCMS) version 2.0, with the RA database series, shown in figure 42, contains 24-hour directional truck counts that can be used in conjunction with the Statewide Truck Model volumes.

3. Source: NJDOT National and Access Network
   The New Jersey National Network is a 545-mile network that includes the major interstate and other through highways in the state. These are the only roads in the state that are available for large (102 inch) interstate (through) truck traffic. The New Jersey Access Network is a 1,812-mile network that includes the National Network as well as major state highways. The Access Network is available to all trucks with a local (in-state) origin or destination. The two networks are shown in figure 43.

4. Source: NJDOT 2002 New Jersey Straight Line Diagrams
   The New Jersey Straight Line Diagrams (SLD) provide detailed information about the geometry, mile posting, capacity, speed limits, and volumes of all state highways and most county routes in the state. This data is not available in GIS format.

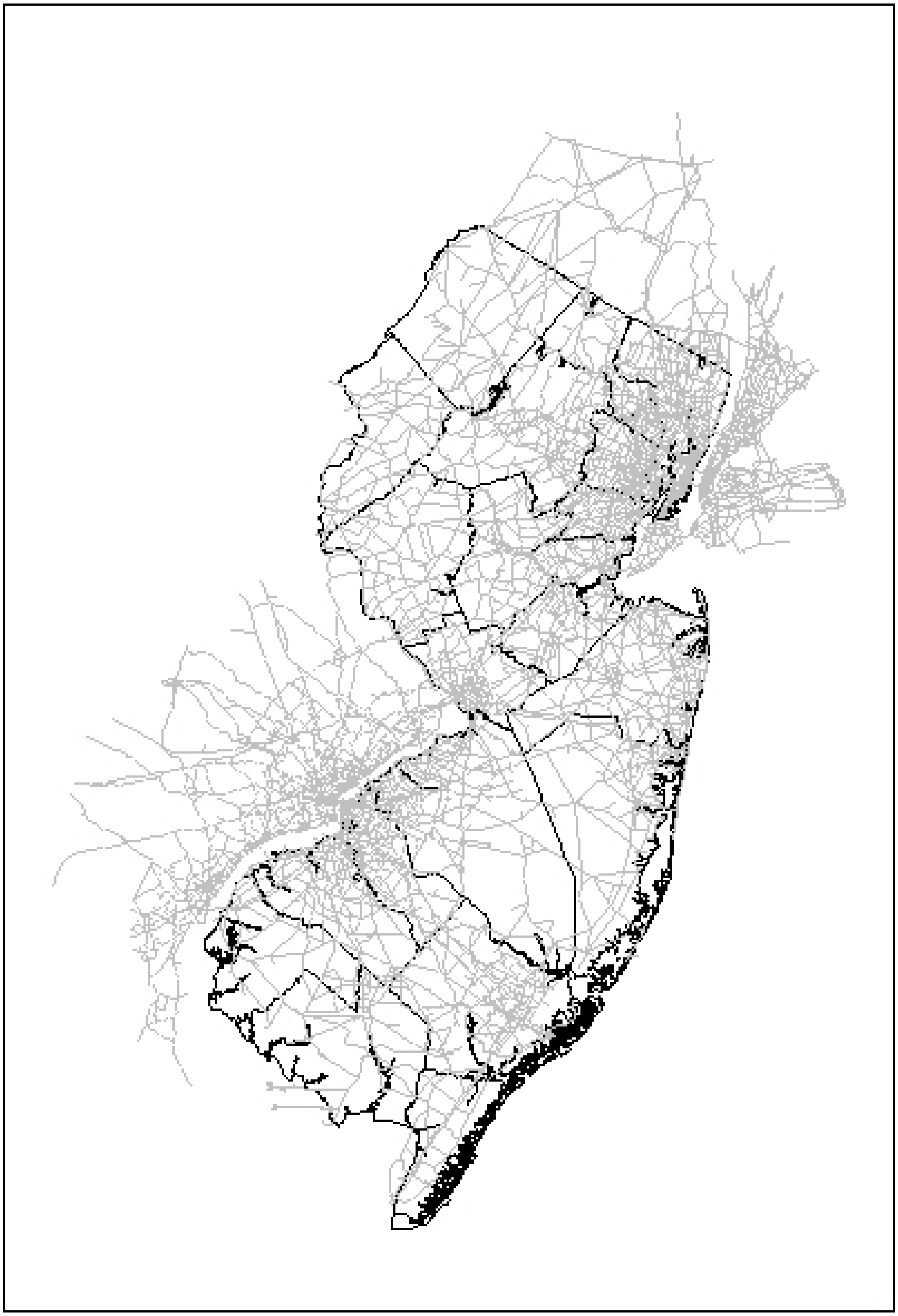

Figure 41: 2000 Statewide Truck Model

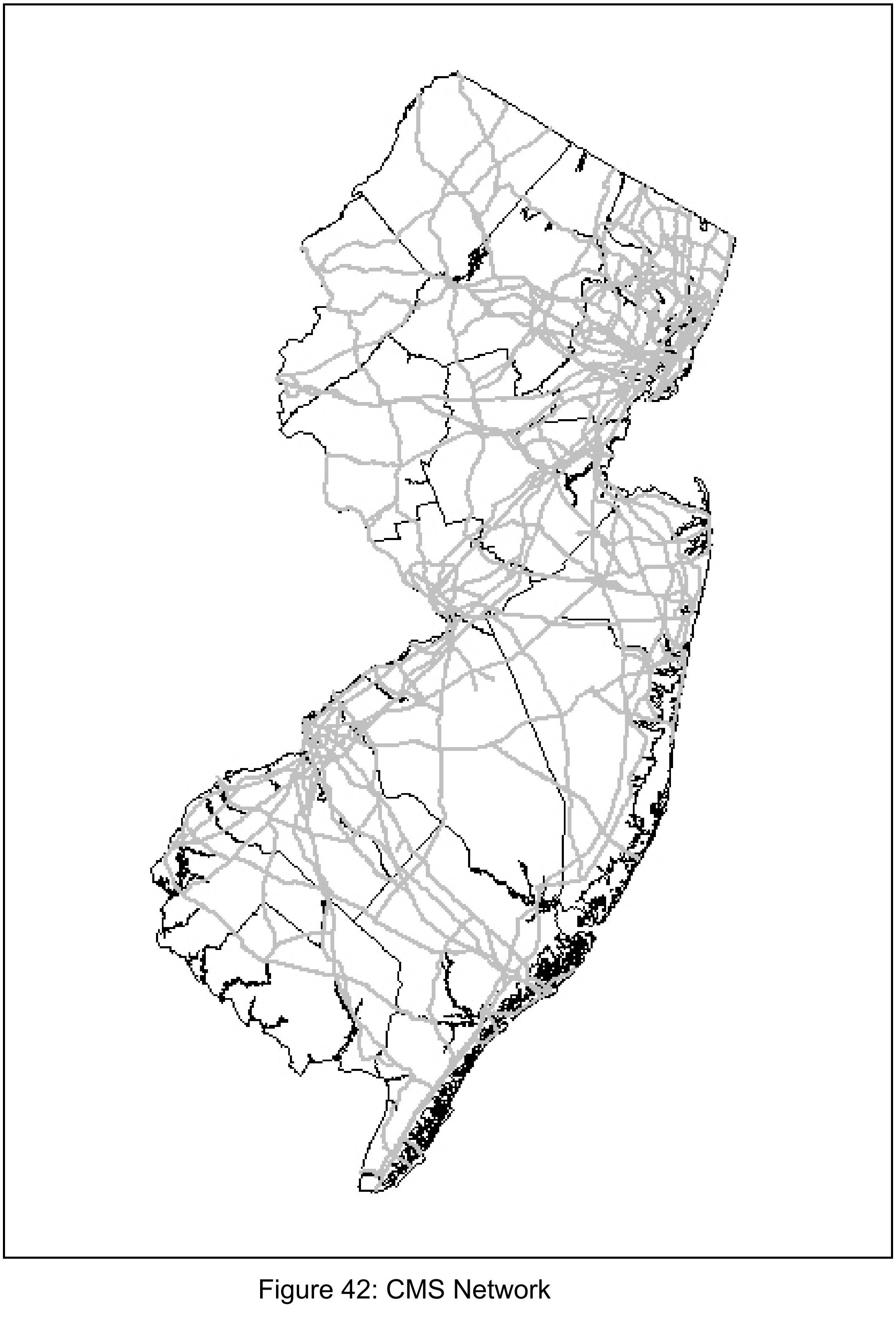

Figure 42: CMS Network

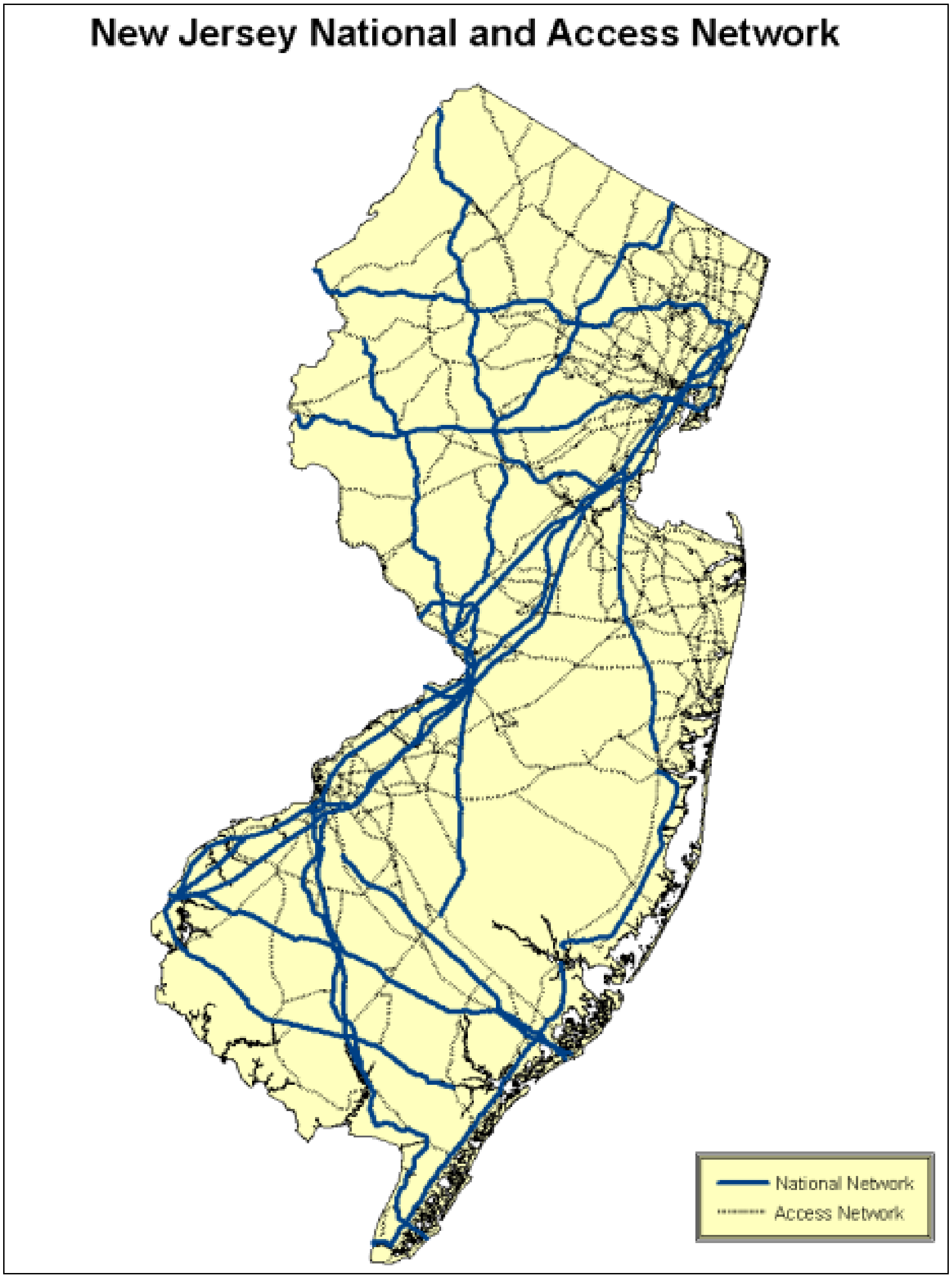

Figure 43: New Jersey National Network and Access Network

Major Truck Generators

Gathered from a variety of sources, major truck generators have been identified, compiled, geo-coded and mapped. The data set of generators is comprised of intermodal facilities such as rail yards, airports, ports; major wholesale and retail facilities; distribution centers; and warehouses.

Several sources have been identified as major truck generators.

1. The ESRI BIS business location data (Environmental Systems Research Institute Business Information Solutions) is extracted from a comprehensive list of businesses licensed from InfoUSA. Data items include business name and location, franchise code, industrial classification code, number of employees, and sales volume. Businesses addresses have been geo-coded to assign a latitude/longitude coordinate to the site and to add a census geographic code (i.e. Block Group) to each data record. Overall, 85 percent of the businesses are coded at the address level, with more accuracy expected in urban areas. 87 percent of the businesses are assigned to a census block group. Businesses not assigned to a block group have been assigned to a census tract or county. InfoUSA, which supplies the data to ESRI BIS, does not divulge how many businesses it thinks are "missing" from its database. The data is gathered from several sources, including: yellow pages and business white pages, annual reports, federal, state, municipal government data, business magazines, newsletters and newspapers, and U.S. Postal Service Information. Telephone verification is conducted annually. For the records that are included in the database, however, the company claims the following accuracy rates. These rates are based on a self-audit the company performed in 2001. A subset of the entire database, which consists of businesses whose North American Industrial Classification code (NAICS) are classified in the sectors of mining, construction,

manufacturing, wholesale trade, retail trade, and warehousing and has 500 or more employee, has been identified to represent major truck generating facilities, shown in figure 44.

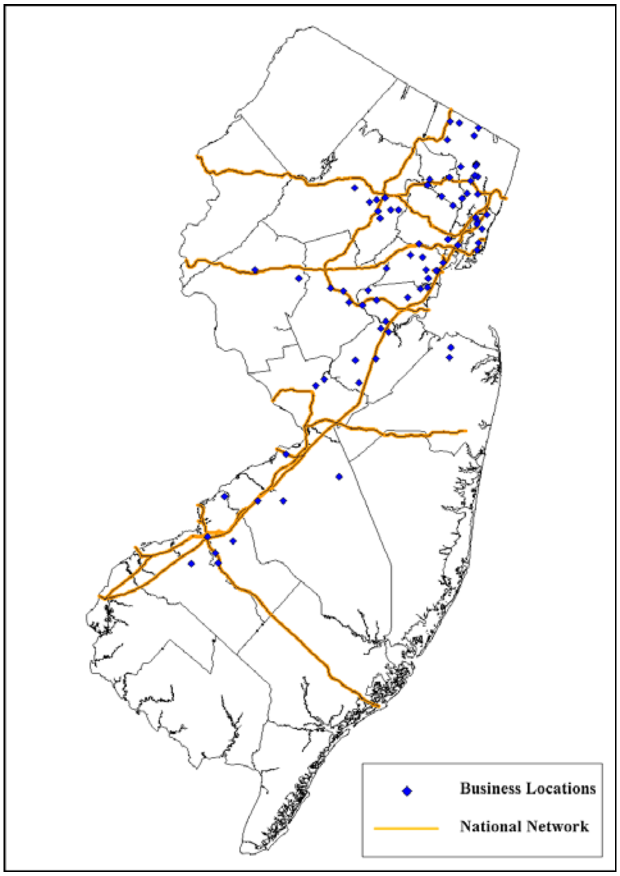

Figure 44: ESRI Business Locations

2. Compiled by the USDOT Bureau of Transportation Statistics (BTS), the <u>Intermodal Terminal Facilities</u> data set contains point-based GIS data for trailer-on-flatcar (TOFC) and container-on-flatcar (COFC) highway, rail and/or rail-water transfer facilities in the United States.
   Attribute data specify:
   - The name of the facility;
   - The intermodal connections at each facility, i.e., the modes involved in the intermodal transfer, and the direction of the transfer;
   - The Association of American Railroads (AAR) reporting marks of the railroad serving the facility (if applicable); and
   - The type of cargo.

Shown in figure 45, there are 90 points in this data set located in New Jersey. Approximately one-half of the points are within five miles of Port Newark/Elizabeth.

3. A database of 243 wholesale distributors for Essex, Hudson, and Union Counties was acquired from the New Jersey Department of Commerce via NJDOT. This database, dated from 2000, was geocoded, mapped and shown in figure 46.

   Attribute data included in this dataset include:
   - Business name;
   - Address location;
   - SIC industry code;
   - Employment;
   - Annual sales totals;
   - The nature of the specific facility (e.g. headquarters, branch, single location); and
   - Several other fields related to the ownership and status of the business.

4. The Louis Berger Group, Inc. created a database for NJDOT in the early 1990s that identified warehouses in New Jersey. This database consists of warehouses grouped into six facility types, as shown in figure 45.
   - Truck terminal
   - Truck stop
   - Truck company
   - Marine terminal
   - Warehouse
   - Pipeline

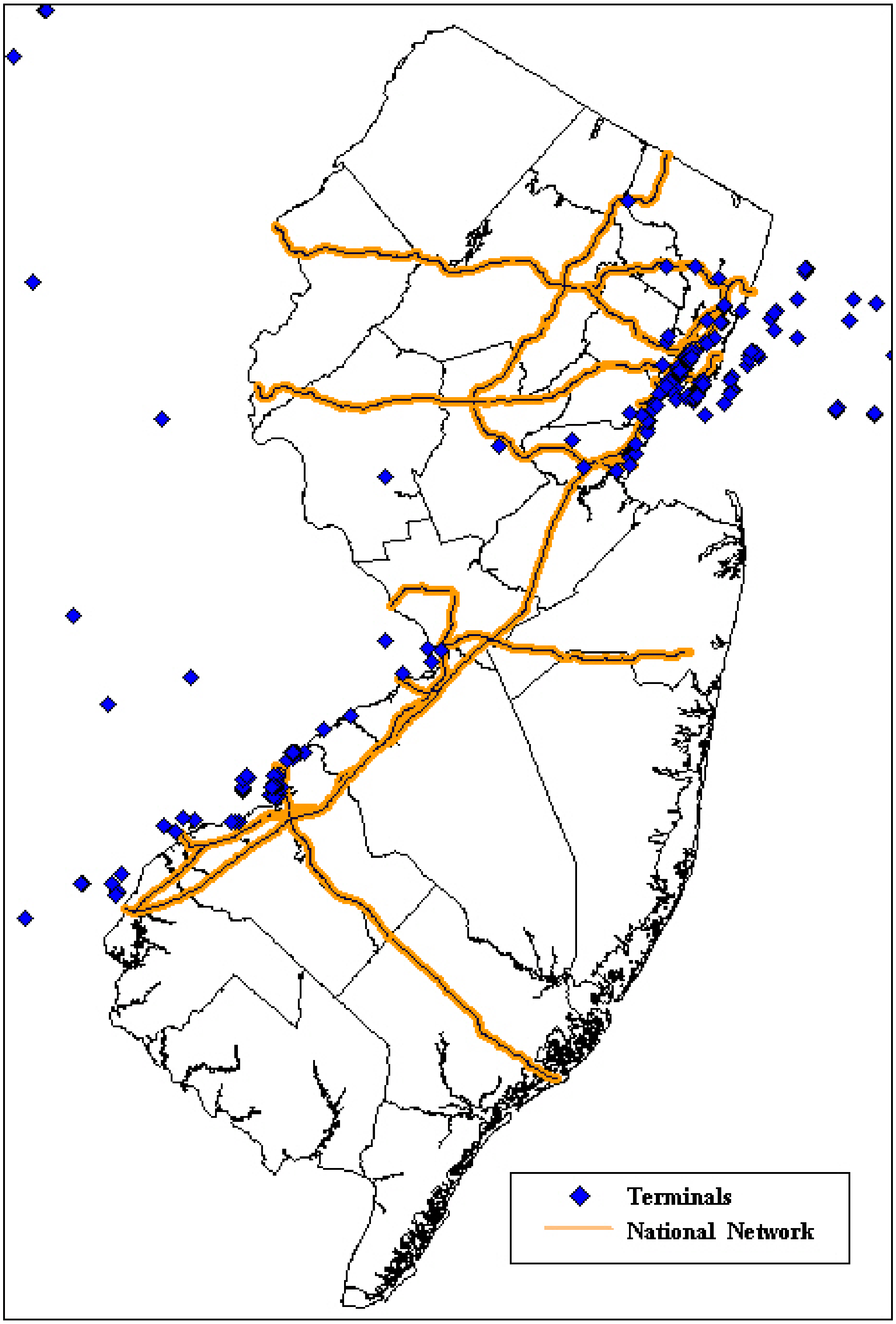

Figure 45: Intermodal Terminal Facility Locations

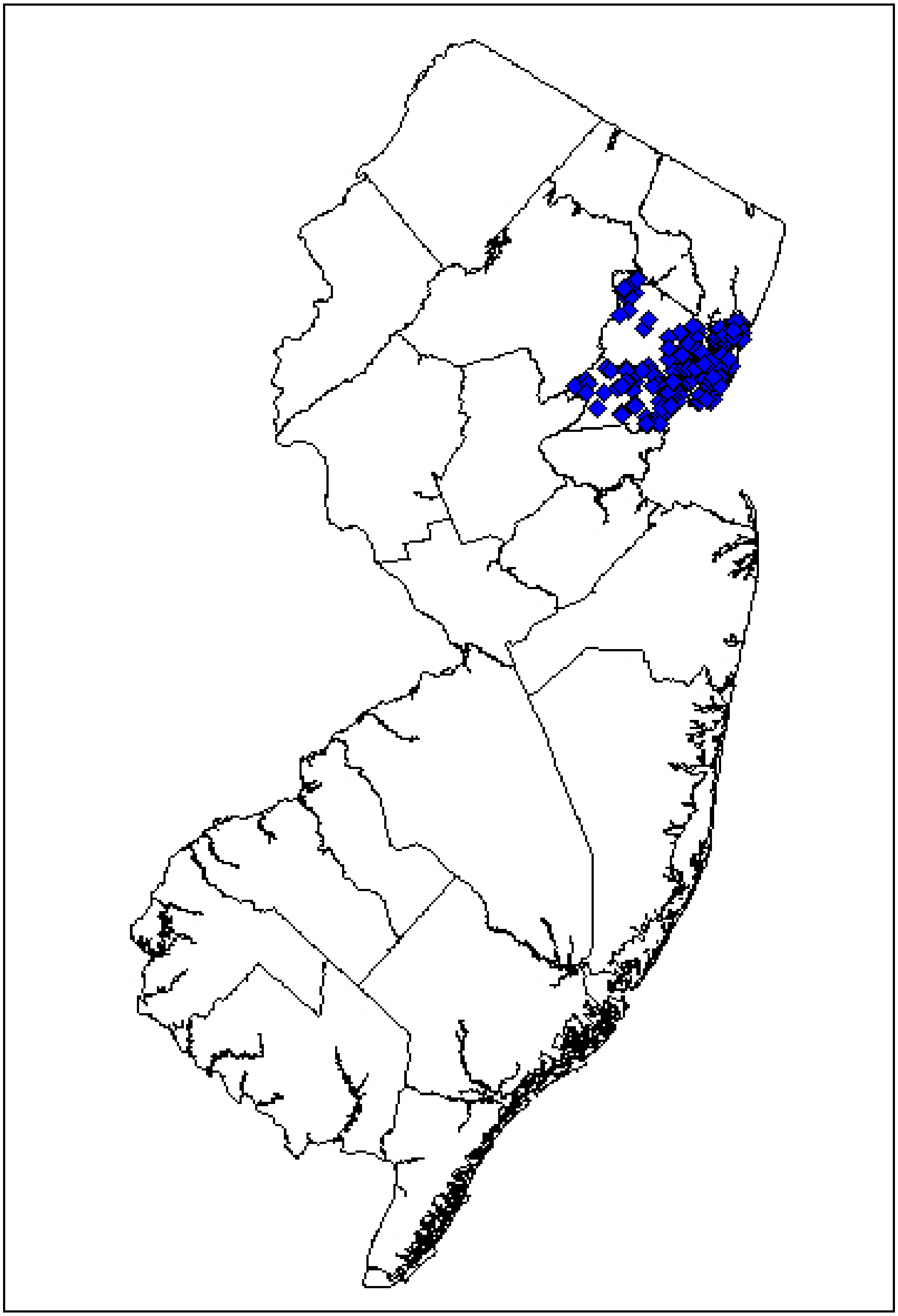

Figure 46: Wholesale Distributor Locations

With a total of 860 records, the database was divided by Metropolitan Planning Organization region. There are 792 records for the NJTPA region (47 percent geocoded) and 68 records for the SJTPO region (26 percent geocoded). No records in the DVRPC region were included.

5. The names and addresses of 82 liquor license warehouses have been obtained from the New Jersey Bureau of Alcohol Beverage Control through NJDOT. These facilities have been geocoded and mapped and are shown in figure 48.

6. The New Jersey Statewide Truck Model (STM), administered by NJDOT, can be used to identify major truck generators. This model's network includes all of New Jersey plus portions of New York, Pennsylvania and Delaware. In the base year 2000 network, 130 "special generator" zones were added to account for truck traffic originating and destined for airports, seaports, rail yards, and freight distribution redevelopment sites; 119 of these zones are located in New Jersey. Unlike the other truck generators, the freight distribution zones do not represent specific locations but areas around Port Newark/Elizabeth where greater detail was added to the zonal structure to account for the development potential that exists in the area from many available Brownfield sites. Specific daily truck generation at each zone is included in the model. The locations of these special generator zones are shown in figure 49.

7. The New Jersey Business & Industry Association publishes a listing of the Top 100 New Jersey Employers[1]. This listing, updated in 2002, gives an indication of the number of employees and the location of the company or agency's headquarters. No indication of branch locations or truck generation is given.

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[1] http://www.njbrc.org/business/top100.html and http://data.njbiz.com/njbrc/employers.html

8. The International Warehouse Logistics Association (IWLA) is an organization of companies which fosters and promotes the growth and success of public and contract warehousing and related logistics services. The organization serves third-party warehousing based logistics firms, warehouse/logistics divisions of industry firms, and warehouse logistics professionals around the world. Members[2] of the association that are based in New Jersey can be identified but no indication of the size of the business is available from the associations website.

9. The New Jersey Department of Labor maintains an Internet accessible listing of employers by industry from its Workforce New Jersey Public Information Network[3]. Nine categories of "trucking and warehousing" are specified such as local trucking, trucking terminals, and general warehousing. There are 2,020 locations listed in the trucking and warehousing industry, with the company name, address, and contact information available. Companies with multiple locations are listed for each location, however no indication of how many employees or the amount of truck trip generation is given.

[2] http://www.iwla.com/Search/DisplayAllMembers.asp?menu=MemberRoster&Background=MemberRoster&tab1=MemberRoster&tab2=MemberRoster&select=MemberRoster
[3] http://wnjpin2.dol.state.nj.us/wnjpin/html/e_top.htm

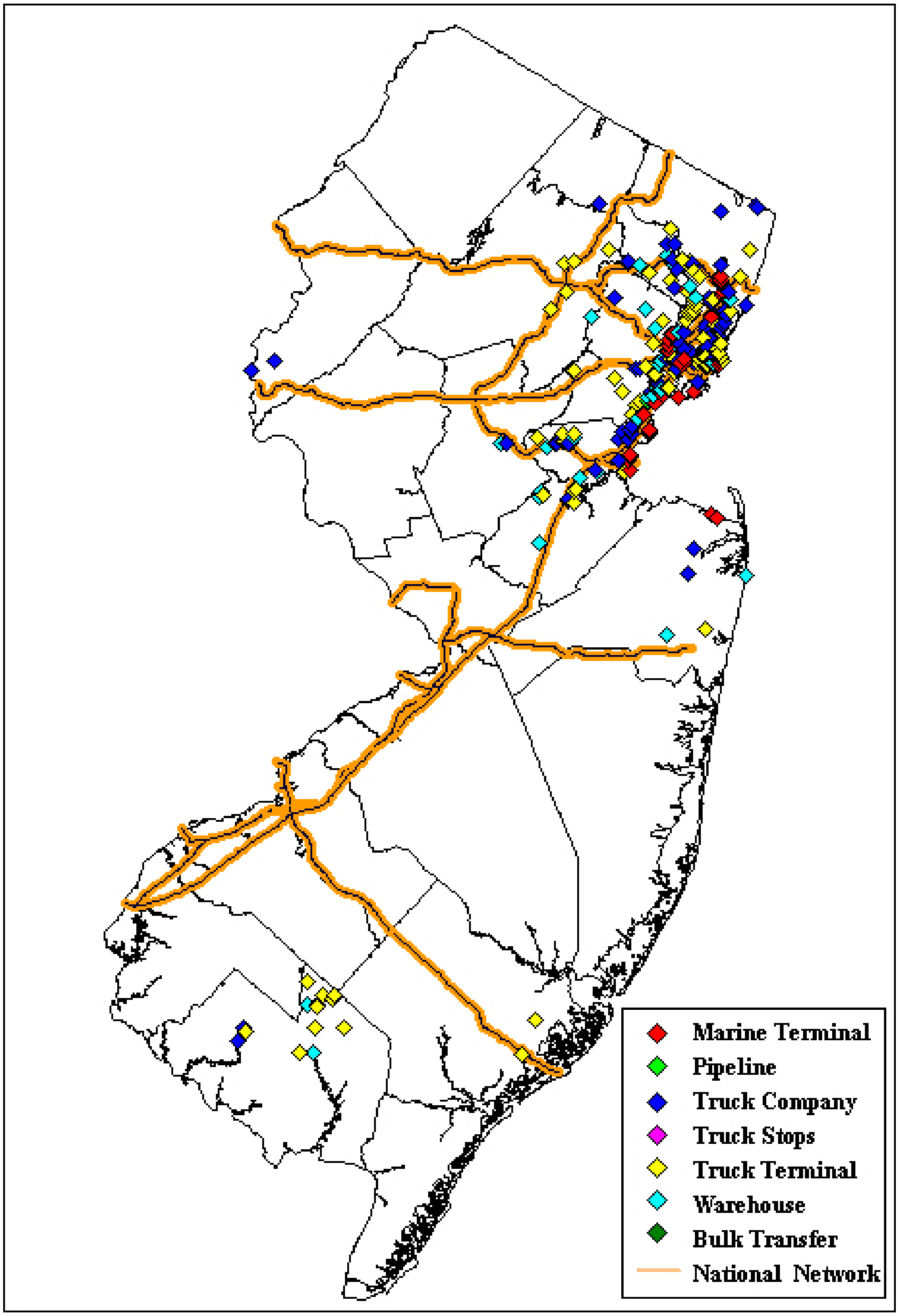


Figure 47: Warehouse Locations by Facility Type

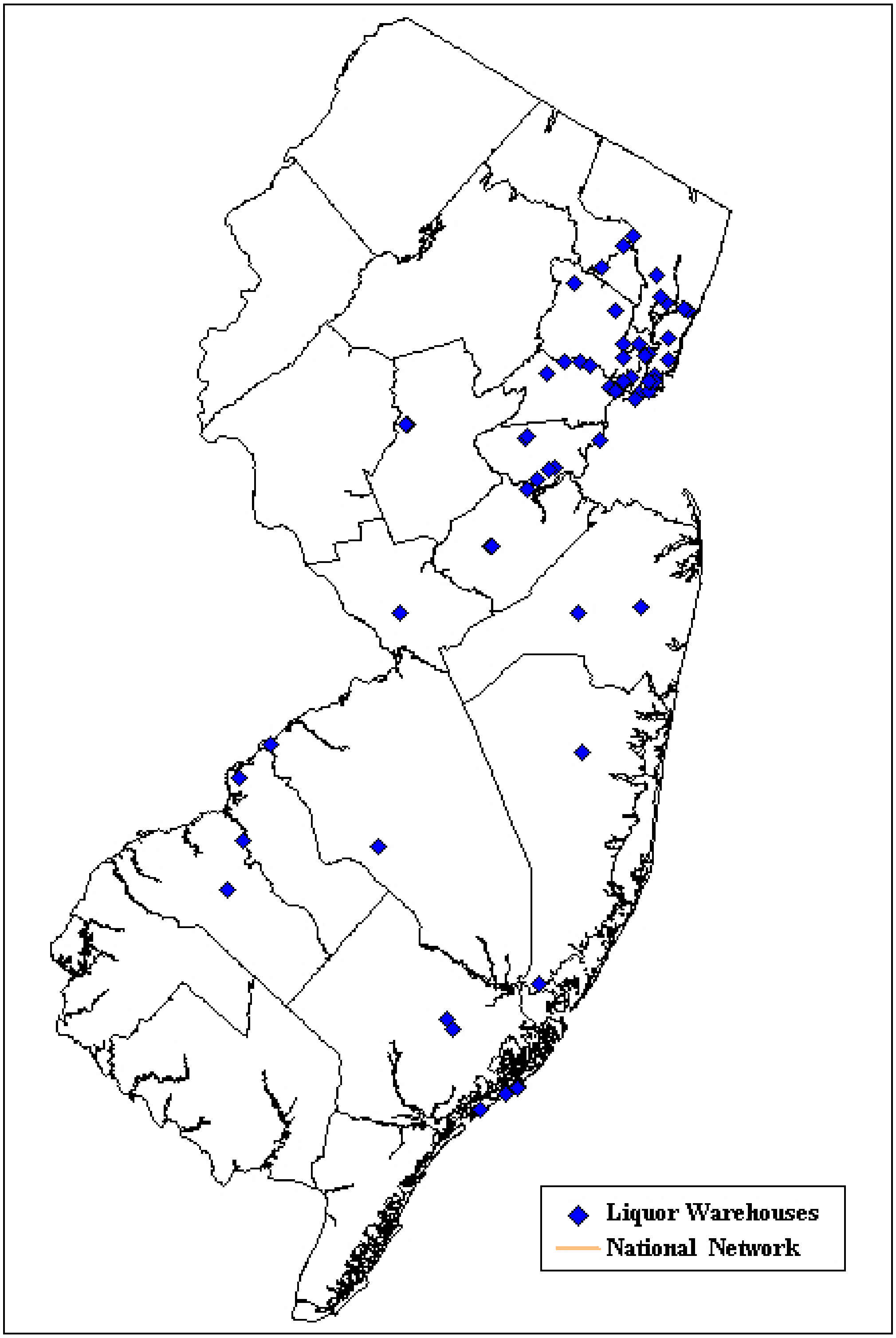


Figure 48: Liquor License Warehouse Locations

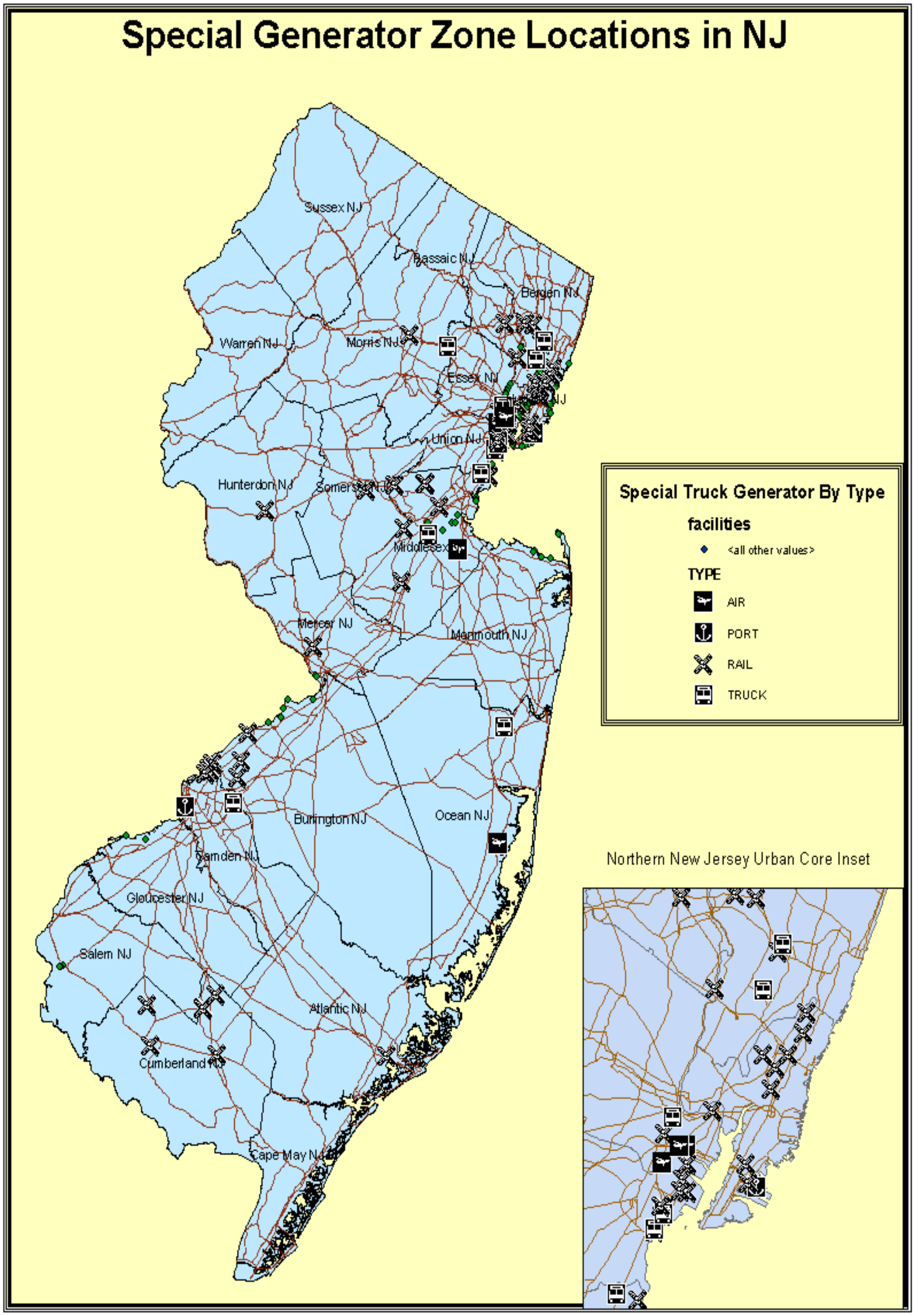


Figure 49: Special Generator Zone Locations

FACTORS INFLUENCING CHANGE IN TRUCK FLOWS

Different criterion or factors that may influence changes in truck flow were identified and defined under this section. All selected roadways were divided into smaller sections for the analysis and to better understand the movement of traffic.

Sections of constant truck characteristics were defined by major interchanges and cross-routes, changes in roadway function, major truck generating facilities and also by ESAL (Equivalent Single Axle Load). Most vehicle classification segments were expected to span several traffic volume segments because truck traffic can remain fairly constant despite changes in total traffic volume. This resulted in smaller number of segments. The following criterion were used to divide the twelve roadways into sections:

1. MAJOR INTERCHANGES AND CROSS-ROUTES

Truck flows usually change when they reach major interchanges. A new section was defined where two roadways that are included in the truck network, crossed. If a cross-route had minimal truck traffic, then it was not included in the network.

2. CHANGES IN ROADWAY FUNCTION

Sections were also defined by major changes in roadway function. For example, US 1 through downtown Trenton is a limited- access highway; this would be defined as a different section than the areas north and south that have no access control.

3. POLITICAL BOUNDARIES

Political boundaries, municipal or county, were *not* used to define sections.

Roadways that were classified as rural or urban, interstates, and arterials qualified for inclusion. The test roadways were selected in such a way that could give us a complete picture of the truck flow on all types of highways; thus the selection comprised of five interstate, five major arterials and two minor arterials, as given below:

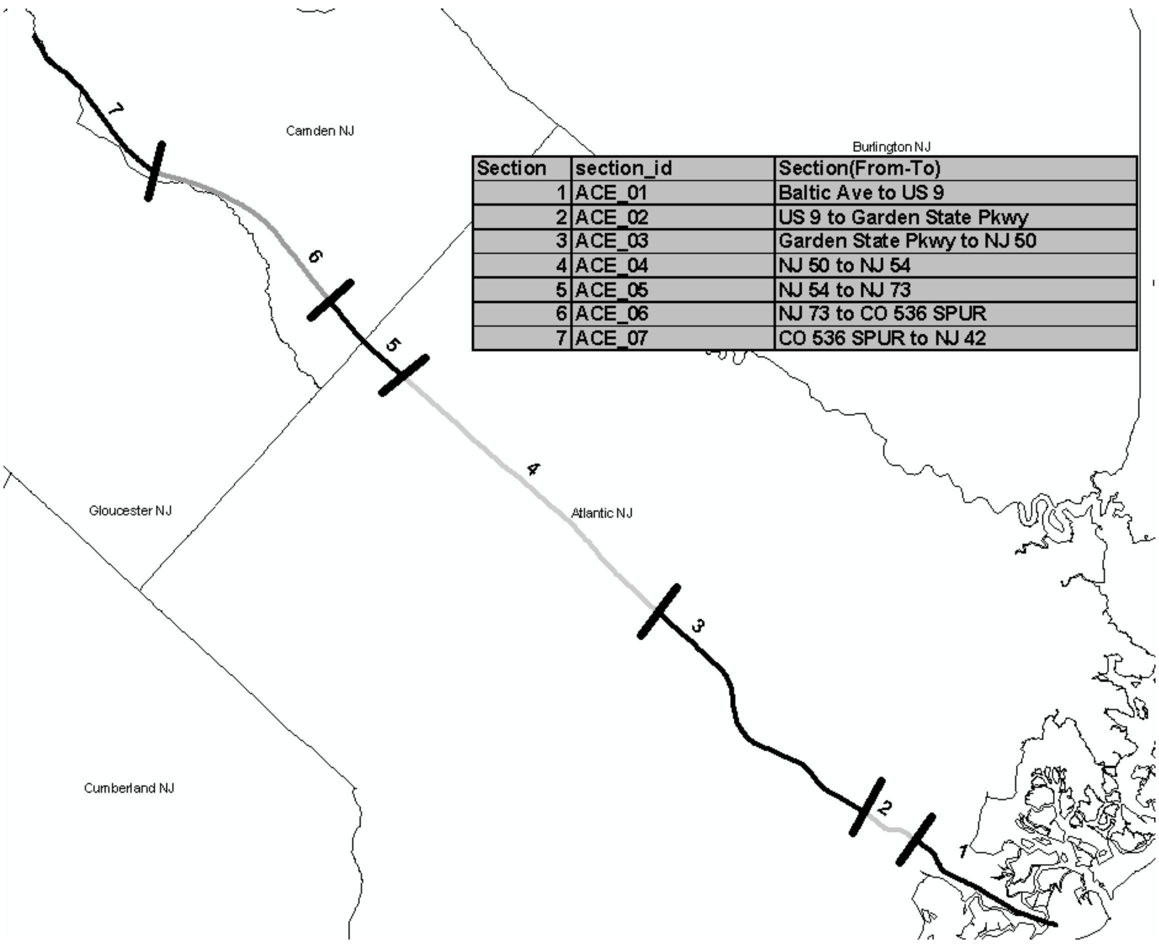
1. I 80
2. I 78
3. I 287
4. New Jersey Turnpike (north)
5. New Jersey Turnpike (south)
6. US 206
7. US 1
8. US 40
9. US 130
10. US 9
11. NJ 31
12. NJ 47

After the meeting with NJDOT in August 2003, it was decided that these selected roadways should be revised and should be considered based on their location, importance and number of available counts on them. Location of the roadway was important so that it could capture the information from the neighboring states as well. Thus a selection of the following 14 highways was selected:

1) Atlantic City Expressway
2) I 287
3) I 295
4) I 78
5) I 80
6) NJ 31
7) NJ 47
8) NJ 49
9) NJ 55
10) US 1
11) US 130
12) US 206
13) US 40
14) US 9

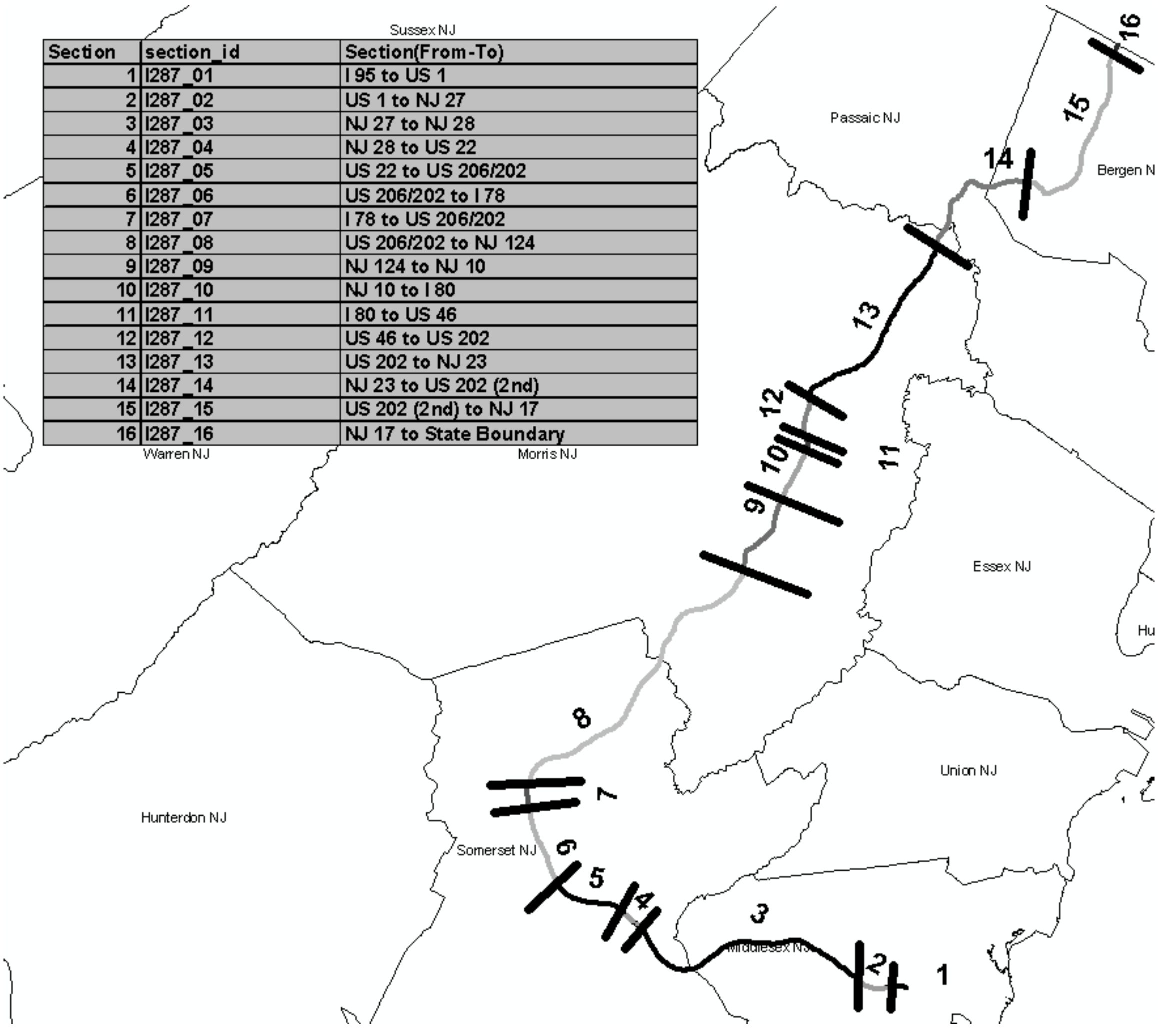
The roadway sections on these selected 14 highways are shown below in the figures. Each section was reviewed to determine whether there were actual truck volumes available. The goal was to have at least one count per section. However, there were some sections that contained no counts and others had more than one count. Sections that had multiple counts were averaged together depending upon if they are similar. Sections that contained dissimilar counts were split into entirely new sections, to reflect the new truck characteristics.

Figures 50 through 63, shown below are the roadway segments for each of the 14 selected roadways.



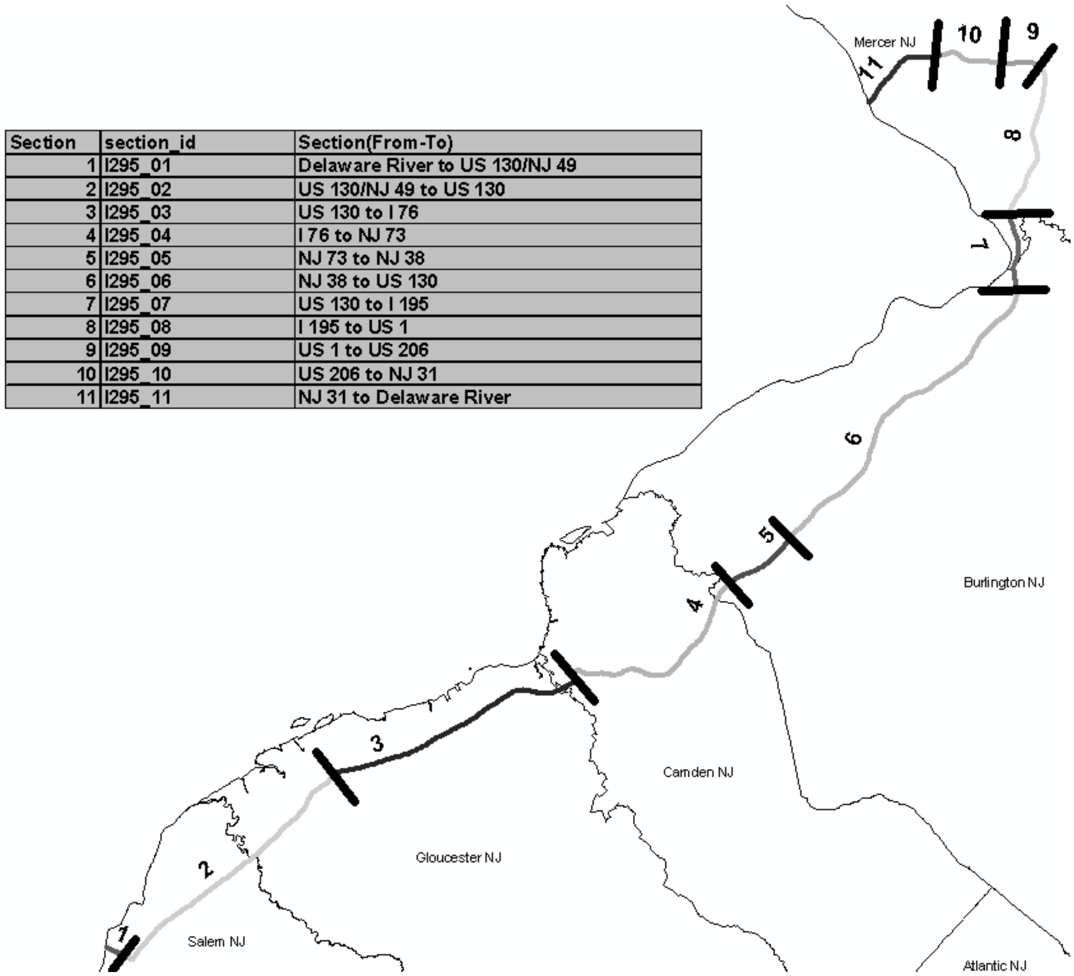
Section	section_id	Section(From-To)
1	ACE_01	Baltic Ave to US 9
2	ACE_02	US 9 to Garden State Pkwy
3	ACE_03	Garden State Pkwy to NJ 50
4	ACE_04	NJ 50 to NJ 54
5	ACE_05	NJ 54 to NJ 73
6	ACE_06	NJ 73 to CO 536 SPUR
7	ACE_07	CO 536 SPUR to NJ 42

Figure 50: Roadway Segments on Atlantic City Expressway



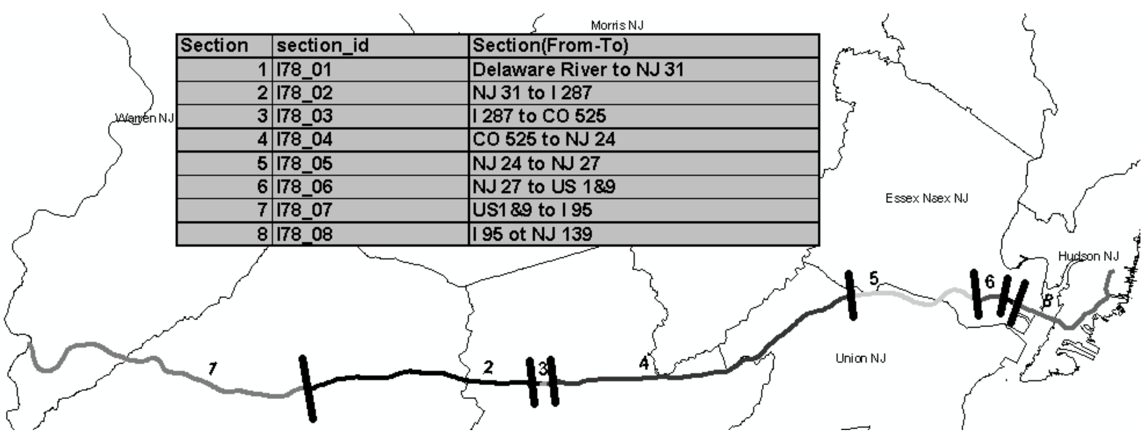
Section	section_id	Section(From-To)
1	I287_01	I 95 to US 1
2	I287_02	US 1 to NJ 27
3	I287_03	NJ 27 to NJ 28
4	I287_04	NJ 28 to US 22
5	I287_05	US 22 to US 206/202
6	I287_06	US 206/202 to I 78
7	I287_07	I 78 to US 206/202
8	I287_08	US 206/202 to NJ 124
9	I287_09	NJ 124 to NJ 10
10	I287_10	NJ 10 to I 80
11	I287_11	I 80 to US 46
12	I287_12	US 46 to US 202
13	I287_13	US 202 to NJ 23
14	I287_14	NJ 23 to US 202 (2nd)
15	I287_15	US 202 (2nd) to NJ 17
16	I287_16	NJ 17 to State Boundary

Figure 51: Roadway Segments on Interstate 287



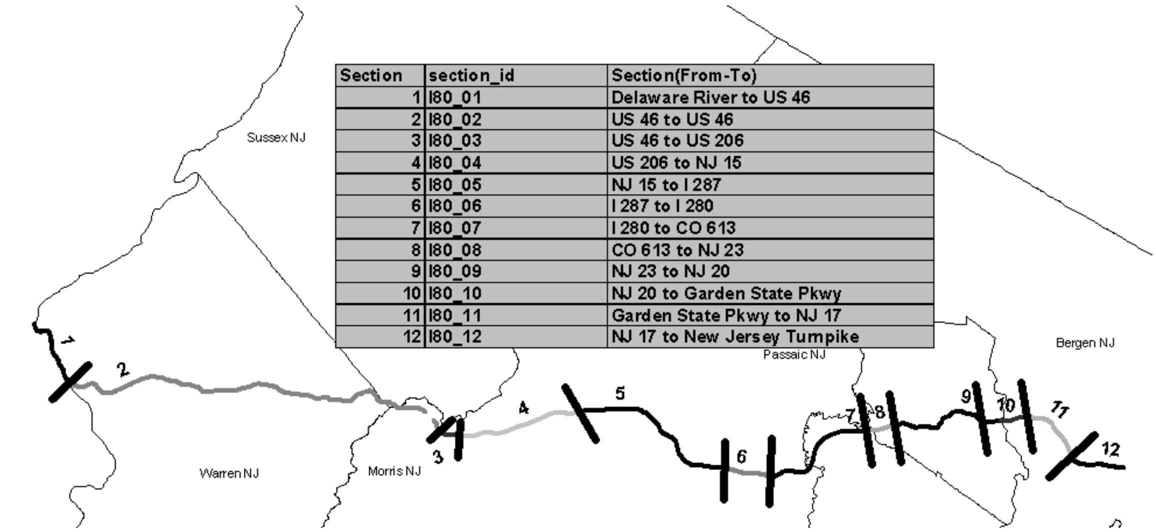
Section	section_id	Section(From-To)
1	I295_01	Delaware River to US 130/NJ 49
2	I295_02	US 130/NJ 49 to US 130
3	I295_03	US 130 to I 76
4	I295_04	I 76 to NJ 73
5	I295_05	NJ 73 to NJ 38
6	I295_06	NJ 38 to US 130
7	I295_07	US 130 to I 195
8	I295_08	I 195 to US 1
9	I295_09	US 1 to US 206
10	I295_10	US 206 to NJ 31
11	I295_11	NJ 31 to Delaware River

Figure 52: Roadway Segments for Interstate 295



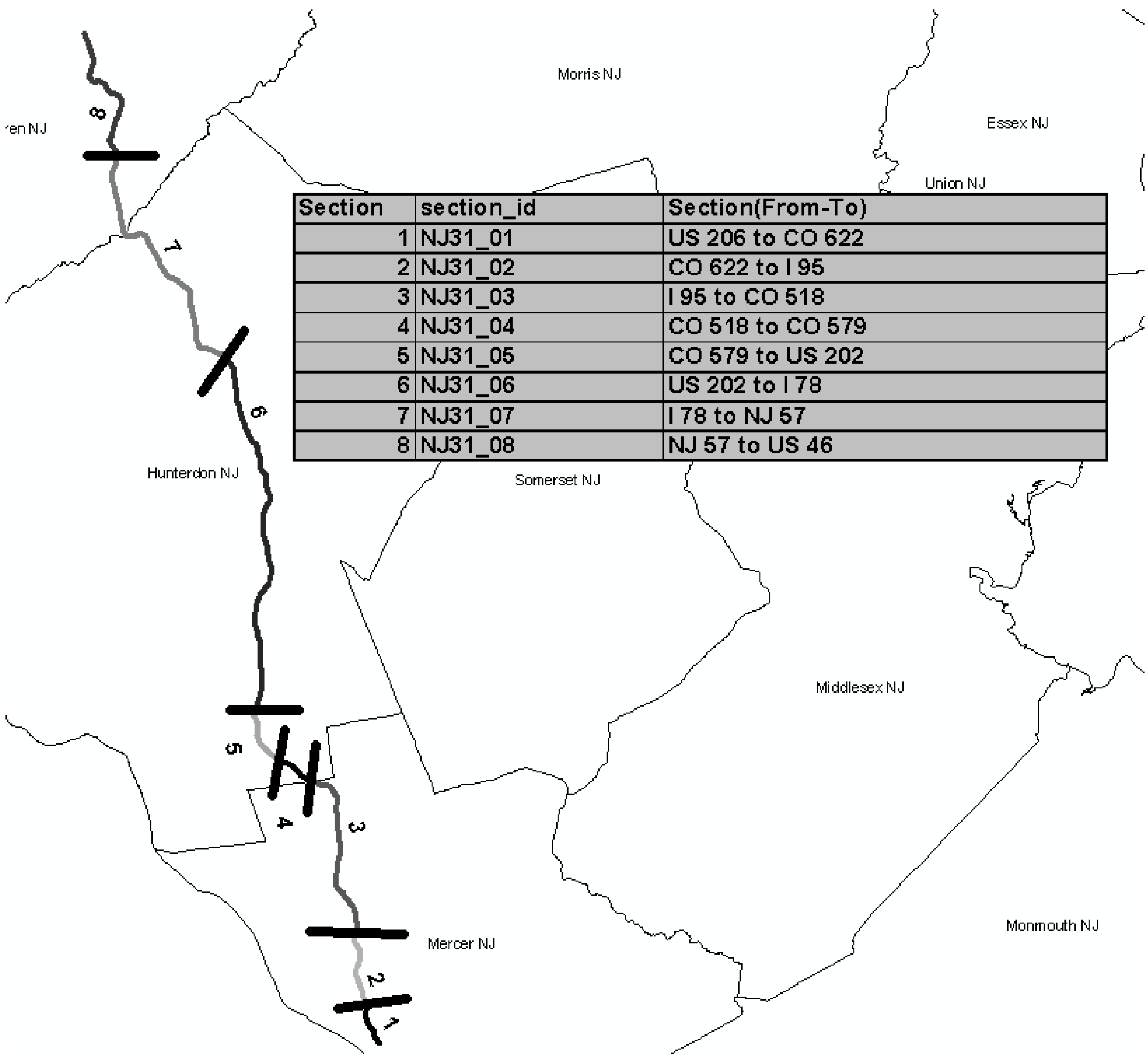
Section	section_id	Section(From-To)
1	I78_01	Delaware River to NJ 31
2	I78_02	NJ 31 to I 287
3	I78_03	I 287 to CO 525
4	I78_04	CO 525 to NJ 24
5	I78_05	NJ 24 to NJ 27
6	I78_06	NJ 27 to US 1&9
7	I78_07	US1 &9 to I 95
8	I78_08	I 95 ot NJ 139

Figure 53: Roadway Segments for Interstate 78



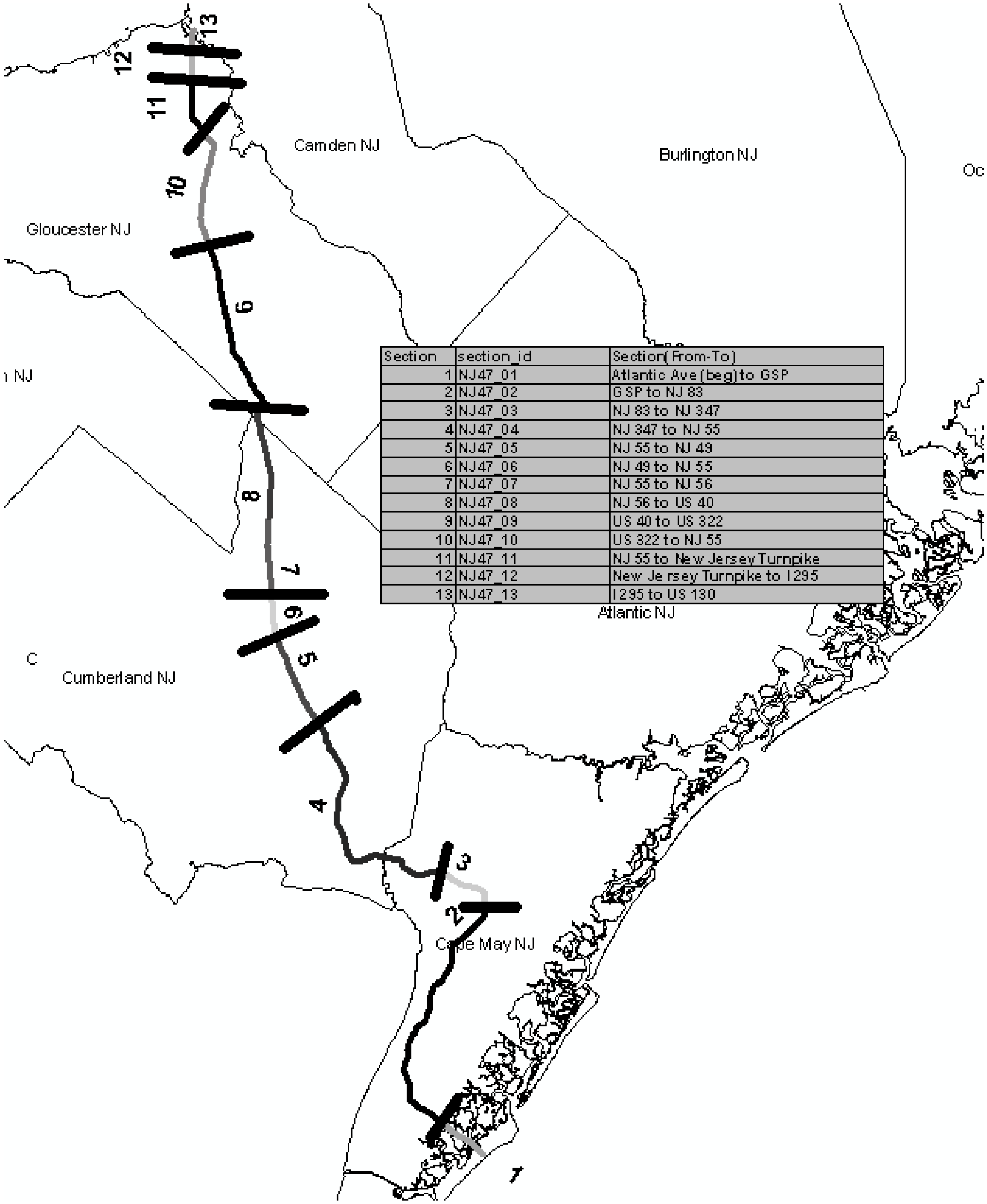
Section	section_id	Section(From-To)
1	I80_01	Delaware River to US 46
2	I80_02	US 46 to US 46
3	I80_03	US 46 to US 206
4	I80_04	US 206 to NJ 15
5	I80_05	NJ 15 to I 287
6	I80_06	I 287 to I 280
7	I80_07	I 280 to CO 613
8	I80_08	CO 613 to NJ 23
9	I80_09	NJ 23 to NJ 20
10	I80_10	NJ 20 to Garden State Pkwy
11	I80_11	Garden State Pkwy to NJ 17
12	I80_12	NJ 17 to New Jersey Turnpike

Figure 54: Roadway Segments for Interstate 80



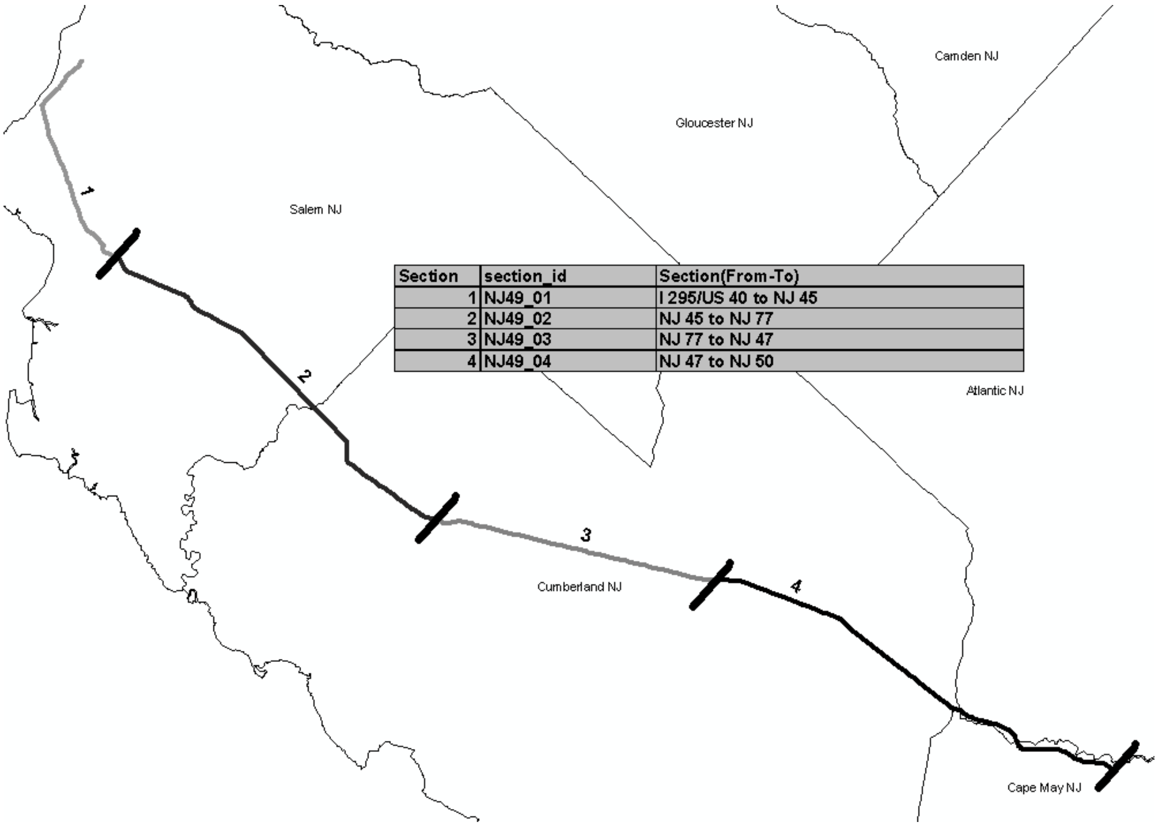
Section	section_id	Section(From-To)
1	NJ31_01	US 206 to CO 622
2	NJ31_02	CO 622 to I 95
3	NJ31_03	I 95 to CO 518
4	NJ31_04	CO 518 to CO 579
5	NJ31_05	CO 579 to US 202
6	NJ31_06	US 202 to I 78
7	NJ31_07	I 78 to NJ 57
8	NJ31_08	NJ 57 to US 46

Figure 55: Roadway Segments for NJ 31



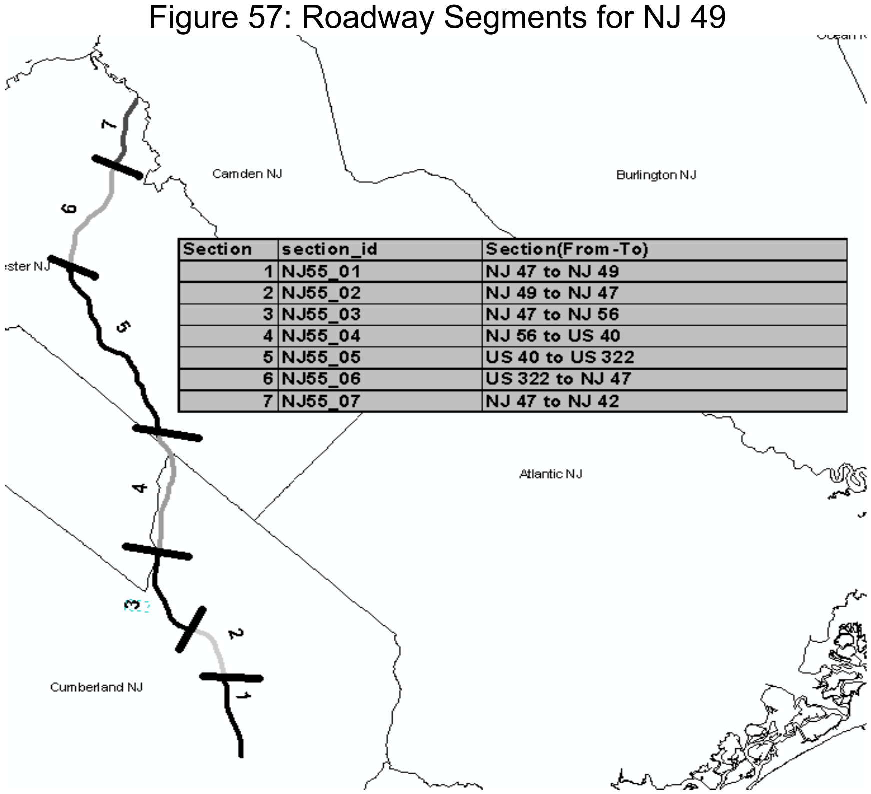
Section	section_id	Section(From-To)
1	NJ47_01	Atlantic Ave (beg) to GSP
2	NJ47_02	GSP to NJ 83
3	NJ47_03	NJ 83 to NJ 347
4	NJ47_04	NJ 347 to NJ 55
5	NJ47_05	NJ 55 to NJ 49
6	NJ47_06	NJ 49 to NJ 55
7	NJ47_07	NJ 55 to NJ 56
8	NJ47_08	NJ 56 to US 40
9	NJ47_09	US 40 to US 322
10	NJ47_10	US 322 to NJ 55
11	NJ47_11	NJ 55 to New Jersey Turnpike
12	NJ47_12	New Jersey Turnpike to I 295
13	NJ47_13	I 295 to US 130

Figure 56: Roadway Segments for NJ 47



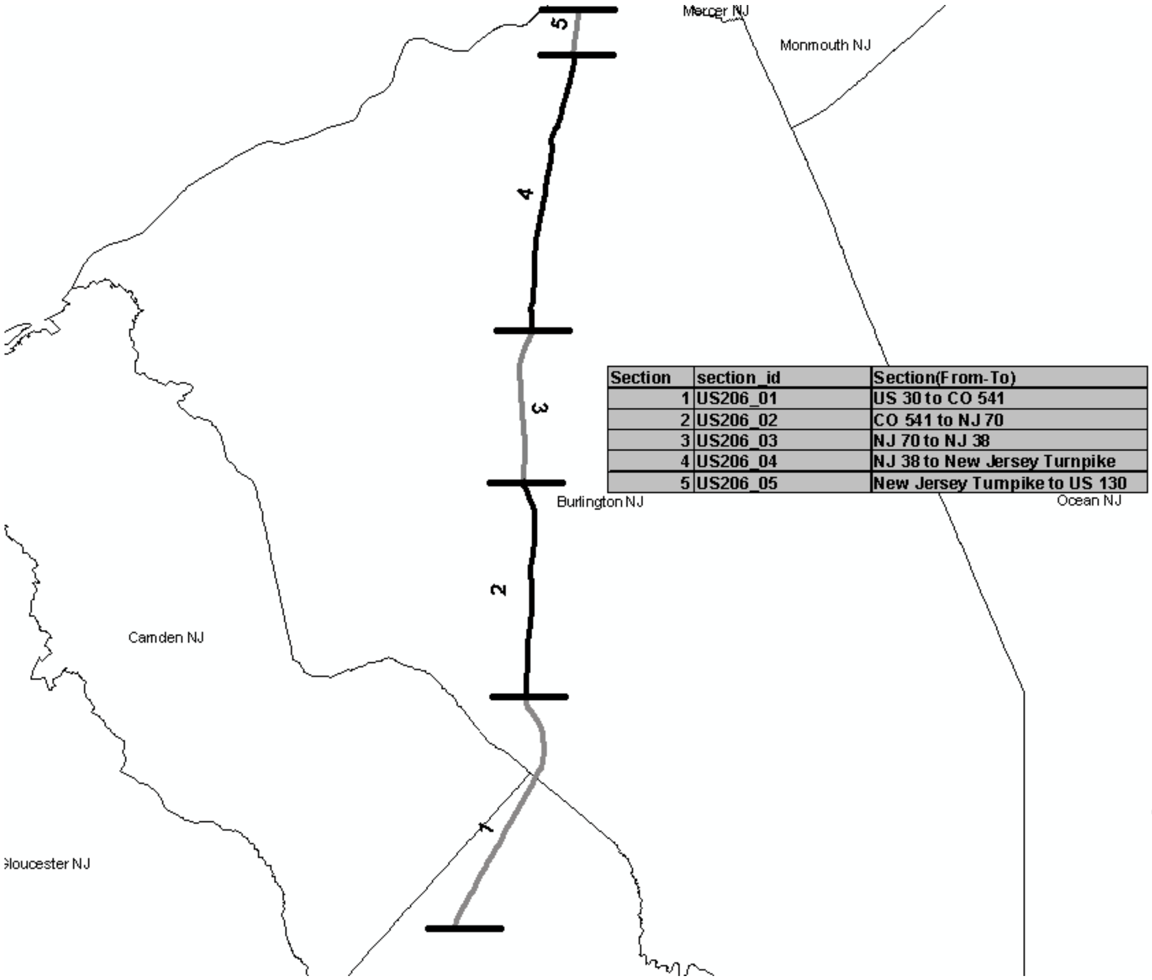
Section	section_id	Section(From-To)
1	NJ49_01	I 295/US 40 to NJ 45
2	NJ49_02	NJ 45 to NJ 77
3	NJ49_03	NJ 77 to NJ 47
4	NJ49_04	NJ 47 to NJ 50

Figure 57: Roadway Segments for NJ 49



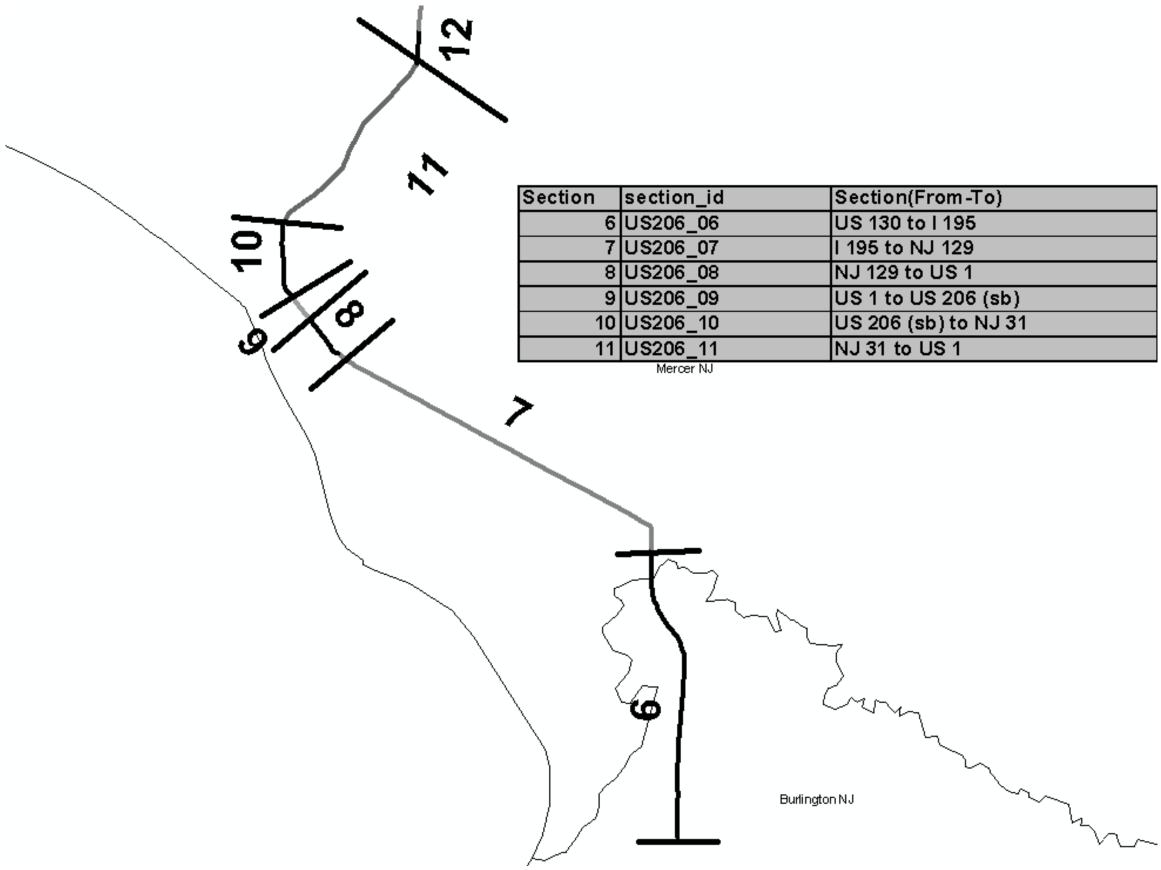
Section	section_id	Section(From-To)
1	NJ55_01	NJ 47 to NJ 49
2	NJ55_02	NJ 49 to NJ 47
3	NJ55_03	NJ 47 to NJ 56
4	NJ55_04	NJ 56 to US 40
5	NJ55_05	US 40 to US 322
6	NJ55_06	US 322 to NJ 47
7	NJ55_07	NJ 47 to NJ 42

Figure 58: Roadway Segments for NJ 55



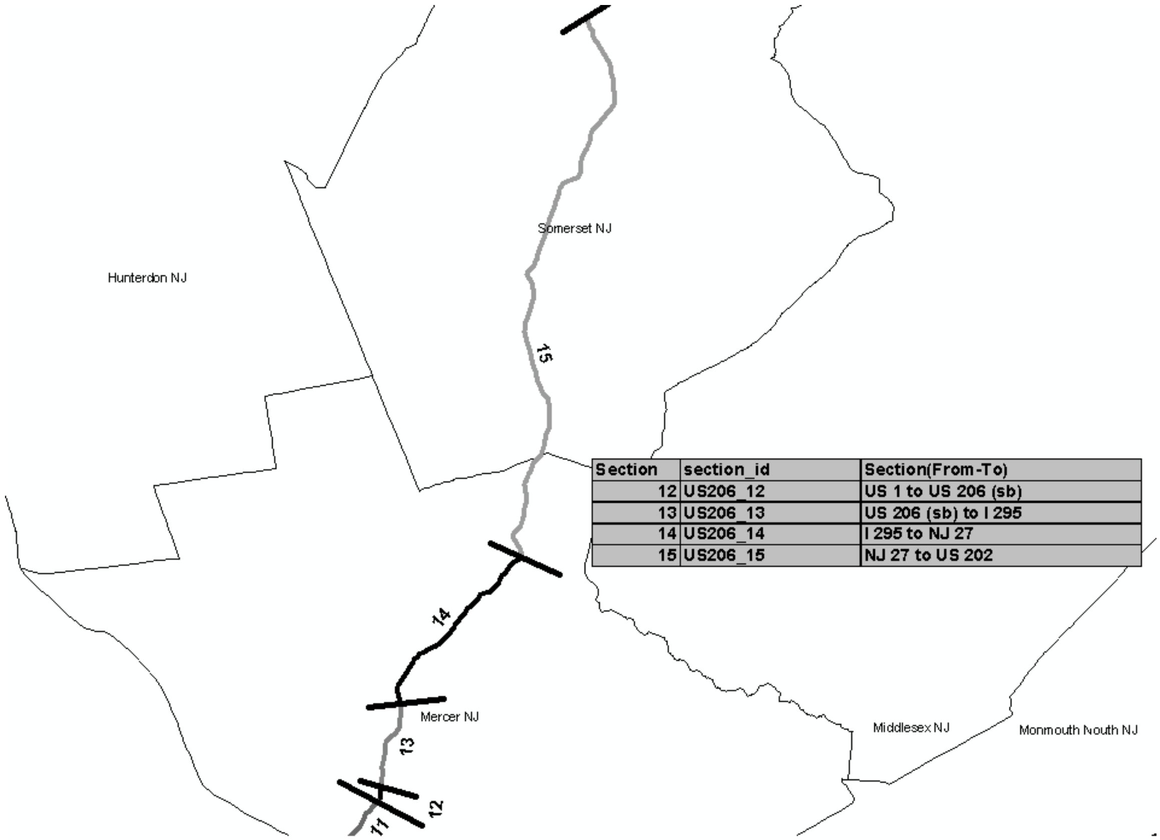
Section	section_id	Section(From-To)
1	US206_01	US 30 to CO 541
2	US206_02	CO 541 to NJ 70
3	US206_03	NJ 70 to NJ 38
4	US206_04	NJ 38 to New Jersey Turnpike
5	US206_05	New Jersey Turnpike to US 130

Figure 59a: Roadway Segments for US 206: Sections 1 to 5



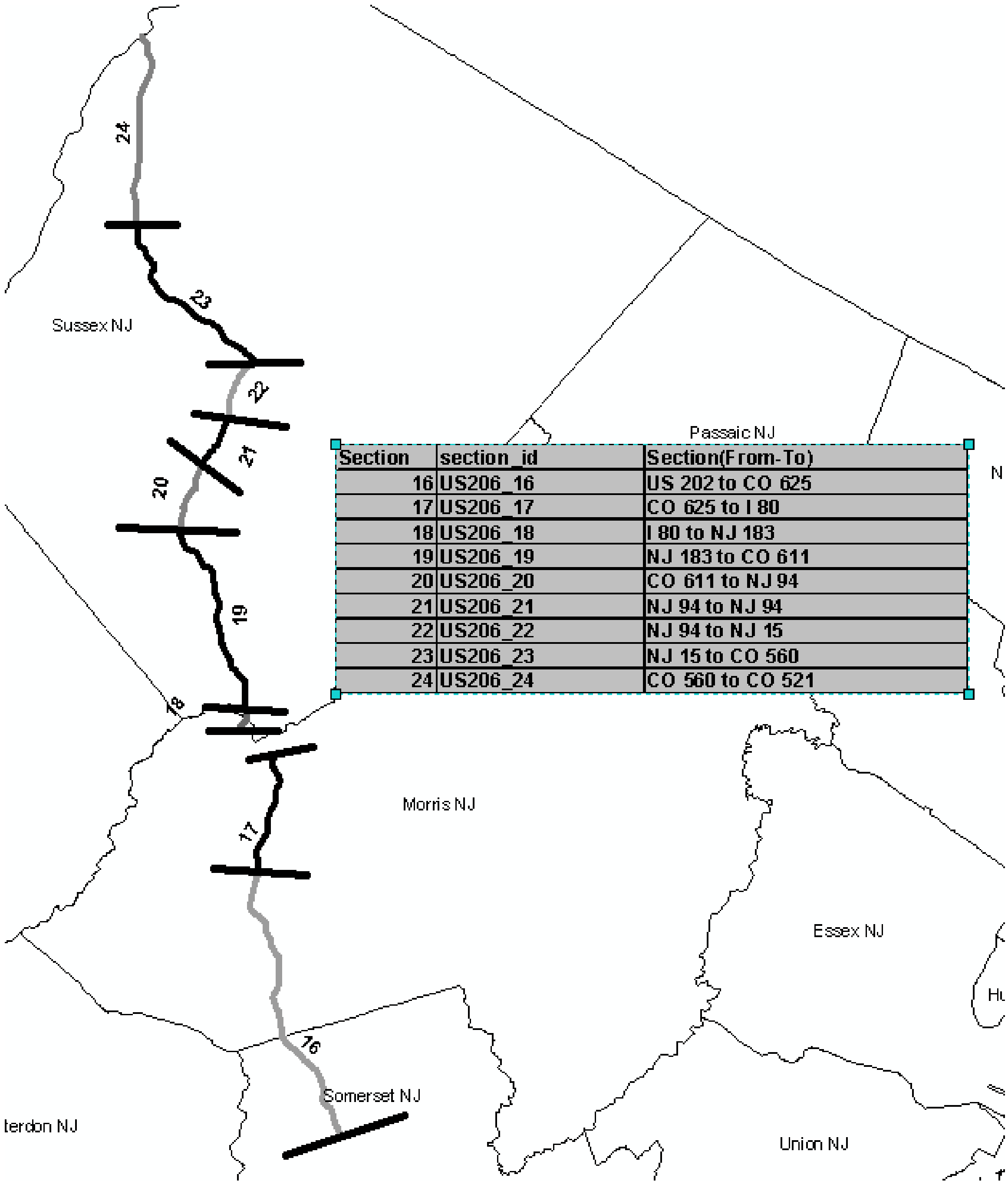
Section	section_id	Section(From-To)
6	US206_06	US 130 to I 195
7	US206_07	I 195 to NJ 129
8	US206_08	NJ 129 to US 1
9	US206_09	US 1 to US 206 (sb)
10	US206_10	US 206 (sb) to NJ 31
11	US206_11	NJ 31 to US 1

Figure 59b: Roadway Segments for US 206: Sections 6 to 11



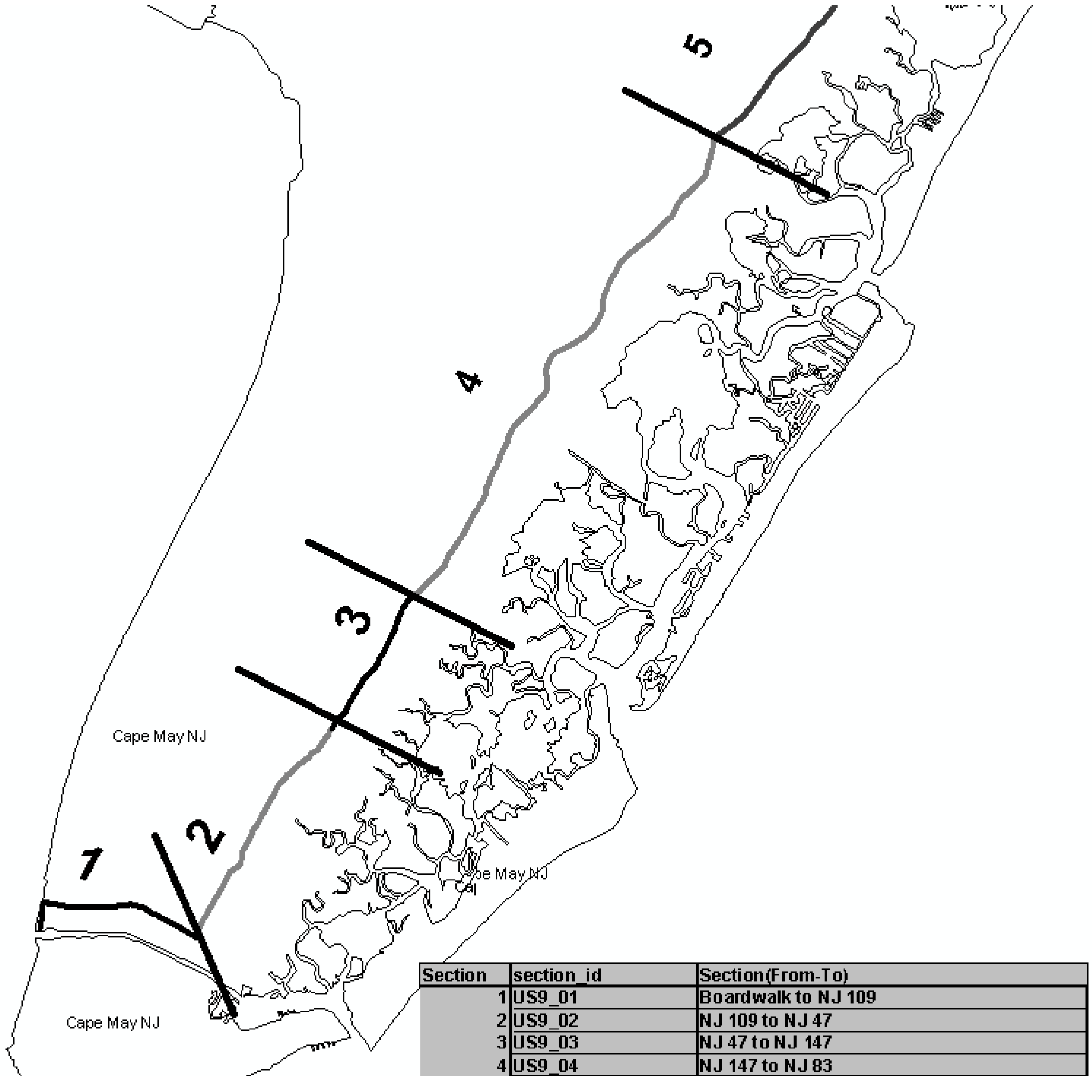
Section	section_id	Section(From-To)
12	US206_12	US 1 to US 206 (sb)
13	US206_13	US 206 (sb) to I 295
14	US206_14	I 295 to NJ 27
15	US206_15	NJ 27 to US 202

Figure 59c: Roadway Segments for US 206: Sections 12 to 15



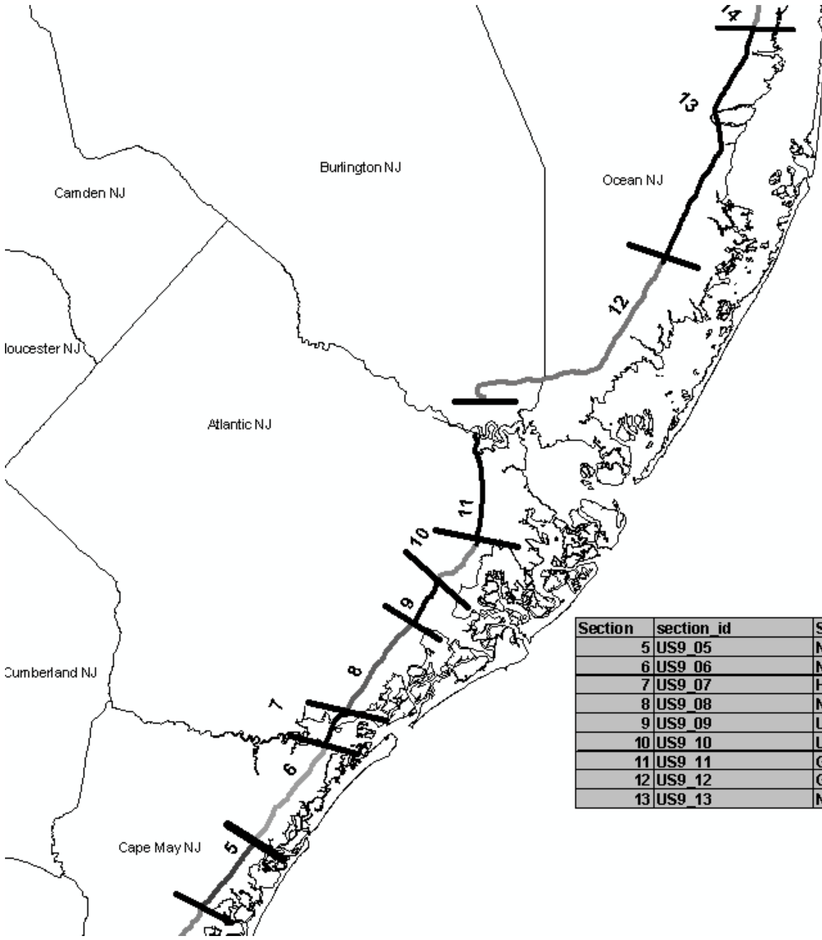
Section	section_id	Section(From-To)
16	US206_16	US 202 to CO 625
17	US206_17	CO 625 to I 80
18	US206_18	I 80 to NJ 183
19	US206_19	NJ 183 to CO 611
20	US206_20	CO 611 to NJ 94
21	US206_21	NJ 94 to NJ 94
22	US206_22	NJ 94 to NJ 15
23	US206_23	NJ 15 to CO 560
24	US206_24	CO 560 to CO 521

Figure 59d: Roadway Segments for US 206: Sections 16 to 24



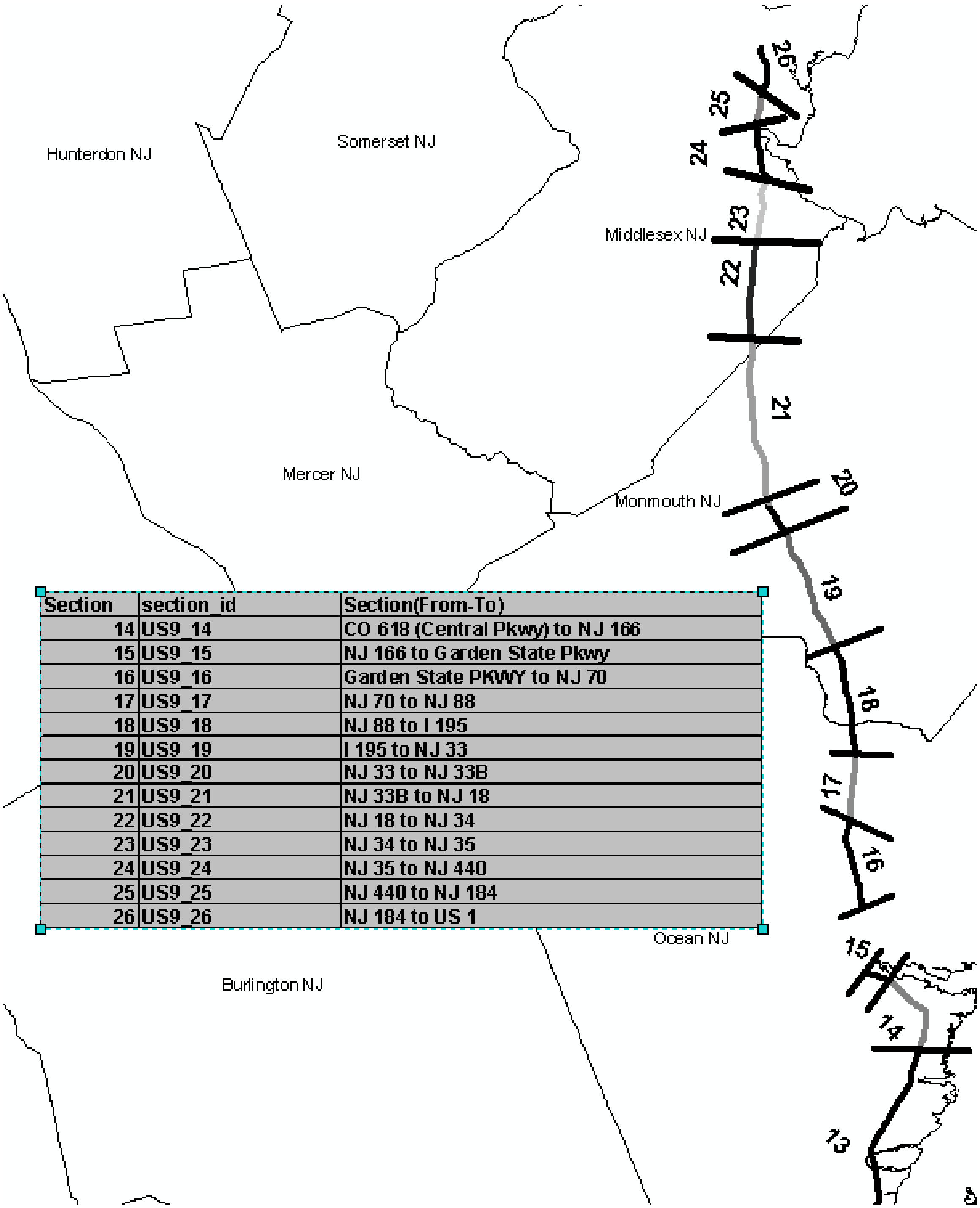
Section	section_id	Section(From-To)
1	US9_01	Boardwalk to NJ 109
2	US9_02	NJ 109 to NJ 47
3	US9_03	NJ 47 to NJ 147
4	US9_04	NJ 147 to NJ 83

Figure 60a: Roadway Segments for US 9: Sections 1 to 4



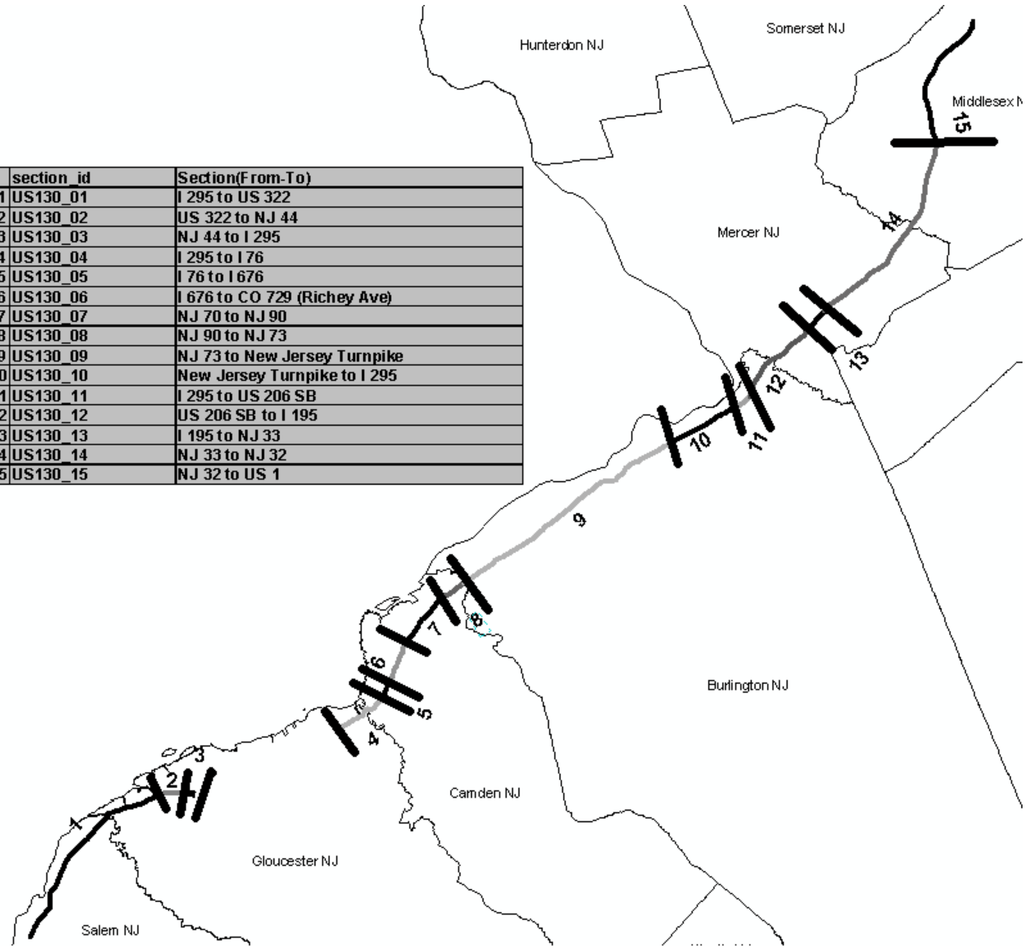
Section	section_id	Section(From-To)
5	US9_05	NJ 83 to NJ 50
6	US9_06	NJ 50 to Harbor Rd
7	US9_07	Harbor Rd to NJ 52
8	US9_08	NJ 52 to US 40
9	US9_09	US 40 to US 30
10	US9_10	US 30 to Great Creek Rd
11	US9_11	Great Creek Rd to Garden State Pkwy
12	US9_12	Garden State Pkwy to NJ 72
13	US9_13	NJ 72 to CO 618 (Central Pkwy)

Figure 60b: Roadway Segments for US 9: Sections 5 to 13



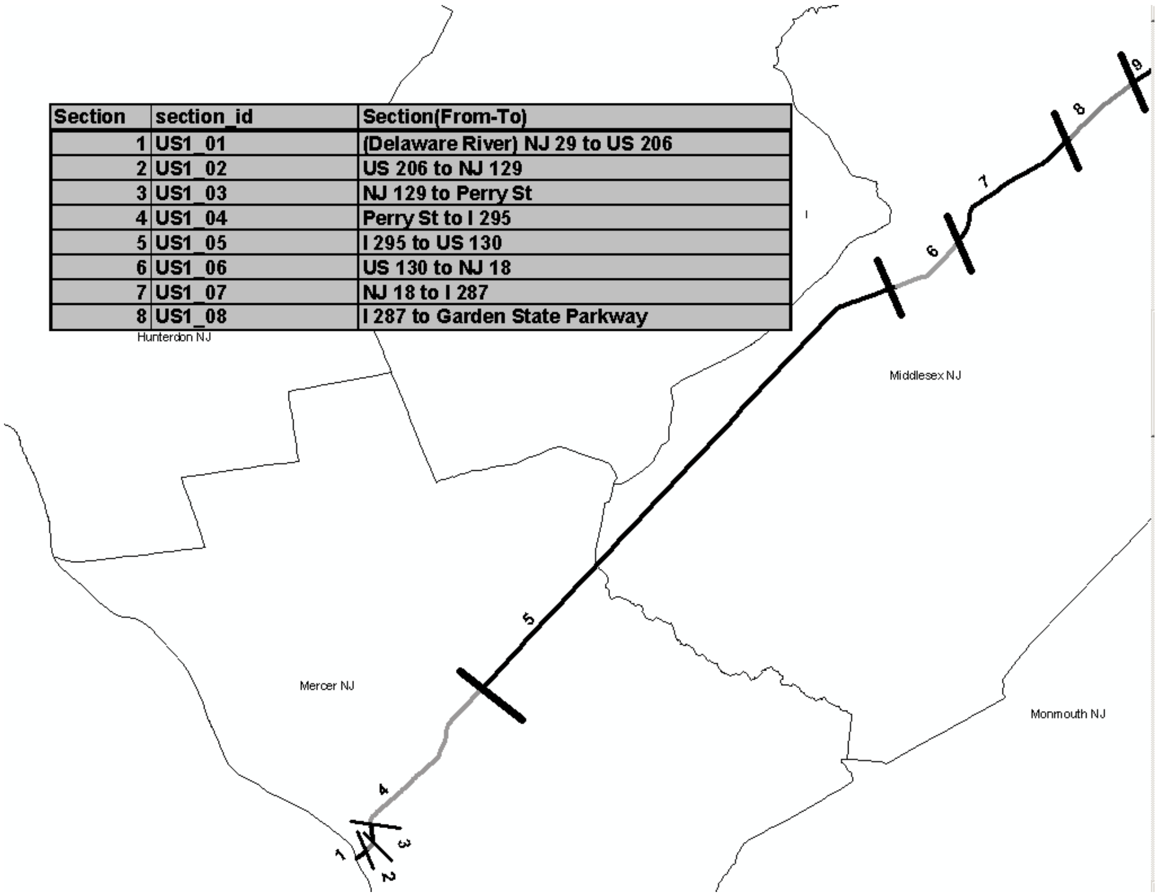
Section	section_id	Section(From-To)
14	US9_14	CO 618 (Central Pkwy) to NJ 166
15	US9_15	NJ 166 to Garden State Pkwy
16	US9_16	Garden State PKWY to NJ 70
17	US9_17	NJ 70 to NJ 88
18	US9_18	NJ 88 to I 195
19	US9_19	I 195 to NJ 33
20	US9_20	NJ 33 to NJ 33B
21	US9_21	NJ 33B to NJ 18
22	US9_22	NJ 18 to NJ 34
23	US9_23	NJ 34 to NJ 35
24	US9_24	NJ 35 to NJ 440
25	US9_25	NJ 440 to NJ 184
26	US9_26	NJ 184 to US 1

Figure 60c: Roadway Segments for US 9: Sections 14-26



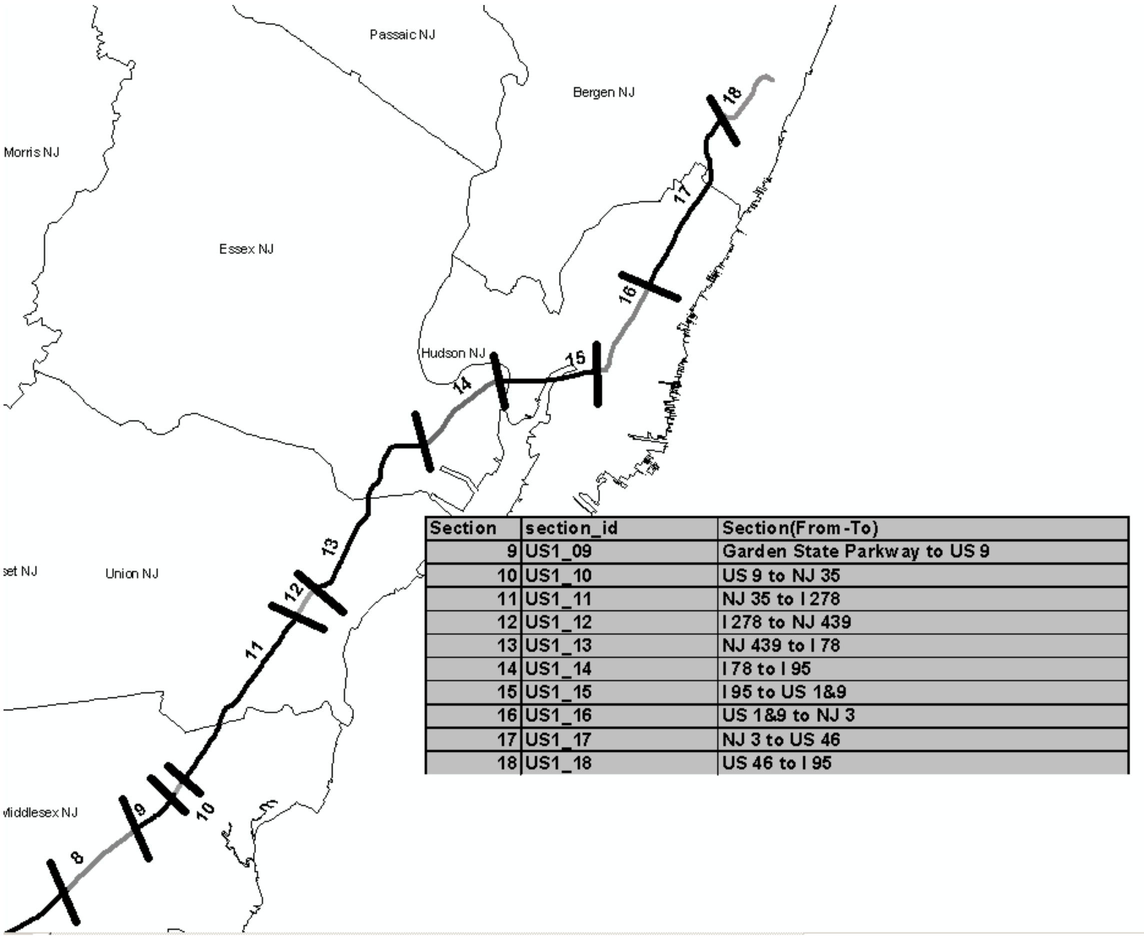
Section	section_id	Section(From-To)
1	US130_01	I 295 to US 322
2	US130_02	US 322 to NJ 44
3	US130_03	NJ 44 to I 295
4	US130_04	I 295 to I 76
5	US130_05	I 76 to I 676
6	US130_06	I 676 to CO 729 (Richey Ave)
7	US130_07	NJ 70 to NJ 90
8	US130_08	NJ 90 to NJ 73
9	US130_09	NJ 73 to New Jersey Turnpike
10	US130_10	New Jersey Turnpike to I 295
11	US130_11	I 295 to US 206 SB
12	US130_12	US 206 SB to I 195
13	US130_13	I 195 to NJ 33
14	US130_14	NJ 33 to NJ 32
15	US130_15	NJ 32 to US 1

Figure 61: Roadway Segments for US 130



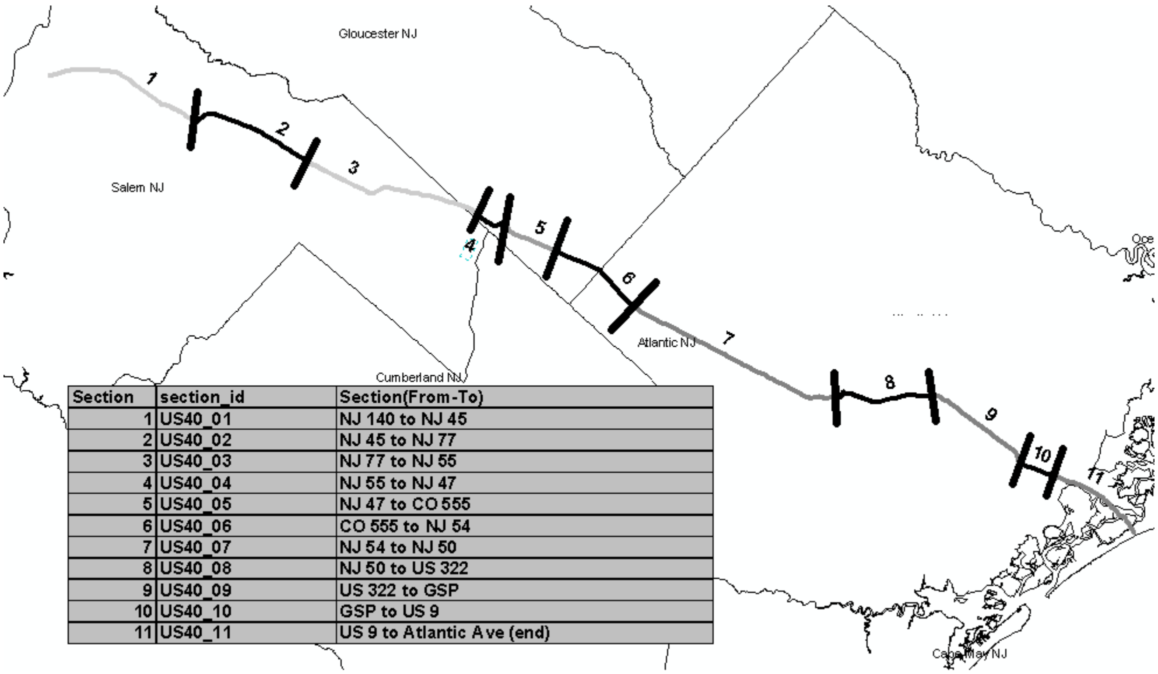
Section	section_id	Section(From-To)
1	US1_01	(Delaware River) NJ 29 to US 206
2	US1_02	US 206 to NJ 129
3	US1_03	NJ 129 to Perry St
4	US1_04	Perry St to I 295
5	US1_05	I 295 to US 130
6	US1_06	US 130 to NJ 18
7	US1_07	NJ 18 to I 287
8	US1_08	I 287 to Garden State Parkway

62a: Roadway Segments for US 1: Sections 1 to 8



Section	section_id	Section(From-To)
9	US1_09	Garden State Parkway to US 9
10	US1_10	US 9 to NJ 35
11	US1_11	NJ 35 to I 278
12	US1_12	I 278 to NJ 439
13	US1_13	NJ 439 to I 78
14	US1_14	I 78 to I 95
15	US1_15	I 95 to US 1&9
16	US1_16	US 1&9 to NJ 3
17	US1_17	NJ 3 to US 46
18	US1_18	US 46 to I 95

62b: Roadway Segments for US 1: Sections 9 to 18



Section	section_id	Section(From-To)
1	US40_01	NJ 140 to NJ 45
2	US40_02	NJ 45 to NJ 77
3	US40_03	NJ 77 to NJ 55
4	US40_04	NJ 55 to NJ 47
5	US40_05	NJ 47 to CO 555
6	US40_06	CO 555 to NJ 54
7	US40_07	NJ 54 to NJ 50
8	US40_08	NJ 50 to US 322
9	US40_09	US 322 to GSP
10	US40_10	GSP to US 9
11	US40_11	US 9 to Atlantic Ave (end)

Figure 63: Roadway Segments for US 40

DEVELOPING RELATION BETWEEN TRUCK VOLUMES & ADJACENT LAND USE

Introduction

Using the truck classification counts from various locations throughout the state of New Jersey, this task aimed at developing the relationship between truck traffic volumes on roadways and their adjacent land uses. As there is no single data source for land use; therefore, arguably by using measures like, employment, estimated sales volumes and number of establishments in the vicinity, it is expected to get useful land usage information.

From all around the State, a total of 270 locations were identified and the data was collected for the vehicle counts from these locations. The analysis areas were defined by taking a buffer area around each location. The buffers were initially taken as circles of radii 0.5, 1.0, 2.0, 3.0 and 5.0 miles, but later were analyzed with buffers as bands along the section of the truck count on the roadway. The data extracted with the bands was with 0.25, 0.5, 0.75, 1.0, 1.25, 1.5, 2.0, 3.0 and 5.0 miles.

Linear Regression approach is used for the task. Regression analysis is a statistical method that helps in finding the relationship between predictor variables and the response variable, so that one variable can be predicted from the others. It is widely used in practice and is one of the most accepted ways of analyzing problems dealing with predictions.

In the study here, the task is to predict the volume or flow of the truck traffic given the predictors. A regression approach would formulate the relationship in a general sense as given below:

Truck Volume$_i$ = a_i * *number of employees in SIC*$_j$ + b_i * *estimated sales volume in thousands of dollar for the SIC*$_j$ + c_i * *Number of businesses for SIC*$_j$

Where:

Truck Volume$_i$ = is the number of two-way daily truck trips of truck class i produced in a zone.

a, b, c.. = Coefficients for the independent variables.

Methodology

The first step in the process was to identify those independent variables that would be capable of estimating truck traffic. Data was collected for available truck traffic counts throughout the state, roadway types and classifications, and independent variables used (number of employees, number of establishments and estimated sales volume for different SICs). Sections were coded for each of the 270 locations available and a database was created. Once the dataset was compiled for the study, figure 64 shows a graphical representation of the methodology developed and adopted.

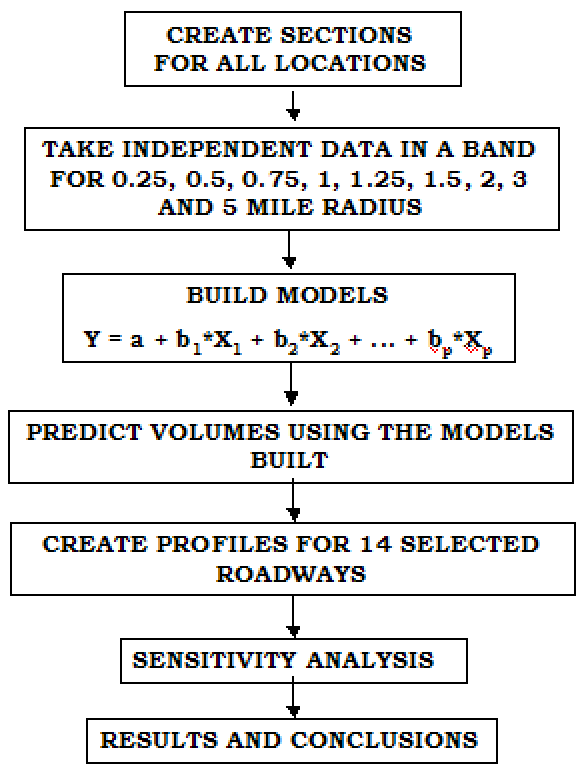


Figure 64: Methodology

Linear regression models of the general form shown earlier were developed. Truck traffic profiles on various roadways of New Jersey were created and a GIS based approach was developed enabling users to determine total truck volumes, truck and car percentages, profiles etc at selected locations on the network. Sensitivity analysis was conducted in the end to determine the sensitivity of various models with change in the size of the activity area considered for the analysis.

Input Data

The data collection effort has been separated into two areas: traffic counts for the dependent data (truck volumes) and the independent variables dataset (Employee, sales and establishments).

Traffic Counts

A majority of the traffic counts have been obtained through New Jersey Department of Transportation's (NJDOT) Bureau of Data Development. The traffic counts are divided into two categories: long and short duration counts. All short duration vehicle classification counts compiled for this task were adjusted using axle correction and pattern factors from the year 2000. A number of supplemental traffic counts were also collected from toll authorities such as the New Jersey Turnpike Authority and the Delaware River Joint Bridge Commission as well as from NJDOT's non-classified Automated Traffic Recorder (ATR) locations.

Independent Dataset

To determine the equation that may predict truck trip generation at a certain location, some independent variables such as number of employees, estimated sales volumes and number of establishments under a particular set of SIC Codes were first established. A list of all SIC Codes with their broad groupings is given in table 5 below.

Table 5: SIC Codes with Groups formed

FIELD	SIC GROUPING
AGRICULTURE	For SIC 01, SIC 02, SIC 07, SIC 08, SIC 09
MINING	For SIC 12 through SIC 14
CONSTRUCTION	For SIC 15 through SIC 17
MANUFACTURING	For SIC 20 through SIC 39
TRANSPORTATION	For SIC 40 through SIC 45
UTILITIES	For SIC 46 through SIC 49
WHOLESALE TRADE	For SIC 50 and SIC 51
RETAIL TRADE	For SIC 52 through SIC 59
FINANCE / INSURANCE	For SIC 60 through SIC 64
REAL ESTATE	For SIC 65, SIC 67, SIC 70
SERVICES	For SIC 72 through SIC 87

The ESRI BIS business location data (Environmental Systems Research Institute Business Information Solutions) is extracted from a comprehensive list of businesses licensed from InfoUSA. Data items include business name and location, franchise code, industrial classification code, number of employees, and sales volume. A database of 243 wholesale distributors for Essex, Hudson, and Union Counties was acquired from the New Jersey Department of Commerce via NJDOT. Attribute data included in this dataset include: business name; address location; SIC industry code; employment; annual sales totals; the nature of the specific facility (e.g. headquarters, branch, single location); and several other fields related to the ownership and status of the business. The New Jersey Business & Industry Association publishes a listing of the Top 100 New Jersey Employers. This listing, updated in 2002, gives an indication of the number of employees and the location of the company.

Along with the gathering data on truck volumes by class and independent dataset, roadway classifications were also factored in the analysis.

Roadway Information

Roadways are classified under different classifications based on the type of the roadway, lane width, traffic, the purpose it serves etc. Much of the roadway information was obtained by the NJDOT Statewide Truck Model, NJDOT – New Jersey Congestion Management System, NJDOT National and Access Network, NJDOT 2002 New Jersey Straight Line Diagrams, etc. A classification chart of different roadways is given in Table 6 below.

Table 6: Roadway Classification

Roadway Classification	Name
1	Rural Interstates
2	Rural Other Principal Arterials
6	Rural Minor Arterials
7	Rural Major Collectors
8	Rural Minor Collectors
9	Rural Local
11	Urban Interstates
12	Urban Other Freeways and Expressways
14	Urban Other Principal Arterials
16	Urban Minor Arterials
17	Urban Collectors
19	Urban Locals

After the data was collected for the traffic counts, independent variables selected, and roadways classified, final dataset was compiled for the analysis. A snapshot from the database is shown below in figure 65.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
1	LOCATION	MILEPOST	TYPE	FC	LENGTH	TOTAL	TRUCKS	CARS	EMP_AGRICU	EMP_MINING	EMP_CONSTR	EMP_MANUFA	EMP_TRANSP	EMP_UTILIT	EMP_WHOLES	EMP_RETAIL
2	I287	46.50	AVC	11	0.14972	68814	14310	54504	10	60	172	810	289	22	292	1241
3	I287	55.35	AVC	11	0.09704	29691	5334	24357	80	60	308	284	144	12	316	823
4	I287	59.30	AVC	11	0.13213	28404	4179	24225	60	0	106	567	201	58	340	394
5	I287	61.70	VIM	11	0.13213	54240	7482	46758	60	0	106	567	201	58	340	394
6	I287	67.10	AVC	11	0.00610	84333	14093	70239	0	0	0	0	0	0	0	0
7	I287	31.70	VIM	1	0.23085	94154	9276	84878	27	0	56	221	4	6422	47	1254
8	I78	14.50	VIM	1	0.32213	75699	11204	64495	9	0	90	308	241	103	129	1315
9	I78	26.90	AVC	1	0.24563	48641	7184	41457	24	0	57	250	263	10	215	586
10	I78	33.90	AVC	1	0.33617	39332	3647	35685	24	0	36	301	3	845	56	334
11	I78	44.20	AVC	11	0.33617	45638	3066	42572	24	0	36	301	3	845	56	334
12	I78	53.70	AVC	11	0.13267	148597	20236	128361	59	8	272	3607	699	360	1516	1578
13	I80	66.20	VIM	11	0.05985	163024	7906	155118	6	3	214	1902	206	663	1407	1258
14	I80	32.40	VIM	11	0.12796	107167	7928	99239	51	0	94	279	38	3	64	219
15	I80	58.60	AVC	11	0.12206	122017	38518	83499	10	5	449	3784	589	112	1056	1628
16	NJ31	0.56	AVC	14	0.02884	8080	223	7857	3	0	54	206	3	87	229	347
17	NJ31	40.40	VIM	2	0.17548	19093	1161	17932	38	12	91	152	180	17	196	581
18	NJ31	44.00	AVC	2	0.09585	13130	1728	11402	0	0	77	467	58	0	6	296
19	NJ47	2.50	AVC	2	0.05277	11410	147	11262	5	0	49	16	54	4	21	1276
20	NJ47	43.00	AVC	16	0.05933	22662	395	22267	10	0	27	84	4	19	122	2998
21	US130	3.40	VIM	16	0.20191	12641	156	12485	1	0	128	632	135	128	220	569
22	US130	57.00	VIM	14	0.09278	24140	1096	23044	5	0	30	316	0	21	120	615
23	US130	71.00	VIM	6	0.20123	31103	1266	29837	126	0	305	1557	126	18	846	1528
24	US1	47.20	AVC	12	0.09439	76775	7124	69651	0	0	248	1969	10805	139	344	2254
25	US1	50.50	AVC	12	0.04583	101918	19740	82177	12	0	250	1919	1257	35	1657	270
26	US1	18.00	VIM	14	0.30267	52575	2234	50341	27	0	1154	3541	217	670	753	7346
27	US206	47.05	AVC	14	0.09806	13537	515	13022	0	0	36	87	17	21	3	621
28	US206	22.00	VIM	2	0.08431	13484	848	12636	0	0	39	27	10	1	33	105
29	US206	39.60	AVC	14	0.05732	12716	180	12536	2	0	167	200	105	51	106	1137
30	US40	3.00	VIM	2	0.14820	12922	1038	11884	36	0	0	0	0	0	25	240
31	US40	61.60	AVC	14	0.09015	15753	154	15599	2	0	91	197	91	112	100	1070
32	US40	24.50	AVC	2	0.16570	10239	1202	9038	37	0	60	26	18	5	18	366
33	US9	111.80	VIM	14	0.08933	54532	886	53646	34	0	214	140	80	102	155	1311
34	US9	15.50	AVC	6	0.14307	9825	184	9641	21	0	221	51	59	93	81	667
35	US9	40.20	AVC	14	0.04557	15634	218	15416	4	0	257	41	361	33	177	1229
36	US1	1.65	AVC	12	0.09008	33251	1441	31809	4	0	208	2217	85	55	473	1302
37	US1	4.40	AVC	12	0.09008	19693	1652	18041	4	0	208	2217	85	55	473	1302
38	US1	1.30	AVC	14	0.00699	53862	6807	47055	0	0	5	916	106	10	53	175
39	NJ31	7.95	AVC	14	0.11475	22425	1998	20427	59	0	86	169	22	2	12	462
40	NJ31	14.10	AVC	2	0.03833	20155	2012	18143	119	0	30	3	2	0	9	29
41	NJ31	13.00	VIM	2	0.02908	14715	1247	13468	2	0	24	20	0	0	0	22
42	US206	9.80	AVC	2	0.11915	5217	363	4854	58	0	39	20	53	0	44	152

Figure 595: Snapshot of the Database

Statistical Analysis

We had a large number of possible explanatory variables in our dataset, (33 independent variables in-all) and thus STEPWISE regression approach was used to get the best possible set of independent variables that may play a significant role for each model.

Multivariate Regression Analysis is used as a method to generate linear regression models that may provide the best predictive power. The purpose of Multivariate Regression aims in determining the effect of K independent variables, on a dependent variable, Y. The relationship between the dependent and the independent variables is assumed to be linear and subject to an additive random disturbance, r; There are some assumptions which are made when using this Multivariate Regression Method that cannot be ignored. These assumptions are:

1. The relationship between Y and X_1 through X_K is linear. (X are the independent variables and Y is the dependent variable)
2. All of the relevant independent variables are included in the model.
3. All of the included independent variables are relevant (i.e., have a true effect on Y).
4. The independent variables are known with certainty. In other words, there is no measurement error in our observations of X_1 through X_K.

There are two modes of operation for any stepwise regression:
Forward Selection: In forward selection, it selects the most significant variable to enter the model, and keeps adding until no more variables are selected. Finally we are then left with a regression equation.

Backward Elimination: In Backward elimination, it starts with all the variables in the regression equation, then removes them one by one if they are not significant. When all the variables remaining are significant, a regression equation is formed.

The forward selection mode of operation is used for the analysis here.

Vehicles are classified into 13 different classes by the FHWA. Based on the meeting and discussion with NJDOT in August 2003, it was decided that Class 5 will be considered as Small/Medium truck, and Class 6-13 will be considered as Heavy Trucks.

Based on the functional classes for each roadway and after performing some preliminary studies on the data, three alternate groups of roadways were formed:
Alternative I:

FC 1,2 = rural interstate and major arterials

FC 6, 7, 8, 9 = rural minor arterials, collectors, and local

FC 11 = urban interstate

FC 12 = urban expressways and parkways

FC 14 = urban major arterials

FC 16, 17, 19 = urban minor arterials, collectors, and local

Alternative II:

FC 1, 2, 6, 7, 8, 9 = rural roadways

FC 11, 12, 14, 16, 17, 19 = urban roadways

Alternative III:

FC 1, 11 = Interstate

FC 2, 12, 14 = State

FC = 6, 7, 8, 9, 16, 17, 19 = Local

The best alternative among the three alternatives was to be used for the final Model building.

Analysis

SAS, the statistical package has been used throughout the project to perform the statistical analysis and help in building mathematical models for truck trip generation.

To judge how well a model fits and how successful the fit is, in explaining the variation of the data, *R-square value* is considered as a standard tool. R-square can be defined as the square of the correlation between the response values and the predicted response values. It is the ratio of the sum of squares of the regression (SSR*)* and the total sum of squares *(*SST). It is also called the square of the multiple correlation coefficient or the coefficient of multiple determination. R-square can take on any value between 0 and 1, with a value closer to 1 indicating a better fit.

Table 7 below shows the R-square values for all the models built. The models were separately built for small trucks, heavy trucks and all trucks with the three different roadway alternatives.

Table 7: Multivariate Analysis: R-square values for the Models

Roads	All Trucks (Class 5-13)	Medium Trucks (Class 5)	Heavy Trucks (Class 6 -13)
Alternate I			
Expressways	0.97	-	0.88
Rural Interstate	0.53	0.59	0.51
Rural Minor	0.8	0.81	0.77
Urban Interstate	0.8	0.58	0.87
Urban Major	-	0.03	-
Urban Minor	0.35	0.26	0.43
Alternate II			
Rural ways	-	0.12	-
Urban ways	0.33	0.14	0.49
Alternate III			
Interstates	0.73	0.58	0.81
States	0.28	-	0.36
Locals	0.33	0.34	0.34

Findings/ Conclusions

1. Grouping I of roadway classes works best and therefore from now on only alternative I will be used.
2. The best Model are found with 'All trucks.'
3. Medium trucks are not seen significantly on Expressways. Heavy trucks accounts more most of the traffic on Expressways.
4. Rural minor roadways contain mostly the local traffic and thus the model is found to have good predictive power to estimate the volume of light/small truck traffic.

REVISION OF THE MODELS - I

NEW DATASET AND ADDITION OF POPULATION AS ONE OF THE INDEPENDENT VARIABLE (SEPTEMBER 2003)

In the quarterly meeting with NJDOT in August 2003, it was found that the dataset that we were using had the axle adjustments made and only seasonal adjustments were required in the dataset. Also, 'population' as one of the independent variable was discussed and asked to test. Thus, regression analysis was rerun in September 2003, with ‘Population’ was added to the existing 33 independent variables. The same roadway classification as used earlier was carried.

Summary Of All Models Tested

Here some transformations were also performed on the dataset so as to get the best fit. Often it happens that a theoretical relationship is expected to exist between the measured quantities and it is not found to be a simple function between them. Under such instances a transformation of the dataset is recommended and IS seen to work the best. Example, in the log transformation, *logarithm* of the concentration gives a straight-line function. Instead of fitting the raw concentration values, we fit the logarithms of the values.

Log transformations are generally carried to get better fits for the model equation. In log transformation, natural logs of the values of the variable are used in the analysis, rather than the original raw values. Log transformation works well for the datasets where the residuals get bigger for bigger values of the dependent variable. In other words, log transformation works well when two groups have positively (right) skewed distribution and when the group with the larger center also has a large spread.

If the dependent variable represents a count (e.g., the number of trucks) or a proportion, analysis becomes a challenge. The problem that comes is of possibly violating one or more of the assumptions we make when calculating confidence limits or the p value. When the lines or curves are fitted, there is always a worry about the non-uniformity of residuals. With counts, this worry becomes prominent, because the variation in a given count from sample to sample depends on how big the count is. One way to deal with non-uniform residuals is to transform the variable. Log transformation is one answer to this but incase where the upper bound of the count is not close to us, a Square root transformation, i.e. just using the square root of the counts in the usual analyses, is worked out.

Table 8 below shows the R-square values under each of the models built and tested.

Table 8: R-square Values for all the Models Built

Roads	**All Trucks (Class 5_13)**			**Medium Trucks (Class 5)**			**Heavy Trucks (Class 6_13)**		
Alternate I	**Original**	**Log**	**Sq. Root**	**Original**	**Log**	**Sq. Root**	**Original**	**Log**	**Sq. Root**
Rural Interstate	0.78	0.43	0.81	0.85	0.62	0.47	0.78	0.7	0.75
Rural Minor	0.84	0.26	0.64	0.83	0.27	0.63	0.83	0.24	0.57
Urban Interstate	0.84	0.81	0.75	0.64	0.58	0.54	0.92	0.79	0.77
Expressways	0.97	0.54	0.67	-	-	-	0.91	0.61	0.96
Urban Major	-	0.2	-	0.04	0.35	0.1	-	0.08	
Urban Minor	0.42	0.53	0.43	0.28	0.51	0.39	0.46	0.28	0.4
Alternate II									
Rural ways	0.4	0.16	0.25	0.31	0.25	0.26	0.39	0.13	0.31
Urban ways	0.43	0.24	0.3	0.15	0.14	0.17	0.49	0.24	0.33
Alternate III									
Interstates	0.89	0.74	0.71	0.64	0.53	0.57	0.95	0.56	0.86
States	0.35	0.26	0.33	-	0.02	-	0.44	0.26	0.37
Locals	0.36	0.29	0.27	0.4	0.34	0.38	0.33	0.09	0.23

Findings/ Conclusions

- Roadway Alternative I is more promising than Alternatives II and III.
- Models built on Original dataset perform better than when used with log or square root transformations.
- Population does not enter in most of the models and where it does, it either has a 'negative' sign before it, i.e. indicating a reverse effect on truck volumes or has a very 'small coefficient', indicating its very less power for prediction. (See in the end, the models are given)

REVISION OF THE MODELS – II

DATASET FROM SEPTEMBER '03 AND REMOVAL OF POPULATION AS ONE OF THE INDEPENDENT VARIABLE (DECEMBER 2003)

The models were rerun again in December 2003, when Population was not found to be significant in predicting the truck volumes. The same roadway classification and groupings were used, as undertaken earlier. Models were built with circular buffer areas around the locations for 0.5, 1.0, 2.0, 5.0 and 10.0-mile radius. The models from 1-mile buffer area were considered as the base data and other radii were used for the sensitivity analysis.

After the models were built and tested, at a few locations the linear regression showed some negative values for the truck counts and thus to overcome this difficulty, constrained models were built and a set of new models were created.

CONSTRAINED LINEAR OPTIMIZATION

Some of the linear regression models experienced: a) negative or extremely high predictions, b) a negative sign on variables that have been known to have a positive effect on truck volumes, and c) non-existence of models. Following difficulties have been shown graphically in the figure 66.

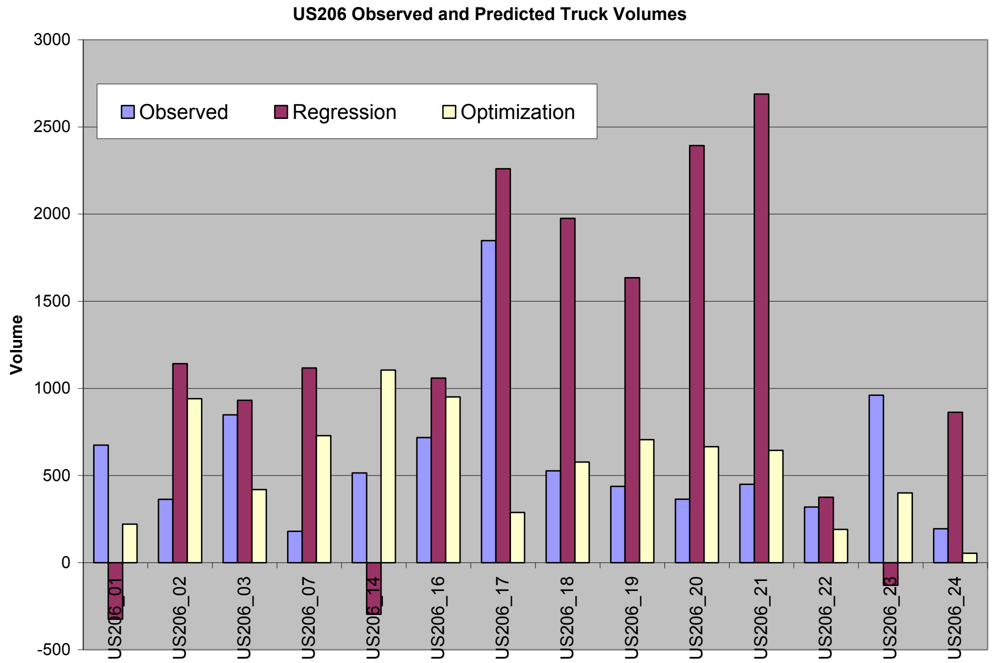


Figure 606: Negativity or Extremely High Predictions

On an effort to further improve the Ordinary Least Square (OLS) models and based on the idea of establishing constraints on coefficients (Normal and Bayesian Linear regression models with linear inequality constraints arise very commonly in the literature), the use of a constrained least squares (CLS) formulation was introduced.

The algorithm (from now on referred as CLSO) uses an objective function that minimizes the sum of squares and at the same time adds constraints, not only to the values of the coefficients, but also to the values of the predicted variables (2.6).

$$\min_{b}\left[\frac{1}{2} (X_{ij}\bar{b}_j - Y_i)^2 \right] \quad (2.6)$$

$$\text{s.t.: } X_{ij}\bar{b}_j \le d_i \quad (2.6a)$$

$$X^{eq}{}_{ij}\bar{b}_j = d^{eq}{}_i \quad (2.6b)$$

$$lb \le b_j \le ub \quad (2.6c)$$

In equation 2.6, lb and ub are the lower and upper bound vectors for the values of the coefficients (b_j), and d_i and d^{eq}_i are the upper and equality bound for the predicted truck volumes.

The above constraints provide a better control over the logic of the model formulation. From the engineering point of view the first constraint (2.6a) captures the range of the expectation for the observed truck volumes. This way the model takes into account the uncertainty and accuracy that exists on the measurement of each station. The third constraint (2.6c) can be considered as a weighting factor of the decision variables. If a priori knowledge for a variable's positive effect is present, we can constraint that variables' beta coefficient to positive values and vice versa. This is especially important since the coefficients are affected by outliers and may enter the model with incorrect size and sign. Outliers can seriously bias the results by "pulling" or "pushing" the regression line in a particular direction, thereby leading to biased regression coefficients. The second constraint (equality constraint) should be used with caution and only when the observed value of the truck volume is known with absolute certainty.

The mathematical constraints are based on the data and the engineers' experience with the study area. We should note that the model goodness of fit is still based on the R^2 value and if no constraints are used the prediction corresponds to the least squares regression solution.

When the problem has only upper and lower bounds, i.e. no linear inequalities or equalities are specified, and the matrix X_{ij} has at least as many rows as columns, the default algorithm uses a large-scale optimization method, is a subspace trust-region method based on the interior-reflective Newton method (2). When linear inequalities or equalities are given the solution takes the form of a medium scale optimization, which uses an active set method similar to that described in Gill, et al. 1981.

We applied the optimization algorithm to the 6 subsets (Alternative I) for each radius. As mentioned before, CLSO offers the advantage of controlling the values of the predictions, in terms of size[4] and sign, for both the coefficients and the predicted variables. The constraint formulation, implemented in this study, is given in equations 4.1 and 4.2.

$$0.25 * Y_{obs} \leq X_{ij}\,\bar{b}_j \leq 1.25 * Y_{obs} \quad (4.1)$$

$$0 \leq b_j \quad (4.2)$$

The first equation (4.1) constraints the estimated truck volume range (on the learn dataset) in an interval of 25% to 115% of the observed value. The range of the predicted truck volumes does not need to be constant for all the stations. It can vary with the functional class of the roadway, the observed count type and location. The limitation in constraint 4.1 is that for relatively small learn datasets, and strict lower bounds of the interval the solution may be infeasible A pseudo-increase of the data, similar to the bootstrap technique [(13)] was performed for all the subsets and the results showed that the lower interval bound is positively correlated to the amount of data. In our study a trial-error method was used in order to determine the lower bound for a feasible solution to exist.

The second constraint incorporates our belief that the each of the predictive variables used in the model have a positive effect on truck volumes. Mean Coefficient Regression was performed for each dataset in order to test this assumption. The results showed positive correlation between predictors and predicted variables in isolation. This constraint was used because due to the small amount of data, one or two outliers were enough to enter a variable into the model with an incorrect sign (which was the case with linear regression). Equality constraints where not used since the accuracy of the observed counts cannot be known with absolute certainty.

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[4] Corresponding to the functional class of the highway and the geographical location of the count the constraints on the min and max value of the expected traffic volumes can vary so that the models account for space variations.

SENSITIVITY ANALYSIS

Sensitivity analysis was performed to determine how "sensitive" a model is with respect to the size of the activity area considered in the analysis. In addition to the one-mile base case, a 0.5, 2, 5, and 10 mile buffer area was used. The models from these different radii are:

Sensitivity Analysis Using Linear Regression

Table 9: Sensitivity Analysis (Regression)

Radius Mile →	**½**	**1**	**2**	**5**	**10**
Rural Interstate	0.45	0.74	0.24	0.51	0.22
Rural Minor	0.91	0.80	0.83	0.68	0.81
Urban Interstate	0.92	0.83	0.96	0.48	0.17
Expressways	0.58	0.97	0.92	0.84	0.59
Urban Major	-	-	0.03	0.03	0.03
Urban Minor	0.51	0.42	0.51	0.36	0.13

The resulting R-square values of the new models are also shown in the figure 67 below.

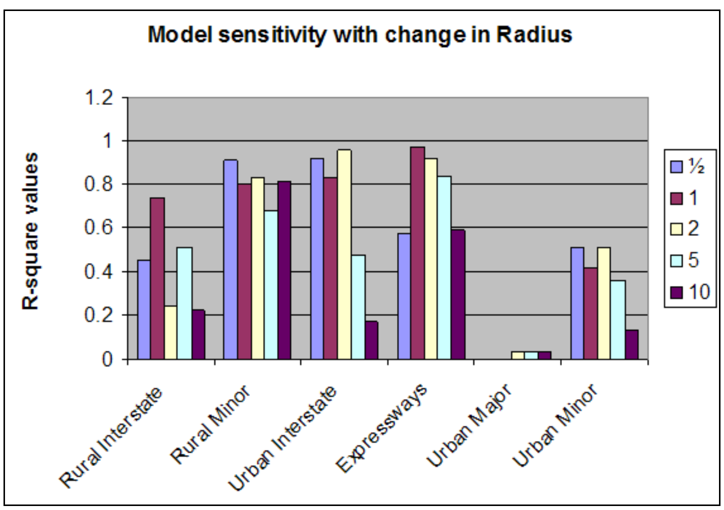


Figure 67: Sensitivity Analysis (Simple Regression Models)

Sensitivity Analysis Using CLSO

The models created by this approach have been tabulated below:

Table 10: Sensitivity Analysis (Optimization)

Radius Mile →	½	1	2	5	10
Rural Interstate	0.67	**0.75**	0.40	0.34	0.30
Rural Minor	0.71	**0.88**	0.50	0.51	0.32
Urban Interstate	0.51	**0.68**	0.62	0.45	0.28
Expressways	**0.81**	0.58	**0.80**	0.61	0.67
Urban Major	**0.48**	0.28	0.21	0.20	0.17
Urban Minor	**0.65**	0.44	0.39	0.28	0.23

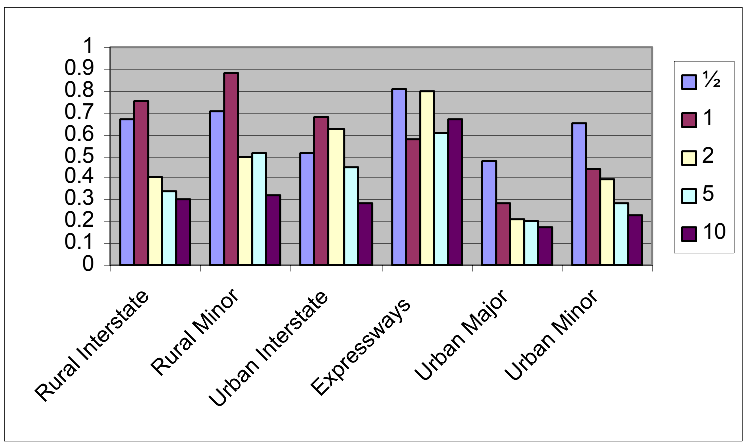


Figure 68: Sensitivity Analysis (CLSO Model)

Both figure 67 and 68 show that the models are sensitive to the area considered in the analysis. A general trend is that for lower level roads a small buffer area seems to work better, whereas for higher-level roads (interstates, expressways) a larger radius performs better. A very large radius negatively affects the models, a result that is expected, since activity in such a large area generates traffic that is distributed over several roadways and is not necessarily part of the traffic in the specific roadway segment under consideration.

The figure shows that the models are sensitive to the area considered in the analysis. A general trend is that for lower level roads a small buffer area seems to work better, whereas for higher-level roads (interstates, expressways) a larger radius performs better. A very large radius negatively affects the models, a result that is expected, since activity in such a large area generates traffic that is distributed over several roadways and is not necessarily part of the traffic in the specific roadway segment under consideration.

REVISION OF THE MODELS – III

NEW DATASET CREATED IN APRIL 2004 with buffer as BANDS ALONG THE SECTION OF THE COUNT

With a meeting with NJDOT in April 2004, it was concluded that Trucks would only be considered between Classes 6 through Class 13. FHWA Vehicle class 5 should be taken out of the analysis for truck volumes and flows.

Analysis was carried over and first the models were rerun with circular buffer radius with truck classes 6 through 13. This yielded the following results with both the linear regression and the constrained optimization approaches. Table 11, 12 summarizes the results and figure 69, 70 show them graphically.

Table 11: Models from Linear Regression (Circular Bands)

	½	**1**	**2**	**5**	**10**
Rural Interstate	0.46	0.75	0.36	0.49	0.21
Rural Minor	0.57	0.74	0.69	0.37	0.67
Urban Interstate	0.9	0.92	0.98	0.84	0.16
Expressways	0.61	0.91	0.95	0.89	0.66
Urban Major	0.33	-	-	-	-
Urban Minor	0.53	0.46	0.38	0.27	0.25

Table 12: Models from Optimization Approach (Circles)

	½	1	2	5	10
Rural Interstate	0.67	0.75	0.40	0.34	0.30
Rural Minor	0.71	0.88	0.50	0.51	0.32
Urban Interstate	0.51	0.68	0.62	0.45	0.28
Expressways	0.81	0.58	0.80	0.61	0.67
Urban Major	0.48	0.28	0.21	0.20	0.17
Urban Minor	0.65	0.44	0.39	0.28	0.23

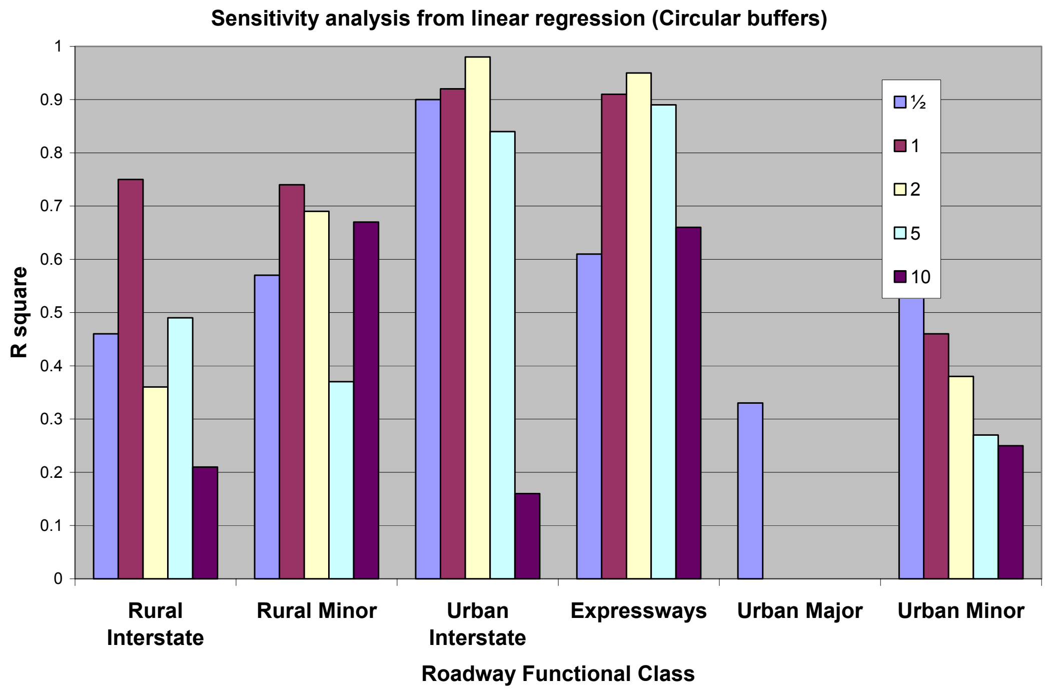


Figure 69: Sensitivity Analysis from Linear Regression (Circular Buffers)

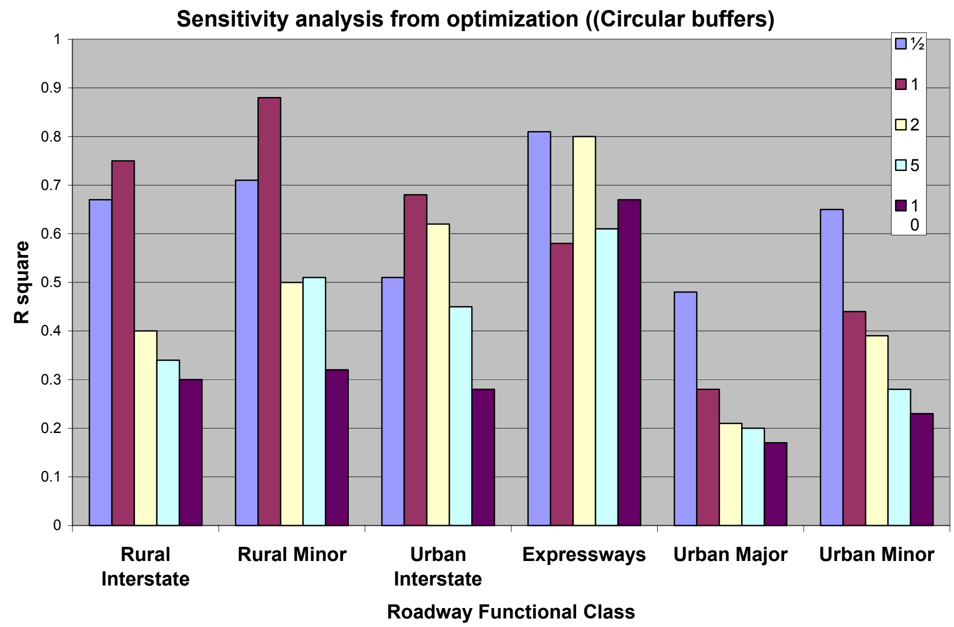


Figure 70: Sensitivity Analysis from Optimization (Circles)

Limitations of the circular buffer radii approach

In the beginning of the project (as described in Task II-1, II-2 and II-3), it was believed that a large number of observed truck counts will be available for the study, which would in-turn allow us for a large number of sections defined on each of the selected highways. Figure 71 shows the sections defined very close to each other capturing the maximum variance or the most of the activity and traffic near the count location. This would give us the best possible understanding of the truck flow. The buffer areas were taken in circular shapes around each location and analysis was carried.

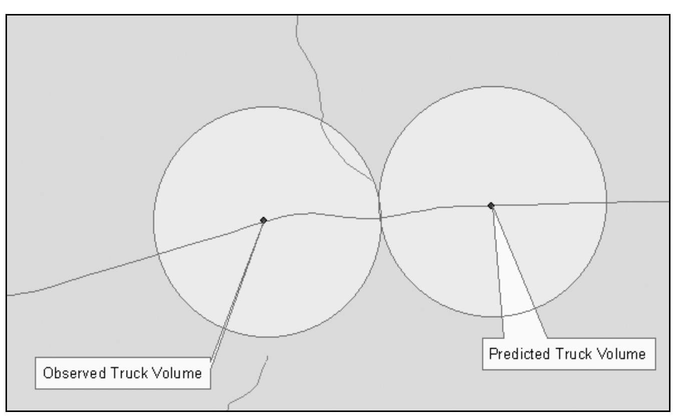


Figure 71: Initial Proposed Highway Segmentation

But later when the data was compiled for the analysis, it was seen that a very strong visual inspection is required in each of the sections. At most of the locations, because the points are so close to one another there was a danger of double counting and overlapping, as shown in figure 72 below.

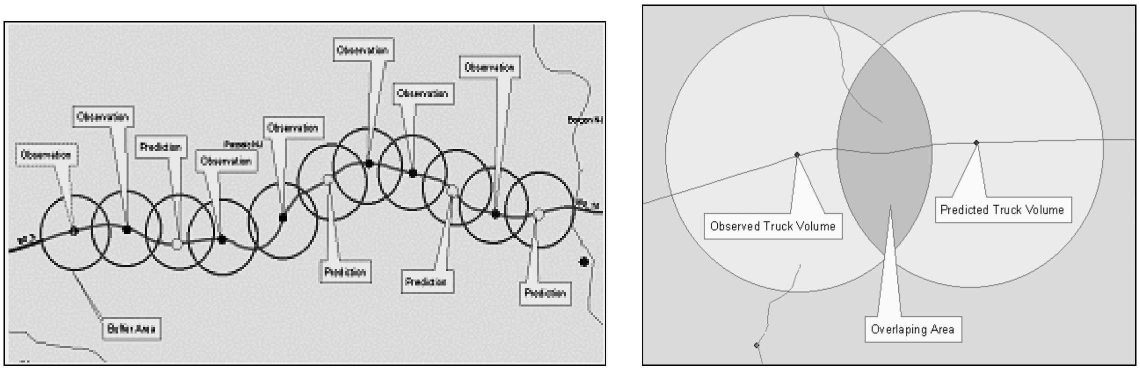


Figure 72: Overlapping and Double Counting

When deciding on the sections, the goal was to have a minimum of one count per section or per other section. This segmentation format, would allow for the independent variable dataset to be extracted using a circular buffer area around each location and the predicted volumes on each section to be uniform.

As explained in task II.3, the sections were selected based on the: a) Major Interchanges and Cross routes along the highway and, b) change in the roadways functional class. Due to limited data (observed truck volumes) most of the sections were aggregated into larger sections, which resulted in the non-uniformity of the predicted truck volumes across the section, as shown pictorially in figure 73. The large length of the section and the use of circular buffer area to extract information for the independent variables showed the inadequacy of the data to predict truck traffic for the section. This led to the generation of different truck volumes at different locations on the same section.

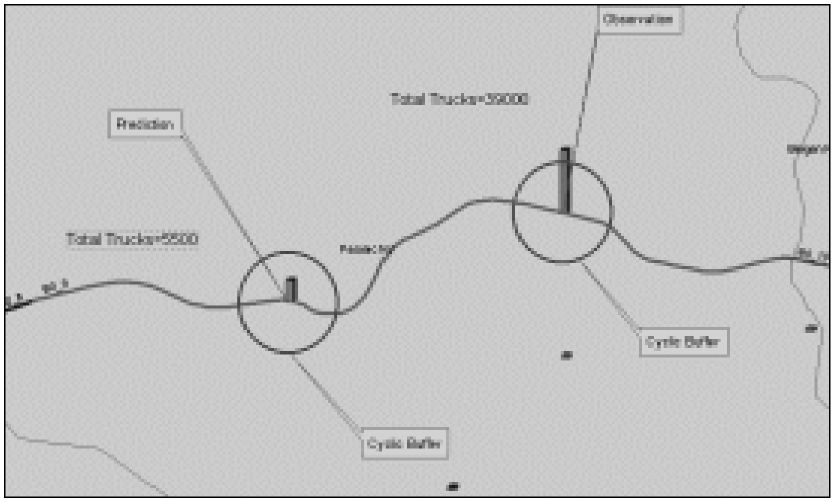


Figure 73: Implemented Segmentation and Problems of Non-Uniformity

In order to deal with these problems (shown in figure 72 and figure 73), roadway sections were created for all the 270 locations throughout the state, and buffers were made in the shape of bands for the sections to extract the independent data. This approach was found to give uniform truck predictions. The independent dataset was reproduced using the new buffer shape for different radiuses. All the statistical analysis performed earlier was reproduced, and new models were built. The approach is shown in figure 74 below.

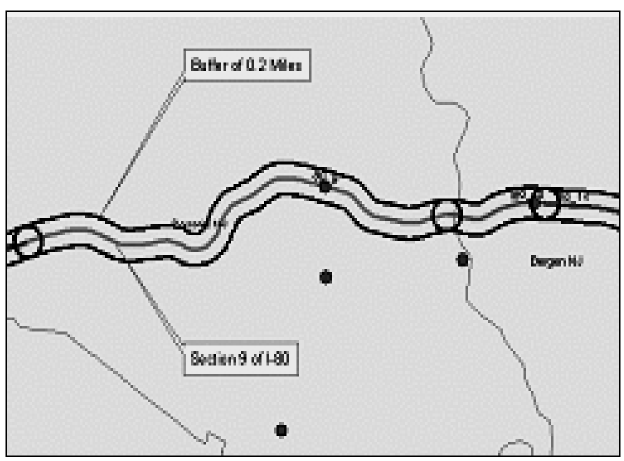


Figure 74: Parallel Band Data Extraction

Models Built

Each variable in the model: (EMP represents number of employees, SALES represent estimated sales volume in thousands of dollars and CNT represent number of businesses. Relevant SIC codes under each business category are given in table 5 before.)

Table 13: Linear Regression Model (0.25-mile Band Buffer)

VARIABLE	RURAL INTERSTATE	RURAL MINOR	URBAN INTERSTATE	EXPRESSWAYS	URBAN MAJOR	URBAN MINOR
Intercept	412.07	75.285	6056.9	2766.2	1501.3	119.44
EMP_AGRICU	0	-2.0101	-60.779	0	0	0
EMP_MINING	0	0	0	0	0	0
EMP_CONSTR	0	0	0	-70.93	0	0
EMP_MANUFA	0	0	0	0	0	0
EMP_TRANSP	22.538	0	0	0	0	0.77756
EMP_UTILIT	0	0	0	0	0	0
EMP_WHOLES	0	0	0	0	3.3976	0
EMP_RETAIL	0	0	0	0	0	-0.38504
EMP_FINANC	0	0	0	0	0	0
EMP_REAL_E	27.833	0	0	0	0	0
EMP_SERVIC	0	-0.14776	0	0	0	0
SALES_AGRI	0.01075	0.00774	0	0	0	0
SALES_MINI	0	0	0	0	0	0
SALES_CONS	0	0	0	0.35071	0	0
SALES_MANU	0	0	0	0	0	0
SALES_TRAN	0	0.0069	0.35868	0	0	0
SALES_UTIL	0	0	0	0	0	0
SALES_WHOL	0.00585	0	0	0	0	0
SALES_RETA	0	0	0	0	0	0.00339
SALES_FINA	0.1719	0	0	0	0	0
SALES_REAL	0	0	0	0	0	0
SALES_SERV	0	0	0	0	0	0
COUNT_AGRI	0	0	0	0	0	-30.143
COUNT_MINI	0	199.71	0	-4436.3	0	818.83
COUNT_CONS	-70.668	0	0	0	0	0
COUNT_MANU	341.6	0	0	0	0	0
COUNT_TRAN	-393.35	0	-275.82	0	0	0
COUNT_UTIL	0	0	0	0	0	0
COUNT_WHOL	0	18.971	0	0	0	0
COUNT_RETA	0	0	0	0	0	0
COUNT_FINA	-469.29	0	0	0	-53.173	13.723
COUNT_REAL	0	0	0	0	0	4.6643
COUNT_SERV	0	0	0	0	0	0

Table 14: Linear Regression Model (0.50-mile Band Buffer)

Variable	RURAL INTERSTATE	RURAL MINOR	URBAN INTERSTATE	URBAN MINOR
Intercept	677.41858	64.44534	9998.64619	122.74233
EMP_AGRICU	0	0	-98.3616	0
EMP_MINING	0	0	0	0
EMP_CONSTR	0	0.72627	108.46415	0
EMP_MANUFA	0	0	0	0
EMP_TRANSP	0	0	0	0
EMP_UTILIT	0	0	-21.29742	0
EMP_WHOLES	0	0	0	0
EMP_RETAIL	0	0	0	0.04621
EMP_FINANC	0	0	6.48943	0
EMP_REAL_E	23.72844	0	0	0
EMP_SERVIC	0	-0.26557	0.95702	-0.05226
SALES_AGRI	0	0	0	0
SALES_MINI	0	0	0	0.03625
SALES_CONS	0	0	-0.59021	0
SALES_MANU	0	0	0.00722	0
SALES_TRAN	0.22729	0	0	0.00391
SALES_UTIL	0.00697	0	0	0
SALES_WHOL	0	0	0	0
SALES_RETA	0	0	0	0
SALES_FINA	0.05266	0	-0.03719	-0.00184
SALES_REAL	0	0	0	0
SALES_SERV	0	0	0	0
COUNT_AGRI	0	0	0	0
COUNT_MINI	0	0	0	0
COUNT_CONS	0	0	0	-3.76842
COUNT_MANU	0	13.27176	0	0
COUNT_TRAN	0	0	0	0
COUNT_UTIL	-294.21526	0	0	0
COUNT_WHOL	0	17.42393	204.20299	0
COUNT_RETA	0	0	0	0
COUNT_FINA	0	0	0	14.00528
COUNT_REAL	-113.79185	0	0	0
COUNT_SERV	0	0	0	0

Table 15: Linear Regression Model (0.75-mile Band Buffer)

Variable	RURAL INTERSTATE	RURAL MINOR	URBAN INTERSTATE	EXPRESSWAYS	URBAN MINOR
Intercept	1007.52175	89.1478	6373.93631	4889.51093	119.35605
EMP_AGRICU	11.25016	0	-33.65549	126.27329	0
EMP_MINING	0	0	0	-500.03564	0
EMP_CONSTR	0	1.10055	0	0	0
EMP_MANUFA	0	0	0	0	0
EMP_TRANSP	0	0	11.35082	0	0
EMP_UTILIT	0	0	-2.78907	0	0
EMP_WHOLES	1.57421	0	0	0	0
EMP_RETAIL	0	0	0	0	0
EMP_FINANC	0	0	0	-1.54792	0
EMP_REAL_E	0	0	0	0	0
EMP_SERVIC	0	-0.16732	0	1.15447	-0.01051
SALES_AGRI	0	0	0	0.30846	0
SALES_MINI	0.45686	0	0	1.34266	0.04045
SALES_CONS	-0.06018	0	0	0	0
SALES_MANU	0	0	0	0	0
SALES_TRAN	0.23649	0	0	0	0.00371
SALES_UTIL	0	0	0	-0.36551	0
SALES_WHOL	0	0	0	0	0
SALES_RETA	0	0.00063598	0	-0.01478	0
SALES_FINA	0	0	0	0	0
SALES_REAL	0	0	0	0	0
SALES_SERV	0	0	0	0	0
COUNT_AGRI	0	0	0	-270.66085	0
COUNT_MINI	-1722.14283	0	0	0	-96.03633
COUNT_CONS	-33.32217	-4.717	0	0	0
COUNT_MANU	0	18.09536	0	0	0
COUNT_TRAN	0	0	0	322.21229	0
COUNT_UTIL	314.06741	0	0	977.54881	0
COUNT_WHOL	0	0	0	-119.01833	0
COUNT_RETA	0	0	0	0	0
COUNT_FINA	0	0	0	0	0
COUNT_REAL	0	0	0	0	0
COUNT_SERV	0	0	0	-46.36678	0

Table 16: Linear Regression Model (1.0-mile Band Buffer)

Variable	RURAL INTERSTATE	RURAL MINOR	URBAN INTERSTATE	EXPRESSWAYS	URBAN MINOR
Intercept	1115.97927	100.97497	5536.76987	3504.75091	124.68764
EMP_AGRICU	0	0	0	0	0
EMP_MINING	0	0	0	0	0
EMP_CONSTR	0	2.70063	0	10.79344	0
EMP_MANUFA	0	0	0	-5.45671	0
EMP_TRANSP	9.97452	0	0	0	0
EMP_UTILIT	1.21507	0	0	-10.95446	0
EMP_WHOLES	2.06582	0	0	0	0
EMP_RETAIL	0	0.14256	0	0	0
EMP_FINANC	0	0	0	0	0
EMP_REAL_E	0	0	0	4.09266	0
EMP_SERVIC	0	0	0	0	-0.01148
SALES_AGRI	0	0	0	0	0
SALES_MINI	0	0	0	0	0.00358
SALES_CONS	0	-0.00531	0	0	0
SALES_MANU	0	0.0003708	0	0.01366	0
SALES_TRAN	0	0	0	0	0.00244
SALES_UTIL	0	0	-0.00833	0	0
SALES_WHOL	0	0	0	0	0
SALES_RETA	0	0	0	0	0
SALES_FINA	0	0	0	0.04464	0
SALES_REAL	0	0	0	0	0
SALES_SERV	0	0	0	0	0
COUNT_AGRI	0	0	0	-202.33934	0
COUNT_MINI	-1822.04129	0	0	0	0
COUNT_CONS	0	-5.67561	0	0	0
COUNT_MANU	0	0	0	0	0
COUNT_TRAN	0	0	0	0	0
COUNT_UTIL	0	0	0	0	0
COUNT_WHOL	0	0	0	0	0
COUNT_RETA	0	0	26.49473	0	0
COUNT_FINA	-48.52011	0	0	0	0
COUNT_REAL	0	0	-154.98942	0	0
COUNT_SERV	0	0	0	0	0

Table 17: Linear Regression Model (1.25-mile Band Buffer)

Variable	RURAL INTERSTATE	RURAL MINOR	URBAN INTERSTATE	EXPRESSWAYS	URBAN MINOR
Intercept	609.01398	68.12296	5395.59811	3977.14304	127.15156
EMP_AGRICU	-8.64513	0	-30.10316	0	0
EMP_MINING	0	0	0	0	0
EMP_CONSTR	0	1.36729	0	0	0
EMP_MANUFA	0	0	0	-2.13091	0
EMP_TRANSP	-10.65603	0	0	0	0
EMP_UTILIT	2.3921	0	0	-13.28775	0
EMP_WHOLES	0	0	0	0	0
EMP_RETAIL	0	0	0	0	0
EMP_FINANC	0	0	0	0	0
EMP_REAL_E	0	0	0	0	0
EMP_SERVIC	0	-0.10104	0	0	-0.01199
SALES_AGRI	0	0	0	0	0
SALES_MINI	0	0	0	0	0.00392
SALES_CONS	0	0	0	0	0
SALES_MANU	0	0	0	0.00544	0
SALES_TRAN	0	0	0	0.00646	0.00202
SALES_UTIL	0	0	-0.01101	0	0
SALES_WHOL	0.01719	0	0	0	0
SALES_RETA	0	0	0	0	0
SALES_FINA	0	0	0	0.03625	0
SALES_REAL	0	0	0	0	0
SALES_SERV	-0.0281	0	0.01431	0	0
COUNT_AGRI	0	0	0	0	0
COUNT_MINI	-1632.38405	0	0	0	0
COUNT_CONS	63.42934	-4.25745	0	0	0
COUNT_MANU	-97.83671	9.73208	0	0	0
COUNT_TRAN	0	0	0	0	0
COUNT_UTIL	0	0	0	0	0
COUNT_WHOL	0	0	0	0	0
COUNT_RETA	0	0.95721	0	0	0
COUNT_FINA	0	0	0	0	0
COUNT_REAL	0	0	-249.584	0	0
COUNT_SERV	0	0	18.48648	0	0

Table 18: Linear Regression Model (1.5-mile Band Buffer)

Variable	RURAL INTERSTATE	RURAL MINOR	URBAN INTERSTATE	EXPRESSWAYS	URBAN MINOR
Intercept	1210.00428	62.5775	1452.94185	3782.37225	148.74245
EMP_AGRICU	0	0	0	0	0
EMP_MINING	0	0	0	0	0
EMP_CONSTR	0	1.08923	0	0	0
EMP_MANUFA	0	0	0	0	0
EMP_TRANSP	5.40582	0	2.37898	1.82135	0
EMP_UTILIT	0	0	0	0	0
EMP_WHOLES	0.66494	0	0	0	0
EMP_RETAIL	0	0	-3.13379	0	0
EMP_FINANC	0	0	0	0	0
EMP_REAL_E	0	0	0	0	0
EMP_SERVIC	0	0	0	0	0
SALES_AGRI	0	0	0	-0.01588	0
SALES_MINI	0	0	0	0	0
SALES_CONS	0	0	0	0	0
SALES_MANU	0	0	0.00534	0	0
SALES_TRAN	0	0	0	0	0.00257
SALES_UTIL	0.0025	0	0	-0.09447	0
SALES_WHOL	0	0	0	0	0
SALES_RETA	0	0	0.02681	0	0
SALES_FINA	0	0	0	0	0
SALES_REAL	0	0	-0.14615	0	0
SALES_SERV	0	-0.00095442	0	-0.01192	0
COUNT_AGRI	0	0	0	0	0
COUNT_MINI	-1599.17209	0	0	-2173.93273	0
COUNT_CONS	0	-2.82528	0	0	0
COUNT_MANU	0	10.20816	0	0	0
COUNT_TRAN	0	0	0	0	-3.63932
COUNT_UTIL	0	0	0	0	0
COUNT_WHOL	0	0	0	0	0
COUNT_RETA	0	0	0	0	0
COUNT_FINA	0	0	-95.88764	161.34126	0
COUNT_REAL	0	0	109.11752	52.17657	0
COUNT_SERV	0	0	0	0	0

Table 19: Linear Regression Model (2.0-mile Band Buffer)

Variable	RURAL INTERSTATE	RURAL MINOR	URBAN INTERSTATE	EXPRESSWAYS	URBAN MAJOR	URBAN MINOR
Intercept	353.92546	36.83806	4870.4524	4454.2874	2200.3076	129.97699
EMP_AGRICU	0	0	0	0	0	0
EMP_MINING	0	0	139.2295	0	0	0
EMP_CONSTR	-4.844	0.67738	0	0	0	0
EMP_MANUFA	1.12963	0.06279	0	-0.73563	0	0
EMP_TRANSP	0	0	1.17897	0	0	0
EMP_UTILIT	0	0	-2.06256	0	0	0
EMP_WHOLES	0	0.21473	0	0	0	0
EMP_RETAIL	0	-0.17744	0	0	0	0
EMP_FINANC	3.04674	0	0	3.09532	0	0
EMP_REAL_E	0	0	0	0	0	0
EMP_SERVIC	0	0	0	0	0	-0.00641
SALES_AGRI	0	0	0	0	-0.00631	0
SALES_MINI	0	0	0	0	0	0
SALES_CONS	0	0	0	0	0	0
SALES_MANU	0	0	0	0	0	0
SALES_TRAN	0	0	0	0	0	0.00151
SALES_UTIL	0.01248	0	0	0	0	-0.00025
SALES_WHOL	0.01221	0	0	0	0	0
SALES_RETA	0	0	0	0	0	0
SALES_FINA	0	0	0	0	0	0
SALES_REAL	0	0	0	0	0	0
SALES_SERV	-0.02465	0	0	0	0	0
COUNT_AGRI	107.94812	0	0	0	0	0
COUNT_MINI	-1715.917	0	0	0	0	0
COUNT_CONS	0	-1.32765	0	0	0	0
COUNT_MANU	-93.49774	0	0	0	0	0
COUNT_TRAN	0	0	0	0	0	0
COUNT_UTIL	-308.3492	0	0	0	0	0
COUNT_WHOL	0	0	0	0	0	0
COUNT_RETA	24.47324	1.45018	0	0	0	0
COUNT_FINA	0	0	0	0	0	0
COUNT_REAL	-10.18679	0	0	0	0	0
COUNT_SERV	0	0	0	0	0	0

Table 20: Linear Regression Model (3.0-mile Band Buffer)

Variable	RURAL INTERSTATE	RURAL MINOR	URBAN INTERSTATE	EXPRESSWAYS	URBAN MINOR
Intercept	658.90811	-5.95222	5059.1518	7224.266	170.7708
EMP_AGRICU	0	0	0	0	0
EMP_MINING	0	0	0	-148.41924	0
EMP_CONSTR	0	0	3.58619	0	0
EMP_MANUFA	1.56498	0	0	0	0
EMP_TRANSP	0	0	0	0	0
EMP_UTILIT	0	0	0	0	0
EMP_WHOLES	1.59451	-0.07689	0	0	0
EMP_RETAIL	0	0	0	0.9955	0
EMP_FINANC	2.72505	0	0	-11.81964	0.02102
EMP_REAL_E	0	-0.23056	0	1.98463	-0.04648
EMP_SERVIC	0	0	0	-0.90022	0
SALES_AGRI	0	0	0	0	-0.00036
SALES_MINI	0	0	0	0.84527	0
SALES_CONS	0	0.00156	0	0	0
SALES_MANU	0.00331	0	0	0	0
SALES_TRAN	0	0	0	0	0
SALES_UTIL	0	0	0	0.02086	0
SALES_WHOL	0	0.0003693	0	0	0
SALES_RETA	0	0	0	0	0
SALES_FINA	0	0	0	0.05236	0
SALES_REAL	0	0	0	0.15167	0.0003732
SALES_SERV	0	0	0	0	0
COUNT_AGRI	82.31913	0	0	0	0
COUNT_MINI	0	0	0	914.33951	0
COUNT_CONS	0	0	0	71.76977	0
COUNT_MANU	-106.9595	0	0	0	0
COUNT_TRAN	53.36999	0	0	0	0
COUNT_UTIL	-215.6551	0	0	0	0
COUNT_WHOL	0	0	0	0	0
COUNT_RETA	0	0	0	0	0
COUNT_FINA	0	0	47.76105	-64.2625	0
COUNT_REAL	0	0	-106.323	-296.30756	0
COUNT_SERV	0	0	0	-10.07423	0

Table 21: Linear Regression Model (5.0-mile Band Buffer)

VARIABLE	RURAL INTERSTATE	RURAL MINOR	URBAN INTERSTATE	EXPRESSWAYS	URBAN MAJOR	URBAN MINOR
Intercept	1333	-56	11348	2844	2429.	167
EMP_AGRICU	0	0	0	0	0	0
EMP_MINING	0	0	0	0	0	0
EMP_CONSTR	0	0	0	0	0	0
EMP_MANUFA	0	0	0.98	0	0	0
EMP_TRANSP	0	0	0	0	0	0
EMP_UTILIT	0.54118	0	0	0	0	0
EMP_WHOLES	0	-0.02898	0	0	0	0
EMP_RETAIL	0	0	0	0	0	0
EMP_FINANC	0	0	0	0.74581	0	0.02758
EMP_REAL_E	0	0	0	0	0	0
EMP_SERVIC	0	0	0	0	0	0
SALES_AGRI	0	0.00037	0	0	-0.00214	0
SALES_MINI	0	0	0	0	0	0
SALES_CONS	0	0	0	0	0	0
SALES_MANU	0	0	-0.00232	0	0	0
SALES_TRAN	0	0.00374	0	0	0	0
SALES_UTIL	0	0	0	0	0	0
SALES_WHOL	0	0	0	0	0	0
SALES_RETA	0	0	0	0	0	0
SALES_FINA	0	0	-0.00618	0	0	0
SALES_REAL	0	0	-0.06684	0	0	0
SALES_SERV	0	0	0.01055	0	0	-0.00006
COUNT_AGRI	0	0	-65.30148	0	0	0
COUNT_MINI	0	40.96708	0	-511.76824	0	0
COUNT_CONS	0	0	0	0	0	0
COUNT_MANU	0	0	0	0	0	0
COUNT_TRAN	0	0	0	0	0	0
COUNT_UTIL	0	0	0	0	0	0
COUNT_WHOL	0	0	0	0	0	0
COUNT_RETA	0	0	0	0	0	0
COUNT_FINA	0	0	0	0	0	0
COUNT_REAL	0	0	0	0	0	0
COUNT_SERV	0	0	0	0	0	0

Summary for all models built:

Table 22: Sensitivity Analysis (Linear Regression Approach)

Radius Mile □	**0.25**	**0.5**	**0.75**	**1**	**1.25**	**1.5**	**2**	**3**	**5**
Rural Interstate	0.97	0.88	0.84	0.79	0.91	0.61	0.96	0.84	0.27
Rural Minor	0.83	0.84	0.81	0.81	0.82	0.75	0.73	0.73	0.63
Urban Interstate	0.65	0.92	0.88	0.77	0.82	0.78	0.56	0.54	0.67
Expressways	0.46	0	0.99	0.94	0.88	0.97	0.60	0.99	0.64
Urban Major	0.13	0	0	0	0	0	0.03	0	0.04
Urban Minor	0.59	0.51	0.37	0.24	0.23	0.21	0.17	0.24	0.23

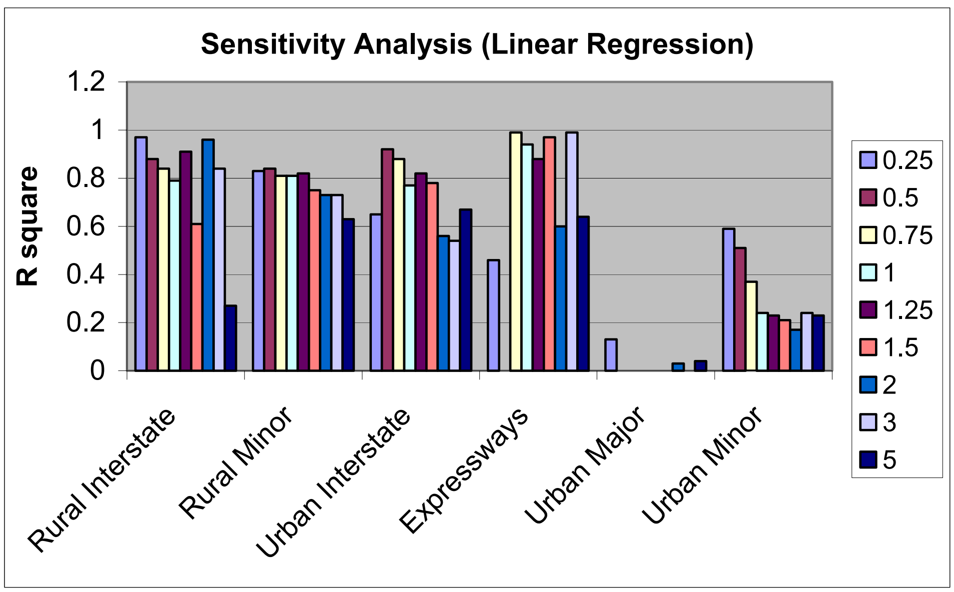


Figure 75: Sensitivity Analysis (Linear Regression Approach)

The sensitivity analysis showed that the minor roadways were predicted better with a smaller radii and higher category roads such as interstates and expressways comparatively need more radius of length for the explanation of the traffic on them. Below are the final models build:

Final Models Built (Linear Regression)

Trucks on Rural Interstate

Y = 412.07 + 22.54 (emp_transp) +27.83 (emp_real) + 0.011 (sales_agri) + 0.006 (sales_whol) + 0.172 (sales_fin) –70.67 (cnt_const) + 341.59 (cnt_manu) – 393.34 (cnt_transp) – 469.29 (cnt_fin)

Trucks on Rural Minor

Y = 64.445 + 0.726 (emp_const) – 0.265 (emp_serv) + 13.27 (cnt_manu) + 17.43 (cnt_whol)

Trucks on Urban Interstates

Y = 9998.6 – 98.36 (emp_agri) + 108.36 (emp_const) – 21.29 (emp_util) + 6.489 (emp_fin) + 0.957 (emp_serv) – 0.59 (sales_const) + 0.007 (sales_manu) – 0.037 (sales_fin) + 204.20 (cnt_whol)

Trucks on Expressways

Y = 4889.5 + 126.27(emp_agri) – 500.03(emp_min) – 1.55 (emp_fin) + 1.15 (emp_serv) + 0.31 (sales_agri) + 1.34(sales_min) + 0.36 (sales_util) – 0.015 (sales_reta) – 270.66 (cnt_agri) + 977.55(cnt_util) + 322.21(cnt_trans) –119.01 (cnt_whol) –46.37 (cnt_serv)

Trucks on Urban Major

Y = 1501.3 + 3.397 (emp_whol) – 53.17 (cnt_fin)

Trucks on Urban Minor

Y = 119.43 + 0.77 (emp_transp) – 0.385(emp_reta) + 0.003 (sales_reta) – 30.14(cnt_agri) + 818.83 (cnt_mini) + 13.72 (cnt_ fin) + 4.664 (cnt_real)

A few points to note for the above built final models used in the analysis:

1. The models for higher-level facilities, such as interstates and expressways, have a substantially higher intercept value compared to those for lower level facilities. The higher intercept accounts for the through traffic on these roadways, meaning traffic that does not have its origin and/or destination within the state or within the proximity but uses state roadways to move between points of origin and destination. Thus, the models implicitly account for this 'overhead truck traffic'. Estimates of through traffic on major highways were not available at the time of the project. If such estimates become available in the future, the value of through traffic could be subtracted from the corresponding observed counts in their respective highway locations, and the procedure described above would be used to develop models to estimate locally generated traffic on higher-level roadway sections. Typically, lower level facilities do not carry large volumes of through traffic, thus inclusion of through truck volume estimates would not affect these models.
2. Though some of the independent variables showed a negative coefficient in these simple linear model equations, (which is suspected because of the nature of the small sample set we have) these models did not give a negative truck volume on the roadways when finally models were calibrated. They actually made estimates quite closer to the observed counts. But, in order to deal with the negativity, in the later part of the study, a different approach (as explained earlier) was undertaken. This

new approach ‘Linear Optimization’ built constrained models with model coefficients as positive.

3. The models created are not intended to forecast, but are built for strategic planning of transportation systems. The models can provide authorities with estimate of truck volumes at the present time. Some of the factors that do not allow it to work as a forecasting took are:
   - Changes and growth in the economy of the region
   - Changes in transportation systems
   - Diversion of flows to new or expanded facilities
   - Diversion of flows across modes due to regulatory actions, pricing policy, capacity changes, changes in service level

Other than these reasons, the regression model cannot be used as a forecasting tool because:

1. In order to develop an Ordinary Least Square (OLS) models for forecasting, it is necessary to provide future values of each independent variable. Developing good forecasts for the independent variable may further require additional model building, extrapolating past trends or acquiring forecasts from outside sources.
2. Forecasting also requires the stability of parameter estimates. If the parameter estimates are sensitive to the input data, the model structure may change over time.
3. Lastly, forecasting involves unforeseen disturbances, which cannot be accounted for and which may alter the relationship between independent

and dependent variables completely. (Example: international disturbances, supply shocks for petroleum, natural disasters as earthquakes, fires etc.)

4. Other than these, factors like; Economic regulations and deregulations, Fuel prices, Environmental and safety policies and restrictions, Congestion, Effect of changes in truck size and weight limits, Centralized warehousing, Effect of low-density shipments creating need for larger truck trailers, etc also influence the analysis and results.

Models Built (Constrained Linear Optimization)

Table 23: Constrained Optimization Model (0.25-mile Band Buffer)

Variable	RURAL INTERSTATE	RURAL MINOR	URBAN INTERSTATE	EXPRESSWAYS	URBAN MAJOR	URBAN MINOR
Intercept	48	3	267	110	26	4
EMP_AGRICU	0.0000	0.0000	0.0000	0.0000	0.0000	0.2402
EMP_MINING	0.0000	0.0312	0.0000	0.0000	4.6725	0.0422
EMP_CONSTR	0.0000	0.0611	0.0000	0.0000	0.0000	0.0211
EMP_MANUFA	0.0000	0.0000	1.7787	0.0000	0.5623	0.0402
EMP_TRANSP	8.5442	0.0000	0.0000	0.0000	0.0000	0.0000
EMP_UTILIT	0.0000	0.0000	0.0000	0.0000	0.0000	0.4584
EMP_WHOLES	0.0000	0.0662	0.0000	1.6259	3.0173	0.0000
EMP_RETAIL	0.0000	0.0000	0.0000	1.3538	0.0000	0.0000
EMP_FINANC	1.2641	0.0000	0.0000	0.0000	0.0000	0.0000
EMP_REAL_E	2.8996	0.0000	2.8378	0.0000	0.0000	0.0000
EMP_SERVIC	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
SALES_AGRI	0.0000	0.0052	0.0000	0.0000	0.0000	0.0000
SALES_MINI	0.0000	0.0233	0.2322	0.0000	0.0000	0.0363
SALES_CONS	0.0000	0.0000	0.0000	0.0741	0.0000	0.0000
SALES_MANU	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
SALES_TRAN	0.1758	0.0051	0.1207	0.0000	0.0594	0.0036
SALES_UTIL	0.0114	0.0000	0.0000	0.0000	0.0000	0.0000
SALES_WHOL	0.0000	0.0000	0.0031	0.0000	0.0000	0.0000
SALES_RETA	0.0000	0.0000	0.0000	0.0000	0.0000	0.0008
SALES_FINA	0.0000	0.0000	0.0000	0.0000	0.0000	0.0015
SALES_REAL	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
SALES_SERV	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
COUNT_AGRI	0.0000	0.0001	0.0000	0.0000	0.0000	0.0000
COUNT_MINI	0.0000	0.0312	0.0000	0.0000	0.0000	0.0422
COUNT_CONS	0.0000	0.0000	79.1140	0.0000	0.0000	0.0000
COUNT_MANU	0.0000	1.4255	0.0000	0.0000	0.0000	0.0000
COUNT_TRAN	0.0000	14.5170	0.0000	0.0000	0.0000	0.0000
COUNT_UTIL	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
COUNT_WHOL	0.0000	10.2030	0.0000	0.0000	0.0000	0.0000
COUNT_RETA	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
COUNT_FINA	0.0000	0.0000	18.4090	0.0000	0.0000	0.0000
COUNT_REAL	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
COUNT_SERV	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 24: Constrained Optimization Model (0.50-mile Band Buffer)

Variable	RURAL INTERSTATE	RURAL MINOR	URBAN INTERSTATE	EXPRESSWAYS	URBAN MAJOR	URBAN MINOR
Intercept	48	3	267	110	26	4
EMP_AGRICU	0.384	0.245	10.258	0.000	0.000	0.903
EMP_MINING	0.000	0.000	23.085	0.000	0.000	0.000
EMP_CONSTR	0.000	1.020	7.710	0.000	1.067	0.015
EMP_MANUFA	0.000	0.000	3.556	0.000	0.598	0.000
EMP_TRANSP	12.304	0.000	0.000	0.000	0.000	0.000
EMP_UTILIT	0.000	0.013	0.000	0.000	0.000	0.000
EMP_WHOLES	0.000	0.000	0.000	1.368	0.068	0.000
EMP_RETAIL	0.000	0.000	0.000	0.627	0.000	0.050
EMP_FINANC	1.006	0.000	0.000	0.000	0.000	0.000
EMP_REAL_E	5.453	0.000	0.000	2.670	0.000	0.000
EMP_SERVIC	0.000	0.000	0.000	0.000	0.000	0.000
SALES_AGRI	0.000	0.001	0.000	0.000	0.000	0.000
SALES_MINI	0.000	0.000	0.157	0.000	0.000	0.038
SALES_CONS	0.000	0.000	0.000	0.031	0.000	0.000
SALES_MANU	0.000	0.001	0.000	0.000	0.000	0.000
SALES_TRAN	0.108	0.000	0.073	0.000	0.005	0.003
SALES_UTIL	0.011	0.000	0.000	0.000	0.000	0.000
SALES_WHOL	0.000	0.000	0.000	0.000	0.000	0.000
SALES_RETA	0.000	0.000	0.000	0.000	0.000	0.000
SALES_FINA	0.000	0.000	0.000	0.000	0.000	0.000
SALES_REAL	0.000	0.000	0.000	0.000	0.000	0.000
SALES_SERV	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_AGRI	0.000	0.000	0.000	0.000	0.000	0.449
COUNT_MINI	0.000	0.000	0.000	0.000	1.186	0.000
COUNT_CONS	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_MANU	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_TRAN	0.000	15.574	0.000	0.000	47.161	0.000
COUNT_UTIL	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_WHOL	0.000	3.142	0.000	0.000	0.000	0.000
COUNT_RETA	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_FINA	0.000	0.000	0.000	0.000	0.000	0.438
COUNT_REAL	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_SERV	0.000	0.000	0.000	0.000	0.000	0.000

Table 25: Constrained Optimization Model (0.75-mile Band Buffer)

Variable	RURAL INTERSTATE	RURAL MINOR	URBAN INTERSTATE	EXPRESSWAYS	URBAN MAJOR	URBAN MINOR
Intercept	48	3	267	110	26	4
EMP_AGRICU	4.143	0.005	0.000	0.000	0.000	1.279
EMP_MINING	0.000	0.000	0.000	0.000	0.000	0.000
EMP_CONSTR	0.000	0.854	0.000	0.000	1.892	0.000
EMP_MANUFA	0.000	0.000	0.000	0.000	0.094	0.001
EMP_TRANSP	4.182	0.000	8.682	0.000	0.000	0.000
EMP_UTILIT	0.000	0.000	0.000	0.000	0.000	0.000
EMP_WHOLES	0.888	0.000	0.000	0.348	0.058	0.000
EMP_RETAIL	0.000	0.000	0.000	0.428	0.000	0.026
EMP_FINANC	0.005	0.000	0.000	0.000	0.000	0.000
EMP_REAL_E	0.000	0.000	0.000	0.000	0.000	0.000
EMP_SERVIC	0.000	0.000	0.000	0.000	0.000	0.000
SALES_AGRI	0.000	0.001	0.000	0.000	0.000	0.000
SALES_MINI	0.000	0.000	0.301	0.000	0.000	0.037
SALES_CONS	0.000	0.000	0.000	0.008	0.000	0.000
SALES_MANU	0.000	0.000	0.001	0.000	0.000	0.000
SALES_TRAN	0.089	0.004	0.000	0.000	0.021	0.003
SALES_UTIL	0.008	0.000	0.000	0.000	0.000	0.000
SALES_WHOL	0.000	0.000	0.000	0.000	0.000	0.000
SALES_RETA	0.000	0.000	0.003	0.000	0.000	0.000
SALES_FINA	0.000	0.001	0.000	0.000	0.000	0.000
SALES_REAL	0.000	0.000	0.000	0.000	0.000	0.000
SALES_SERV	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_AGRI	0.000	0.000	0.000	0.000	1.547	0.003
COUNT_MINI	0.000	0.000	0.000	268.570	500.000	0.000
COUNT_CONS	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_MANU	0.000	4.010	0.000	0.000	0.000	0.000
COUNT_TRAN	0.000	0.144	0.000	29.976	0.000	0.000
COUNT_UTIL	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_WHOL	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_RETA	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_FINA	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_REAL	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_SERV	0.000	0.000	0.000	0.000	0.000	0.000

Table 26: Constrained Optimization Model (1.0-mile Band Buffer)

Variable	RURAL INTERSTATE	RURAL MINOR	URBAN INTERSTATE	EXPRESSWAYS	URBAN MAJOR	URBAN MINOR
Intercept	48	3	267	110	26	4
EMP_AGRICU	0.000	0.000	0.000	11.260	0.000	0.000
EMP_MINING	0.000	0.000	0.000	0.000	0.000	0.000
EMP_CONSTR	0.000	1.080	0.000	0.000	0.673	0.000
EMP_MANUFA	0.000	0.000	0.000	0.000	0.129	0.000
EMP_TRANSP	0.000	0.000	0.634	0.000	0.000	0.000
EMP_UTILIT	0.102	0.000	0.000	0.000	0.000	0.000
EMP_WHOLES	0.962	0.011	0.000	0.000	0.076	0.000
EMP_RETAIL	0.000	0.000	0.000	0.000	0.000	0.000
EMP_FINANC	0.000	0.000	0.000	0.000	0.000	0.000
EMP_REAL_E	0.000	0.000	0.000	0.000	0.000	0.000
EMP_SERVIC	0.000	0.000	0.000	0.000	0.000	0.000
SALES_AGRI	0.000	0.000	0.000	0.000	0.000	0.001
SALES_MINI	0.000	0.000	0.692	0.000	0.000	0.004
SALES_CONS	0.000	0.000	0.000	0.013	0.000	0.000
SALES_MANU	0.000	0.000	0.001	0.000	0.000	0.000
SALES_TRAN	0.104	0.004	0.000	0.002	0.007	0.002
SALES_UTIL	0.003	0.000	0.000	0.000	0.001	0.000
SALES_WHOL	0.000	0.000	0.002	0.000	0.000	0.000
SALES_RETA	0.000	0.000	0.002	0.000	0.000	0.000
SALES_FINA	0.000	0.000	0.000	0.000	0.000	0.000
SALES_REAL	0.000	0.002	0.000	0.000	0.000	0.000
SALES_SERV	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_AGRI	0.000	0.000	0.000	0.000	13.213	1.226
COUNT_MINI	0.000	0.000	0.000	72.094	257.390	36.084
COUNT_CONS	0.000	0.000	0.000	0.000	0.000	0.336
COUNT_MANU	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_TRAN	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_UTIL	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_WHOL	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_RETA	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_FINA	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_REAL	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_SERV	0.000	0.000	0.000	0.000	0.000	0.000

Table 27: Constrained Optimization Model (1.25-mile Band Buffer)

Variable	RURAL INTERSTATE	RURAL MINOR	URBAN INTERSTATE	EXPRESSWAYS	URBAN MAJOR	URBAN MINOR
Intercept	48	3	267	110	26	4
EMP_AGRICU	0.000	0.000	0.000	0.000	3.853	0.000
EMP_MINING	0.000	0.000	0.000	0.000	0.000	0.000
EMP_CONSTR	0.000	1.015	0.000	0.000	0.279	0.000
EMP_MANUFA	0.000	0.000	0.000	0.000	0.069	0.000
EMP_TRANSP	0.711	0.000	0.438	0.000	0.000	0.000
EMP_UTILIT	0.695	0.000	0.000	0.000	0.000	0.000
EMP_WHOLES	0.987	0.010	0.000	0.000	0.074	0.000
EMP_RETAIL	0.000	0.000	0.000	0.000	0.000	0.000
EMP_FINANC	0.000	0.000	0.000	0.000	0.000	0.000
EMP_REAL_E	0.000	0.000	0.000	0.000	0.000	0.000
EMP_SERVIC	0.000	0.000	0.000	0.000	0.000	0.000
SALES_AGRI	0.000	0.000	0.000	0.000	0.000	0.000
SALES_MINI	0.000	0.000	0.574	0.000	0.000	0.004
SALES_CONS	0.000	0.000	0.000	0.013	0.000	0.000
SALES_MANU	0.000	0.000	0.003	0.000	0.000	0.000
SALES_TRAN	0.054	0.003	0.000	0.002	0.005	0.002
SALES_UTIL	0.000	0.000	0.000	0.000	0.001	0.000
SALES_WHOL	0.000	0.000	0.000	0.000	0.000	0.000
SALES_RETA	0.000	0.000	0.000	0.000	0.000	0.000
SALES_FINA	0.000	0.000	0.000	0.000	0.000	0.000
SALES_REAL	0.000	0.001	0.000	0.000	0.000	0.000
SALES_SERV	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_AGRI	0.000	0.000	0.000	19.567	8.008	2.980
COUNT_MINI	0.000	0.000	0.000	0.000	159.970	24.995
COUNT_CONS	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_MANU	0.000	0.002	0.000	0.000	0.000	0.000
COUNT_TRAN	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_UTIL	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_WHOL	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_RETA	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_FINA	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_REAL	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_SERV	0.000	0.000	0.000	0.000	0.000	0.000

Table 28: Constrained Optimization Model (1.5-mile Band Buffer)

Variable	RURAL INTERSTATE	RURAL MINOR	URBAN INTERSTATE	EXPRESSWAYS	URBAN MAJOR	URBAN MINOR
Intercept	48	3	267	110	26	4
EMP_AGRICU	0.000	0.000	0.000	0.000	0.000	0.000
EMP_MINING	0.000	0.000	0.000	0.000	0.000	0.919
EMP_CONSTR	0.000	0.912	0.000	0.000	0.000	0.000
EMP_MANUFA	0.000	0.015	0.000	0.000	0.068	0.000
EMP_TRANSP	0.000	0.000	0.592	0.646	0.000	0.000
EMP_UTILIT	0.633	0.000	0.000	0.000	0.000	0.000
EMP_WHOLES	0.728	0.000	0.000	0.000	0.020	0.000
EMP_RETAIL	0.000	0.000	0.000	0.000	0.000	0.000
EMP_FINANC	0.000	0.000	0.000	1.975	0.000	0.000
EMP_REAL_E	0.000	0.000	0.000	0.000	0.000	0.000
EMP_SERVIC	0.000	0.000	0.000	0.000	0.000	0.000
SALES_AGRI	0.001	0.000	0.000	0.000	0.000	0.001
SALES_MINI	0.000	0.000	0.537	0.000	0.000	0.000
SALES_CONS	0.000	0.000	0.000	0.000	0.000	0.000
SALES_MANU	0.000	0.000	0.003	0.000	0.000	0.000
SALES_TRAN	0.036	0.001	0.000	0.000	0.007	0.002
SALES_UTIL	0.000	0.000	0.000	0.000	0.000	0.000
SALES_WHOL	0.000	0.000	0.000	0.000	0.000	0.000
SALES_RETA	0.000	0.000	0.000	0.000	0.000	0.000
SALES_FINA	0.000	0.000	0.000	0.000	0.000	0.000
SALES_REAL	0.000	0.001	0.000	0.000	0.000	0.000
SALES_SERV	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_AGRI	0.000	0.000	0.000	23.297	17.581	0.808
COUNT_MINI	0.000	0.000	0.000	7.440	149.670	0.000
COUNT_CONS	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_MANU	0.000	0.023	0.000	0.000	0.000	0.000
COUNT_TRAN	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_UTIL	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_WHOL	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_RETA	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_FINA	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_REAL	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_SERV	0.000	0.000	0.000	0.000	0.000	0.000

Table 29: Constrained Optimization Model (2.0-mile Band Buffer)

Variable	RURAL INTERSTATE	RURAL MINOR	URBAN INTERSTATE	EXPRESSWAYS	URBAN MAJOR	URBAN MINOR
Intercept	48	3	267	110	26	4
EMP_AGRICU	0.000	0.000	1.711	0.000	0.000	0.000
EMP_MINING	0.000	0.000	110.920	0.000	0.000	0.000
EMP_CONSTR	0.000	0.460	0.000	0.000	0.000	0.000
EMP_MANUFA	0.000	0.000	0.000	0.000	0.000	0.000
EMP_TRANSP	0.000	0.000	0.000	0.542	0.000	0.000
EMP_UTILIT	0.532	0.000	0.000	0.000	0.000	0.000
EMP_WHOLES	0.681	0.019	0.000	0.000	0.000	0.000
EMP_RETAIL	0.000	0.000	0.000	0.000	0.000	0.009
EMP_FINANC	0.000	0.000	0.000	0.000	0.000	0.000
EMP_REAL_E	0.000	0.000	0.000	0.000	0.000	0.000
EMP_SERVIC	0.000	0.000	0.000	0.000	0.000	0.000
SALES_AGRI	0.000	0.000	0.000	0.000	0.000	0.000
SALES_MINI	0.000	0.000	0.115	0.000	0.000	0.004
SALES_CONS	0.000	0.000	0.000	0.000	0.000	0.000
SALES_MANU	0.000	0.000	0.001	0.000	0.000	0.000
SALES_TRAN	0.029	0.000	0.003	0.000	0.008	0.000
SALES_UTIL	0.000	0.000	0.000	0.000	0.000	0.000
SALES_WHOL	0.000	0.000	0.000	0.000	0.000	0.000
SALES_RETA	0.000	0.000	0.000	0.000	0.000	0.000
SALES_FINA	0.000	0.000	0.000	0.005	0.000	0.000
SALES_REAL	0.000	0.000	0.000	0.000	0.000	0.000
SALES_SERV	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_AGRI	0.000	0.000	0.000	14.291	15.632	0.707
COUNT_MINI	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_CONS	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_MANU	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_TRAN	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_UTIL	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_WHOL	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_RETA	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_FINA	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_REAL	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_SERV	0.000	0.000	0.000	0.000	0.000	0.000

Table 30: Constrained Optimization Model (3.0-mile Band Buffer)

Variable	RURAL INTERSTATE	RURAL MINOR	URBAN INTERSTATE	EXPRESSWAYS	URBAN MAJOR	URBAN MINOR
Intercept	48	3	267	110	26	4
EMP_AGRICU	0.258	0.000	0.000	0.000	0.293	0.000
EMP_MINING	0.000	0.000	4.499	0.000	0.000	0.756
EMP_CONSTR	0.000	0.000	0.589	0.000	0.000	0.000
EMP_MANUFA	0.000	0.000	0.332	0.000	0.000	0.000
EMP_TRANSP	0.000	0.000	0.000	0.098	0.000	0.000
EMP_UTILIT	0.427	0.025	0.000	0.000	0.000	0.000
EMP_WHOLES	0.645	0.000	0.000	0.000	0.000	0.000
EMP_RETAIL	0.000	0.000	0.000	0.000	0.000	0.001
EMP_FINANC	0.000	0.000	0.000	0.000	0.000	0.000
EMP_REAL_E	0.000	0.000	0.000	0.000	0.000	0.000
EMP_SERVIC	0.000	0.000	0.000	0.000	0.000	0.000
SALES_AGRI	0.000	0.000	0.000	0.000	0.000	0.000
SALES_MINI	0.000	0.000	0.032	0.000	0.000	0.000
SALES_CONS	0.000	0.001	0.000	0.000	0.000	0.000
SALES_MANU	0.000	0.000	0.000	0.000	0.000	0.000
SALES_TRAN	0.009	0.002	0.000	0.000	0.001	0.000
SALES_UTIL	0.000	0.000	0.000	0.000	0.000	0.000
SALES_WHOL	0.000	0.000	0.000	0.000	0.000	0.000
SALES_RETA	0.000	0.000	0.000	0.000	0.000	0.000
SALES_FINA	0.000	0.000	0.000	0.007	0.000	0.000
SALES_REAL	0.000	0.000	0.000	0.000	0.000	0.000
SALES_SERV	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_AGRI	0.000	0.171	0.000	0.000	9.384	0.867
COUNT_MINI	0.000	12.836	0.000	0.000	179.040	0.000
COUNT_CONS	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_MANU	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_TRAN	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_UTIL	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_WHOL	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_RETA	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_FINA	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_REAL	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_SERV	0.000	0.000	0.000	0.000	0.000	0.000

Table 31: Constrained Optimization Model (5.0-mile Band Buffer)

Variable	RURAL INTERSTATE	RURAL MINOR	URBAN INTERSTATE	EXPRESSWAYS	URBAN MAJOR	URBAN MINOR
Intercept	48	1	267	110	26	4
EMP_AGRICU	2.195	0.000	2.419	0.186	0.272	0.049
EMP_MINING	0.000	0.000	7.260	0.000	0.000	0.000
EMP_CONSTR	0.000	0.000	0.000	0.000	0.000	0.000
EMP_MANUFA	0.000	0.000	0.165	0.000	0.000	0.000
EMP_TRANSP	0.000	0.000	0.000	0.000	0.000	0.000
EMP_UTILIT	0.331	0.000	0.000	0.000	0.000	0.000
EMP_WHOLES	0.052	0.000	0.021	0.000	0.000	0.000
EMP_RETAIL	0.000	0.000	0.000	0.000	0.000	0.000
EMP_FINANC	0.000	0.000	0.000	0.498	0.000	0.016
EMP_REAL_E	0.000	0.000	0.000	0.000	0.000	0.000
EMP_SERVIC	0.000	0.000	0.000	0.000	0.000	0.000
SALES_AGRI	0.000	0.000	0.000	0.000	0.000	0.000
SALES_MINI	0.000	0.000	0.000	0.000	0.000	0.002
SALES_CONS	0.000	0.000	0.000	0.000	0.000	0.000
SALES_MANU	0.000	0.000	0.000	0.000	0.000	0.000
SALES_TRAN	0.000	0.003	0.000	0.000	0.000	0.000
SALES_UTIL	0.000	0.000	0.000	0.000	0.000	0.000
SALES_WHOL	0.000	0.000	0.000	0.000	0.000	0.000
SALES_RETA	0.000	0.000	0.000	0.000	0.000	0.000
SALES_FINA	0.000	0.000	0.000	0.000	0.000	0.000
SALES_REAL	0.000	0.000	0.000	0.002	0.000	0.000
SALES_SERV	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_AGRI	2.105	0.000	0.000	3.676	0.360	0.172
COUNT_MINI	0.000	35.411	0.000	0.000	199.380	0.000
COUNT_CONS	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_MANU	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_TRAN	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_UTIL	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_WHOL	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_RETA	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_FINA	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_REAL	0.000	0.000	0.000	0.000	0.000	0.000
COUNT_SERV	0.000	0.000	0.000	0.000	0.000	0.000

Summary of all the models built

Table 32: Sensitivity Analysis (Optimization Approach)

	R Square Values Band Buffer Area					
Mile/FC	**Rural Interstate**	**Rural Minor**	**Urban Interstate**	**Expressways**	**Urban Major**	**Urban Minor**
0.25	0.83	0.79	0.75	0.28	0.23	0.76
0.50	0.76	0.79	0.77	0.62	0.26	0.14
0.75	0.14	0.68	0.70	0.87	0.84	0.29
1.00	0.29	0.13	0.59	0.70	0.87	0.55
1.25	0.55	0.60	0.11	0.39	0.70	0.82
1.50	0.82	0.47	0.55	0.10	0.38	0.64
2.00	0.64	0.78	0.45	0.62	0.10	0.37
3.00	0.37	0.65	0.74	0.61	0.58	0.09
5.00	0.09	0.29	0.59	0.61	0.38	0.66

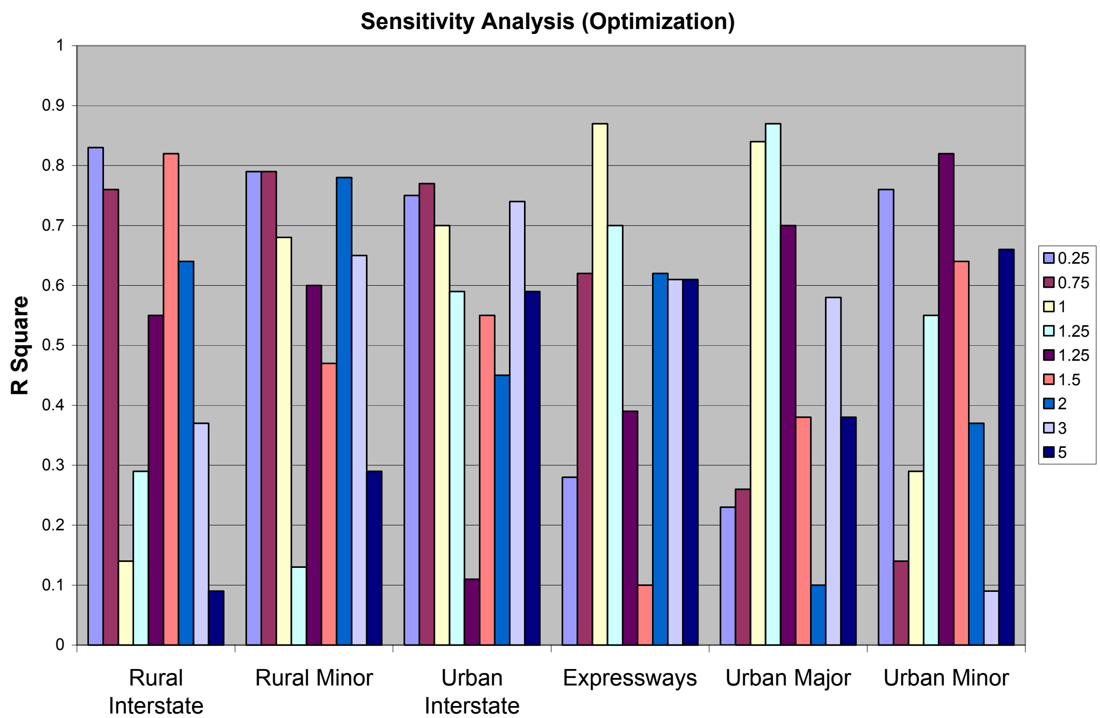


Figure 76: Sensitivity Analysis (Optimization Approach)

After the sensitivity analysis was performed over the optimized models for all radii and for all roadway categories, following models, shown in Table 33 were considered as the final models.

Table 33: Final Models Built (Optimization Approach)

Variable	RURAL INTERSTATE	RURAL MINOR	URBAN INTERSTATE	EXPRESSWAYS	URBAN MAJOR	URBAN MINOR
Intercept	48	3	267	110	26	4
EMP_AGRICU	0	0.245	10.258	0	0	0
EMP_MINING	0	0	23.085	0	0	0
EMP_CONSTR	0	1.02	7.71	0	0.673	0
EMP_MANUFA	0	0	3.556	0	0.129	0
EMP_TRANSP	8.5442	0	0	0	0	0
EMP_UTILIT	0	0.013	0	0	0	0
EMP_WHOLES	0	0	0	0.348	0.076	0
EMP_RETAIL	0	0	0	0.428	0	0
EMP_FINANC	1.2641	0	0	0	0	0
EMP_REAL_E	2.8996	0	0	0	0	0
EMP_SERVIC	0	0	0	0	0	0
SALES_AGRI	0	0.001	0	0	0	0
SALES_MINI	0	0	0.157	0	0	0.004
SALES_CONS	0	0	0	0.008	0	0
SALES_MANU	0	0.001	0	0	0	0
SALES_TRAN	0.1758	0	0.073	0	0.007	0.002
SALES_UTIL	0.0114	0	0	0	0.001	0
SALES_WHOL	0	0	0	0	0	0
SALES_RETA	0	0	0	0	0	0
SALES_FINA	0	0	0	0	0	0
SALES_REAL	0	0	0	0	0	0
SALES_SERV	0	0	0	0	0	0
COUNT_AGRI	0	0	0	0	13.213	2.98
COUNT_MINI	0	0	0	268.57	257.39	24.995
COUNT_CONS	0	0	0	0	0	0
COUNT_MANU	0	0	0	0	0	0
COUNT_TRAN	0	15.574	0	29.976	0	0
COUNT_UTIL	0	0	0	0	0	0
COUNT_WHOL	0	3.142	0	0	0	0
COUNT_RETA	0	0	0	0	0	0
COUNT_FINA	0	0	0	0	0	0
COUNT_REAL	0	0	0	0	0	0
COUNT_SERV	0	0	0	0	0	0

Final Models Built (Optimization)

Trucks on Rural Interstate

Y = 48+8.5442*EMP_TRANSP+ 1.2641*EMP_FINANC+ 2.8996*EMP_REAL_E+ 0.1758*SALES_TRAN+ 0.0114*SALES_UTIL

Trucks on Rural Minor

Y = 3+0.245*EMP_AGRICU+ 1.02*EMP_CONSTR+ 0.013*EMP_UTILIT+ 0.001*SALES_AGRI+ 0.001*SALES_MANU+ 15.574*COUNT_TRAN+ 3.142*COUNT_WHOL

Trucks on Urban Interstates

Y = 267+10.258*EMP_AGRICU+ 23.085*EMP_AGRICU+ 7.71*EMP_MINING+ 3.556*EMP_CONSTR+ 0.157*EMP_MANUFA+ 0.073*SALES_MINI

Trucks on Expressways

Y = 110+0.348*EMP_WHOLES+ 0.428*EMP_RETAIL+ 0.008*SALES_CONS+ 268.57*COUNT_MINI+ 29.976*COUNT_TRAN

Trucks on Urban Major

Y = 26+0.673*EMP_CONSTR+ 0.129*EMP_MANUFA+ 0.076*EMP_WHOLES+ 0.007*SALES_TRAN+ 0.001*SALES_UTIL+ 13.213*COUNT_AGRI+ 257.39*COUNT_MINI

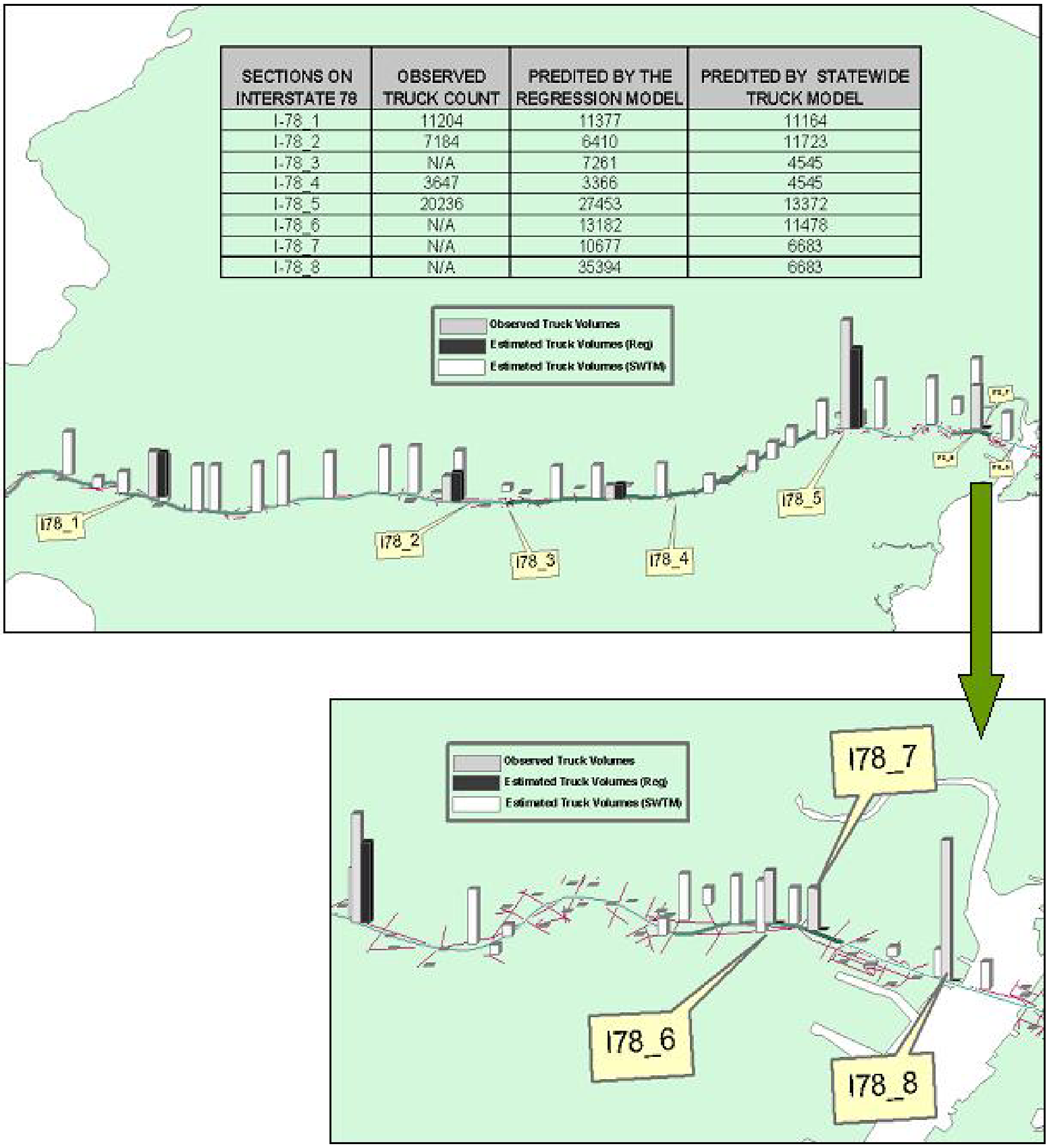
Trucks on Urban Minor

Y = 4+0.004*SALES_MINI+ 0.002*SALES_TRAN+ 2.98*COUNT_AGRI+ 24.995*COUNT_MINI

Comparison with the QRFM and the NJ Statewide Model

The Quick Response Freight Manual (QRFM) or three-step approach for modeling truck traffic was compared with the regression approach presented in this paper. The two approaches are similar in that they predict truck traffic based on adjacent economic and land-use activity, and categorize employment data by SIC. A major point of distinction between the two approaches was that regression did not make as many assumptions as the QRFM approach and avoided inconsistencies that are typical among the steps of sequential processes such as QRFM. Regression is thus found to be closer to the real world situation and more practical in its application.

Predictions were made using the regression models and the predicted truck volumes were compared with those from the existing statewide truck model for New Jersey, which is based on a QRFM-like approach. Regression and statewide truck model results are plotted in GIS along with the observed truck volumes (from the vehicle classification counts). Comparison of the results shows that the regression approach made, in general, better estimates (closer to the observed counts) than the statewide model. Figure 77 below shows a snapshot of Interstate 78 in New Jersey with observed truck volumes and predicted volumes from both regression and the statewide truck model.



SECTIONS ON INTERSTATE 78	OBSERVED TRUCK COUNT	PREDITED BY THE REGRESSION MODEL	PREDITED BY STATEWIDE TRUCK MODEL
I-78_1	11204	11377	11164
I-78_2	7184	6410	11723
I-78_3	N/A	7261	4545
I-78_4	3647	3366	4545
I-78_5	20236	27453	13372
I-78_6	N/A	13182	11478
I-78_7	N/A	10677	6683
I-78_8	N/A	35394	6683

Figure 77: Comparison with the Existing Statewide Approach

Truck Traffic and Percentage Profiles

After the models were created and sensitivity analysis performed, truck volume and percentage profiles were created for sections on the 14 selected roadways. These profiles will help the State Authorities in understanding traffic (passenger cars and trucks) flow patterns along the selected highway. Below in the figure 78 and 78 below show the observed and the predicted truck volumes by the two approaches (Linear Regression and Optimization) along the Interstate 78. Figure 79 and 80 show the truck percentage profile along Interstate 78. These profiles are available in a GIS background.

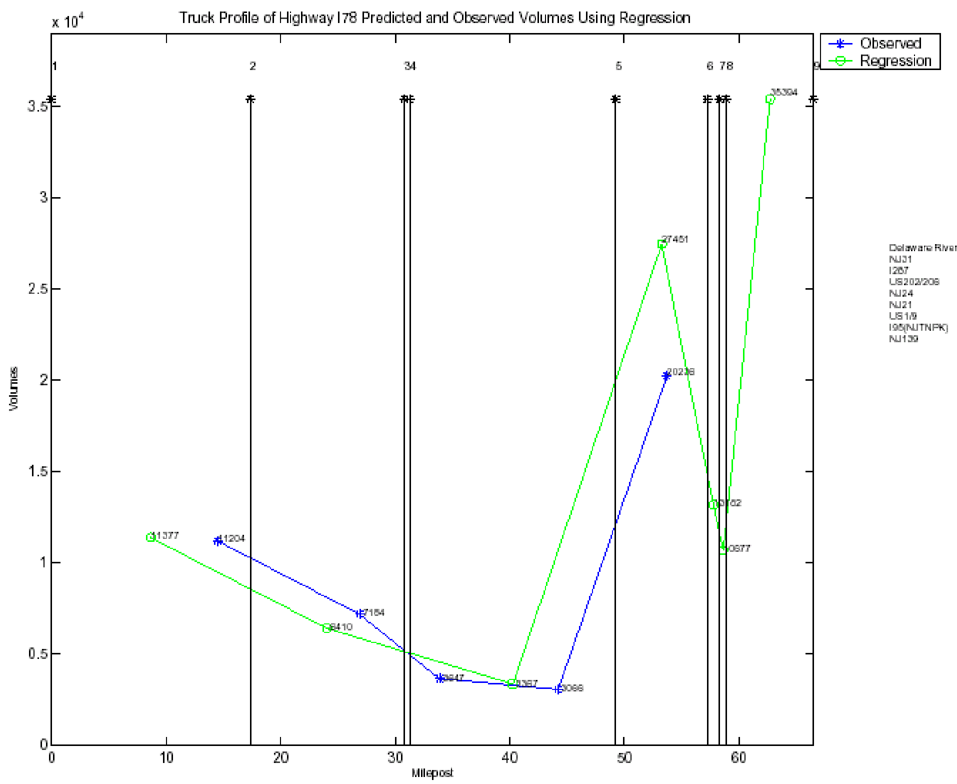


Figure 78: Profile of Observed and Predicted Truck Volumes along I-78 (Linear Regression)

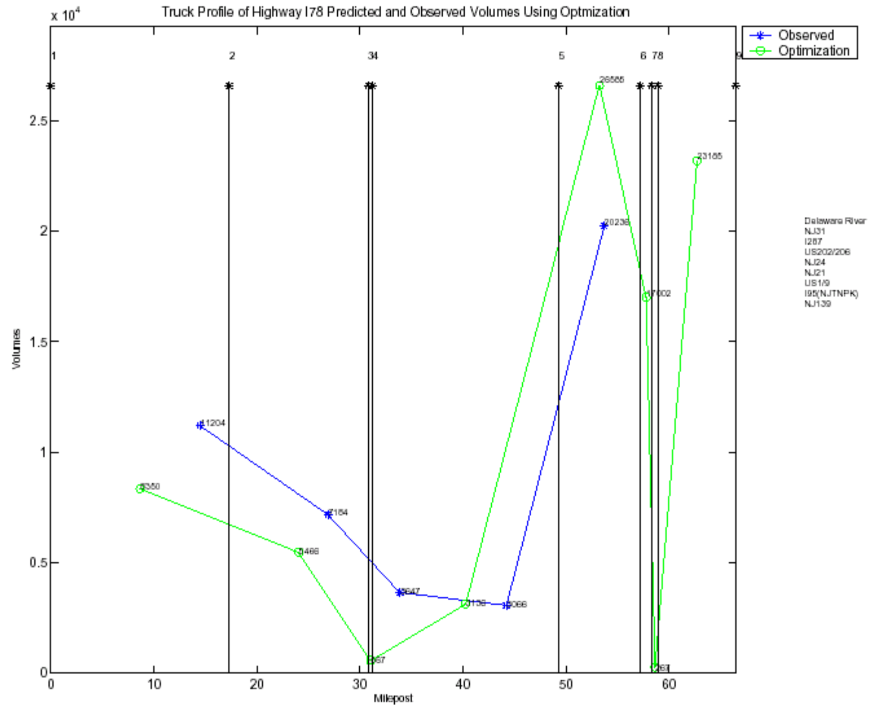


Figure 79: Profile of Observed and Predicted Truck Volumes along I-78 (Optimization Approach)

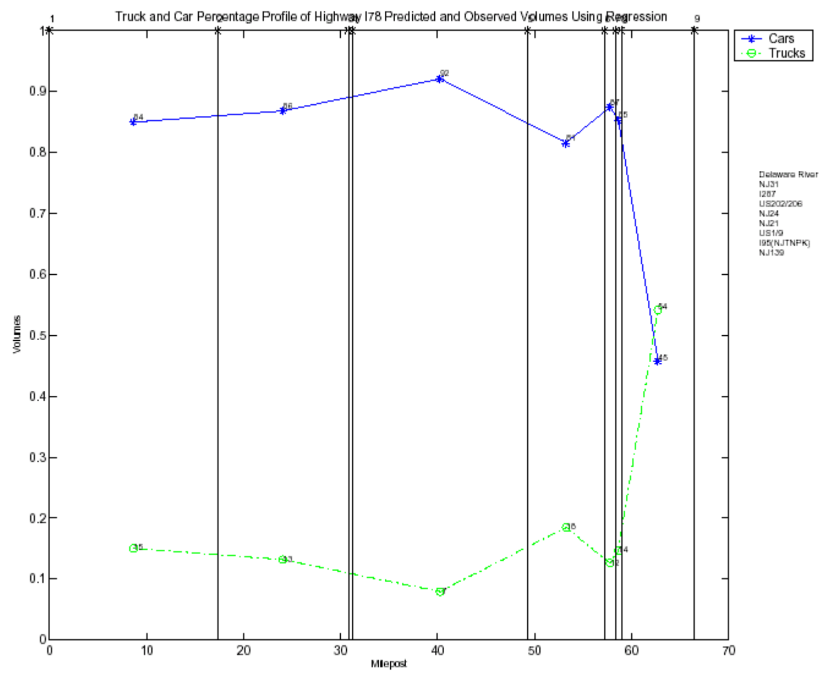


Figure 80: Predicted Percentage Profiles (Regression)

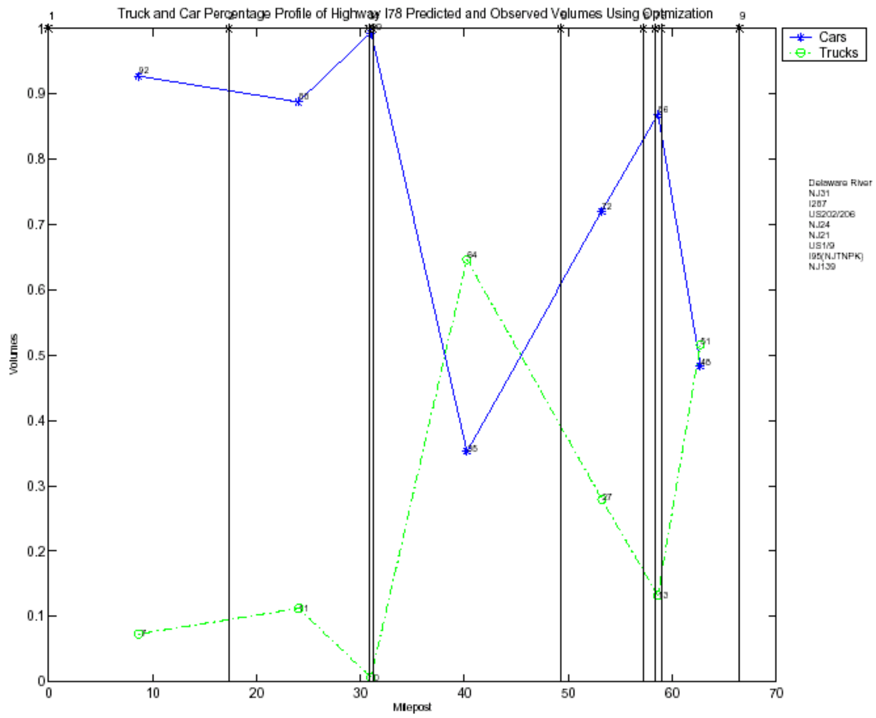


Figure 81: Predicted Percentage Profiles (Optimization)

GIS based Interactive Tool

A GIS database was developed in an effort to take better advantage of the technique described above and to extend this technique into an easy to use statewide tool.

For this purpose, 14 roadways were selected and divided in relatively uniform sections in terms of truck traffic and functional characteristics. All the necessary data required to use the developed models to make truck volume predictions on these sections were collected and entered into the GIS platform.

The resulting tool allows the user to select a roadway segment and, depending on its functional grouping, use the appropriate model to estimate truck volumes and truck percentages. Graphical images showing the traffic profile on the selected segment and the adjacent ones are also generated.

Snapshots of the application of this tool are shown in Figure 82.

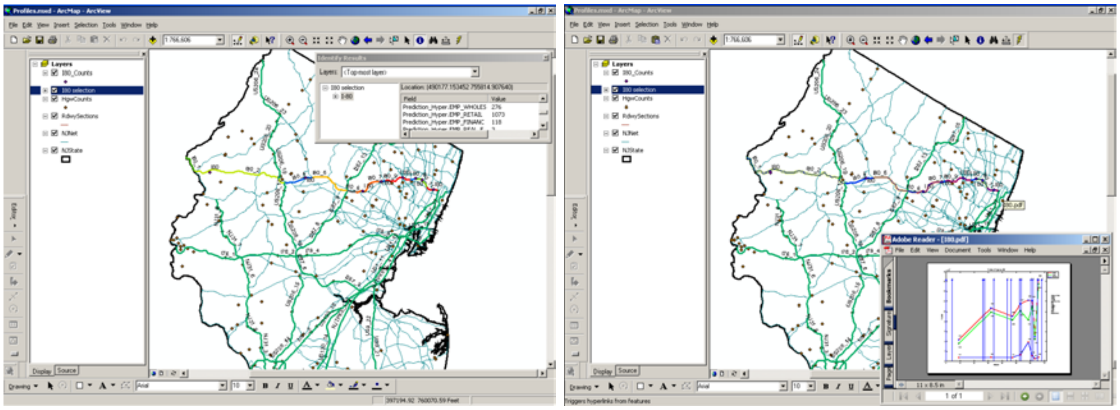


Figure 82: GIS-based Modeling Tool Application

Creating databases on a statewide basis and collecting and including additional counts in this model will result in a more powerful predictive tool.

RESULTS AND CONCLUSIONS

- Building models considering roadway classes is significant as different roadways attract different types of truck traffic and truck volumes.
- Number of Employees, Estimated Sales Volume and the Number of Establishments based on the Standard Industrial Classification for the region, can be considered as good predictors for truck volumes.
- Creating vehicle profiles for different roadway sections helps in understanding the traffic flow patterns within the state
- More counts should be collected throughout the state, to ensure robust models. Additional data would also help increase the accuracy of the proposed method and would better enable engineers to differentiate between locally generated and through traffic.

Although the preliminary results obtained through this study are promising in terms of the proposed methodology, it is recognized that a much larger set of counts should be considered, in order to obtain more sound statistical models and more accurate results. The proposed technique, however, and its implementation within a statewide GIS tool as the one proposed herein, may provide state transportation professionals with a valuable tool to predict truck volumes, flows and percentages on state highways, generate volume and percentage profiles, and better understand truck movements in the state.

BAYESIAN LINEAR REGRESSION MODELING

Introduction

This part of the report describes the formulation and implementation of a final statistical method for creating linear relationships between truck volumes on highway links and adjacent socioeconomic and land-use data. Bayesian Linear Regression and Gibbs variable selection are used to generate linear regression models. This approach is presented as a complementary to the other methodologies presented previously in this report.

Bayesian Inference In Transportation

Bayesian Inference in the field of Transportation is a somewhat new concept. A very small number of publications exist in the literature that uses Bayesian modeling in traffic engineering or transportation planning. Maher [(30)] proposed a new method for estimating trip matrices from traffic counts using Bayesian inference. Confidence intervals for the estimates of the trip matrix elements were estimated. Vardi [(31)] follows a Bayesian approach in the estimation of O-D matrices; an idea originated on a problem regarding computer data networks. The problem of estimating node-to-node traffic intensity from repeated measurements of traffic on the links of a network is formulated using a Poisson assumption for the number of messages measured on a link per period. Tebaldi and West [(32)] addressed the network count inference problem also from a Bayesian prospective. They studied Bayesian methods for estimating the traffic matrix using a Metropolis within Gibbs algorithm. West [(33)] explores the stochastic parameter variation of Gravity models via Markov Chain Monte Carlo (MCMC). In addition a discussion of the general concepts of Bayesian modeling and stochastic simulation is discussed.

Tebaldi et. al. [34], implement a hierarchical linear regression framework to predict minute-to-minute traffic flows. An investigation of using short-period counts to obtain Mean Daily Traffic (MDT) Volumes was done by Davis and Guan [35], who solved the factor group assignment problem by applying Bayesian decision methods to a log-normal model of daily traffic counts and computed the posterior probability of non-automatic traffic recorders (ATR). Davis and Yang [36] assessed the uncertainty of the estimates of forecasts of total traffic volume by combining two types of uncertainty via Bayesian Inference. They computed quantiles of a traffic total's predictive distribution, given a sample of daily traffic volumes. Finally, Yang and Davis [37] developed a Bayes estimator of classified MDT reducing prediction error substantially.

Bayesian Inference Framework

Bayesian methods have increased in popularity, in large part due to advances in statistical computing that allow for the evaluation of complex posterior distributions. These methods are currently being implemented into a variety of software (such as: WinBugs, JAGS, MatLab, MSOffice add-on) that will make Bayesian inference more attractive to researchers and field practitioners in the future.

Looking at a regression problem from its Bayesian perspective both observable (truck volumes: Y) and parameters (regression coefficients: beta) are considered to be random quantities. The components of Bayesian inference problems are: a) the prior distribution of the parameters involved (P(beta), and P(Y)) that expresses the uncertainty or the information that is available at the start of the study about the unknown variables by means of a probability distribution, b) the likelihood of the data given the unknown parameters that relates all the variables into a 'full probability model' that summarizes the current knowledge of the phenomenon, and c) the posterior distribution for the unknown parameters (P(beta|X), and P(Y|beta,X), where X are the predictors), that expresses our uncertainty about the parameters after *seeing* the data. The task of each Bayesian analysis is to build a model for the relationship between parameters and the observable quantity, and then calculate the probability distribution of the parameters conditional on the data. In addition, the Bayesian analysis may calculate the predicted distribution of unobserved data (P(Y'|beta,X'), where X' is the new independent dataset and Y' are the new estimation). This of course is not a free-trouble method. Advantages and disadvantages of the Bayesian approach are summarized in table 34.

Table 34: Advantages and Disadvantages of Bayesian Inference Methods

Advantages of the Bayesian Approach	**Disadvantages of the Bayesian Approach**
Basis of Inference is Probability Theory	Inferences Need to Be Justified
Less Computational Burden for Small/Medium Problems	Computational Burden for Very Complex Models
No Need for Significance Tests, P-values etc	Reasonable Prior Distribution Selection
Complex models to meet reality demands	Model Adequacy for the Data

Markov Chain Monte Carlo Simulation

MCMC simulation is a procedure where a Markov Chain (MC) is created whose stationary distribution is the same as the target distribution. If a large sample is drawn from the chain then the final distribution should be the correct one. In the absence of an accessible analytic solution, and by using numerical methods, MCMC summarizes the marginal distributions for the models parameters.

One of the most crucial issues of this approach is the convergence of the chain. In other words: *When do we stop sampling and how well do the samples approximate the target distribution.* The answers to both of these questions remain a bit *ad hoc*, since the results are only true asymptotically, and in order to answer, different approaches can be used (measures of goodness). A rule of thumb is that the number of iterations should increase with the number of dimensions. The more variables whose target distribution we are trying to predict the bigger the number of iterations. Checking the chain is a need-to-do task to ensure convergence and good mixing. Running parallel chains and/or thinning the chain can improve the sampling and decrease the iteration number that is needed for convergence. In figure 83 the history of two parallel chains illustrating a good mixing history of the simulation is illustrated. It should be mentioned that recommendations in the literature have been conflicting and range from many short chains, to several long ones, to a very long one [38]. If the mixing of the chain is not good then several options exist such as thinning the chain or re-parameterization of the model.

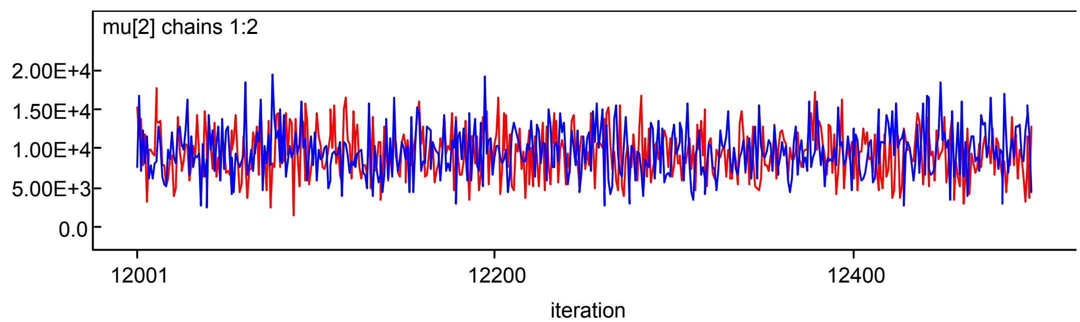


Figure 83: Good Mixing of 2 Parallel Chains

A more formal way to check for the simulations convergence is the Gelman-Rubin statistic. Convergence refers to the idea that the Gibbs sampler or other MCMC technique that we choose will eventually reach a stationary distribution. From this point on it stays in this distribution and moved about throughout the subspace forever. The statistic is based on the following procedure: a) estimate the model with a variety of different initial values and iterate for an n-iteration burn-in and an n-iteration monitored period, and then b) use n-monitored draws of m parameters and calculate the following statistics:

$$\text{Within chain variance W} = \frac{1}{m(n-1)}\sum_{j=1}^{m}\sum_{i=1}^{n}\left(\theta_j^i - \overline{\theta}_j\right)^2$$

$$\text{Between chain variance B} = \frac{n}{m-1}\sum_{j=1}^{m}\left(\theta_j - \overline{\theta}\right)^2$$

$$\text{Estimated variance } \hat{V}(\theta) = \left(1 - \frac{1}{n}\right)W + \frac{1}{n}B$$

$$\text{The Gelman - Rubin Statistic } \sqrt{\text{R}} = \sqrt{\frac{\hat{V}(\theta)}{W}}$$

Once convergence is reached, W and V(θ) should be almost equivalent (variation within the chains should follow the variations between the chains), so R should approximately equal one. The drawback of this statistic is that its value mainly depends on the choice of the starting values of the chains. In this project 3 chains were used with different starting points, for each model. 1000 burn-in update and 5000 update iterations where used to sample the parameters for all the models. The Gelman-Rubin statistic showed that the chains had converged after 5000 iterations.

Bayesian Linear Regression and Hierarchical Modeling

Many methodologies have been proposed in the context of Bayesian regression and model or variable selection. There is a large literature dealing with the choice of the best model (variable selection) in the multiple-regression modeling. Some of the papers which propose related procedures include: a) the Stochastic Search Variable Selection (SSVS) of George and McCulloch [39], b) the model selection approach of Carlin and Chib [40], c) model averaging and accounting for a models uncertainty using ‘Occam’s Window’ by Madigan and Raftery [41], Raftery et al. [42], d) simultaneous variable selection and outlier identification based on the computation of posterior model probabilities by Hoeting et. al [43], and e) the Gibbs Variable Selection (GVS) by Dellaportas et al. [44, 45].

A large part of statistical analysis based on linear regression can be thought of as a Bayesian inference problem based on a non-informative prior distribution for the parameters of the linear model. In the simplest case of regression, ordinary linear regression (OLS), the observation errors are assumed to be independent and have equal variation: $Y \mid \beta, \sigma^2, \mathrm{X} \sim \mathrm{N}(\mathrm{X} * \beta, \sigma^2 * \mathrm{I})$, where I is the identity n*n matrix and n is the number of cases (observations). This case of regression makes several assumptions: a) linearity of the expectations of Y as a function of X, b) normality of the error terms, and c) independent observations with equal variances. Bayesian inference allows the training of models that depart from these assumptions and a variety of parametric models for unequal variances have been used.

Variable selection, in the Bayesian framework, can be implemented via hierarchical (or multilevel) modeling, most commonly found in the social science field. Hierarchical modeling helps in understanding multi-parameter problems and plays an important role in establishing computational strategies. Especially when the problem involves many parameters and few observations[5] hierarchical models avoid over-fitting the data. Bishop and Tipping [(46)] explain in detail how adopting a Bayesian viewpoint can treat the phenomenon of over-fitting the data, a pathological property of point estimation. They apply complex models to small data sets without encountering these problems.

Suppose data is collected about some random variable Y with n observations (in this case truck volumes on specific links). In the standard Bayesian setup a prior distribution is assigned on the observed variable: $Y_i \sim f(\theta_i)$, where θ_i is a vector of parameters (regression coefficients). Furthermore a prior distribution on the parameter θ_i is also assigned: $\theta_i \sim g(K)$ where K may be a vector of parameters. By introducing prior distributions for the elements of K (hyperpriors) *we enter the world of hierarchical modeling*. The hyperparameters of K express the belief

[5] This is the case in this paper where at some cases the number of observations were less then the independent variables

about K and may or not be known. Another level of hierarchy can be implemented by assigning priors to the hyperparameters of K and so forth. The conceptual or computational difficulty added by extending the model to more levels is usually negligible. A simple example of a linear regression model with three levels of variation can be formulated as:

$Y \sim \mathrm{N}(\beta, \sigma^2)$, 'likelihood'

$\beta \sim \mathrm{N}(\mu, \tau^2)$, 'parameter distribution'

$\tau \sim \exp(\mu_\tau, \sigma_\tau)$, 'hyperprior distribution of parameter precision'

Model Formulation

As mentioned in the previous section a large number of independent variables were initially considered to have predictive power over the dependent variable set (truck volumes). One of the main objectives of this approach was to use a Bayesian variable selection technique in order to choose the most predictive variables, based solely on available data. A variety of MCMC methods have been proposed for variable selection in the regression framework. In this project the approach and notation introduced by Dellaportas et. al. [44, 45] is implemented. The approach is similar to the ones introduced by George and McCullough [38].

Assume a linear model of the form: $Y_i = \sum_{j=1}^{p} \gamma_j X_{ij} \beta_j$, where X_{ij} is the design matrix (j data vectors of the independent variables) and β_j the parameter vector (regression coefficients) of the j^{th} term. The indicator γ identifies the possible covariates (independent variables: X_{ij}) that will enter the final model. Before presenting the implemented model and its parameters the general terminology of the approach is introduced:

Model Likelihood: $f(Y \mid \beta, \gamma)$

Model Prior: $f(\beta, \gamma) = f(\beta \mid \gamma) * f(\gamma)$

Coefficient Prior: $f(\beta \mid \gamma)$

Included Coefficient: β_{γ}

Not Included Coefficient: $\beta_{\setminus\gamma}$

The covariates included and excluded in each model are sampled by:

$$f(\beta_{\gamma} \mid \beta_{\setminus\gamma}, \gamma, y) \propto f(y \mid \beta, \gamma) * f(\beta_{\gamma}) * f(\beta_{\setminus\gamma} \mid \beta_{\gamma}, \gamma)$$

$$f(\beta_{\setminus\gamma} \mid \beta_{\gamma}, \gamma, y) \propto f(\beta_{\setminus\gamma} \mid \beta_{\gamma}, \gamma)$$

The variable indicator γ_i is sampled from a Bernoulli distribution with success probability a_j defined as:

$$a_j = \frac{f(Y \mid \beta, \gamma_j = 1, \gamma_{\setminus j}) * f(\beta \mid \gamma_j = 1, \gamma_{\setminus j}) * f(\gamma_j = 1, \gamma_{\setminus j})}{f(Y \mid \beta, \gamma_j = 0, \gamma_{\setminus j}) * f(\beta \mid \gamma_j = 0, \gamma_{\setminus j}) * f(\gamma_j = 0, \gamma_{\setminus j})}$$

A linear regression form on the expectation of Y, with a variety of different error structures was assumed. Specifically:

$m_i = b_0 + b_1 z_{1i} + b_2 z_{2i} + b_3 z_{3i} + \ldots\ldots + b_j z_{ji}$ (Equation 1)

$Yi \sim \text{Normal}(m_i, t)$ (Equation 2)

$Yi \sim$ Double $\exp(m_i, t)$ (Equation 3)

$Yi \sim t(m, t, d)$ (Equation 4)

where $z_{ij} = (X_{ij}/X_{mean_j})$ are the covariates standardized, j=1:34, i=1:n, and n=number of cases.

Maximum likelihood estimates for the double exponential distribution (Eq. 3) are essentially equivalent to minimizing the sum of absolute deviations (LAD), while the other options (Eq. 2 and 4) are alternative heavy-tailed distributions. In this paper the standard normal linear model was used. The other two options, which are equivalent to shrinkage coefficient methods (Ridge and Lasso Regression), are to be investigated as part of future work.

Mean Coefficient Regression [47] was performed for each dataset and the results showed positive correlation between predictors and predicted variables in isolation. Further prior information for the beta values did not exist. The priors for the betas where set to a neutral value (Eq. 5) so that all the terms have priory a zero mean value. Results from the SLR models were used as prior information for the intercept that was removed from models with small values (FC=6-9, FC=14, FC=16-19). The assumption of zero intercept for models used on local access roads is valid since truck traffic on these types of roadways should not be expected if the traffic generating variables are all zero. Both distributions (beta and intercept) where truncated at zero.

beta(j) ~ Normal(0, betaTau(j)) (Equation 5)

inter~dnorm(0,1.0E-6) (Equation 6)

A gamma distribution was used instead of a vague prior for the coefficient precision.

betaTau(j) ~ dgamma(1.0E-2, 1.0E-2) (Equation 7)

A Bernoulli distribution, with success probability a_j (Eq. 8, 9), was used as the means for the variable selection.

g[j]~dbern(a[j]) (Equation 8)

b[j]=beta[j]*g[j] (Equation 9)

In order to quantify the uncertainty of the success probability, a hierarchical framework was introduced via Eq. 10 where the success probability follows a beta(2,2) distribution, which is basically a Normal with mean 0.5, truncated at zero and one. By using this distribution for the success probability we assume that priory all of the covariates have the same probability (50%) of entering the model.

a[j]~dbeta(2,2) (Equation 10)

The full model is graphically presented in figure 84 and was implemented in WinBugs, a package that enables a flexible approach to Bayesian modeling, in which the specification of the full conditional densities is not necessary and so small changes in program code can achieve a wide variation in modeling options. This enables performing sensitivity analysis to likelihood and prior assumptions be performed with ease.

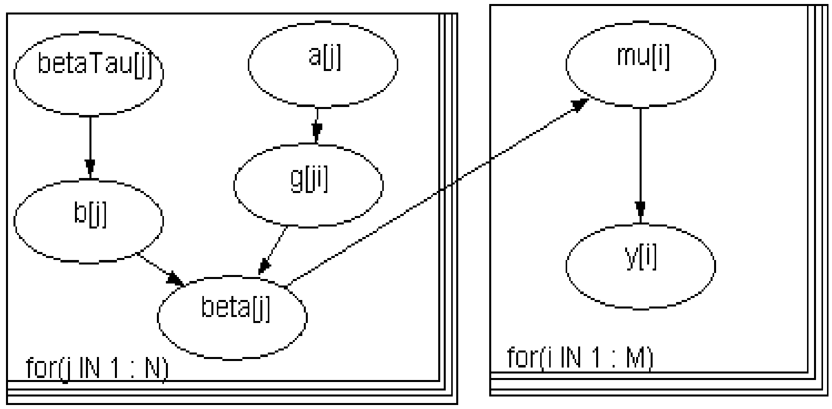


Figure 84: WinBugs Graphical Presentation of the Model

RESULTS

For all the models a 1000 burn-in update and 5000 update iterations where used to sample the parameters of the model[6]. Following is a presentation of the results and comments for each FC of roadway. The original dataset was split into a training and test data set[7]. The number of observations used as the test dataset was relative to the number of observations available for each FC. Presented for every model are:

a. Band Used to Train and Test Models
b. R^2 values (using the 2.5%, median and 96.5% predictions)
c. Mean values of train data with confidence intervals
d. Bar chart with the Observed and Predicted (2.5%, median and 96.5%) Truck Volumes
e. Mean values of test data with confidence intervals[8]
f. Mean values of the beta coefficients with confidence intervals

Rural Interstate

(FC=1-2, Band=0.5 miles, R^2=[0.4389, 0.5436, 0.8443])

[6] The GRS and Autocorrelation graphs showed that after 5000 iterations the chain had converged
[7] Part of the data that was not used in the creation of the models
[8] For the different datasets different sizes of test data was chosen analogous to the number of available training data

Table 35: Truck Volume Predictions on Training Dataset (FC=1-2)

node	Observed	mean	sd	MC error	2.50%	median	97.50%
mu[1]	2004	1356	297.6	6.64	849.7	1328	2017
mu[2]	9276	9172	993.1	11.31	7231	9164	11160
mu[3]	3506	2836	605	21.05	1765	2791	4127
mu[4]	11204	6340	762.1	18.03	4859	6320	7842
mu[5]	7184	4357	718.7	22.6	3020	4340	5814
mu[6]	3647	3182	1016	18.26	1482	3077	5334
mu[7]	7178	3111	707.3	25.44	1847	3057	4609
mu[8]	50	372.1	198.5	2.935	52.13	357.5	797.1
mu[9]	1247	359.1	199.1	2.94	39.81	343.6	784.5
mu[10]	2012	578.2	345.6	4.891	99.32	511.4	1447
mu[11]	886	4777	495	9.132	3841	4768	5784
mu[12]	1161	3601	437.1	11.12	2783	3586	4496
mu[13]	1728	1386	209.3	4.081	986.1	1384	1809
mu[14]	617	426	201.3	3.034	94.49	411.8	854.9
mu[15]	147	2461	717.3	14.34	1271	2392	3955
mu[16]	343	347.6	199.9	2.938	26.45	331.7	774.9
mu[17]	797	418.1	197.8	2.859	95.61	404.2	838.9
mu[18]	335	394.8	200.4	3.301	66.25	380.6	818.5
mu[19]	437	1327	231.5	5.35	895.6	1321	1804
mu[20]	319	551.4	197.2	2.855	212	539.7	965.1
mu[21]	961	968.2	268.8	6.914	474.2	955.4	1532
mu[22]	194	400.3	204.8	3.179	66.84	384.7	846.1
mu[23]	848	701.4	191.8	2.92	370.1	690.4	1108
mu[24]	718	954.8	304.5	8.895	380.9	950.4	1561
mu[25]	1470	954.8	304.5	8.895	380.9	950.4	1561
mu[26]	363	1122	255.4	5.588	651.4	1112	1645
mu[27]	1202	1056	230.5	4.451	630.8	1047	1527
mu[28]	458	523.8	204.8	3.912	173.5	513.1	951.3
mu[29]	1038	525.9	209.4	3.531	157.9	513.6	971
mu[30]	416	529.3	199.6	3.406	194.8	515.7	945.3
mu[31]	1169	3672	398.7	6.442	2926	3661	4490

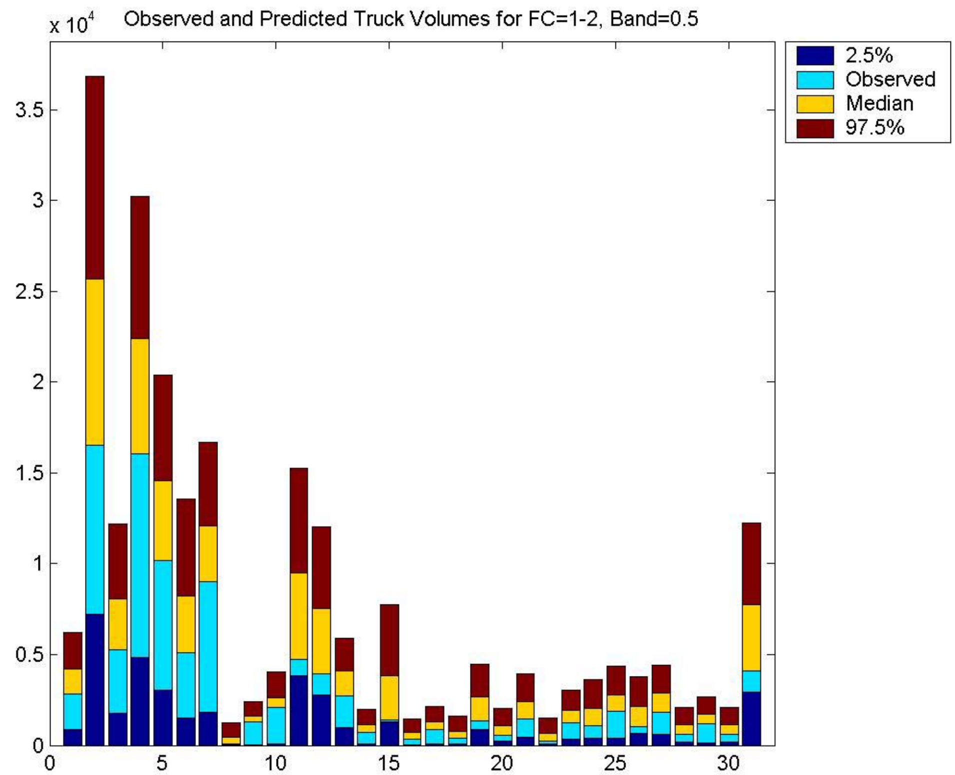


Figure 85: Observed and Predicted Truck Volumes (2.5%, median, 97.5%), (FC=1-2)

Table 36:Regression Coefficients, (FC=1-2)

node	mean	sd	MC error	2.50%	median	97.50%
Constant	401.6	208.6	4.473	45.91	393.2	836.2
EMP_AGRICULTURE	21.73	51.49	0.5815	0	0	183
EMP_MINING	1.03	6.15	0.06819	0	0	15.15
EMP_CONSTRUCTION	3.652	14.83	0.1639	0	0	50.31
EMP_MANUFACTURING	5.545	20.31	0.2267	0	0	70.48
EMP_UTILITIES	401.9	214.2	6.958	0	396.6	840.8
EMP_TRANSPORTATION	59.18	95.25	4.218	0	0	314.7
EMP_WHOLESALE TRADE	58.04	98.99	1.78	0	0	334.5
EMP_RETAIL TRADE	4.057	16.9	0.1688	0	0	54.56
EMP_FINANCE/INSURANCE	45.31	59.55	1.448	0	0	188.1
EMP_REAL ESTATE	248.6	153.2	3.561	0	259.6	534.2
EMP_SERVICES	8.576	28.52	0.3359	0	0	102.4
SALES_AGRICULTURE	5.9	21.54	0.2387	0	0	75.29
SALES_MINING	2.671	11.46	0.1327	0	0	38.39
SALES_CONSTRUCTION	2.266	10.89	0.106	0	0	33.16
SALES_MANUFACTURING	9.581	29.5	0.3457	0	0	106.7
SALES_UTILITIES	348.2	233.9	8.026	0	339.6	872.9
SALES_TRANSPORTATION	260.4	119.4	5.118	0	288	432.3
SALES_WHOLESALE TRADE	26.74	60.38	0.7149	0	0	216.5
SALES_RETAIL TRADE	3.52	14.89	0.1586	0	0	51.29
SALES_FINANCE/INSURANCE	52.56	90.2	1.722	0	0	305.2
SALES_REAL ESTATE	17.57	47.14	0.6828	0	0	171
SALES_SERVICES	10.51	33.1	0.3639	0	0	119.6
CNT_AGRICULTURE	2.636	12.66	0.1249	0	0	37.96
CNT_MINING	2.392	10.82	0.1133	0	0	34.87
CNT_CONSTRUCTION	2.387	11.06	0.1083	0	0	34.67
CNT_MANUFACTURING	7.228	25.02	0.295	0	0	90.05
CNT_UTILITIES	3.598	15.3	0.1497	0	0	51.62
CNT_TRANSPORTATION	4.289	17.06	0.1897	0	0	58.78
CNT_WHOLESALE TRADE	12.98	38.49	0.464	0	0	135.9
CNT_RETAIL TRADE	3.556	14.81	0.1639	0	0	51.9
CNT_FINANCE/INSURANCE	12.93	38.13	0.4267	0	0	140.6
CNT_REAL ESTATE	1.925	9.645	0.1059	0	0	28.86
CNT_SERVICES	3.841	16.15	0.1596	0	0	51.61

Table 37: Truck Volume Prediction on Test Dataset, (FC=1-2)

node	Observed	mean	sd	MC error	2.50%	median	97.50%
Y[3]	3506	2845	1133	24.47	704.6	2793	5149
Y[7]	7178	3129	1206	29.62	864.8	3100	5571
Y[29]	1038	1048	725	7.947	54.59	928.1	2730

Rural Minor

(FC=6-9, Band=0.5 miles, R^2=[0.37, 0.50, 0.56])

Table 38:Truck Volume Predictions on Training Dataset, (FC=6-9)

node	Observed	mean	sd	MC error	2.50%	median	97.50%
mu[1]	6	36.34	15.15	0.4656	10.98	34.91	70.3
mu[2]	6	6.946	4.055	0.101	1.178	6.201	16.78
mu[3]	2	3.944	2.835	0.06543	0.3471	3.336	11.22
mu[4]	42	41.05	17.96	0.5569	12.27	39.12	82.15
mu[5]	53	149	143.7	1.935	7.182	99.76	517.6
mu[6]	8	26.82	19.59	0.4592	3.324	21.86	78.01
mu[7]	19	27.17	12.34	0.3532	8.243	25.45	56.07
mu[8]	22	37.63	17.43	0.513	10.81	35.12	78.11
mu[9]	41	2.374	2.882	0.05091	0	1.187	10.13
mu[10]	434	3.912	4.882	0.07787	0	2.042	17.3
mu[11]	11	52.9	52.12	1.084	3.801	35.35	194
mu[12]	16	51.54	24.92	0.6869	15.41	47.31	113.9
mu[13]	16	9.28	5.642	0.1282	1.435	8.275	22.97
mu[14]	462	323.8	146.5	5.062	84.13	308.1	654
mu[15]	68	21.97	9.917	0.3278	6.293	20.68	44.55
mu[16]	177	78.48	33.4	1.136	23.66	74.43	153.3
mu[17]	21	23.56	12.94	0.3895	4.785	21.39	54.55
mu[18]	13	0.4401	0.4748	0.007731	0	0.2913	1.711
mu[19]	39	0.6296	0.6931	0.01122	0	0.4085	2.502
mu[20]	129	5.061	3.087	0.08548	0.7566	4.472	12.62
mu[21]	17	14.19	8.508	0.2354	2.378	12.65	34.75
mu[22]	120	13.98	9.665	0.2169	2.194	11.58	39.07
mu[23]	15	76.57	49.57	1.145	13.9	64.32	201.6
mu[24]	2	0	0	7.07E-13	0	0	0
mu[25]	47	1.183	1.283	0.02262	0	0.7317	4.648
mu[26]	52	21.42	10.49	0.3042	5.492	19.91	45.86
mu[27]	106	46.16	18.93	0.6636	14.65	44.28	87.63
mu[28]	162	205.2	79.51	2.914	67.91	198.4	373.6
mu[29]	131	10.57	5.756	0.1793	2.16	9.56	24.16
mu[30]	296	27.03	15.56	0.3822	5.751	24.03	65.06
mu[31]	1124	375.6	149.8	5.911	120.4	362.8	708.2
mu[32]	407	169.8	63.51	2.431	57.24	166.3	303.6

mu[33]	144	45.29	26.33	0.7483	10.38	39.69	112
mu[34]	375	463	170.8	5.662	162	453	831.4
mu[35]	279	0.171	0.2214	0.003286	0	0.08616	0.7873
mu[36]	242	22.79	10.72	0.3377	5.996	21.43	47.09
mu[37]	134	379.9	135.7	5.156	135.3	374.7	658.4
mu[38]	1	15.87	10.82	0.2432	2.54	13.27	43.42
mu[39]	3	4.173	3.491	0.07261	0.1855	3.266	13.26
mu[40]	282	107.3	43.07	1.438	35.29	103	204.5
mu[41]	340	87.39	34.49	1.185	29.11	84.14	164.2
mu[42]	39	7.891	4.573	0.1199	1.302	7.165	18.99
mu[43]	201	45.43	20.63	0.677	12.58	43.27	92.61
mu[44]	165	138.7	50.24	1.85	48.21	136.2	244.9
mu[45]	10	3.342	4.194	0.06104	0	1.729	14.87
mu[46]	3	40.51	19.01	0.6158	10.72	38.04	83.75
mu[47]	1266	788.1	314	12.19	264	757.3	1481
mu[48]	432	561.5	215.3	5.252	196.8	541.9	1031
mu[49]	268	48.05	20.48	0.7313	14.16	45.99	92.67
mu[50]	341	291.1	105.4	4.202	101.6	285.7	509
mu[51]	184	322.2	112.4	4.213	118.3	316.3	557.2

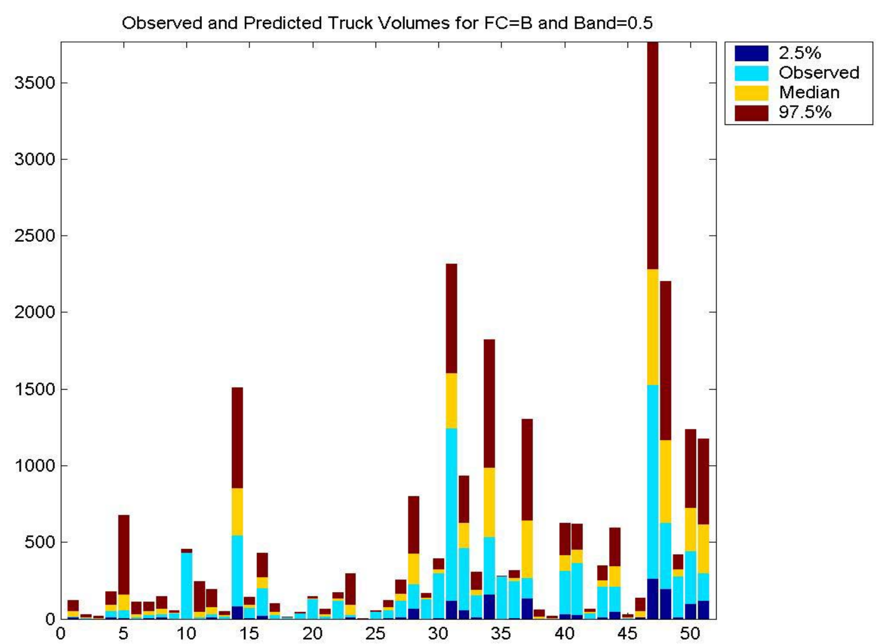


Figure 86: Observed and Predicted Truck Volumes (2.5%, median, 97.5%), (FC=6-9)

Table 39: Regression Coefficients (FC=6-9)

node	mean	sd	MC error	2.50%	median	97.50%
EMP_AGRICULTURE	3.711	5.635	0.09975	0	0.5863	19.15
EMP_MINING	1.268	2.397	0.03051	0	0	8.298
EMP_CONSTRUCTION	5.213	6.929	0.1344	0	2.489	24.07
EMP_MANUFACTURING	4.035	5.903	0.09812	0	1.046	20.6
EMP_UTILITIES	3.303	5.133	0.07270	0	0.1719	17.48
EMP_TRANSPORTATION	1.683	3.008	0.03686	0	0	10.43
EMP_WHOLESALE TRADE	3.962	5.673	0.09635	0	1.158	19.16
EMP_RETAIL TRADE	2.997	4.82	0.06661	0	0	16.49
EMP_FINANCE/INSURANCE	2.526	4.129	0.0532	0	0	13.91
EMP_REAL ESTATE	2.44	4.126	0.04986	0	0	14.07
EMP_SERVICES	2.854	4.642	0.06547	0	0	16.27
SALES_AGRICULTURE	3.813	5.564	0.07578	0	0.9239	18.91
SALES_MINING	1.216	2.329	0.0297	0	0	8.063
SALES_CONSTRUCTION	4.543	6.259	0.1026	0	1.79	20.97
SALES_MANUFACTURING	4.523	6.489	0.1333	0	1.604	21.75
SALES_UTILITIES	3.488	5.149	0.07477	0	0.5309	17.41
SALES_TRANSPORTATION	1.864	3.213	0.03818	0	0	11.2
SALES_WHOLESALE TRADE	3.69	5.494	0.08998	0	0.6032	18.44
SALES_RETAIL TRADE	3.147	4.975	0.0712	0	0	17.11
SALES_FINANCE/INSURANCE	2.709	4.39	0.06012	0	0	14.87
SALES_REAL ESTATE	2.184	3.706	0.04363	0	0	12.66
SALES_SERVICES	3.06	4.78	0.06345	0	0.01281	16.47
CNT_AGRICULTURE	3.192	4.993	0.0627	0	0.08893	16.97
CNT_MINING	1.27	2.392	0.02706	0	0	8.276
CNT_CONSTRUCTION	3.606	5.398	0.07826	0	0.5534	18.2
CNT_MANUFACTURING	4.153	5.941	0.09598	0	1.305	19.95
CNT_UTILITIES	4.014	5.84	0.09658	0	1.028	19.98
CNT_TRANSPORTATION	2.785	4.454	0.05684	0	0	14.93
CNT_WHOLESALE TRADE	3.974	5.866	0.08543	0	0.8845	19.92
CNT_RETAIL TRADE	2.981	4.737	0.06407	0	0	16.39
CNT_FINANCE/INSURANCE	2.448	4.137	0.04951	0	0	14.01
CNT_REAL ESTATE	2.94	4.7	0.05926	0	0	15.81
CNT_SERVICES	3.095	4.891	0.07492	0	0.04126	16.76

Note: For this model the intercept was set to zero

Table 40: Truck Volume Prediction on Test Dataset, (FC=6-9)

node	Observed	mean	sd	MC error	2.50%	median	97.50%
Y[44]	165	310.6	219.7	2.38	14.66	272.7	817.8
Y[47]	1266	811.6	421.8	11.48	96.41	777.9	1711

Urban Interstate

(FC=11, Band=0.5, R^2=[0.54, 0.63, 0.99])

Table 41: Truck Volume Predictions on Training Dataset, (FC=11)

node	Observed	mean	sd	MC error	2.50%	median	97.50%
mu[1]	2603	3115	572	9.069	2079	3084	4297
mu[2]	3283	10990	1082	19.74	9.00E+03	10950	13260
mu[3]	11702	8171	1097	18.95	6114	8139	10410
mu[4]	5163	13230	1377	28.59	10680	13160	16080
mu[5]	2300	4752	868	20.57	3130	4728	6490
mu[6]	1514	4752	868	20.57	3130	4728	6490
mu[7]	14310	10150	2904	63.23	5924	9858	16220
mu[8]	5334	9605	3007	67.6	5117	9341	15910
mu[9]	4179	4692	625.6	8.256	3536	4663	5966
mu[10]	7482	4692	625.6	8.256	3536	4663	5966
mu[11]	14093	2624	688.3	20	1430	2581	4069
mu[12]	4170	2935	616.1	9.154	1855	2894	4242
mu[13]	3821	2935	616.1	9.154	1855	2894	4242
mu[14]	6938	11770	1298	20.42	9417	11700	14470
mu[15]	6057	5317	940.9	14.75	3638	5268	7286
mu[16]	3930	5317	940.9	14.75	3638	5268	7286
mu[17]	6660	5317	940.9	14.75	3638	5268	7286
mu[18]	4238	6149	1140	24.97	4232	6026	8666
mu[19]	3066	5211	1199	25.89	3199	5086	7829
mu[20]	20236	20520	1572	21.1	17480	20480	23670
mu[21]	7928	3168	591	8.868	2061	3148	4392
mu[22]	7426	6175	975.1	26.09	4386	6135	8157
mu[23]	12913	5553	1073	29.87	3534	5532	7707
mu[24]	38518	28970	3081	120.7	23130	28890	35330
mu[25]	11353	7528	1402	28.25	5158	7447	10680
mu[26]	5014	11890	1610	35.87	8998	11800	15310
mu[27]	7906	11890	1506	38.15	9302	11790	15110
mu[28]	3914	1775	580.1	9.687	784.2	1735	2982
mu[29]	2430	3677	801.5	14.28	2224	3644	5344

Table 42: Regression Coefficients, (FC=11)

node	mean	sd	MC error	2.50%	median	97.50%
Constant	1100	625.7	37.37	107.9	1046	2520
EMP_AGRICULTURE	77.25	194.8	2.731	0	0	692.8
EMP_MINING	77.29	169.2	2.829	0	0	609.8
EMP_CONSTRUCTION	95.68	229.7	3.647	0	0	820.9
EMP_MANUFACTURING	147.5	302	4.459	0	0	1048
EMP_UTILITIES	2582	1005	47.8	854.1	2501	4690
EMP_TRANSPORTATION	3.415	20.63	0.2818	0	0	48.14
EMP_WHOLESALE TRADE	128.8	279.5	4.734	0	0	1007
EMP_RETAIL TRADE	273.1	453.6	9.342	0	0	1568
EMP_FINANCE/INSURANCE	44.92	130.6	1.558	0	0	479.6
EMP_REAL ESTATE	6.095	30.66	0.4626	0	0	93.83
EMP_SERVICES	26.73	93.05	1.231	0	0	325.9
SALES_AGRICULTURE	35.24	112.6	1.435	0	0	404.4
SALES_MINING	368.1	364.8	8.81	0	321.3	1132
SALES_CONSTRUCTION	83.87	209.9	3.07	0	0	755.1
SALES_MANUFACTURING	278	438.9	8.833	0	0	1475
SALES_UTILITIES	649.5	681.2	23.08	0	510.2	2171
SALES_TRANSPORTATION	2.36	15.94	0.1972	0	0	30.45
SALES_WHOLESALE TRADE	244.6	407.7	8.066	0	0	1357
SALES_RETAIL TRADE	294.3	473.8	8.368	0	0	1621
SALES_FINANCE/INSURANCE	61.12	171.7	2.162	0	0	613.9
SALES_REAL ESTATE	45.68	141.9	1.716	0	0	511.1
SALES_SERVICES	71.95	189.2	2.584	0	0	675.3
CNT_AGRICULTURE	111.5	249.3	3.341	0	0	879.1
CNT_MINING	19.9	76.85	0.9727	0	0	259.7
CNT_CONSTRUCTION	196.2	367.7	6.553	0	0	1262
CNT_MANUFACTURING	156.9	315.8	6.212	0	0	1105
CNT_UTILITIES	49.71	146.2	2.245	0	0	514.3
CNT_TRANSPORTATION	42.79	133	1.781	0	0	468.8
CNT_WHOLESALE TRADE	112.4	257.5	4.192	0	0	901.8
CNT_RETAIL TRADE	133.3	284.3	5.302	0	0	1015
CNT_FINANCE/INSURANCE	68.77	184.5	2.607	0	0	672.6
CNT_REAL ESTATE	38.31	122	1.483	0	0	440.9
CNT_SERVICES	50.93	150.8	2.139	0	0	557.2

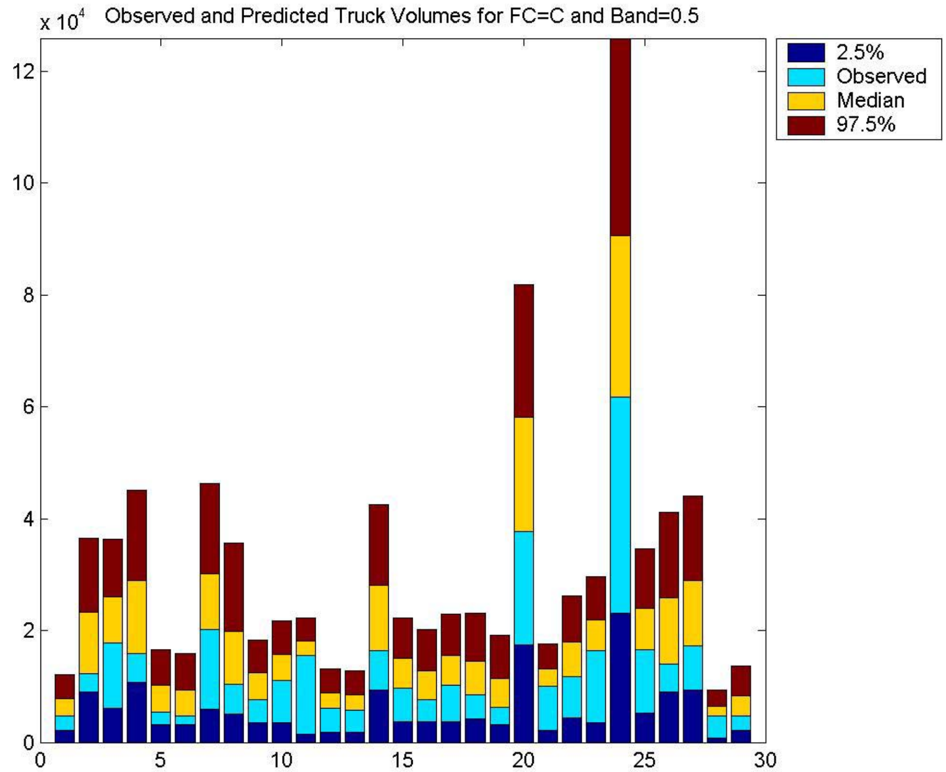


Figure 87: Observed and Predicted Truck Volumes (2.5%, median, 97.5%), (FC=11)

Table 43: Truck Volume Prediction on Test Dataset, (FC=11)

node	Observed	mean	sd	MC error	2.50%	median	97.50%
Y[8]	9605	9625	4277	83.34	1928	9433	18550
Y[22]	6175	6409	3042	39.67	905.8	6297	12670
Y[28]	1775	3328	2264	23.42	183.5	2977	8609

Expressway

(FC=12, Band=0.75, R^2=[0.077, 0.08, 0.15])

Table 44:Truck Volume Predictions on Training Dataset, (FC=12)

node	observed	mean	sd	MC error	2.50%	median	97.50%
mu[1]	4300	2659	367.4	13.63	1943	2658	3382
mu[2]	660	3100	363.8	12.65	2420	3080	3837
mu[3]	2417	4365	312.8	6.848	3765	4360	4987
mu[4]	2258	5345	478.8	9	4475	5322	6348
mu[5]	5370	3293	275.8	7.191	2744	3291	3828
mu[6]	13869	4117	352.5	8.654	3450	4111	4830
mu[7]	470	4308	321.7	5.873	3696	4303	4964
mu[8]	9199	3005	338.2	13.26	2331	3013	3648
mu[9]	1428	3066	345.6	13.96	2391	3064	3742
mu[10]	3067	3501	256.3	4.834	2989	3506	3995
mu[11]	396	2973	339	11.72	2309	2974	3626
mu[12]	1707	3075	306.2	8.825	2482	3073	3674
mu[13]	2183	3075	306.2	8.825	2482	3073	3674
mu[14]	2215	2990	343.3	12.25	2304	2999	3637
mu[15]	726	3643	316.2	4.215	3022	3639	4294
mu[16]	696	3643	316.2	4.215	3022	3639	4294
mu[17]	1441	4819	340.2	5.151	4184	4808	5522
mu[18]	1652	4819	340.2	5.151	4184	4808	5522
mu[19]	7124	8967	1122	48.76	6809	8970	11190
mu[20]	19740	5286	650.6	36.15	4213	5214	6657

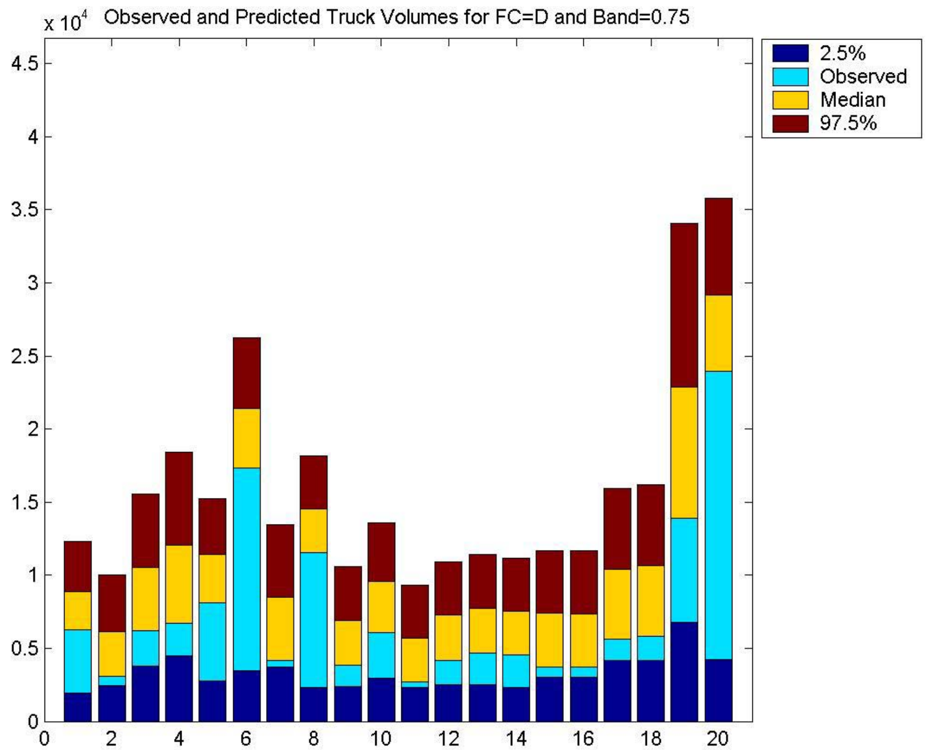


Figure 88: Observed and Predicted Truck Volumes (2.5%, median, 97.5%), (FC=12)

Table 45:Regression Coefficients, (FC=12)

node	mean	sd	MC error	2.50%	median	97.50%
Constant	2638	375.9	31.71	1879	2641	3337
EMP_AGRICULTURE	19.12	43.59	0.6111	0	0	152.6
EMP_MINING	4.905	16.6	0.218	0	0	55.87
EMP_CONSTRUCTION	18.37	42.14	0.6972	0	0	145.5
EMP_MANUFACTURING	9.95	27.68	0.4667	0	0	98.24
EMP_UTILITIES	59.01	78.52	2.488	0	5.851	251.2
EMP_TRANSPORTATION	25.66	50.93	1.122	0	0	173.4
EMP_WHOLESALE TRADE	95	127.7	2.574	0	38.24	433.5
EMP_RETAIL TRADE	76.08	119.4	2.42	0	5.776	416
EMP_FINANCE/INSURANCE	21.25	47.54	0.6866	0	0	172.6
EMP_REAL ESTATE	27.08	53.78	0.959	0	0	185.7
EMP_SERVICES	7.434	23.1	0.3283	0	0	81.35
SALES_AGRICULTURE	13.74	34.53	0.4297	0	0	122.3
SALES_MINING	3.062	11.63	0.1628	0	0	39.21
SALES_CONSTRUCTION	84.08	131.1	2.626	0	12.3	459.4
SALES_MANUFACTURING	19.18	43.33	0.82	0	0	154.8
SALES_UTILITIES	14.63	32.65	0.8128	0	0	114.6
SALES_TRANSPORTATION	19.35	43.25	0.855	0	0	150.7
SALES_WHOLESALE TRADE	41.43	74.94	1.272	0	0	259.7
SALES_RETAIL TRADE	17.05	41.07	0.5331	0	0	138.9
SALES_FINANCE/INSURANCE	27.22	55.06	0.8436	0	0	192.2
SALES_REAL ESTATE	24.2	51.54	0.7866	0	0	178
SALES_SERVICES	16.7	39.51	0.6384	0	0	137.9
CNT_AGRICULTURE	11.22	30.08	0.4167	0	0	109.2
CNT_MINING	8.905	26.15	0.3652	0	0	87.96
CNT_CONSTRUCTION	21.14	48.13	0.6985	0	0	165.1
CNT_MANUFACTURING	30.16	60.26	0.9667	0	0	209.9
CNT_UTILITIES	435.5	382.6	23.82	0	311.4	1375
CNT_TRANSPORTATION	99.46	131.6	2.787	0	48.39	455
CNT_WHOLESALE TRADE	55.64	91.17	1.597	0	0	307.4
CNT_RETAIL TRADE	31.38	62.63	0.8735	0	0	213.5
CNT_FINANCE/INSURANCE	24.4	52.71	0.7293	0	0	182.2
CNT_REAL ESTATE	6.552	20.31	0.2983	0	0	71.04
CNT_SERVICES	9.85	27.49	0.3664	0	0	96.28

Table 46: Truck Volume Prediction on Test Dataset

node	Observed	mean	sd	MC error	2.50%	median	97.50%
Y[9]	1428	3076	1054	18.64	1044	3074	5188

Urban Major

(FC=14, Band=1.0 miles, R^2=[0.143, 0.12, 0.15])

Table 47: Truck Volume Predictions on Training Dataset, (FC=14)

node	Observed	mean	sd	MC error	2.50%	median	97.50%
mu[1]	443	182.3	34.13	1.312	124.7	180.9	254.7
mu[2]	781	1193	204.7	10.29	840.8	1168	1627
mu[3]	684	304.4	102.5	3.567	144.7	291.5	549.7
mu[4]	90	612.8	152.6	6.068	377.9	594.2	988.5
mu[5]	1738	1246	346.4	17.08	699	1204	2004
mu[6]	677	1456	344.2	15.9	883.7	1422	2194
mu[7]	234	569	115.1	4.832	360.7	562.8	810.4
mu[8]	5225	4358	838.9	27.96	2895	4286	6113
mu[9]	2550	355.5	66.66	2.977	236.9	350.2	494.8
mu[10]	318	177.8	41.85	1.779	103.9	173.9	270.1
mu[11]	260	253.5	61	1.953	151.3	247.1	386.4
mu[12]	316	2136	335.3	18.07	1508	2113	2863
mu[13]	223	1096	183.1	6.61	759	1083	1486
mu[14]	1618	1548	338.8	11.46	949.9	1531	2326
mu[15]	1998	571.4	198.6	6.135	258.5	541.2	1025
mu[16]	885	1081	287.9	17.76	605.6	1057	1705
mu[17]	728	1658	316.9	13.09	1083	1638	2340
mu[18]	590	524	86.26	3.259	368.7	518.6	715.7
mu[19]	187	574.8	131.6	3.915	341.7	571.4	863.7
mu[20]	144	1349	284.8	18.58	840.1	1320	1959
mu[21]	168	262.1	66.46	2.772	150.9	255.4	407.2
mu[22]	125	1097	264.4	15.42	663.4	1079	1653
mu[23]	264	1684	257.4	9.334	1206	1684	2208
mu[24]	202	1198	283.6	15.52	720	1168	1796
mu[25]	2004	431.8	126.2	8.182	240.7	411.3	720.3
mu[26]	167	944	209.9	8.316	586	929.2	1444
mu[27]	406	616.4	172.7	5.727	340.1	599.3	1008
mu[28]	225	710.6	136.9	5.277	465.8	703.1	994
mu[29]	89	507.2	144.8	6.506	271.3	492.2	831.7
mu[30]	1666	3909	519.4	24.18	2937	3900	4984
mu[31]	696	1366	213.9	8.879	975.1	1365	1798
mu[32]	507	110.7	30.71	1.07	61.9	106.1	184.3
mu[33]	428	254.8	73.2	3.499	136.7	246.7	412.9
mu[34]	203	829	173.6	12.02	528.3	814.4	1202
mu[35]	311	357.6	81.48	2.979	212.7	349.8	537.4
mu[36]	476	278.1	188.6	9.243	18.79	251.6	711
mu[37]	6807	852.2	161.3	5.389	547.4	847.5	1186
mu[38]	2234	3154	498.1	19.08	2271	3109	4223
mu[39]	1096	621	108.5	4.971	426.8	614.8	847.5
mu[40]	364	608.6	179	8.508	331.9	588.3	1017

mu[41]	450	630.8	179.5	8.188	341.1	609.8	1031
mu[42]	675	204.9	52.41	1.987	110.8	198.9	321
mu[43]	180	889.7	158.5	5.962	592	884	1243
mu[44]	515	1278	448.2	13.66	573.4	1216	2336
mu[45]	1848	516	102.3	4.685	338.8	508.7	750.2
mu[46]	526	483.2	112.2	4.778	280.4	477.6	714.9
mu[47]	3319	276.7	50.93	2.088	185.7	275.8	378
mu[48]	8497	643.2	136.9	5.086	403.2	633.8	932.2
mu[49]	1243	1408	605.9	29.72	583.5	1351	2802
mu[50]	8663	1083	232.8	11.94	667.9	1066	1590
mu[51]	178	323.3	91.88	4.274	168.3	315.7	525.2
mu[52]	926	453.3	181.2	6.377	239.2	395.3	920.1
mu[53]	995	596.1	153.6	9.647	338.8	581.4	935.2
mu[54]	19054	424.5	135.2	9.617	213.8	405.7	732.8
mu[55]	154	1065	372.1	13.9	577.3	970.1	2026
mu[56]	2157	2183	459.9	21.66	1481	2108	3243
mu[57]	886	1150	246.7	11.15	734.9	1134	1702
mu[58]	218	1013	163.5	8.555	717.8	1006	1330
mu[59]	2551	1035	377.8	15.18	441.1	982.7	1882

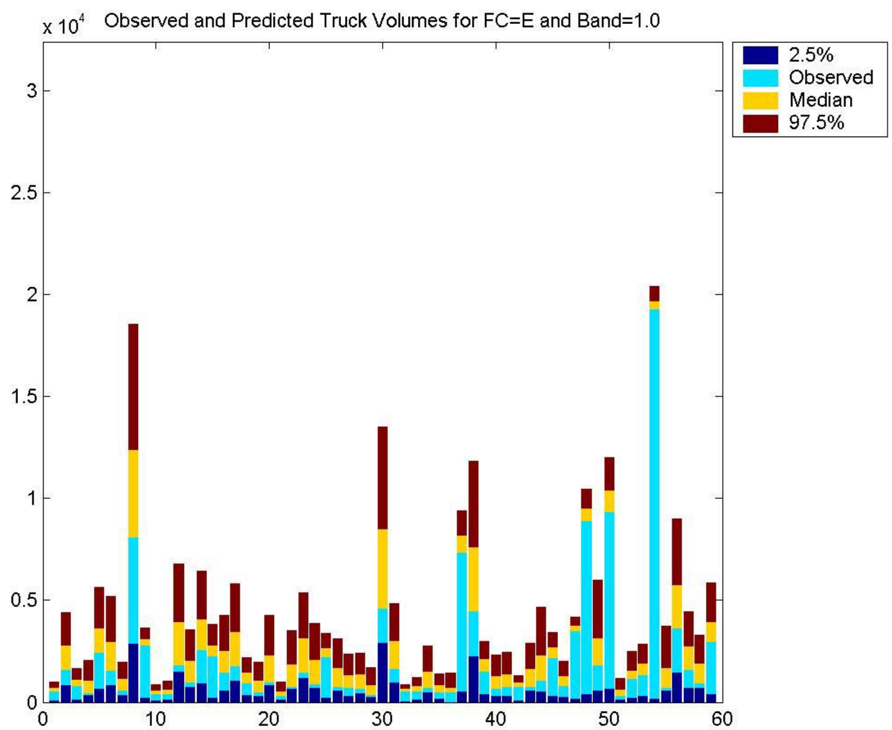


Figure 89: Observed and Predicted Truck Volumes (2.5%, median, 97.5%), (FC=14)

Table 48: Regression Coefficients , (FC=14)

node	mean	sd	MC error	2.50%	median	97.50%
EMP_AGRICULTURE	28.48	42.72	1.583	0	0	140
EMP_MINING	12.18	22.57	0.9963	0	0	77.1
EMP_CONSTRUCTION	77.34	70.97	3.705	0	67.23	228.3
EMP_MANUFACTURING	54.9	66.52	2.939	0	33.44	224.4
EMP_UTILITIES	20.59	34.5	1.43	0	0	114.3
EMP_TRANSPORTATION	24.4	35.2	1.591	0	0	121.6
EMP_WHOLESALE TRADE	55.43	50.99	2.554	0	51.1	170.4
EMP_RETAIL TRADE	17.6	31.49	1.373	0	0	111.7
EMP_FINANCE/INSURANCE	7.747	17.07	0.6669	0	0	60.1
EMP_REAL ESTATE	6.604	15.54	0.6449	0	0	50.86
EMP_SERVICES	23.21	38.22	1.547	0	0	132.2
SALES_AGRICULTURE	28.5	42.78	1.67	0	0	146.9
SALES_MINING	9.237	20.05	0.7147	0	0	75.27
SALES_CONSTRUCTION	24.63	40.3	1.574	0	0	137.2
SALES_MANUFACTURING	32.71	44.55	1.742	0	3.9	149.1
SALES_UTILITIES	68.63	65.24	3.263	0	58.63	209.6
SALES_TRANSPORTATION	28.57	33.81	1.436	0	15.52	111.2
SALES_WHOLESALE TRADE	33.65	48.6	2.132	0	4.677	169.5
SALES_RETAIL TRADE	9.547	20.03	0.7763	0	0	69.72
SALES_FINANCE/INSURANCE	6.378	16.11	0.5868	0	0	55.08
SALES_REAL ESTATE	4.977	12.55	0.6013	0	0	44.9
SALES_SERVICES	8.849	20.4	0.6793	0	0	70.29
CNT_AGRICULTURE	59.69	65.17	3.502	0	42.7	220.7
CNT_MINING	62.6	60.87	3.781	0	51.39	201.2
CNT_CONSTRUCTION	30.05	45.59	1.622	0	0	150
CNT_MANUFACTURING	42.23	55.45	2.564	0	15.86	180.4
CNT_UTILITIES	50.53	65.27	2.163	0	20.92	233.2
CNT_TRANSPORTATION	17.56	32.66	1.18	0	0	116.4
CNT_WHOLESALE TRADE	25.93	40.79	1.603	0	0	135.6
CNT_RETAIL TRADE	30.76	46.08	1.69	0	0	156.6
CNT_FINANCE/INSURANCE	14.29	26.84	1.03	0	0	91.31
CNT_REAL ESTATE	15.77	29.28	0.9273	0	0	104.7
CNT_SERVICES	27.43	40.83	1.408	0	0	134.1

Table 49: Truck Volume Prediction on Test Dataset, (FC=14)

node	Observed	mean	sd	MC error	2.50%	median	97.50%
Y[5]	1738	1159	762.8	13.49	64.49	1050	2924
Y[26]	167	1156	756.6	10.14	57.69	1054	2801
Y[48]	8497	1366	829.5	13	87.45	1281	3171
Y[52]	926	1009	704.7	10.27	51.53	889	2619

Urban Minor

(FC=16-19, Band=1.25 miles, R^2=[0.48, 0.36, 0.035])

Table 50: Truck Volume Predictions on Training Dataset, (FC=16-19)

node	Observed	mean	sd	MC error	2.50%	median	97.50%
mu[1]	13	58	26	1	12	57	112
mu[2]	9	21	10	0	4	20	43
mu[3]	69	73	36	1	15	69	157
mu[4]	6	11	7	0	2	10	28
mu[5]	9	50	26	1	10	46	111
mu[6]	233	94	44	1	19	90	192
mu[7]	78	36	17	1	7	34	73
mu[8]	11	61	33	1	12	55	141
mu[9]	431	0	0	0	0	0	0
mu[10]	24	13	6	0	3	12	26
mu[11]	58	509	199	6	127	506	914
mu[12]	120	103	43	2	23	102	193
mu[13]	71	29	17	0	5	27	69
mu[14]	70	123	52	2	27	121	227
mu[15]	182	5	3	0	1	5	12
mu[16]	8	85	37	1	18	83	165
mu[17]	1	13	6	0	3	12	26
mu[18]	10	20	10	0	4	19	42
mu[19]	75	43	30	1	8	35	126
mu[20]	232	52	22	1	11	51	98
mu[21]	184	42	19	1	9	41	83
mu[22]	795	272	130	4	55	259	564
mu[23]	29	57	26	1	12	55	113
mu[24]	138	70	42	1	12	61	173
mu[25]	129	3	2	0	1	3	7
mu[26]	31	23	13	0	4	21	55
mu[27]	53	44	28	1	8	38	117
mu[28]	134	45	21	1	9	43	90
mu[29]	85	33	17	1	6	31	72
mu[30]	328	84	38	1	17	81	163
mu[31]	91	25	13	0	5	24	54
mu[32]	103	91	55	2	16	81	229
mu[33]	78	50	22	1	11	49	97
mu[34]	55	48	20	1	11	47	90
mu[35]	634	71	31	1	15	69	136
mu[36]	23	32	14	1	7	31	61
mu[37]	1	146	74	2	30	135	317
mu[38]	130	276	116	4	60	274	512

mu[39]	10	51	30	1	9	45	127
mu[40]	7	82	38	1	17	79	163
mu[41]	25	42	27	1	7	35	115
mu[42]	8	76	36	1	16	73	157
mu[43]	6	46	28	1	8	40	120
mu[44]	1	51	24	1	10	48	104
mu[45]	20	15	7	0	3	14	30
mu[46]	95	75	34	1	16	73	146
mu[47]	88	142	60	2	31	140	266
mu[48]	591	4	2	0	1	4	10
mu[49]	6	47	29	1	8	41	121
mu[50]	526	103	44	2	22	101	194
mu[51]	6	10	4	0	2	10	19
mu[52]	753	180	134	4	20	148	523
mu[53]	395	93	40	1	20	91	175
mu[54]	69	81	36	1	17	79	158
mu[55]	50	189	82	3	41	185	364
mu[56]	50	189	82	3	41	185	364
mu[57]	143	5	3	0	1	5	12
mu[58]	320	11	5	0	2	10	23
mu[59]	9	12	6	0	2	12	26
mu[60]	9	50	24	1	11	48	104
mu[61]	114	52	22	1	11	51	100
mu[62]	32	114	59	2	22	106	251
mu[63]	40	153	66	2	33	151	292
mu[64]	136	96	65	2	13	80	259
mu[65]	310	638	540	17	53	495	2049
mu[66]	48	124	52	2	28	122	230
mu[67]	152	66	29	1	14	65	128
mu[68]	85	46	26	1	8	42	107
mu[69]	192	25	12	0	5	23	53
mu[70]	526	59	30	1	12	55	129
mu[71]	361	59	30	1	12	55	129
mu[72]	54	83	40	1	16	79	175
mu[73]	281	39	18	1	8	37	79
mu[74]	6	80	39	1	16	75	168
mu[75]	26	44	20	1	9	42	87
mu[76]	126	21	11	0	4	19	46
mu[77]	156	60	29	1	12	58	125
mu[78]	574	39	19	1	8	36	83
mu[79]	2	46	20	1	10	45	90
mu[80]	68	44	28	1	8	38	117

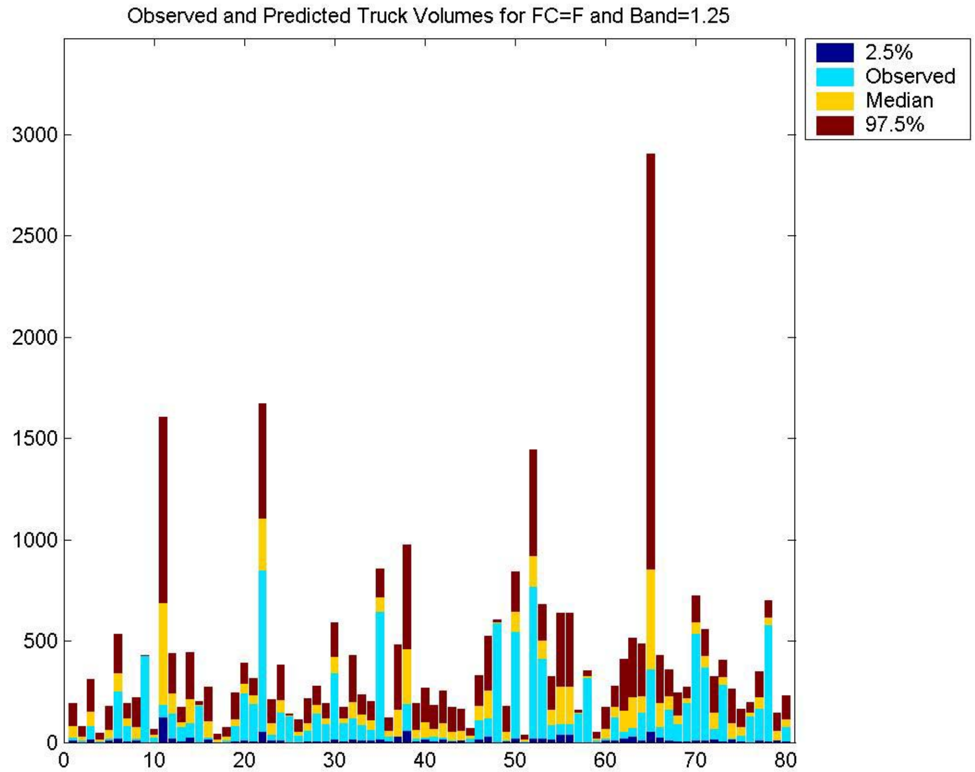


Figure 90: Observed and Predicted Truck Volumes (2.5%, median, 97.5%), (FC=16-19)

Table 51: Regression Coefficients, (FC=16-19)

Node	mean	sd	MC error	2.50%	median	97.50%
EMP_AGRICULTURE	2.601	4.182	0.05586	0	0.1349	14.3
EMP_MINING	4.265	5.905	0.1485	0	1.877	20.6
EMP_CONSTRUCTION	2.15	3.646	0.04191	0	0	12.66
EMP_MANUFACTURING	2.388	3.85	0.04652	0	0.09395	13.28
EMP_UTILITIES	2.283	3.765	0.04627	0	0	12.84
EMP_TRANSPORTATION	1.152	2.194	0.0198	0	0	7.6
EMP_WHOLESALE TRADE	2.41	3.929	0.04861	0	0.05434	13.66
EMP_RETAIL TRADE	2.792	4.415	0.05963	0	0.3562	15
EMP_FINANCE/INSURANCE	1.482	2.649	0.02539	0	0	9.104
EMP_REAL ESTATE	1.532	2.763	0.02681	0	0	9.613
EMP_SERVICES	1.709	3.097	0.03053	0	0	10.74
SALES_AGRICULTURE	2.874	4.549	0.06258	0	0.4351	15.66
SALES_MINING	4.347	5.965	0.1478	0	1.885	21.12
SALES_CONSTRUCTION	2.192	3.73	0.04027	0	0	12.62
+-						
SALES_MANUFACTURING	2.256	3.792	0.04601	0	0	12.96
SALES_UTILITIES	3.507	4.994	0.07983	0	1.162	17.09
SALES_TRANSPORTATION	0.8703	1.786	0.01517	0	0	6.338
SALES_WHOLESALE TRADE	2.427	3.961	0.04834	0	0.05438	13.45
SALES_RETAIL TRADE	2.897	4.592	0.06703	0	0.5319	15.5
SALES_FINANCE/INSURANCE	2.334	3.9	0.04675	0	0	13.26
SALES_REAL ESTATE	2.155	3.581	0.03895	0	0	12.45
SALES_SERVICES	2.268	3.757	0.04197	0	0	12.95
CNT_AGRICULTURE	3.018	4.719	0.06984	0	0.5682	15.92
CNT_MINING	2.264	3.669	0.046	0	0	12.6
CNT_CONSTRUCTION	2.643	4.326	0.05884	0	0.1571	14.97
CNT_MANUFACTURING	2.018	3.46	0.03786	0	0	11.89
CNT_UTILITIES	2.495	4.127	0.05073	0	0.04689	14.23
CNT_TRANSPORTATION	1.862	3.236	0.03368	0	0	11.23
CNT_WHOLESALE TRADE	2.285	3.792	0.0425	0	0	13
CNT_RETAIL TRADE	1.998	3.442	0.03851	0	0	11.75
CNT_FINANCE/INSURANCE	2.279	3.814	0.0467	0	0	13.3
CNT_REAL ESTATE	2.451	4.041	0.04973	0	0.0735	13.78
CNT_SERVICES	1.946	3.381	0.03673	0	0	11.6

Table 52:Truck Volume Prediction on Test Dataset, (FC=16-19)

node	Observed	mean	sd	MC error	2.50%	median	97.50%
Y[6]	233	291.9	208.6	1.564	13.71	252.9	775.5
Y[20]	232	273.3	200.6	1.431	11.03	235.7	747.8
Y[32]	103	288.9	208	1.644	14.43	252.8	783.4
Y[54]	69	283.2	206.8	1.448	11.71	243.9	767.1
Y[65]	310	707.2	562.7	16.13	34.91	573.6	2140
Y[66]	48	302.8	213.4	1.744	14.25	267.6	794.5

Comments

In this type of problems, where limited training data is available, the major advantage of using a Bayesian framework, is that the models can be tested on real data[9]. Using SRL or CLSSO did not permit to create a test sample since omitting one or more observations from an already limited training dataset would results in erroneous models. Table 56 presents the results of each trained model on real observations (test dataset) while table 57 summarizes the R^2 values of the models. Figures 91 and 92 present the results in a graphical format (Bar-Chart).

Bayesian Regression produces a distribution for the predicted truck volumes and not a point estimate. Thus 3 different R^2 values are presented each corresponding to the 2.5%, median and 97.5% interval of the predicted truck volumes. It is observed that using the models on the test sample gives predictions that follow the pattern of the R^2 values. It should be pointed out is that the worst model was produced by the smallest training dataset (FC=12) while the rest of the models seemed to be moving in the same area of success (similar R^2 values).

The main problem of this approach is its implementation into an automated

[9] By holding out few observations the results do not change and thus cross-validation (1-fold in this thesis) is possible

software tool (similar to the one presented in the last section) will require a large amount of time.

Table 53: Observed and Predicted Truck Volumes Using Trained Models

FC	node	Observed	mean	sd	2.50%	median	97.5%
1-2	Y[3]	3506	2845	1133	705	2793	5149
	Y[7]	7178	3129	1206	865	3100	5571
	Y[29]	1038	1048	725	8	928	2730
6-9	Y[44]	165	311	220	15	273	818
	Y[47]	1266	812	422	96	778	1711
11	Y[8]	9605	9625	4277	1928	9433	18550
	Y[22]	6175	6409	3042	906	6297	12670
	Y[28]	1775	3328	2264	184	2977	8609
12	Y[9]	1428	3076	1054	1044	3074	5188
14	Y[5]	1738	1159	763	64	1050	2924
	Y[26]	167	1156	757	58	1054	2801
	Y[48]	8497	1366	830	87	1281	3171
	Y[52]	926	1009	705	52	889	2619
16-19	Y[6]	233	292	209	2	253	776
	Y[20]	232	273	201	1	236	748
	Y[32]	103	289	208	2	253	783
	Y[54]	69	283	207	1	244	767
	Y[65]	310	707	563	35	574	2140
	Y[66]	48	303	213	2	268	795

Table 54: R^2 Values from Bayesian Regression, CLLSO and SLR (Best Models)

	R^2 Values from Bayesian Regression, CLLSO and SLR					
		Bayesian Regression			Optimization	SLR
	Band	2.50%	Median	97.50%		
A	0.25	0.44	0.54	0.84	0.76	0.88
B	0.50	0.37	0.50	0.56	0.79	0.84
C	0.50	0.54	0.63	0.99	0.77	0.92
D	0.75	0.08	0.08	0.15	0.87	0.99
E	1.00	0.14	0.12	0.15	0.87	0.13*
F	1.25	0.48	0.36	0.04	0.82	0.59*

*Band Used = 0.25 miles

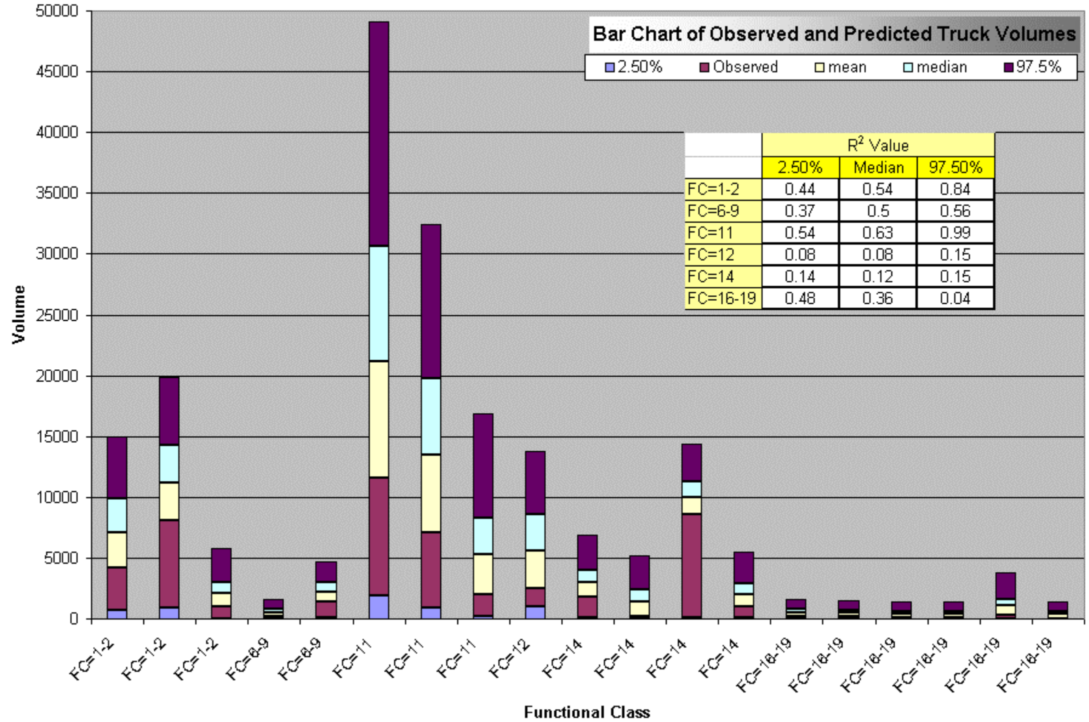


Figure 91: Bar Chart of Observed and Predicted Truck Volumes

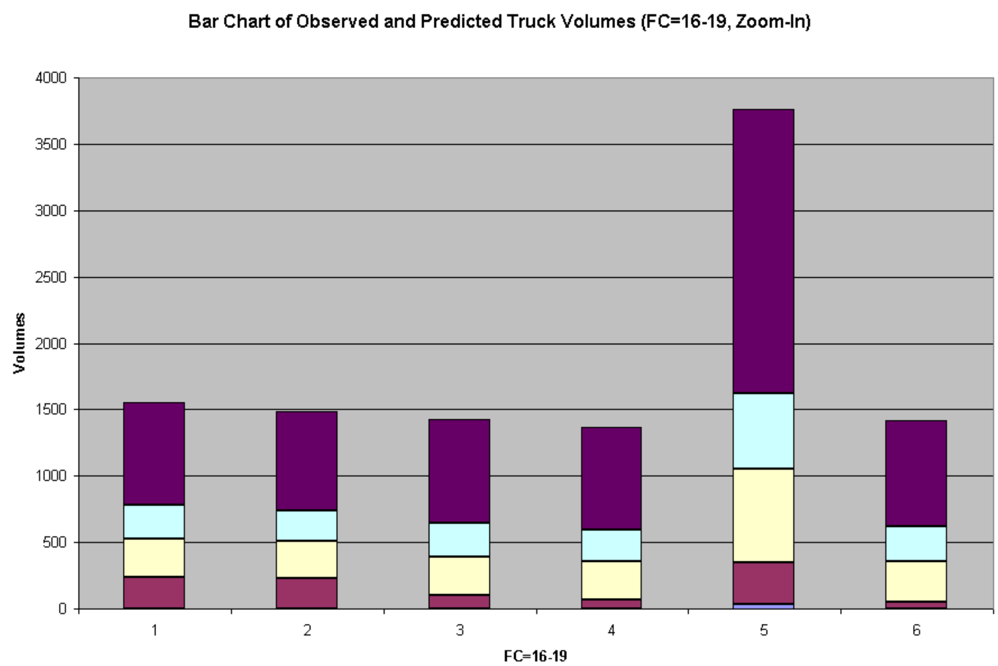


Figure 92: Bar Chart of Observed and Predicted Truck Volumes for FC=16-19 (Zoom-In from fig. 6-2)

ESTIMATION OF TRUCK VOLUMES AND FLOWS: A STATEWIDE APPROACH

The product of this task describes a plan that will extend the proposed methodology into a statewide basis. The actual implementation will need to be done as part of a future project. Attached with this report is a CD-ROM that contains an interactive detailed presentation of the proposed tool and its functionality. If needed a web page with the presentation can be created.

Introduction

State DOTs obtain information on truck activity on state highways through their traffic monitoring systems. These systems typically include information on traffic counts taken at various locations throughout the state. Although these counts usually provide a good geographic and temporal coverage for the overall traffic, there are a limited number of classification counts, providing information explicitly on truck volumes. In the future, the increasing use of Intelligent Transportation Systems such as global positioning systems for vehicle tracking, a wider use of Weight-In-Motion stations and better video imaging, have the potential to lessen the problem of limited and insufficient data. These additional data would provide a better geographic coverage in terms of truck volumes on state highways. The proposed statewide approach will enable NJDOT transportation planners to estimate truck volumes on sections of the highway system where such information is not currently available.

The main idea is to create a GIS-platform tool that when linked to a state DOT's traffic monitoring database system will allow for the update of the models (created using the same methodology as in Task II-4) and the display of truck volumes (both observed and estimated) on state highways, whenever new data enters the DOT's database. The tool described in this task will be an easy to use, in-house application, giving state transportation planners the ability to develop truck volume, flow and percentage profiles for any highway in the state and obtain an estimate of truck activity throughout the state. This information can be part of a statewide freight network modeling effort, which state DOTs typically outsource to their consultants. The proposed approach requires much less data to be available, avoids the series of assumptions made in typical freight models and is an easy to use, in-house application which yields fairly accurate results.

The rest of this task will describe in detail the proposed tool and its use, the data needed for the tool to be fully functional, a proposed time frame requirement for the creation of the tool and a proposed training program for the appropriate NJDOT staff.

GIS Application

The main goal of the GIS-based tool will be to use the statistical techniques that were presented and used in Task II-4, to create predictive models for truck volumes on New Jersey roadways, based on nearby land use activities and observations of traffic volumes on some sections of the roadway network. The overall framework of the tool (fig-93), described in detail in this section, can be summarized as: a) define roadway sections, b) develop the socioeconomic data tables, c) estimate new or update current models, d) predict truck volumes on selected highway sections, and e) create truck volume and percentage profiles for each highway or selected section. The final product is a GIS add-on feature that automates most of the modeling steps, described in the previous tasks of this report, and minimizes user-modeling efforts. Following is a presentation and description of the seven steps of the procedure using snapshots of the application's interface and describing the tool's functionality.

Step 1: Highway Section Definition

The first step of the process is to segment each highway into uniform sections. Econometric data associated with these sections can then be extracted and used as input in the model estimation process. Uniform sections may be defined based on a set of criteria such as major interchanges, changes in roadway functionality and changes in roadway geometry (fig-94). Provided that these data are available in an electronic format, the user would be able to choose among a set of criteria and create sections for a selected highway or the full road network. If for any of the user defined criteria data are not available in an electronic form, visual observation may be used along with a manual procedure to define the roadway segments.

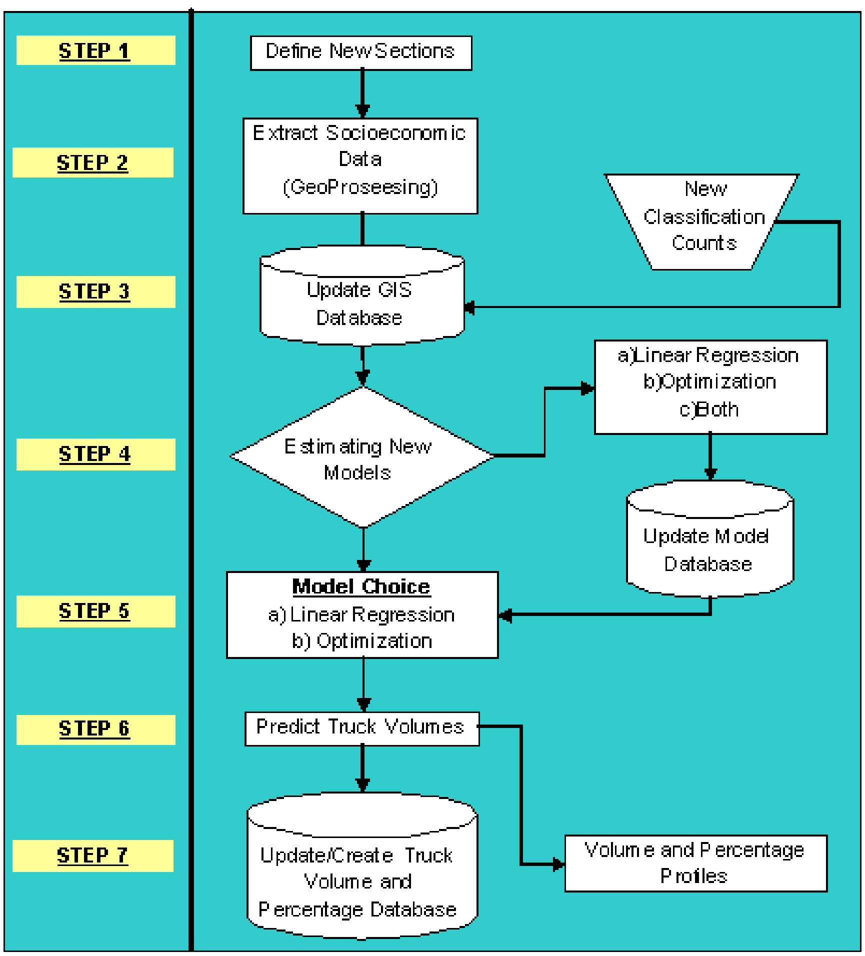


Figure 93: Overall Tool Framework

The length of the sections is highly dependent on the amount of observed counts (the more counts available the smaller the length of the sections). One of the advantages of automating this process is that roadway sections can be re-defined, with a decreased length, whenever a larger dataset of truck classification counts becomes available. Creating smaller sections would produce more accurate estimates and profiles.

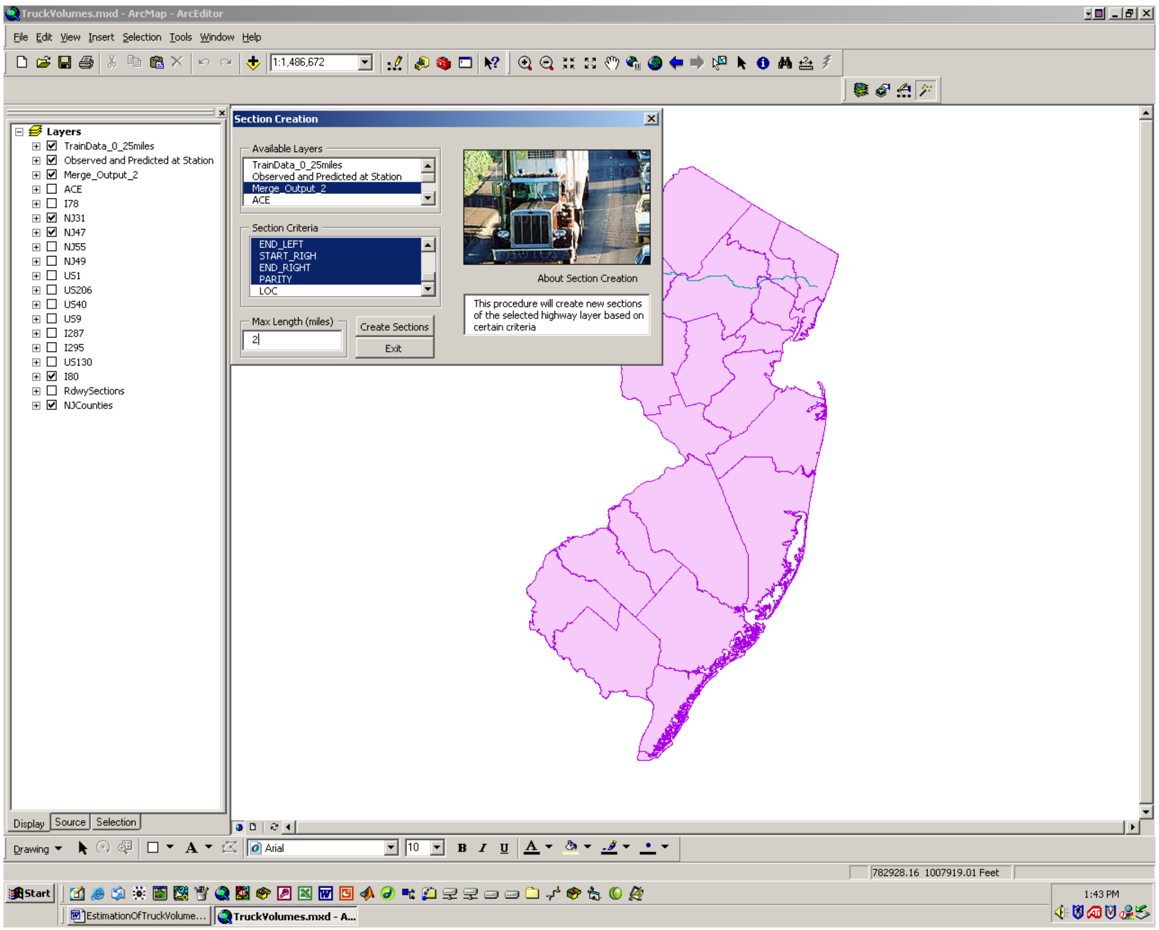


Figure 94: New Roadway Section Creation

Step 2 and 3: Input Data

New Jersey DOT has developed a traffic data collection program, through which classified traffic counts are taken at certain locations throughout the state each year. An effort is made to provide good geographic, temporal and spatial, coverage through these counts. It is expected that in the future a larger amount of truck classification counts would be available, which would provide a better geographic coverage in terms of truck volumes on New Jersey state highways. Socioeconomic data, which are also used as input in the modeling process, are available in electronic form. Related databases are easily updatable whenever new or additional data become available.

Step 4: Model Estimation

Once the necessary input data are obtained the option of using the existing models or estimating new models based on the new data becomes available (fig 95). Two different statistical techniques are used: a) Linear Regression, b) Constrained Least Squares Optimization and, c) Stepwise Linear Regression. All models assume the linear relationship between truck volumes and socioeconomic data presented in Task II-4:

$$Y_j = b_0 + b_1 X_{1j} + b_2 X_{2j} + ... + b_i X_{ij}$$

Where: Y_j = Truck Volume on link j, b_i = linear model coefficients,

X_{ij} = Socioeconomic Data of Variable i on link j

The independent variables that should be considered in these models and which are typically used for these types of applications are: a) number of employees, b) sales volume, and c) number of establishments, for different Standard Industrial Classification (SIC) categories. Nevertheless the user is able to perform the analysis using any type and number of variables.

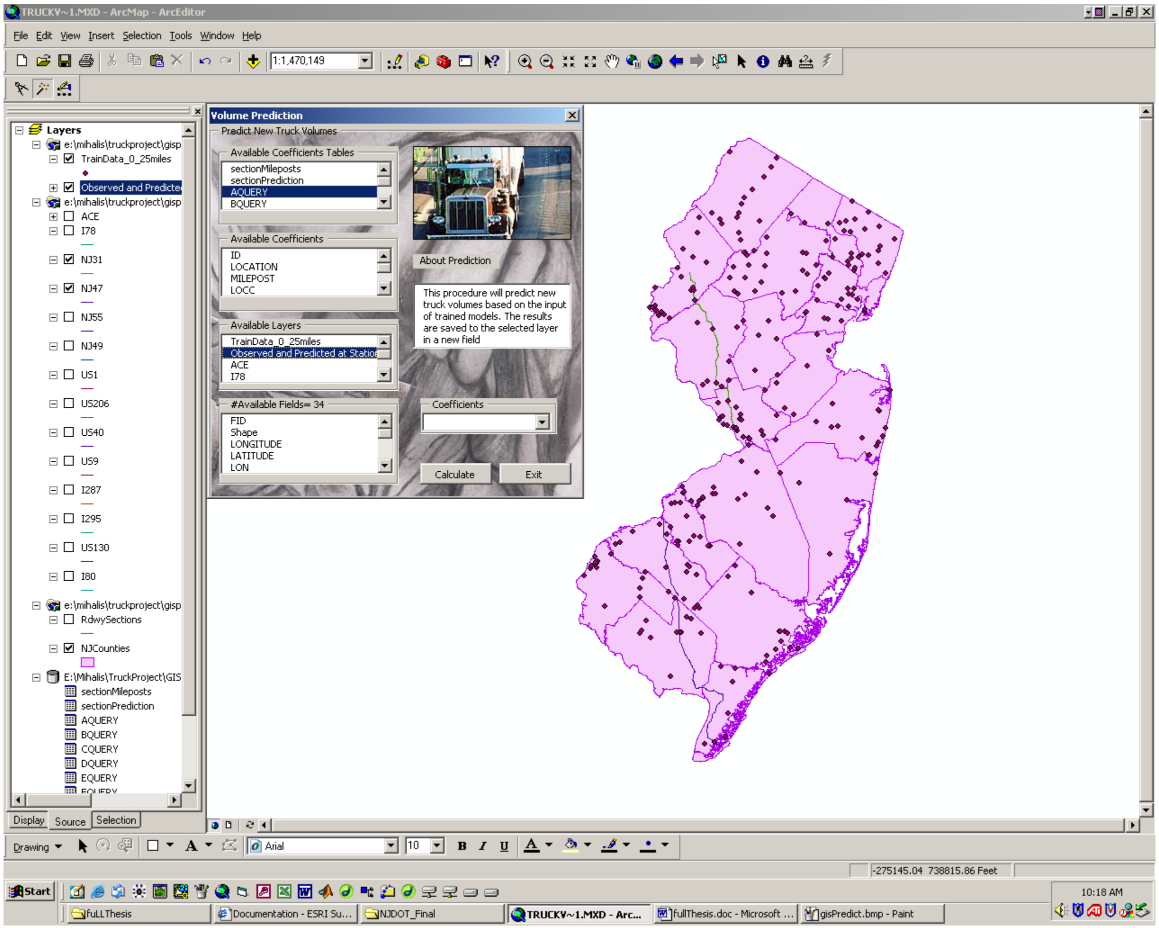


Figure 95: Estimating New Models

Sensitivity analysis may be performed, according to which truck generating activity within a band of varying width around each selected roadway link is considered. Sensitivity analysis was performed for the models in Task II-5. This analysis showed that, in general, selecting a wider band produces models that yield better estimates for sections of interstates and higher level roadways, while a narrower band produces models that yield better estimates for sections of lower level roads.

One of the advantages of this tool is that there is no limitation on the number and type of independent and dependent variables to consider when estimating new models. Furthermore, the tool provides the ability to choose among different band sizes for the independent variable dataset, estimate the new models and perform sensitivity analysis in a straightforward manner.

The models will take into account the impact of the roadway functional class (FC) by using clustered data and estimating different models for each class. This clustering considers the fact that different roadways attract different types of truck traffic. In this study a total of 6 different categories where considered: a) Rural interstate and major arterials (FC=1-2), b) Rural minor arterials, collectors, and local (FC=6-9), c) Urban interstate (FC=11), d) Urban expressways and parkways (FC=12), e) Urban major arterials (FC=14), and f) Urban minor arterials, collectors, and local (FC=16-19). Another advantage of this tool is that the user will have no limitation on the categories that may be used to cluster the data based on the roadway FC.

Step 5-6: Prediction

The next two steps of this process will use the estimated models to predict truck traffic volumes on sections of the NJ street network (fig-96). The user will be able to select an existing or a newly estimated model to predict truck volumes and generate truck percentage profiles.

Step 7: Visualization

After model estimation and truck volume prediction have been completed, the user may select a highway and view the observed and estimated truck volumes on each defined section, model information for each section (R-square value, band width, etc.), and the profiles of truck volumes and percentages (fig-97). Several profiles may be displayed for each roadway, including Predicted Truck Volume Profile (PTVP) using the Regression Model, PTVP using the Optimization Model, Observed Truck and Car Volumes, and Percentages. The user may select a section on a roadway and view the predicted and the observed truck volumes and a comparison of the truck volume on that section of the highway with those on adjacent sections.

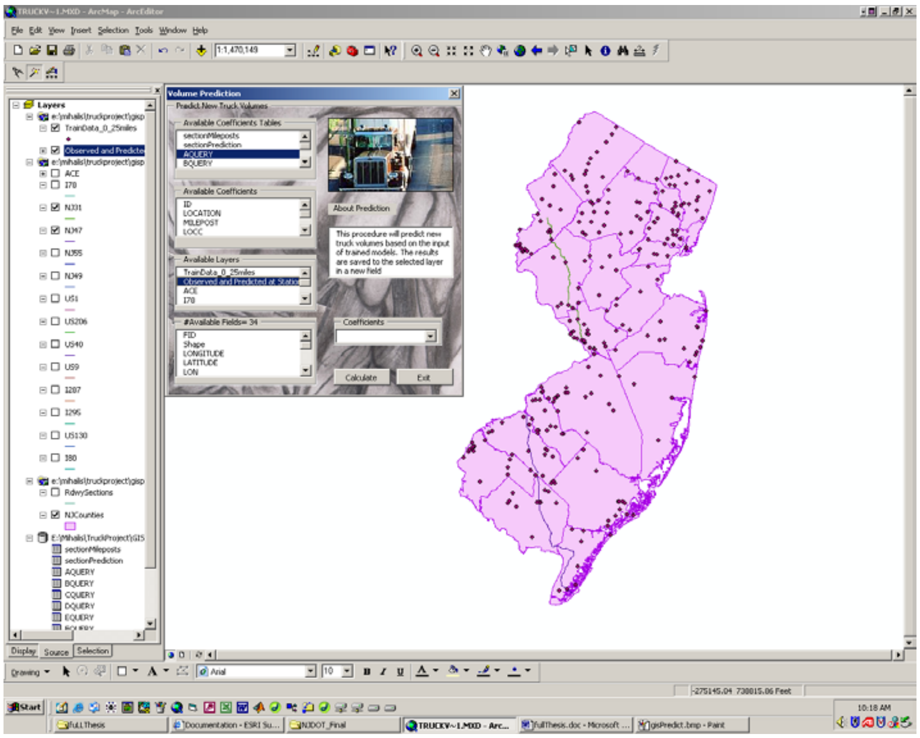


Figure 96: Predict Truck Volumes

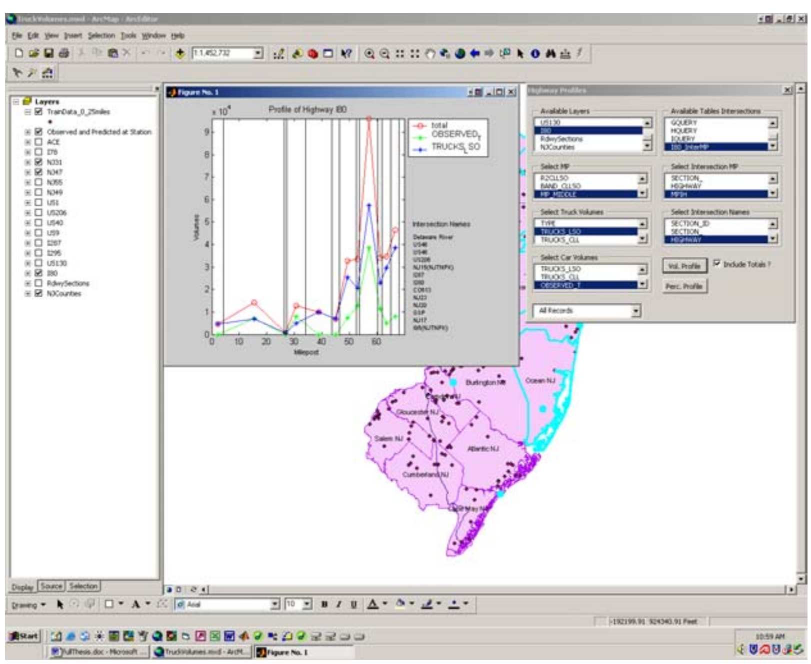


Figure 97: Roadway Volumes Profile Creation

Implementation and Training

The Rutgers team will formulate an Implementation and Training Plan that will promote the application of the tool and provide training of appropriate NJDOT and other personnel on the use of these products. The audience is expected to be NJDOT personnel will work with truck data. In addition, this product would also be appropriate for MPO and county personnel who work with truck data as well. The application program will be user-friendly, but users should have some familiarity with GIS applications. There will be a number of formal training sessions conducted by the Rutgers research team, lasting up to a full day. These sessions will provide an opportunity for all potential users to offer comments and an opportunity for some hands-on testing of the programs capabilities. All NJDOT input will be incorporated into a new and final tool which will be demonstrated at a final training session. This final training session can be held after NJDOT personnel have had an opportunity to familiarize themselves with the software.

Deliverable Formats

The GIS tool will be available in two different deliverable formats. The first will consist of an add-on tool to be used with ArcInfo, ArcEditor or ArcView software. The second deliverable will be a ready to use Windows standalone executable application.

Software Requirements

ArcInfo, ArcEditor or ArcView 8.0 and later versions are needed for the add-on tool.

Proposed Time Frame

Task	Time Requirements
Finalize Statewide Approach Framework and Product Deliverables	1 Months
Development of Product I: GIS Add-On Tool	6-9 Months
Development of Product II: Stand-Alone Application	3-9 Months
Training	1-2 Months
Testing and Finalizing Product	1-3 Month
Project Total Time Framework	**12-24 Months***

* Depending on the amount of desired deliverables

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APPENDIX A

Table A1. Observed AADT and Truck Volumes and Predicted Truck Volumes (Stepwise Regression and CLLSO) for 271 Locations

ID	LOCATION/ROUTE	MILEPOST	FC	TYPE	ADT	DAILY TRUCK VOLUMES	DAILY CAR VOLUMES	OBSERVED	OPTIMIZATION MODEL		REGRESSION MODEL	
								TRUCK PERCENTAGES (See note 1 at the end of table)	PREDICTED TRUCK VOLUMES	TRUCK PERCENTAGES (See note 2 at the end of table)	PREDICTED TRUCK VOLUMES	TRUCK PERCENTAGES (See Note 3 at the end of table)
1	2NDST	0.00	19	AVC	288	13	275	4.40%	96	33.33%	138	46.53%
2	4THAVENUE	0.00	19	AVC	66	9	57	14.29%	12	17.39%	134	70.16%
3	ASBURY	0.00	16	AVC	2121	69	2052	3.24%	95	4.42%	493	19.37%
4	ATLANTISAVE	0.00	19	AVC	883	6	877	0.72%	31	3.41%	89	9.21%
5	BEATRICEPKWY	0.00	19	AVC	464	9	455	2.05%	80	14.95%	113	19.89%
6	BRICKRD	0.00	19	AVC	9246	233	9013	2.52%	95	1.04%	149	1.63%
7	BRINDLETONRD	0.00	9	AVC	756	6	750	0.81%	7	0.92%	91	10.82%
8	BURNETTRD	0.00	9	AVC	486	6	480	1.27%	6	1.23%	78	13.98%
9	CARLTONAVE	0.00	19	AVC	1121	78	1043	6.96%	74	6.62%	89	7.86%
10	CIDERMILLRD	0.00	9	AVC	393	2	391	0.52%	3	0.76%	98	20.04%
11	CO502	12.28	14	AVC	12078	443	11636	3.66%	188	1.59%	1501	11.43%
12	CO504	6.07	16	AVC	489	11	478	2.31%	66	12.13%	233	32.77%
13	CO517	4.52	7	AVC	5944	42	5902	0.70%	28	0.47%	158	2.61%
14	CO539	29.00	17	WIM	9074	431	8643	4.75%	4	0.05%	119	1.36%
15	CO551	7.00	16	WIM	1747	24	1723	1.37%	17	0.98%	119	6.46%
16	CO601	0.00	6	AVC	2974	53	2920	1.80%	3	0.10%	81	2.70%
17	CO602	0.00	9	AVC	375	8	367	2.19%	73	16.59%	90	19.69%
18	CO602	0.19	8	AVC	1059	19	1040	1.84%	41	3.79%	77	6.89%
19	CO603	1.76	16	AVC	9490	58	9432	0.62%	344	3.52%	758	7.44%
20	CO605	0.00	16	AVC	3803	120	3683	3.16%	71	1.89%	115	3.03%
21	CO605	2.72	8	AVC	601	41	560	6.83%	5	0.88%	90	13.85%
22	CO607	0.00	16	AVC	21765	71	21694	0.33%	63	0.29%	108	0.50%
23	CO610	0.00	7	AVC	3843	434	3409	11.29%	3	0.09%	64	1.84%
24	CO612	0.00	9	AVC	705	11	693	1.60%	170	19.70%	105	13.16%
25	CO615	0.00	17	AVC	4502	70	4431	1.56%	89	1.97%	232	4.98%
26	CO617	2.07	8	AVC	766	16	750	2.14%	21	2.72%	171	18.57%
27	CO619	2.34	16	AVC	4169	182	3988	4.35%	26	0.65%	89	2.18%
28	CO621	0.00	8	AVC	152	16	135	10.81%	24	15.09%	77	36.32%
29	CO621	1.40	14	AVC	13508	781	12727	5.78%	1292	9.22%	1517	10.65%
30	CO622	0.00	9	AVC	4635	462	4173	9.96%	475	10.22%	685	14.10%
31	CO624	0.00	8	AVC	2224	68	2156	3.04%	16	0.74%	155	6.71%
32	CO628	0.00	16	AVC	2150	8	2142	0.38%	49	2.24%	119	5.26%
33	CO629	0.00	17	AVC	971	1	970	0.10%	17	1.72%	119	10.93%
34	CO637	0.00	17	AVC	890	10	880	1.14%	28	3.08%	133	13.13%
35	CO639	1.00	7	AVC	7943	177	7765	2.23%	81	1.03%	217	2.72%
36	CO640	0.00	19	AVC	3174	75	3099	2.36%	27	0.86%	119	3.70%
37	CO642	2.75	16	AVC	2570	232	2338	9.02%	62	2.58%	89	3.67%
38	CO644	2.49	7	AVC	1673	21	1652	1.25%	77	4.45%	111	6.30%
39	CO645	0.16	16	AVC	1975	184	1792	9.29%	70	3.76%	213	10.62%
40	CO646	0.00	8	AVC	3024	13	3010	0.44%	3	0.10%	64	2.08%
41	CO653	3.00	16	WIM	9698	795	8903	8.20%	711	7.40%	1030	10.37%
42	CO654	2.31	7	AVC	6477	39	6438	0.60%	3	0.05%	64	0.98%
43	CO662	0.35	16	AVC	3968	29	3939	0.72%	62	1.55%	215	5.18%
44	CO669	0.64	16	AVC	4885	138	4747	2.83%	124	2.55%	44	0.92%
45	CO670	0.00	7	AVC	3000	129	2871	4.30%	21	0.73%	71	2.41%
46	CO670	0.00	16	AVC	3000	129	2871	4.30%	21	0.73%	71	2.41%
47	CO670	0.00	7	AVC	3000	129	2871	4.30%	6	0.21%	125	4.17%
48	CO670	0.00	16	AVC	3000	129	2871	4.30%	6	0.21%	125	4.17%

Table A1. (Continued)

49	CO672	0.00	19	AVC	1455	31	1424	2.10%	98	6.44%	59	3.98%
50	CO685	0.00	16	AVC	5121	53	5068	1.04%	54	1.05%	119	2.29%
51	CO687	3.28	16	AVC	5478	134	5344	2.45%	98	1.80%	130	2.37%
52	CO699	0.00	17	AVC	1548	85	1463	5.51%	51	3.37%	69	4.50%
53	CO708	0.00	17	AVC	12644	328	12316	2.59%	123	0.99%	121	0.97%
54	CO713	1.05	16	AVC	3046	91	2955	3.00%	50	1.66%	10	0.34%
55	CO759	0.00	16	AVC	12891	103	12789	0.80%	125	0.97%	187	1.44%
56	CO85	0.97	16	AVC	4869	78	4791	1.60%	86	1.76%	124	2.52%
57	DELLRD	0.00	19	AVC	2194	55	2139	2.50%	80	3.61%	133	5.85%
58	EDGEBORORD	0.00	19	AVC	2159	634	1525	29.36%	127	7.69%	532	25.86%
59	EDWARDSST	0.00	19	AVC	233	23	210	9.95%	42	16.67%	171	44.88%
60	EFOXCHASE	0.00	8	AVC	805	17	788	2.17%	14	1.75%	101	11.36%
61	ERIEAVE	0.00	19	AVC	208	1	207	0.51%	90	30.30%	125	37.65%
62	FIRSTAVE	0.00	19	AVC	2739	130	2610	4.74%	271	9.41%	241	8.45%
63	FLOCKTOWNRD	0.00	8	AVC	4462	120	4342	2.69%	10	0.23%	85	1.92%
64	GAINESBORORD	0.00	17	AVC	2369	10	2358	0.43%	74	3.04%	64	2.64%
65	HANDZELRD	0.00	19	AVC	117	7	110	6.31%	96	46.60%	119	51.97%
66	HEMPSTEADRD	0.00	17	AVC	3083	25	3058	0.82%	78	2.49%	119	3.75%
67	HICKEYPL	0.00	19	AVC	222	8	213	3.81%	58	21.40%	117	35.45%
68	HIGHLANDBLVD	0.00	17	AVC	1862	6	1856	0.33%	60	3.13%	153	7.62%
69	HILLSIDEDR	0.00	19	AVC	333	1	332	0.32%	44	11.70%	89	21.14%
70	I195	10.00	1	WIM	39320	2004	37316	5.10%	370	0.98%	1191	3.09%
71	I195	5.84	11	AVC	21337	2603	18735	12.20%	4226	18.41%	-6775	~~56.65%~~
72	I278	0.80	11	AVC	20814	3283	17531	15.77%	9958	36.23%	-17644	~~15614.16%~~
73	I280	13.70	11	AVC	89012	11702	77310	13.15%	7235	8.56%	-7354	~~10.51%~~
74	I280	14.70	11	AVC	40129	5163	34966	12.87%	12718	26.67%	-6067	~~20.99%~~
75	I280	5.00	11	WIM	93430	2300	91130	2.46%	7738	7.83%	-25284	~~38.40%~~
76	I280	5.40	11	AVC	51739	1514	50225	2.93%	7738	13.35%	-25284	~~101.38%~~
77	I287	31.70	1	WIM	94154	9276	84878	10.00%	9784	10.34%	-11059	~~14.98%~~
78	I287	46.50	11	AVC	68814	14310	54504	21.00%	9828	15.28%	-5780	~~11.86%~~
79	I287	55.35	11	AVC	29691	5334	24357	18.00%	8763	26.46%	-19491	~~400.55%~~
80	I287	59.30	11	AVC	28404	4179	24225	15.00%	4966	17.01%	1587	6.15%
81	I287	61.70	11	WIM	54240	7482	46758	14.00%	4966	9.60%	1587	3.28%
82	I287	67.10	11	AVC	84333	14093	70239	17.00%	267	0.38%	9999	12.46%
83	I295	12.00	1	AVC	16623	3506	13117	21.00%	4165	24.10%	2427	15.61%
84	I295	2.90	11	WIM	29744	4170	25574	14.00%	3076	10.74%	370	1.43%
85	I295	3.10	11	AVC	24226	3821	20406	16.00%	3076	13.10%	370	1.78%
86	I295	35.70	11	WIM	109017	6938	102079	6.00%	8394	7.60%	-38364	~~60.21%~~
87	I295	38.70	11	AVC	76613	6057	70557	8.00%	5433	7.15%	613	0.86%
88	I295	39.58	11	AVC	32521	3930	28591	12.00%	5433	15.97%	613	2.10%
89	I295	39.60	11	WIM	86689	6660	80029	8.00%	5433	6.36%	613	0.76%
90	I295	43.70	11	AVC	24389	4238	20151	17.00%	9263	31.49%	-12202	~~153.59%~~
91	I700	0.00	12	WIM	37726	4300	33426	11.40%	221	0.66%	4621	12.15%
92	I78	14.50	1	WIM	75699	11204	64495	15.00%	7706	10.67%	-1022	~~1.61%~~
93	I78	26.90	1	AVC	48641	7184	41457	15.00%	5466	11.65%	3004	6.76%
94	I78	33.90	1	AVC	39332	3647	35685	9.00%	3571	9.10%	443	1.23%
95	I78	44.20	11	AVC	45638	3066	42572	7.00%	1881	4.23%	-2866	~~7.22%~~
96	I78	53.70	11	AVC	148597	20236	128361	14.00%	23750	15.61%	-8453	~~7.05%~~
97	I80	32.40	11	WIM	107167	7928	99239	7.00%	2792	2.74%	-3929	~~4.12%~~
98	I80	47.20	11	AVC	90744	7426	83318	8.00%	2060	2.41%	3989	4.57%
99	I80	52.85	11	AVC	114604	12913	101691	11.00%	741	0.72%	11949	10.51%
100	I80	58.60	11	AVC	122017	38518	83499	32.00%	24170	22.45%	2491	2.90%
101	I80	61.30	11	AVC	120934	11353	109581	9.00%	11771	9.70%	857	0.78%
102	I80	63.20	11	AVC	49604	5014	44590	10.00%	5767	11.45%	-6788	~~17.96%~~
103	I80	66.20	11	WIM	163024	7906	155118	5.00%	10312	6.23%	-15429	~~11.05%~~

Table A1. (Continued)

104	I80	8.50	1	WIM	43130	7178	35952	17.00%	4885	11.96%	4455	11.03%
105	I95	2.00	11	WIM	52960	3914	49046	7.39%	1101	2.20%	-304	~~0.62%~~
106	I95	5.60	11	AVC	31754	2430	29323	7.65%	4772	14.00%	-15515	~~112.36%~~
107	JANVIERRD	0.00	9	AVC	1566	15	1551	0.98%	98	5.94%	210	11.93%
108	MEMORIALAVE	0.00	19	AVC	1105	20	1085	1.81%	14	1.27%	149	12.07%
109	MONMOUTHAVE	0.00	19	AVC	7966	95	7871	1.19%	152	1.89%	158	1.97%
110	MOUNTAINCHURCHRD	0.00	9	AVC	178	2	176	1.15%	3	1.68%	64	26.67%
111	MOUNTRD	0.00	9	AVC	7419	47	7372	0.64%	3	0.04%	66	0.89%
112	MYRTLEST	0.00	19	AVC	7866	88	7778	1.11%	165	2.08%	149	1.88%
113	NJ122	3.00	14	AVC	9026	684	8342	7.58%	434	4.95%	1437	14.69%
114	NJ140	0.20	16	AVC	6252	591	5662	9.45%	4	0.07%	119	2.06%
115	NJ147	2.80	2	AVC	6870	50	6821	0.73%	48	0.70%	341	4.76%
116	NJ15	7.00	12	WIM	38122	660	37462	1.73%	1412	3.63%	1508	3.87%
117	NJ157	0.30	16	AVC	3794	6	3788	0.16%	74	1.92%	133	3.39%
118	NJ166	0.60	16	AVC	26747	526	26221	1.97%	114	0.43%	580	2.16%
119	NJ168	1.00	14	WIM	11893	90	11803	0.76%	625	5.03%	1360	10.33%
120	NJ169	3.90	14	AVC	11121	1738	9384	15.62%	1732	15.58%	1443	13.33%
121	NJ173	1.10	7	AVC	5749	52	5697	0.90%	25	0.44%	96	1.66%
122	NJ173	2.27	7	AVC	5260	106	5154	2.01%	32	0.62%	170	3.19%
123	NJ175	2.40	16	AVC	1414	6	1408	0.44%	12	0.85%	133	8.63%
124	NJ18	27.00	12	WIM	42608	2417	40191	5.67%	3945	8.94%	12352	23.51%
125	NJ181	5.10	16	AVC	12638	753	11885	5.96%	177	1.47%	1045	8.08%
126	NJ182	0.40	14	AVC	35896	677	35219	1.89%	1695	4.59%	2080	5.58%
127	NJ183	0.85	14	AVC	22881	234	22646	1.02%	664	2.85%	1339	5.58%
128	NJ19	1.30	12	AVC	20547	2258	18289	10.99%	6187	25.28%	-4094	~~28.84%~~
129	NJ208	6.50	14	AVC	67023	5225	61798	7.80%	4513	6.81%	3193	4.91%
130	NJ21	5.00	12	AVC	19203	5370	13833	27.97%	1932	12.25%	-2731	~~24.60%~~
131	NJ23	19.10	14	AVC	28453	2550	25903	8.96%	443	1.68%	1773	6.41%
132	NJ23	24.00	14	WIM	25996	318	25678	1.22%	202	0.78%	1508	5.55%
133	NJ24	8.40	12	AVC	81047	13869	67178	17.11%	4237	5.93%	13575	16.81%
134	NJ27	9.10	14	AVC	23141	260	22881	1.12%	196	0.85%	1358	5.60%
135	NJ28	22.06	14	AVC	13765	316	13449	2.29%	2642	16.42%	1031	7.12%
136	NJ284	2.50	6	AVC	3637	162	3474	4.46%	87	2.44%	461	11.72%
137	NJ284	5.80	6	AVC	1636	131	1505	8.00%	42	2.71%	117	7.21%
138	NJ29	7.40	12	AVC	18034	470	17564	2.60%	4135	19.06%	-2441	~~16.14%~~
139	NJ3	0.80	12	AVC	93906	9199	84708	9.80%	1703	1.97%	10756	11.27%
140	NJ31	0.56	14	AVC	8080	223	7857	3.00%	1049	11.78%	2135	21.37%
141	NJ31	13.00	2	WIM	14715	1247	13468	8.00%	48	0.36%	612	4.35%
142	NJ31	14.10	2	AVC	20155	2012	18143	10.00%	109	0.60%	194	1.06%
143	NJ31	30.10	2	WIM	23156	886	22270	4.00%	5104	18.65%	-9645	~~76.40%~~
144	NJ31	40.40	2	WIM	19093	1161	17932	6.00%	3794	17.46%	-4270	~~31.25%~~
145	NJ31	42.65	14	AVC	15642	1618	14024	10.00%	1640	10.47%	530	3.64%
146	NJ31	44.00	2	AVC	13130	1728	11402	13.00%	1256	9.92%	-718	~~6.72%~~
147	NJ31	7.95	14	AVC	22425	1998	20427	9.00%	528	2.52%	1060	4.93%
148	NJ33	0.40	14	AVC	11427	885	10542	7.74%	1469	12.23%	1940	15.54%
149	NJ33	24.00	2	WIM	22730	617	22113	2.71%	71	0.32%	636	2.80%
150	NJ33	29.90	14	AVC	20145	728	19418	3.61%	2058	9.58%	1556	7.42%
151	NJ33	7.20	14	AVC	9883	590	9293	5.97%	541	5.50%	1717	15.59%
152	NJ34	1.00	6	WIM	32874	296	32578	0.90%	47	0.14%	88	0.27%
153	NJ34	6.00	6	WIM	25537	1124	24413	4.40%	938	3.70%	1305	5.07%
154	NJ35	10.50	14	AVC	24716	187	24529	0.75%	572	2.28%	1116	4.35%
155	NJ36	9.80	14	AVC	13780	144	13636	1.05%	1675	10.94%	2001	12.80%
156	NJ38	0.90	14	AVC	24683	168	24515	0.68%	267	1.08%	1448	5.58%
157	NJ38	11.40	14	AVC	23459	125	23334	0.53%	1197	4.88%	1286	5.22%
158	NJ38	2.30	14	AVC	28400	264	28137	0.93%	1642	5.51%	533	1.86%

Table A1. (Continued)

159	NJ38	5.35	14	AVC	33939	202	33738	0.59%	1824	5.13%	1579	4.47%
160	NJ41	4.00	14	AVC	26421	2004	24416	7.59%	583	2.33%	1248	4.86%
161	NJ42	0.30	14	AVC	14582	167	14415	1.15%	983	6.38%	887	5.80%
162	NJ42	6.50	12	AVC	17423	1428	15995	8.19%	1215	7.06%	5682	26.21%
163	NJ440	3.00	12	AVC	52928	3067	49861	5.79%	2125	4.09%	11654	18.94%
164	NJ47	2.50	2	AVC	11410	147	11262	1.00%	2861	20.26%	-218	~~-1.97%~~
165	NJ47	43.00	16	AVC	22662	395	22267	2.00%	72	0.32%	172	0.77%
166	NJ49	2.83	14	AVC	13297	406	12892	3.00%	812	5.93%	697	5.13%
167	NJ49	25.40	14	AVC	8952	225	8728	3.00%	738	7.80%	1005	10.33%
168	NJ49	53.60	6	AVC	4903	407	4495	8.00%	475	9.56%	487	9.78%
169	NJ52	2.58	14	AVC	9530	89	9441	0.93%	711	7.00%	1425	13.11%
170	NJ55	28.80	12	AVC	2186	396	1790	18.00%	1413	44.11%	12312	87.31%
171	NJ55	36.50	12	AVC	23214	1707	21508	7.00%	1500	6.52%	4154	16.19%
172	NJ55	37.00	12	WIM	28781	2183	26598	8.00%	1500	5.34%	4154	13.51%
173	NJ55	57.00	12	WIM	57048	2215	54833	4.00%	1952	3.44%	11007	16.72%
174	NJ63	1.20	14	AVC	21111	1666	19445	7.89%	3902	16.71%	1809	8.51%
175	NJ68	3.00	6	WIM	5818	144	5674	2.48%	59	1.03%	110	1.90%
176	NJ71	14.60	16	AVC	10107	69	10038	0.68%	118	1.16%	95	0.94%
177	NJ71	15.00	16	AVC	11598	50	11548	0.43%	214	1.82%	232	1.97%
178	NJ71	4.60	16	AVC	11598	50	11548	0.43%	214	1.82%	232	1.97%
179	NJ72	2.00	2	WIM	8765	343	8422	3.91%	48	0.57%	412	4.66%
180	NJ73	26.72	14	AVC	28658	696	27962	2.43%	1172	4.02%	279	0.99%
181	NJ77	0.70	16	AVC	7508	143	7365	1.90%	26	0.35%	89	1.19%
182	NJ77	10.18	6	AVC	8284	375	7909	4.53%	348	4.21%	576	6.79%
183	NJ77	12.40	6	AVC	2245	279	1966	12.41%	3	0.15%	64	3.15%
184	NJ77	17.50	6	AVC	2351	242	2109	10.29%	28	1.31%	134	5.97%
185	NJ77	3.70	16	AVC	6671	320	6351	4.80%	36	0.56%	147	2.26%
186	NJ90	2.40	12	AVC	12621	726	11895	5.75%	2450	17.08%	488	3.94%
187	NJ90	3.00	12	AVC	10379	696	9683	6.71%	2450	20.19%	488	4.80%
188	NJ94	17.30	6	AVC	6037	134	5903	2.22%	313	5.04%	871	12.86%
189	NORTHEASTBLVD	0.00	17	AVC	225	9	216	4.05%	30	12.20%	80	27.03%
190	OCEANAVE	0.00	19	AVC	1880	9	1870	0.51%	32	1.68%	199	9.62%
191	OLDFARMERS	0.00	9	AVC	446	1	445	0.23%	44	9.00%	84	15.88%
192	OLDMIDDLEVLE	0.00	9	AVC	32	3	29	9.68%	3	9.38%	70	70.71%
193	PARKAVE	0.00	17	AVC	7735	114	7621	1.47%	32	0.42%	144	1.85%
194	ROCKMANAVE	0.00	17	AVC	3481	32	3449	0.93%	324	8.59%	29	0.83%
195	ROWLANDAVE	0.00	19	AVC	1715	40	1675	2.34%	119	6.63%	97	5.47%
196	RT502	22.03	14	AVC	12022	507	11515	4.21%	110	0.95%	1493	11.48%
197	RT502	5.63	16	AVC	8952	136	8815	1.52%	113	1.27%	133	1.49%
198	RT519	46.97	7	AVC	4651	282	4369	6.06%	175	3.85%	261	5.64%
199	RT522	0.00	16	AVC	6393	310	6083	4.85%	442	6.77%	497	7.55%
200	RT524	1.16	14	AVC	12426	428	11998	3.45%	378	3.05%	1367	10.23%
201	RT524	39.24	16	AVC	9334	48	9286	0.52%	158	1.67%	149	1.58%
202	RT530	2.93	7	AVC	14483	340	14143	2.35%	80	0.56%	187	1.30%
203	RT540	0.00	16	AVC	8421	152	8269	1.80%	127	1.51%	220	2.59%
204	RT543	0.00	14	AVC	6607	203	6405	3.07%	1175	15.50%	1688	20.86%
205	RT546	0.00	16	AVC	9126	85	9041	0.93%	61	0.67%	133	1.45%
206	RT552	0.00	16	AVC	5959	192	5767	3.22%	43	0.74%	59	1.01%
207	RT553	0.00	7	AVC	763	39	725	5.05%	21	2.82%	90	11.04%
208	RT559	1.24	16	AVC	10968	526	10442	4.80%	139	1.31%	167	1.57%
209	RT559ALT	0.00	16	AVC	8754	361	8393	4.12%	139	1.63%	167	1.95%
210	RT565	3.50	8	AVC	9117	201	8916	2.20%	114	1.26%	237	2.59%
211	RT571	35.00	14	AVC	12088	311	11777	2.58%	454	3.71%	1134	8.78%
212	RT579	0.00	14	AVC	17229	476	16753	2.76%	330	1.93%	1501	8.22%
213	RT579	7.10	7	AVC	7855	165	7689	2.10%	177	2.25%	280	3.51%

Table A1. (Continued)

214	RUNNYMEDERD	0.00	17	AVC	5118	54	5064	1.05%	120	2.31%	125	2.41%
215	SANHICANDR	0.00	19	AVC	16505	281	16225	1.70%	36	0.22%	169	1.03%
216	SBEAUMONTPL	0.00	19	AVC	206	6	199	3.08%	46	18.78%	119	37.42%
217	SHANNONRD	0.00	9	AVC	324	10	314	3.16%	4	1.26%	64	16.93%
218	SMITHST	0.00	9	AVC	177	3	174	1.73%	52	23.01%	166	48.82%
219	TILLEYAVE	0.00	19	AVC	1621	26	1595	1.63%	68	4.09%	120	7.00%
220	UNIONMILLRD	0.00	17	AVC	2878	126	2752	4.37%	27	0.97%	133	4.61%
221	US1	1.30	14	AVC	53862	6807	47055	13.00%	756	1.58%	1183	2.45%
222	US1	1.65	12	AVC	33251	1441	31809	4.00%	5288	14.25%	7625	19.34%
223	US1	18.00	14	WIM	52575	2234	50341	4.00%	3282	6.12%	1746	3.35%
224	US1	4.40	12	AVC	19693	1652	18041	8.00%	5288	22.67%	7625	29.71%
225	US1	47.20	12	AVC	76775	7124	69651	9.00%	11377	14.04%	104629	60.04%
226	US1	50.50	12	AVC	101918	19740	82177	19.00%	5801	6.59%	35436	30.13%
227	US130	3.40	16	WIM	12641	156	12485	1.00%	158	1.25%	292	2.29%
228	US130	57.00	14	WIM	24140	1096	23044	5.00%	706	2.97%	1543	6.28%
229	US130	71.00	6	WIM	31103	1266	29837	4.00%	1296	4.16%	1579	5.03%
230	US202	1.90	2	AVC	9940	797	9143	8.02%	48	0.52%	412	4.31%
231	US202	4.00	2	WIM	9675	335	9340	3.46%	48	0.51%	683	6.81%
232	US206	101.50	2	AVC	14251	437	13814	3.00%	1034	6.96%	-161	~~1.18%~~
233	US206	108.70	14	AVC	20278	364	19913	2.00%	665	3.23%	869	4.18%
234	US206	109.70	14	AVC	23319	450	22869	2.00%	644	2.74%	1000	4.19%
235	US206	112.35	2	AVC	8632	319	8313	4.00%	169	1.99%	-500	~~6.40%~~
236	US206	114.60	2	AVC	14555	961	13594	7.00%	400	2.86%	-3506	~~34.75%~~
237	US206	129.10	2	AVC	5414	194	5220	4.00%	54	1.02%	739	12.40%
238	US206	22.00	2	WIM	13484	848	12636	6.00%	419	3.21%	-609	~~5.06%~~
239	US206	3.40	14	AVC	9415	675	8741	7.00%	221	2.47%	1463	14.34%
240	US206	39.60	14	AVC	12716	180	12536	1.00%	728	5.49%	1077	7.91%
241	US206	47.05	14	AVC	13537	515	13022	4.00%	1105	7.82%	-292	~~2.20%~~
242	US206	61.10	2	AVC	19349	718	18631	4.00%	183	0.97%	-2213	~~12.48%~~
243	US206	88.40	2	AVC	21106	1470	19637	7.00%	183	0.92%	-2213	~~12.70%~~
244	US206	9.80	2	AVC	5217	363	4854	7.00%	941	16.24%	380	7.26%
245	US206	93.00	14	AVC	31991	1848	30143	6.00%	665	2.16%	1913	5.97%
246	US206	97.50	14	AVC	17657	526	17131	3.00%	577	3.26%	1460	7.85%
247	US22	0.40	14	AVC	35958	3319	32639	9.23%	366	1.11%	1334	3.93%
248	US22	0.90	14	AVC	46197	8497	37701	18.39%	815	2.12%	909	2.35%
249	US22	27.00	6	WIM	29695	432	29263	1.45%	432	1.45%	630	2.11%
250	US22	32.00	16	WIM	36752	574	36178	1.56%	32	0.09%	198	0.54%
251	US22	37.60	14	AVC	45329	1243	44086	2.74%	1740	3.80%	1463	3.21%
252	US22	4.10	14	AVC	40423	8663	31760	21.43%	1628	4.88%	7589	19.29%
253	US30	19.00	14	AVC	11228	178	11050	1.58%	499	4.32%	1205	9.83%
254	US30	28.60	14	AVC	18998	926	18072	4.88%	402	2.18%	1547	7.89%
255	US322	24.60	14	AVC	10478	995	9484	9.49%	847	8.20%	998	9.52%
256	US322	28.00	6	WIM	17007	268	16739	1.58%	75	0.45%	262	1.54%
257	US40	24.50	2	AVC	10239	1202	9038	12.00%	675	6.95%	-551	~~6.49%~~
258	US40	28.40	2	WIM	8683	458	8225	5.00%	348	4.06%	-82	~~1.01%~~
259	US40	3.00	2	WIM	12922	1038	11884	8.00%	108	0.90%	-571	~~5.05%~~
260	US40	33.00	14	AVC	23875	1905	2196	8.00%	685	23.78%	1789	44.89%
261	US40	61.60	14	AVC	15753	154	15599	1.00%	755	4.62%	1271	7.53%
262	US46	16.40	6	AVC	10766	341	10425	3.17%	376	3.48%	704	6.33%
263	US46	25.00	2	WIM	23982	416	23566	1.73%	176	0.74%	524	2.18%
264	US46	6.30	2	AVC	8718	1169	7548	13.41%	2187	22.47%	-3959	~~110.31%~~
265	US46	63.70	14	AVC	22446	2157	20289	9.61%	2529	11.08%	1825	8.25%
266	US9	111.80	14	WIM	54532	886	53646	2.00%	1369	2.49%	1065	1.95%
267	US9	15.50	6	AVC	9825	184	9641	2.00%	414	4.12%	601	5.87%
268	US9	40.20	14	AVC	15634	218	15416	1.00%	1167	7.04%	1820	10.56%

Table A1. (End)

269	W59THST	0.00	14	AVC	14266	2551	11715	17.88%	1429	10.87%	1649	12.34%
270	WEISSRD	0.00	19	AVC	593	2	591	0.36%	41	6.49%	119	16.76%
271	WESTCOAT	0.00	16	AVC	5095	68	5028	1.33%	54	1.06%	119	2.31%

Note 1. Observed Truck Percentages are calculated as follows: Observed Truck % = A/(B+C)
where: A= Observed Truck Daily Volumes, B=Observed Car Daily Volumes
Note 2. Predicted Truck Percentages are calculated as follows: Predicted Truck % = A/(C+B)
where: A= Predicted Truck Daily Volumes Using the Optimization Models, B=Observed Car Daily Volumes, C= Observed Truck Daily Volumes
Note 3. Predicted Truck Percentages are calculated as follows: Predicted Truck % = A/(C+B)
where: A= Predicted Truck Daily Volumes Using the Regression Models, B=Observed Car Daily Volumes, C= Observed Truck Daily Volumes

TABLE A 2: OBSERVED AADT AND TRUCK VOLUMES AND OBSERVED TRUCK VOLUMES ON SELECTED HIGHWAY SECTIONS

							OBSERVED				OPTIMIZATION MODEL		REGRESSION MODEL	
SECTION	FC	TYPE	SECTION	HIGHWAY	MPIH	LENGTH OF SECTION	ADT	DAILY TRUCK VOLUMES	DAILY CAR VOLUMES	TRUCK PERCENTAGES	PREDICTED TRUCK VOLUMES	TRUCK PERCENTAGES	PREDICTED TRUCK VOLUMES	TRUCK PERCENTAGES
I278														
I287_08	1	Rural Interstate	US 206/202 to NJ 124	US 206/202	22.21	13.68	94154	9276	84878	9.85%	3049	3.24%	9269	9.84%
I287_13	11	Urban Interstate	US 202 to NJ 23	US 202	47.11	6.03	68814	14310	54504	20.80%	11637	16.91%	10086	14.66%
I287_14	11	Urban Interstate	NJ 23 to US 202 (2nd)	NJ 23	53.14	5.72	29691	5334	24357	17.97%	8578	28.89%	12167	40.98%
I287_15	11	Urban Interstate	US 202 (2nd) to NJ 17	US 202	58.86	8.08	28404	4179	24225	14.71%	5712	20.11%	10826	38.11%
I287_15	11	Urban Interstate	US 202 (2nd) to NJ 17	US 202	58.86	8.08	54240	7482	46758	13.79%	5712	10.53%	10826	19.96%
I287_16	11	Urban Interstate	NJ 17 to State Boundary	NJ 17	66.94	0.4	84333	14093	70239	16.71%	267	0.32%	10004	11.86%

							OBSERVED				OPTIMIZATION MODEL		REGRESSION MODEL	
SECTION	FC	TYPE	SECTION	HIGHWAY	MPIH	LENGTH OF SECTION	ADT	DAILY TRUCK VOLUMES	DAILY CAR VOLUMES	TRUCK PERCENTAGES	PREDICTED TRUCK VOLUMES	TRUCK PERCENTAGES	PREDICTED TRUCK VOLUMES	TRUCK PERCENTAGES
I295														
I295_02	1	Rural Interstate	US 130/NJ 49 to US 130	US130/NJ49	0.95	13.35	16623	3506	13117	21.09%	3659	22.01%	3794	22.82%
I295_02	1	Rural Interstate	US 130/NJ 49 to US 130	US130/NJ49	0.95	13.35	29744	4170	25574	14.02%	3659	12.30%	3794	12.76%
I295_02	1	Rural Interstate	US 130/NJ 49 to US 130	US130/NJ49	0.95	13.35	24226	3821	20406	15.77%	3659	15.10%	3794	15.66%
I295_04	11	Urban Interstate	I 76 to NJ 73	I76	27.1	9.76	109017	6938	102079	6.36%	8465	7.76%	6786	6.22%
I295_05	11	Urban Interstate	NJ 73 to NJ 38	NJ73	36.86	3.74	76613	6057	70557	7.91%	7281	9.50%	16281	21.25%
I295_05	11	Urban Interstate	NJ 73 to NJ 38	NJ73	36.86	3.74	32521	3930	28591	12.08%	7281	22.39%	16281	50.06%
I295_05	11	Urban Interstate	NJ 73 to NJ 38	NJ73	36.86	3.74	86689	6660	80029	7.68%	7281	8.40%	16281	18.78%
I295_06	1	Rural Interstate	NJ 38 to US 130	NJ38	40.6	16.22	24389	4238	20151	17.38%	11709	48.01%	19729	80.89%

Table A 2 (Continued)

							OBSERVED				OPTIMIZATION MODEL		REGRESSION MODEL	
SECTION	FC	TYPE	SECTION	HIGHWAY	MPIH	LENGTH OF SECTION	ADT	DAILY TRUCK VOLUMES	DAILY CAR VOLUMES	TRUCK PERCENTAGES	PREDICTED TRUCK VOLUMES	TRUCK PERCENTAGES	PREDICTED TRUCK VOLUMES	TRUCK PERCENTAGES
I78														
I78_01	1	Rural Interstate	Delaware River to NJ 31	Delaware River	0	17.33	75699	11204	64495	14.80%	8350	11.03%	11377	15.03%
I78_02	1	Rural Interstate	NJ 31 to I 287	NJ31	17.33	13.47	48641	7184	41457	14.77%	5466	11.24%	6410	13.18%
I78_04	1	Rural Interstate	CO 525 to NJ 24	US202/206	31.25	18.01	39332	3647	35685	9.27%	3136	7.97%	3366	8.56%
I78_04	1	Rural Interstate	CO 525 to NJ 24	US202/206	31.25	18.01	45638	3066	42572	6.72%	3136	6.87%	3366	7.38%
I78_05	11	Urban Interstate	NJ 24 to NJ 27	NJ24	49.26	7.97	148597	20236	128361	13.62%	26585	17.89%	27453	18.47%
I80														
I80_02	1	Rural Interstate	US 46 to US 46	US46	4.32	21.93	43130	7178	35952	16.64%	4884	11.32%	7015	16.26%
I80_04	1	Rural Interstate	US 206 to NJ 15	US206	27.19	6.83	107167	7928	99239	7.40%	2376	2.22%	4829	4.51%
I80_07	11	Urban Interstate	I 280 to CO 613	I280	46.36	6.12	90744	7426	83318	8.18%	5080	5.60%	25284	27.86%
I80_08	11	Urban Interstate	CO 613 to NJ 23	CO613	52.48	1.14	114604	12913	101691	11.27%	3225	2.81%	20583	17.96%
I80_09	11	Urban Interstate	NJ 23 to NJ 20	NJ23	53.62	6.79	122017	38518	83499	31.57%	27509	22.55%	57541	47.16%
I80_10	11	Urban Interstate	NJ 20 to Garden State Pkwy	NJ20	60.41	1.41	120934	11353	109581	9.39%	9396	7.77%	22793	18.85%
I80_11	11	Urban Interstate	Garden State Pkwy to NJ 17	GSP	61.82	3.37	49604	5014	44590	10.11%	8228	16.59%	29545	59.56%
I80_12	11	Urban Interstate	NJ 17 to New Jersey Turnpike	NJ17	65.19	2.94	163024	7906	155118	4.85%	12520	7.68%	38608	23.68%

Table A 2 (Continued)

							OBSERVED				OPTIMIZATION MODEL		REGRESSION MODEL	
SECTION	FC	TYPE	SECTION	HIGHWAY	MPIH	LENGTH OF SECTION	ADT	DAILY TRUCK VOLUMES	DAILY CAR VOLUMES	TRUCK PERCENTAGES	PREDICTED TRUCK VOLUMES	TRUCK PERCENTAGES	PREDICTED TRUCK VOLUMES	TRUCK PERCENTAGES
NJ31														
NJ31_01	14	Urban Major	US 206 to CO 622	US206	0	1.79	8080	223	7857	2.76%	1049	12.98%	2226	27.55%
NJ31_03	2	Rural Principal Arterial	I 95 to CO 518	I95	4.84	7.37	22425	1998	20427	8.91%	528	2.35%	3713	16.56%
NJ31_04	2	Rural Principal Arterial	CO 518 to CO 579	CO518	12.21	1.76	14715	1247	13468	8.47%	48	0.33%	636	4.32%
NJ31_05	2	Rural Principal Arterial	CO 579 to US 202	CO579	13.97	2.4	20155	2012	18143	9.98%	109	0.54%	1713	8.50%
NJ31_06	2	Rural Principal Arterial	US 202 to I 78	US202/NJ31	16.37	15.52	23156	886	22270	3.83%	5104	22.04%	749	3.23%
NJ31_06	2	Rural Principal Arterial	US 202 to I 78	US202/NJ31	16.37	15.52	15642	1618	14024	10.34%	5104	32.63%	749	4.79%
NJ31_07	2	Rural Principal Arterial	I 78 to NJ 57	I78/US22	31.89	10.95	19093	1161	17932	6.08%	1849	9.68%	1924	10.08%
NJ31_08	2	Rural Principal Arterial	NJ 57 to US 46	NJ57	42.84	6.09	13130	1728	11402	13.16%	1256	9.57%	1111	8.46%
							OBSERVED				OPTIMIZATION MODEL		REGRESSION MODEL	
SECTION	FC	TYPE	SECTION	HIGHWAY	MPIH	LENGTH OF SECTION	ADT	DAILY TRUCK VOLUMES	DAILY CAR VOLUMES	TRUCK PERCENTAGES	PREDICTED TRUCK VOLUMES	TRUCK PERCENTAGES	PREDICTED TRUCK VOLUMES	TRUCK PERCENTAGES
NJ47														
NJ47_01	2	Rural Principal Arterial	GSP to NJ 83	GSP	3.08	14.46	11410	147	11262	1.29%	2861	25.07%	269	2.36%
NJ47_07	16	Urban Minor	NJ 56 to US 40	NJ56	46.55	5.97	22662	395	22267	1.74%	72	0.32%	647	2.85%
							OBSERVED				OPTIMIZATION MODEL		REGRESSION MODEL	
SECTION	FC	TYPE	SECTION	HIGHWAY	MPIH	LENGTH OF SECTION	ADT	DAILY TRUCK VOLUMES	DAILY CAR VOLUMES	TRUCK PERCENTAGES	PREDICTED TRUCK VOLUMES	TRUCK PERCENTAGES	PREDICTED TRUCK VOLUMES	TRUCK PERCENTAGES
NJ49														
NJ49_01	2	Rural Principal Arterial	I 295/US 40 to NJ 45	I295	0	19.72	13297	406	12892	3.05%	812	6.11%	-80	-0.60%
NJ49_02	2	Rural Principal Arterial	NJ 45 to NJ 77	NJ45	19.72	5.86	8952	225	8728	2.51%	738	8.24%	4164	46.51%
NJ49_04	14	Urban Major	NJ 47 to NJ 50	NJ47	36.4	17.36	4903	407	4495	8.30%	73	1.49%	1238	25.25%

Table A 2 (Continued)

SECTION	FC	TYPE	SECTION	HIGHWAY	MPIH	LENGTH OF SECTION	OBSERVED				OPTIMIZATION MODEL		REGRESSION MODEL	
							ADT	DAILY TRUCK VOLUMES	DAILY CAR VOLUMES	TRUCK PERCENTAGES	PREDICTED TRUCK VOLUMES	TRUCK PERCENTAGES	PREDICTED TRUCK VOLUMES	TRUCK PERCENTAGES
NJ55														
NJ55_03	12	Expressways	NJ 47 to NJ 56	NJ47	27.79	4.9	2186	396	1790	18.12%	1413	64.64%	847	38.75%
NJ55_04	12	Expressways	NJ 56 to US 40	NJ56	32.69	6.67	23214	1707	21508	7.35%	1500	6.46%	2833	12.20%
NJ55_04	12	Expressways	NJ 56 to US 40	NJ56	32.69	6.67	28781	2183	26598	7.58%	1500	5.21%	2833	9.84%
NJ55_07	12	Expressways	NJ 47 to NJ 42	NJ47	56.37	4.12	57048	2215	54833	3.88%	1952	3.42%	2385	4.18%

SECTION	FC	TYPE	SECTION	HIGHWAY	MPIH	LENGTH OF SECTION	OBSERVED				OPTIMIZATION MODEL		REGRESSION MODEL	
							ADT	DAILY TRUCK VOLUMES	DAILY CAR VOLUMES	TRUCK PERCENTAGES	PREDICTED TRUCK VOLUMES	TRUCK PERCENTAGES	PREDICTED TRUCK VOLUMES	TRUCK PERCENTAGES
US1														
US1_03	12	Expressways	NJ 129 to Perry St	NJ129	0.76	0.58	53862	6807	47055	12.64%	1430	2.65%	5537	10.28%
US1_04	12	Expressways	Perry St to I 295	Perry St	1.34	5.42	33251	1441	31809	4.33%	2766	8.32%	1468	4.41%
US1_04	12	Expressways	Perry St to I 295	Perry St	1.34	5.42	19693	1652	18041	8.39%	2766	14.05%	1468	7.45%
US1_05	14	Urban Major	I 295 to US 130	I295	6.76	17.88	52575	2234	50341	4.25%	3282	6.24%	2039	3.88%
US1_13	2	Rural Principal Arterial	NJ 439 to I 78	NJ439	43.11	4.73	76775	7124	69651	9.28%	27171	35.39%	273500	356.24%
US1_14	12	Expressways	I 78 to I 95	I78	47.84	3.69	101918	19740	82177	19.37%	5800	5.69%	19763	19.39%

SECTION	FC	TYPE	SECTION	HIGHWAY	MPIH	LENGTH OF SECTION	OBSERVED				OPTIMIZATION MODEL		REGRESSION MODEL	
							ADT	DAILY TRUCK VOLUMES	DAILY CAR VOLUMES	TRUCK PERCENTAGES	PREDICTED TRUCK VOLUMES	TRUCK PERCENTAGES	PREDICTED TRUCK VOLUMES	TRUCK PERCENTAGES
US130														
US130_01	6	Rural Minor	I 295 to US 322	I295/US40	0	12.21	12641	156	12485	1.23%	158	1.25%	362	2.86%
US130_12	14	Urban Major	US 206 SB to I 195	US206SB	56.44	4.93	24140	1096	23044	4.54%	706	2.92%	1590	6.59%
US130_14	2	Rural Principal Arterial	NJ 33 to NJ 32	NJ33	62.64	11.87	31103	1266	29837	4.07%	1296	4.17%	14192	45.63%

Table A 2 (Continued)

							OBSERVED				OPTIMIZATION MODEL		REGRESSION MODEL	
SECTION	FC	TYPE	SECTION	HIGHWAY	MPIH	LENGTH OF SECTION	ADT	DAILY TRUCK VOLUMES	DAILY CAR VOLUMES	TRUCK PERCENTAGES	PREDICTED TRUCK VOLUMES	TRUCK PERCENTAGES	PREDICTED TRUCK VOLUMES	TRUCK PERCENTAGES
US206														
US206_01	2	Rural Principal Arterial	US 30 to CO 541	US30	0	9.45	9415	675	8741	7.17%	221	2.35%	-324	-3.44%
US206_02	2	Rural Principal Arterial	CO 541 to NJ 70	C0541	9.45	8.21	5217	363	4854	6.96%	941	18.04%	1142	21.89%
US206_03	2	Rural Principal Arterial	NJ 70 to NJ 38	NJ70	17.66	5.82	13484	848	12636	6.29%	419	3.11%	931	6.90%
US206_07	14	Urban Major	I 195 to NJ 129	I195	38.71	3.26	12716	180	12536	1.42%	728	5.73%	1117	8.78%
US206_14	14	Urban Major	I 295 to NJ 27	I295	48.01	5.94	13537	515	13022	3.80%	1105	8.16%	-296	-2.19%
US206_16	14	Urban Major	US 202 to CO 625	US202	71.31	18.8	19349	718	18631	3.71%	951	4.91%	1059	5.47%
US206_16	14	Urban Major	US 202 to CO 625	US202	71.31	18.8	21106	1470	19637	6.96%	951	4.51%	1059	5.02%
US206_17	2	Rural Principal Arterial	CO 625 to I 80	CO625	90.11	7.1	31991	1848	30143	5.78%	288	0.90%	2260	7.06%
US206_18	2	Rural Principal Arterial	I 80 to NJ 183	I80	97.21	0.69	17657	526	17131	2.98%	577	3.27%	1976	11.19%
US206_19	14	Urban Major	NJ 183 to CO 611	NJ183	97.9	8.33	14251	437	13814	3.07%	706	4.95%	1635	11.47%
US206_20	2	Rural Principal Arterial	CO 611 to NJ 94	CO611	106.23	3.02	20278	364	19913	1.80%	665	3.28%	2393	11.80%
US206_21	2	Rural Principal Arterial	NJ 94 to NJ 94	NJ94	109.25	2.32	23319	450	22869	1.93%	644	2.76%	2689	11.53%
US206_22	2	Rural Principal Arterial	NJ 94 to NJ 15	NJ94	111.57	2.57	8632	319	8313	3.70%	191	2.21%	375	4.34%
US206_23	2	Rural Principal Arterial	NJ 15 to CO 560	NJ15	114.14	7.86	14555	961	13594	6.60%	400	2.75%	-130	-0.89%
US206_24	2	Rural Principal Arterial	CO 560 to CO 521	CO560	122	7.3	5414	194	5220	3.58%	54	1.00%	863	15.94%

Table A 2 (End)

SECTION	FC	TYPE	SECTION	HIGHWAY	MPIH	LENGTH OF SECTION	OBSERVED				OPTIMIZATION MODEL		REGRESSION MODEL	
							ADT	DAILY TRUCK VOLUMES	DAILY CAR VOLUMES	TRUCK PERCENTAGES	PREDICTED TRUCK VOLUMES	TRUCK PERCENTAGES	PREDICTED TRUCK VOLUMES	TRUCK PERCENTAGES
US40														
US40_01	2	Rural Principal Arterial	NJ 140 to NJ 45	NJ140	1.85	8.17	12922	1038	11884	8.03%	108	0.84%	290	2.24%
US40_03	2	Rural Principal Arterial	NJ 77 to NJ 55	NJ77	16.52	9.02	10239	1202	9038	11.74%	675	6.59%	1049	10.25%
US40_05	14	Urban Major	NJ 47 to CO 555	NJ47	26.71	3.5	8683	458	8225	5.27%	569	6.55%	1668	19.21%
US40_06	2	Rural Principal Arterial	CO 555 to NJ 54	CO555	30.21	4.92	238751	19054	219696	7.98%	2227	0.93%	-1404	-0.59%
US40_11	14	Urban Major	US 9 to Atlantic Ave (end)	US9	59.09	5.19	15753	154	15599	0.98%	755	4.79%	1309	8.31%
SECTION	FC	TYPE	SECTION	HIGHWAY	MPIH	LENGTH OF SECTION	OBSERVED				OPTIMIZATION MODEL		REGRESSION MODEL	
							ADT	DAILY TRUCK VOLUMES	DAILY CAR VOLUMES	TRUCK PERCENTAGES	PREDICTED TRUCK VOLUMES	TRUCK PERCENTAGES	PREDICTED TRUCK VOLUMES	TRUCK PERCENTAGES
US9														
US9_04	2	Rural Principal Arterial	NJ 147 to NJ 83	NJ147	9.64	8.97	9825	184	9641	1.87%	414	4.21%	52	0.53%
US9_09	14	Urban Major	US 40 to US 30	US 40	39.39	3.47	15634	218	15416	1.39%	1167	7.46%	1890	12.09%
US9_19	2	Rural Principal Arterial	I 195 to NJ 33	I 195	107.05	5.86	54532	886	53646	1.62%	1368	2.51%	-9749	-17.88%

TABLE A 3: OBSERVED AADT AND TRUCK VOLUMES AND OBSERVED TRUCK VOLUMES ON 205 HIGHWAY SECTIONS OF 16 SELECTED HIGHWAYS (INCLUDING NJTPK EAST AND SOUTH)

SECTION	FC	TYPE	SECTION	HIGHWAY	MPIH	Begin MP	End MP		DAILY TRUCK VOLUMES				DAILY TRUCK VOLUME PERCENTAGES BASED ON CMS AADT		
									OBSERVED TRUCK VOLUMES	PREDICTED BY					
								OBSERVED ADT		REGRESSION	OPTIMIZATION	CMS ADT	OBSERVED	REGRESSION	OPTIMIZATION
Atlantic City Expressway															
ACE_01	12	Express ways	Baltic Ave to US 9	Baltic Ave	0.0000	0.00	5.40			30179	4927	57417	0	52.56%	8.58%
ACE_02	12	Express ways	US 9 to Garden State Pkwy	US9	5.4000	5.40	7.20			-36342	1617	52754	0	-68.89%	3.07%
ACE_03	2	Rural Interstate	Garden State Pkwy to NJ 50	GSP	7.2000	7.20	16.80			1873	2338	31717	0	5.91%	7.37%
ACE_04	2	Rural Interstate	NJ 50 to NJ 54	NJ50	16.8000	16.80	27.80			431	127	36895	0	1.17%	0.34%
ACE_05	2	Rural Interstate	NJ 54 to NJ 73	NJ54	27.8000	27.80	31.40			412	158	34275	0	1.20%	0.46%
ACE_06	2	Rural Interstate	NJ 73 to CO 536 SPUR	NJ73	31.4000	31.40	36.25			330	447	29401	0	1.12%	1.52%
ACE_07	12	Express ways	CO 536 SPUR to NJ 42	CO536	36.2500	36.25	44.19			2197	850	44052	0	4.99%	1.93%

Table A 3 (Continued)

SECTION	FC	TYPE	SECTION	HIGHWAY	MPIH	Begin MP	End MP	OBSERVED ADT	DAILY TRUCK VOLUMES OBSERVED TRUCK VOLUMES	PREDICTED BY REGRESSION	PREDICTED BY OPTIMIZATION	CMS ADT	DAILY TRUCK VOLUME PERCENTAGES BASED ON CMS AADT OBSERVED	REGRESSION	OPTIMIZATION
I287															
I287_01	11	Urban Interstate	I 95 to US 1	I 95	0.00000	0	0.93			7268	1157	83214	0.00%	8.73%	1.39%
I287_02	11	Urban Interstate	US 1 to NJ 27	US 1	0.93000	0.93	2.24			16450	2039	90576	0.00%	18.16%	2.25%
I287_03	11	Urban Interstate	NJ 27 to NJ 28	NJ 27	2.24000	2.24	13.5			19244	22113	100200	0.00%	19.21%	22.07%
I287_04	11	Urban Interstate	NJ 28 to US 22	NJ 28	13.50000	13.5	14.24			478	4516	101265	0.00%	0.47%	4.46%
I287_05	11	Urban Interstate	US 22 to US 206/202	US 22	14.24000	14.24	17.73			8978	8727	66514	0.00%	13.50%	13.12%
I287_06	11	Urban Interstate	US 206/202 to I 78	US 206/202	17.73000	17.73	21.08			8521	1033	98878	0.00%	8.62%	1.04%
I287_07	11	Urban Interstate	I 78 to US 206/202	I 78	21.08000	21.08	22.21			4181	1286	83902	0.00%	4.98%	1.53%
I287_08	1	Rural Interstate	US 206/202 to NJ 124	US 206/202	22.21000	22.21	35.89	94154	9276	9269	3049	81102	11.44%	11.43%	3.76%
I287_09	11	Urban Interstate	NJ 124 to NJ 10	NJ 124	35.89000	35.89	39.55			8001	8232	114765	0.00%	6.97%	7.17%
I287_10	11	Urban Interstate	NJ 10 to I 80	NJ 10	39.55000	39.55	42.02			10269	9369	135575	0.00%	7.57%	6.91%
I287_11	11	Urban Interstate	I 80 to US 46	I 80	42.02000	42.02	42.47			5995	2331	69532	0.00%	8.62%	3.35%
I287_12	11	Urban Interstate	US 46 to US 202	US 46	42.47000	42.47	47.11			14684	2053	57167	0.00%	25.69%	3.59%
I287_13	11	Urban Interstate	US 202 to NJ 23	US 202	47.11000	47.11	53.14	68814	14310	10086	11637	69140	20.70%	14.59%	16.83%
I287_14	11	Urban Interstate	NJ 23 to US 202 (2nd)	NJ 23	53.14000	53.14	58.86	29691	5334	12167	8578	83059	6.42%	14.65%	10.33%
I287_15	11	Urban Interstate	US 202 (2nd) to NJ 17	US 202	58.86000	58.86	58.86	28404	4179	10826	5712	62232	6.72%	17.40%	9.18%
I287_15	11	Urban Interstate	US 202 (2nd) to NJ 17	US 202	58.86000	58.86	66.94	54240	4179	10826	5712	72202	5.79%	14.99%	7.91%
I287_16	11	Urban Interstate	NJ 17 to State Boundary	NJ 17	66.94000	66.94	67.34	84333	14093	10004	267	87646	16.08%	11.41%	0.30%

Table A 3 (Continued)

SECTION	FC	TYPE	SECTION	HIGHWAY	MPIH	Begin MP	End MP		DAILY TRUCK VOLUMES				DAILY TRUCK VOLUME PERCENTAGES BASED ON CMS AADT		
									OBSERVED TRUCK VOLUMES	PREDICTED BY					
								OBSERVED ADT		REGRESSION	OPTIMIZATION	CMS ADT	OBSERVED	REGRESSION	OPTIMIZATION
I295															
I295_01	11	Urban Interstate	Delaware River to US 130/NJ 49	Delaware River	0.00000	0.00	0.95			10177	267	91396	0.0%	11.1%	0.3%
I295_02	1	Rural Interstate	US 130/NJ 49 to US 130	US130/NJ49	0.95000	0.95	14.3	16623	3821	3794	3659	33654	11.4%	11.3%	10.9%
I295_02	1	Rural Interstate	US 130/NJ 49 to US 130	US130/NJ49	0.95000	0.95	14.3	29744	3821	3794	3659	33654	11.4%	11.3%	10.9%
I295_02	1	Rural Interstate	US 130/NJ 49 to US 130	US130/NJ49	0.95000	0.95	14.3	24226	3821	3794	3659	33654	11.4%	11.3%	10.9%
I295_03	1	Rural Interstate	US 130 to I 76	US130	14.30000	14.30	27.1			23059	19209	69287	0.0%	33.3%	27.7%
I295_04	11	Urban Interstate	I 76 to NJ 73	I76	27.10000	27.10	36.86	109017	6938	6786	8465	105334	6.6%	6.4%	8.0%
I295_05	11	Urban Interstate	NJ 73 to NJ 38	NJ73	36.86000	36.86	40.6	76613	3930	16281	7281	77158	5.1%	21.1%	9.4%
I295_05	11	Urban Interstate	NJ 73 to NJ 38	NJ73	36.86000	36.86	40.6	32521	3930	16281	7281	77158	5.1%	21.1%	9.4%
I295_05	11	Urban Interstate	NJ 73 to NJ 38	NJ73	36.86000	36.86	40.6	86689	3930	16281	7281	77158	5.1%	21.1%	9.4%
I295_06	1	Rural Interstate	NJ 38 to US 130	NJ38	40.60000	40.60	56.82	24389	4238	19729	11709	66776	6.3%	29.5%	17.5%
I295_07	11	Urban Interstate	US 130 to I 195	US130	56.82000	56.82	60.23			6544	937	41020	0.0%	16.0%	2.3%
I295_08	11	Urban Interstate	I 195 to US 1	I195	60.23000	60.23	67.67			-20020	4216	42588	0.0%	-47.0%	9.9%
I295_09	11	Urban Interstate	US 1 to US 206	US1	67.67000	67.67	69.63			5572	1686	42856	0.0%	13.0%	3.9%
I295_10	11	Urban Interstate	US 206 to NJ 31	US206	69.63000	69.63	72.49			9494	488	NA	NA	NA	NA
I295_11	11	Urban Interstate	NJ 31 to Delaware River	NJ31	72.49000	72.49	76.69			7385	724	NA	NA	NA	NA

Table A 3 (Continued)

SECTION	FC	TYPE	SECTION	HIGHWAY	MPIH	Begin MP	End MP	OBSERVED ADT	DAILY TRUCK VOLUMES OBSERVED TRUCK VOLUMES	PREDICTED BY REGRESSION	PREDICTED BY OPTIMIZATION	CMS ADT	DAILY TRUCK VOLUME PERCENTAGES BASED ON CMS AADT OBSERVED	REGRESSION	OPTIMIZATION
I78															
I78_01	1	Rural Interstate	Delaware River to NJ 31	Delaware River	0.00000	0	17.33	75699	11204	11377	8350	61085	18.3%	18.6%	13.7%
I78_02	1	Rural Interstate	NJ 31 to I 287	NJ31	17.33000	17.33	30.8	48641	7184	6410	5466	70466	10.2%	9.1%	7.8%
I78_03	11	Urban Interstate	I 287 to CO 525	I287	30.80000	30.8	31.25			-7281	567	41114	0.0%	-17.7%	1.4%
I78_04	1	Rural Interstate	CO 525 to NJ 24	US202/206	31.25000	31.25	49.26	39332	3647	3366	3136	58634	6.2%	5.7%	5.3%
I78_04	1	Rural Interstate	CO 525 to NJ 24	US202/206	31.25000	31.25	49.26	45638	3647	3366	3136	163515	2.2%	2.1%	1.9%
I78_05	11	Urban Interstate	NJ 24 to NJ 27	NJ24	49.26000	49.26	57.23	148597	20236	27453	26585	153406	13.2%	17.9%	17.3%
I78_06	11	Urban Interstate	NJ 27 to US 1&9	NJ21	57.23000	57.23	58.32			13182	17002	113814	0.0%	11.6%	14.9%
I78_07	11	Urban Interstate	US1&9 to I 95	US1/9	58.32000	58.32	58.93			10677	267	69942	0.0%	15.3%	0.4%
I78_08	11	Urban Interstate	I 95 at NJ 139	I95	58.93000	58.93	66.5			35394	23185	88471	0.0%	40.0%	26.2%

Table A 3 (Continued)

SECTION	FC	TYPE	SECTION	HIGHWAY	MPIH	Begin MP	End MP	OBSERVED ADT	DAILY TRUCK VOLUMES OBSERVED TRUCK VOLUMES	PREDICTED BY REGRESSION	OPTIMIZATION	CMS ADT	DAILY TRUCK VOLUME PERCENTAGES BASED ON CMS AADT OBSERVED	REGRESSION	OPTIMIZATION
I80															
I80_01	1	Rural Interstate	Delaware River to US 46	Delaware River	0.00000	0	4.32			4576	551	47839	0.0%	9.6%	1.2%
I80_02	1	Rural Interstate	US 46 to US 46	US46	4.32000	4.32	26.25	43130	7178	7015	4884	52719	13.6%	13.3%	9.3%
I80_03	1	Rural Interstate	US 46 to US 206	US46	26.25000	26.25	27.19			694	2038	79023	0.0%	0.9%	2.6%
I80_04	1	Rural Interstate	US 206 to NJ 15	US206	27.19000	27.19	34.02		7928	4829	2376	92981	8.5%	5.2%	2.6%
I80_05	11	Urban Interstate	NJ 15 to I 287	NJ15	34.02000	34.02	43.62	107167		9890	8405	126104	0.0%	7.8%	6.7%
I80_06	11	Urban Interstate	I 287 to I 280	I287	43.62000	43.62	46.36			6777	6950	130637	0.0%	5.2%	5.3%
I80_07	11	Urban Interstate	I 280 to CO 613	I280	46.36000	46.36	52.48	90744	7426	25284	5080	107678	6.9%	23.5%	4.7%
I80_08	11	Urban Interstate	CO 613 to NJ 23	CO613	52.48000	52.48	53.62	114604	12913	20583	3225	114896	11.2%	17.9%	2.8%
I80_09	11	Urban Interstate	NJ 23 to NJ 20	NJ23	53.62000	53.62	60.41	122017	38518	57541	27509	124952	30.8%	46.1%	22.0%
I80_10	11	Urban Interstate	NJ 20 to Garden State Pkwy	NJ20	60.41000	60.41	61.82	120934	11353	22793	9396	131580	8.6%	17.3%	7.1%
I80_11	11	Urban Interstate	Garden State Pkwy to NJ 17	GSP	61.82000	61.82	65.19	49604	5014	29545	8228	127052	3.9%	23.3%	6.5%
I80_12	11	Urban Interstate	NJ 17 to New Jersey Turnpike	NJ17	65.19000	65.19	68.4	163024	7906	38608	12520	129040	6.1%	29.9%	9.7%

Table A 3 (Continued)

SECTION	FC	TYPE	SECTION	HIGHWAY	MPIH	Begin MP	End MP	OBSERVED ADT	DAILY TRUCK VOLUMES OBSERVED TRUCK VOLUMES	DAILY TRUCK VOLUMES PREDICTED BY REGRESSION	DAILY TRUCK VOLUMES PREDICTED BY OPTIMIZATION	CMS ADT	DAILY TRUCK VOLUME PERCENTAGES BASED ON CMS AADT OBSERVED	REGRESSION	OPTIMIZATION
NJ31															
NJ31_01	14	Urban Major	US 206 to CO 622	US206	0.00000	0	1.79	8080	223	2226	1049	9875	2.3%	22.5%	10.6%
NJ31_02	14	Urban Major	CO 622 to I 95	CO622	1.79000	1.79	4.84			1312	881	15172	0.0%	8.6%	5.8%
NJ31_03	2	Rural Interstate	I 95 to CO 518	I95	4.84000	4.84	12.21	22425	1998	3713	528	18998	10.5%	19.5%	2.8%
NJ31_04	2	Rural Interstate	CO 518 to CO 579	CO518	12.21000	12.21	13.97	14715	1247	636	48	15094	8.3%	4.2%	0.3%
NJ31_05	2	Rural Interstate	CO 579 to US 202	CO579	13.97000	13.97	16.37	20155	2012	1713	109	18370	11.0%	9.3%	0.6%
NJ31_06	2	Rural Interstate	US 202 to I 78	US202/NJ31	16.37000	16.37	16.37	23156	1618	749	5104	21490	7.5%	3.5%	23.8%
NJ31_06	2	Rural Interstate	US 202 to I 78	US202/NJ31	16.37000	16.37	31.89	15642	1618	749	5104	21490	7.5%	3.5%	23.8%
NJ31_07	2	Rural Interstate	I 78 to NJ 57	I78/US22	31.89000	31.89	42.84	19093	1161	1924	1849	21058	5.5%	9.1%	8.8%
NJ31_08	2	Rural Interstate	NJ 57 to US 46	NJ57	42.84000	42.84	49.00	13130	1728	1111	1256	12241	14.1%	9.1%	10.3%

Table A 3 (Continued)

SECTION	FC	TYPE	SECTION	HIGHWAY	MPIH	Begin MP	End MP	DAILY TRUCK VOLUMES					DAILY TRUCK VOLUME PERCENTAGES BASED ON CMS AADT		
									OBSERVED TRUCK VOLUMES	PREDICTED BY					
								OBSERVED ADT		REGRESSION	OPTIMIZATION	CMS ADT	OBSERVED	REGRESSION	OPTIMIZATION
NJ55															
NJ55_01	2	Rural Interstate	NJ 47 to NJ 49	NJ47	20.00000	20	24.6			1404	398	11208	0.0%	12.5%	3.6%
NJ55_02	12	Express ways	NJ 49 to NJ 47	NJ49	24.60000	24.6	27.79			1775	0	21658	0.0%	8.2%	0.0%
NJ55_03	12	Express ways	NJ 47 to NJ 56	NJ47	27.79000	27.79	32.69	2186	398	847	1413	25331	1.6%	3.3%	5.6%
NJ55_04	12	Express ways	NJ 56 to US 40	NJ56	32.69000	32.69	39.38	23214	1707	2833	1500	26208	6.5%	10.8%	5.7%
NJ55_04	12	Express ways	NJ 56 to US 40	NJ56	32.69000	32.69	39.38	28781	1707	2833	1500	26208	6.5%	10.8%	5.7%
NJ55_05	2	Rural Interstate	US 40 to US 322	US40	39.38000	39.38	50.5			-212	788	31985.3	0.0%	-0.7%	2.5%
NJ55_06	2	Rural Interstate	US 322 to NJ 47	US322	50.50000	50.5	56.37			234	853	40576	0.0%	0.6%	2.1%
NJ55_07	12	Express ways	NJ 47 to NJ 42	NJ47	56.37000	56.37	60.49	57048	2215	2385	1952	44925	4.9%	5.3%	4.3%

Table A 3 (Continued)

SECTION	FC	TYPE	SECTION	HIGHWAY	MPIH	Begin MP	End MP	DAILY TRUCK VOLUMES					DAILY TRUCK VOLUME PERCENTAGES BASED ON CMS AADT		
								OBSERVED ADT	OBSERVED TRUCK VOLUMES	PREDICTED BY REGRESSION	PREDICTED BY OPTIMIZATION	CMS ADT	OBSERVED	REGRESSION	OPTIMIZATION
NJ47															
NJ47_01	2	Rural Interstate	GSP to NJ 83	GSP	3.08000	0	3.08	11410	147	269	2861	17503	0.8%	1.5%	16.3%
NJ47_02	6	Rural Minor	NJ 83 to NJ 347	NJ83	17.54000	3.08	17.54			386	280	12576	0.0%	3.1%	2.2%
NJ47_03	2	Rural Interstate	NJ 347 to NJ 55	NJ347	20.91000	17.54	20.91			-256	354	12165	0.0%	-2.1%	2.9%
NJ47_04	2	Rural Interstate	NJ 55 to NJ 49	NJ55	35.08000	20.91	35.08			-71	57	9298	0.0%	-0.8%	0.6%
NJ47_05	6	Rural Minor	NJ 49 to NJ 55	NJ49	40.20000	35.08	40.2			355	73	11099	0.0%	3.2%	0.7%
NJ47_06	16	Urban Minor	NJ 55 to NJ 56	NJ55	42.50000	40.2	42.5			1080	51	17168	0.0%	6.3%	0.3%
NJ47_07	16	Urban Minor	NJ 56 to US 40	NJ56	46.55000	42.5	46.55	22882	395	647	72	19383	2.0%	3.3%	0.4%
NJ47_08	16	Urban Minor	US 40 to US 322	US40	52.52000	46.55	52.52			1091	145	11728	0.0%	9.3%	1.2%
NJ47_09	16	Urban Minor	Atlantic Ave (beg) to GSP	Atlantic Avenue	0.00000	52.52	62.45			19	152	12030	0.0%	0.2%	1.3%
NJ47_10	14	Urban Major	US 322 to NJ 55	US322	62.45000	62.45	69.36			1643	297	18883	0.0%	8.7%	1.6%
NJ47_11	16	Urban Minor	NJ 55 to New Jersey Turnpike	NJ55	69.36000	69.36	72.52			64	99	20805	0.0%	0.3%	0.5%
NJ47_12	16	Urban Minor	New Jersey Turnpike to I 295	NJTNPK	72.52000	72.52	74			125	111	14429	0.0%	0.9%	0.8%
NJ47_13	16	Urban Minor	I 295 to US 130	I295	74.00000	74	75.18			163	152	11383	0.0%	1.4%	1.3%
SECTION	FC	TYPE	SECTION	HIGHWAY	MPIH	Begin MP	End MP	OBSERVED ADT	DAILY TRUCK VOLUMES OBSERVED TRUCK VOLUMES	PREDICTED BY REGRESSION	PREDICTED BY OPTIMIZATION	CMS ADT	DAILY TRUCK VOLUME PERCENTAGES BASED ON CMS AADT OBSERVED	REGRESSION	OPTIMIZATION
NJ49															
NJ49_01	2	Rural Interstate	I 295/US 40 to NJ 45	I295	0.00000	0	19.72	13297	408	-80	812	10296	3.9%	-0.8%	7.9%
NJ49_02	2	Rural Interstate	NJ 45 to NJ 77	NJ45	19.72000	19.72	25.58	8952	225	4164	738	10755	2.1%	38.7%	6.9%
NJ49_03	2	Rural Interstate	NJ 77 to NJ 47	NJ77	25.58000	25.58	36.4			8656	660	12777	0.0%	67.7%	5.2%
NJ49_04	14	Urban Major	NJ 47 to NJ 50	NJ47	36.40000	36.4	36.4	4903	407	1238	73	7232	5.6%	17.1%	1.0%

Table A 3 (Continued)

SECTION	FC	TYPE	SECTION	HIGHWAY	MPH	Begin MP	End MP	OBSERVED ADT	DAILY TRUCK VOLUMES			CMS ADT	DAILY TRUCK VOLUME PERCENTAGES BASED ON CMS AADT		
									OBSERVED TRUCK VOLUMES	PREDICTED BY REGRESSION	PREDICTED BY OPTIMIZATION		OBSERVED	REGRESSION	OPTIMIZATION
NJTPKE															
NJTPKE_01	2	Rural Interstate	Delaware Memorial Bridge to US 322	Delaware Bridge	0.00000	0	19.59			1103	102	40400	0.0%	2.7%	0.3%
NJTPKE_02	2	Rural Interstate	US 322 to NJ 168	US322	19.59000	19.59	33.29			46602	4169	43132	0.0%	108.0%	9.7%
NJTPKE_03	12	Express ways	NJ 168 to NJ 73	NJ168	33.29000	33.29	41.72			1153	6176	45808	0.0%	2.5%	13.5%
NJTPKE_04	12	Express ways	NJ 73 to CO 541	NJ73	41.72000	41.72	56.55			2483	3917	56642	0.0%	4.4%	6.9%
NJTPKE_05	2	Rural Interstate	CO 541 to I 276 (Penn. Turnpike)	CO541	56.55000	56.55	63.35			2452	735	67412	0.0%	3.6%	1.1%
NJTPKE_06	1	Rural Interstate	I 276 (Penn. Turnpike) to US 130	I276	63.35000	63.35	69.52			368	251	33614	0.0%	1.1%	0.7%
NJTPKE_07	1	Rural Interstate	US 130 to Bridge	US130	69.52000	69.52	71.87			11642	12714	33614	0.0%	34.6%	37.8%
NJTPKE_08	1	Rural Interstate	I 276 (Penn. Turnpike) to US 206	I276	71.87000	71.87	73.75			131	104	101026	0.0%	0.1%	0.1%
NJTPKE_09	11	Urban Interstate	US 206 to I 195	US206	73.75000	73.75	84.07			2294	558	101026	0.0%	2.3%	0.6%
NJTPKE_10	1	Rural Interstate	I 195 to NJ 33	I195	84.07000	84.07	97.57			4793	3452	122024	0.0%	3.9%	2.8%
NJTPKE_11	11	Urban Interstate	NJ 33 to NJ 32	NJ33	97.57000	97.57	103.7			14821	1763	114202	0.0%	13.0%	1.5%

Table A 3 (Continued)

SECTION	FC	TYPE	SECTION	HIGHWAY	MPH	Begin MP	End MP	OBSERVED ADT	DAILY TRUCK VOLUMES OBSERVED TRUCK VOLUMES	DAILY TRUCK VOLUMES PREDICTED BY REGRESSION	DAILY TRUCK VOLUMES PREDICTED BY OPTIMIZATION	CMS ADT	DAILY TRUCK VOLUME PERCENTAGES BASED ON CMS AADT OBSERVED	DAILY TRUCK VOLUME PERCENTAGES BASED ON CMS AADT REGRESSION	DAILY TRUCK VOLUME PERCENTAGES BASED ON CMS AADT OPTIMIZATION
NJTPKE L															
NJTPKE_L_01	1	Rural Interstate	NJ 32 to NJ 18	NJ32	0.00000	0	13.06			7703	6105	134534	0.0%	5.7%	4.5%
NJTPKE_L_02	11	Urban Interstate	NJ 18 to I 287	NJ18	13.06000	13.06	27.56			21786	4623	168462	0.0%	12.9%	2.7%
NJTPKE_L_03	11	Urban Interstate	I 287 to Garden State Pkwy	I287	27.56000	27.56	29.35			10367	1589	160000	0.0%	6.5%	1.0%
NJTPKE_L_04	11	Urban Interstate	Garden State Pkwy to Carteret	GSP	29.35000	29.35	40.99			17699	4836	200000	0.0%	8.8%	2.4%
NJTPKE_L_05	11	Urban Interstate	Carteret to I 278	CARTERET	40.99000	40.99	44.19			8005	8014	212000	0.0%	3.8%	3.8%
NJTPKE_L_06	11	Urban Interstate	I 278 to NJ 81 (Newark Airport)	I287	44.19000	44.19	48.42			20708	6439	224000	0.0%	9.2%	2.9%
NJTPKE_L_07	11	Urban Interstate	NJ 81 (Newark Airport) to I 78	NJ18	48.42000	48.42	51.88			11283	5090	200000	0.0%	5.6%	2.5%
NJTPKE_L_11	11	Urban Interstate	I 78 to CO 169	I78	51.88000	51.88	54.47			-28092	7939	112000	0.0%	-25.1%	7.1%
NJTPKE_L_15	11	Urban Interstate	CO 169 to I495	CO169	54.47000	54.47	69.99			28858	9678	90682	0.0%	31.8%	10.7%
NJTPKE_L_16	11	Urban Interstate	I495 to NJ3	I495	69.99000	69.99	75.41			21073	2561	50000	0.0%	42.1%	5.1%
NJTPKE_L_17	11	Urban Interstate	NJ3 to I80	NJ3	75.41000	75.41	81.75			34579	4798	72000	0.0%	48.0%	6.7%
NJTPKE_L_12	11	Urban Interstate	US 1&9 to I 280	US1&9	0.00000	0	1.43			10406	497	120000	0.0%	8.7%	0.4%
NJTPKE_L_13	11	Urban Interstate	I 280 to NJ 3	I280	1.43000	1.43	7.3			5976	287	120000	0.0%	5.0%	0.2%
NJTPKE_L_14	11	Urban Interstate	NJ 3 to Turnpike Merge	NJ3	7.30000	7.3	10.81			8636	510	156000	0.0%	5.5%	0.3%

Table A 3 (Continued)

SECTION	FC	TYPE	SECTION	HIGHWAY	MPIH	Begin MP	End MP	OBSERVED ADT	DAILY TRUCK VOLUMES OBSERVED TRUCK VOLUMES	DAILY TRUCK VOLUMES PREDICTED BY REGRESSION	DAILY TRUCK VOLUMES PREDICTED BY OPTIMIZATION	CMS ADT	DAILY TRUCK VOLUME PERCENTAGES BASED ON CMS AADT OBSERVED	DAILY TRUCK VOLUME PERCENTAGES BASED ON CMS AADT REGRESSION	DAILY TRUCK VOLUME PERCENTAGES BASED ON CMS AADT OPTIMIZATION
US1															
US1_01	12	Express ways	(Delaware River) NJ 29 to US 206	NJ29	0.13000	0.13	0.13			7683	1061	49758	0.0%	15.8%	2.1%
US1_02	12	Express ways	US 206 to NJ 129	US206	0.55000	0.13	0.55			5489	1274	49758	0.0%	11.0%	2.6%
US1_03	12	Express ways	NJ 129 to Perry St	NJ129	0.76000	0.55	0.76	53862	6807	5537	1430	35274	19.3%	15.7%	4.1%
US1_04	12	Express ways	Perry St to I 295	Perry St	1.34000	0.76	1.34	33251	1652	1468	2766	49580	3.3%	3.0%	5.6%
US1_04	12	Express ways	Perry St to I 295	Perry St	1.34000	1.34	6.76	19693	1652	1468	2766	49580	3.3%	3.0%	5.6%
US1_05	14	Urban Major	I 295 to US 130	I295	6.76000	6.76	24.64	52575	2234	2039	3282	66056	3.4%	3.1%	5.0%
US1_06	14	Urban Major	US 130 to NJ 18	NJ130	24.64000	24.64	27.19			1342	1340	80488	0.0%	1.7%	1.7%
US1_07	14	Urban Major	NJ 18 to I 287	NJ18	27.19000	27.19	31.96			1615	2493	74411	0.0%	2.2%	3.4%
US1_08	14	Urban Major	I 287 to Garden State Parkway	I287	31.96000	31.96	34.5			1185	1340	68874	0.0%	1.7%	1.9%
US1_09	14	Urban Major	Garden State Parkway to US 9	GSP	34.50000	34.5	35.89			1938	1603	53094	0.0%	3.7%	3.0%
US1_10	14	Urban Major	US 9 to NJ 35	US9	35.89000	35.89	36.42			1455	778	65115	0.0%	2.2%	1.2%
US1_11	14	Urban Major	NJ 35 to I 278	NJ35	36.42000	36.42	42.3			12804	8075	69463	0.0%	18.4%	11.6%
US1_12	14	Urban Major	I 278 to NJ 439	I278	42.30000	42.3	43.11			1998	1247	72994	0.0%	2.7%	1.7%
US1_13	2	Rural Interstate	NJ 439 to I 78	NJ439	43.11000	43.11	47.84	76775	7124	273500	27171	93587	7.6%	292.2%	29.0%
US1_14	12	Express ways	I 78 to I 95	I78	47.84000	47.84	51.53	101918	19740	19763	5800	91445	21.6%	21.6%	6.3%
US1_15	12	Express ways	I 95 to US 1&9	I95	51.53000	51.53	54			1910	7804	50080	0.0%	3.8%	15.6%
US1_16	14	Urban Major	US 1&9 to NJ 3	US1/9	54.00000	54	57.27			6334	4973	52085	0.0%	12.2%	9.6%
US1_17	14	Urban Major	NJ 3 to US 46	NJ3	57.27000	57.27	62.8			6422	6360	34526	0.0%	18.6%	18.4%
US1_18	14	Urban Major	US 46 to I 95	US46	62.80000	62.8	64.72			2013	2443	60039	0.0%	3.4%	4.1%

Table A 3 (Continued)

SECTION	FC	TYPE	SECTION	HIGHWAY	MPH	Begin MP	End MP		DAILY TRUCK VOLUMES				DAILY TRUCK VOLUME PERCENTAGES BASED ON CMS AADT		
									OBSERVED TRUCK VOLUMES	PREDICTED BY					
								OBSERVED ADT		REGRESSION	OPTIMIZATION	CMS ADT	OBSERVED	REGRESSION	OPTIMIZATION
US130															
US130_01	6	Rural Minor	I 295 to US 322	I295/US40	0.00000	0	12.21	12641	156	362	158	10080	1.6%	3.6%	1.6%
US130_02	2	Rural Interstate	US 322 to NJ 44	US322	12.21000	12.21	13.46			2738	3475	19389	0.0%	14.1%	17.9%
US130_03	2	Rural Interstate	NJ 44 to I 295	NJ44	13.46000	13.46	14.1			412	48	34580	0.0%	1.2%	0.1%
US130_04	14	Urban Major	I 295 to I 76	I295	14.10000	14.1	25.23			1714	1257	18074	0.0%	9.5%	7.0%
US130_05	14	Urban Major	I 76 to I 676	I76	25.23000	25.23	28.13			1634	872	34973	0.0%	4.7%	2.5%
US130_06	14	Urban Major	I 676 to CO 729 (Richey Ave)	I676	28.13000	28.13	29.39			1841	1200	39271	0.0%	4.7%	3.1%
US130_07	14	Urban Major	NJ 70 to NJ 90	CO729	29.39000	29.39	30.53			3038	2933	38072	0.0%	8.0%	7.7%
US130_08	14	Urban Major	NJ 90 to NJ 73	NJ70/38	30.53000	30.53	35.52			6478	2283	40490	0.0%	16.0%	5.6%
US130_09	14	Urban Major	NJ 73 to New Jersey Turnpike	NJ73	35.52000	35.52	50.25			1039	4162	39274	0.0%	2.6%	10.6%
US130_10	14	Urban Major	New Jersey Turnpike to I 295	NJTNPK	50.25000	50.25	54.9			1398	867	25409	0.0%	5.5%	3.4%
US130_11	14	Urban Major	I 295 to US 206 SB	I295	54.90000	54.9	56.44			1292	524	33629	0.0%	3.8%	1.6%
US130_12	14	Urban Major	US 206 SB to I 195	US206SB	56.44000	56.44	61.37	24140	1096	1590	706	25500	4.3%	6.2%	2.8%
US130_13	14	Urban Major	I 195 to NJ 33	I195	61.37000	61.37	62.64			1670	226	27425	0.0%	6.1%	0.8%
US130_14	2	Rural Interstate	NJ 33 to NJ 32	NJ33	62.64000	62.64	74.51	31103	1268	14192	1298	28415	4.5%	49.9%	4.6%
US130_15	16	Urban Minor	NJ 32 to US 1	NJ32	74.51000	74.51	83.73			397	229	32411	0.0%	1.2%	0.7%

Table A 3 (Continued)

SECTION	FC	TYPE	SECTION	HIGHWAY	MPIH	Begin MP	End MP	OBSERVED ADT	DAILY TRUCK VOLUMES OBSERVED TRUCK VOLUMES	DAILY TRUCK VOLUMES PREDICTED BY REGRESSION	DAILY TRUCK VOLUMES PREDICTED BY OPTIMIZATION	CMS ADT	DAILY TRUCK VOLUME PERCENTAGES BASED ON CMS AADT OBSERVED	DAILY TRUCK VOLUME PERCENTAGES BASED ON CMS AADT REGRESSION	DAILY TRUCK VOLUME PERCENTAGES BASED ON CMS AADT OPTIMIZATION
US206															
US206_01	2	Rural Interstate	US 30 to CO 541	US30	0.00000	0	9.45	9415	675	-324	221	9336	7.2%	-3.4%	2.4%
US206_02	2	Rural Interstate	CO 541 to NJ 70	C0541	9.45000	9.45	17.66	5217	363	1142	941	12645	2.9%	9.0%	7.4%
US206_03	2	Rural Interstate	NJ 70 to NJ 38	NJ70	17.66000	17.66	23.48	13484	848	931	419	8324	10.2%	11.2%	5.0%
US206_04	2	Rural Interstate	NJ 38 to New Jersey Turnpike	NJ38	23.48000	23.48	33.98			860	1263	8176	0.0%	10.5%	15.4%
US206_05	14	Urban Major	New Jersey Turnpike to US 130	NJTPK	33.98000	33.98	35.61			1289	539	19807	0.0%	6.5%	2.7%
US206_06	14	Urban Major	US 130 to I 195	US130	35.61000	35.61	38.71			1474	433	16688	0.0%	8.8%	2.6%
US206_07	14	Urban Major	I 195 to NJ 129	I195	38.71000	38.71	41.97	12716	180	1117	728	13540	1.3%	8.2%	5.4%
US206_08	14	Urban Major	NJ 129 to US 1	NJ129	41.97000	41.97	42.34			1455	603	9458	0.0%	15.4%	6.4%
US206_09	14	Urban Major	US 1 to US 206 (sb)	US1	42.34000	42.34	42.59			1261	503	6654	0.0%	19.0%	7.6%
US206_10	14	Urban Major	US 206 (sb) to NJ 31	US206SB	42.59000	42.59	43.22			869	685	5902	0.0%	14.7%	11.6%
US206_11	14	Urban Major	NJ 31 to US 1	NJ31	43.22000	43.22	45			2415	1894	4605	0.0%	52.4%	41.1%
US206_12	14	Urban Major	US 1 to US 206 (sb)	US1/18	45.00000	45	45.36			1395	1298	4946	0.0%	28.2%	26.2%
US206_13	14	Urban Major	US 206 (sb) to I 295	US206SB	45.36000	45.36	48.01			1458	1562	5101	0.0%	28.6%	30.6%
US206_14	14	Urban Major	I 295 to NJ 27	I295	48.01000	48.01	53.95	13537	515	-296	1105	5979	8.6%	-5.0%	18.5%
US206_15	14	Urban Major	NJ 27 to US 202	NJ27	53.95000	53.95	71.31			-1201	4576	13592	0.0%	-8.8%	33.7%
US206_16	14	Urban Major	US 202 to CO 625	US202	71.31000	71.31	90.11	19349	718	1059	951	19851	3.6%	5.3%	4.8%
US206_16	14	Urban Major	US 202 to CO 625	US202	71.31000	71.31	90.11	21106	718	1059	951	19851	3.6%	5.3%	4.8%
US206_17	2	Rural Interstate	CO 625 to I 80	CO625	90.11000	90.11	97.21	31991	1848	2260	288	22975	8.0%	9.8%	1.3%
US206_18	2	Rural Interstate	I 80 to NJ 183	I80	97.21000	97.21	97.9	17657	526	1976	577	21700	2.4%	9.1%	2.7%
US206_19	14	Urban Major	NJ 183 to CO 611	NJ183	97.90000	97.9	106.2	14251	437	1635	706	36188	1.2%	4.5%	2.0%
US206_20	2	Rural Interstate	CO 611 to NJ 94	CO611	106.23000	106.23	109.3	20278	384	2393	665	46781	0.8%	5.1%	1.4%
US206_21	2	Rural Interstate	NJ 94 to NJ 94	NJ94	109.25000	109.25	111.6	23319	450	2689	644	51525	0.9%	5.2%	1.2%
US206_22	2	Rural Interstate	NJ 94 to NJ 15	NJ94	111.57000	111.57	114.1	8832	319	375	191	45382	0.7%	0.8%	0.4%
US206_23	2	Rural Interstate	NJ 15 to CO 560	NJ15	114.14000	114.14	122	14555	961	-130	400	52420	1.8%	-0.2%	0.8%
US206_24	2	Rural Interstate	CO 560 to CO 521	CO560	122.00000	122	129.3	5414	194	863	54	66645	0.3%	1.3%	0.1%

Table A 3 (Continued)

SECTION	FC	TYPE	SECTION	HIGHWAY	MPIH	Begin MP	End MP	DAILY TRUCK VOLUMES				CMS ADT	DAILY TRUCK VOLUME PERCENTAGES BASED ON CMS AADT		
								OBSERVED ADT	OBSERVED TRUCK VOLUMES	PREDICTED BY REGRESSION	PREDICTED BY OPTIMIZATION		OBSERVED	REGRESSION	OPTIMIZATION
US40															
US40_01	2	Rural Interstate	NJ 140 to NJ 45	NJ140	1.85000	1.85	10.02	12922	1038	290	108	13076	7.9%	2.2%	0.8%
US40_02	2	Rural Interstate	NJ 45 to NJ 77	NJ45	10.02000	10.02	16.52			-1534	1463	14085	0.0%	-10.9%	10.4%
US40_03	2	Rural Interstate	NJ 77 to NJ 55	NJ77	16.52000	16.52	25.54	10239	1202	1049	675	10351	11.6%	10.1%	6.5%
US40_04	14	Urban Major	NJ 55 to NJ 47	NJ55	25.54000	25.54	26.71			1620	170	11795	0.0%	13.7%	1.4%
US40_05	14	Urban Major	NJ 47 to CO 555	NJ47	26.71000	26.71	30.21	8853	458	1668	569	9748	4.7%	17.1%	5.8%
US40_06	2	Rural Interstate	CO 555 to NJ 54	CO555	30.21000	30.21	35.13	238751	19054	-1404	2227	8786	216.9%	-16.0%	25.3%
US40_07	2	Rural Interstate	NJ 54 to NJ 50	NJ54	35.13000	35.13	46.35			741	408	10932	0.0%	6.8%	3.7%
US40_08	2	Rural Interstate	NJ 50 to US 322	NJ50	46.35000	46.35	51.73			1370	2942	22589	0.0%	6.1%	13.0%
US40_09	2	Rural Interstate	US 322 to GSP	US322	51.73000	51.73	57.42			-2892	1255	31049	0.0%	-9.3%	4.0%
US40_10	14	Urban Major	GSP to US 9	GSP	57.42000	57.42	59.09			1528	1029	25382	0.0%	6.0%	4.1%
US40_11	14	Urban Major	US 9 to Atlantic Ave (end)	US9	59.09000	59.09	64.28	15753	154	1309	755	34249	0.4%	3.8%	2.2%

Table A 3 (End)

SECTION	FC	TYPE	SECTION	HIGHWAY	MPIH	Begin MP	End MP	OBSERVED ADT	OBSERVED TRUCK VOLUMES	DAILY TRUCK VOLUMES PREDICTED BY REGRESSION	DAILY TRUCK VOLUMES PREDICTED BY OPTIMIZATION	CMS ADT	DAILY TRUCK VOLUME PERCENTAGES BASED ON CMS AADT OBSERVED	DAILY TRUCK VOLUME PERCENTAGES BASED ON CMS AADT REGRESSION	DAILY TRUCK VOLUME PERCENTAGES BASED ON CMS AADT OPTIMIZATION
US9															
US9_01	2	Rural Interstate	Boardwalk to NJ 109	Boardwalk	0.00000	0	3.06			-2467	1177	11102	0.0%	-22.2%	10.6%
US9_02	6	Rural Minor	NJ 109 to NJ 47	NJ 109	3.06000	3.06	7.09			495	176	8835	0.0%	5.6%	2.0%
US9_03	6	Rural Minor	NJ 47 to NJ 147	NJ 47	7.09000	7.09	9.64			412	333	8531	0.0%	4.8%	3.9%
US9_04	2	Rural Interstate	NJ 147 to NJ 83	NJ147	9.64000	9.64	18.61	9825	184	52	414	12565	1.5%	0.4%	3.3%
US9_05	6	Rural Minor	NJ 83 to NJ 50	NJ 83	18.61000	18.61	23.7			209	85	7588	0.0%	2.8%	1.1%
US9_06	16	Urban Minor	NJ 50 to Harbor Rd	NJ 50	23.70000	23.7	30.65			383	96	8123	0.0%	4.7%	1.2%
US9_07	14	Urban Major	Harbor Rd to NJ 52	Harbor Rd	30.65000	30.65	33.23			1506	143	8238	0.0%	18.3%	1.7%
US9_08	14	Urban Major	NJ 52 to US 40	NJ 52	33.23000	33.23	39.39			-773	1942	17442	0.0%	-4.4%	11.1%
US9_09	14	Urban Major	US 40 to US 30	US 40	39.39000	39.39	42.86	15634	218	1890	1167	12084	1.8%	15.6%	9.7%
US9_10	16	Urban Minor	US 30 to Great Creek Rd	US 30	42.86000	42.86	46.89			932	77	4970	0.0%	18.8%	1.5%
US9_11	16	Urban Minor	Great Creek Rd to Garden State Pkwy	Great Creek Rd	46.89000	46.89	52.22			29	18	4892	0.0%	0.6%	0.4%
US9_12	6	Rural Minor	Garden State Pkwy to NJ 72	GSP	52.22000	52.22	70.53			814	138	13026	0.0%	6.2%	1.1%
US9_13	6	Rural Minor	NJ 72 to CO 618 (Central Pkwy)	NJ 72	70.53000	70.53	85.74			1194	989	18097	0.0%	6.6%	5.5%
US9_14	16	Urban Minor	CO 618 (Central Pkwy) to NJ 166	CO 618 (Central Pkwy)	85.74000	85.74	89.84			98	114	26944	0.0%	0.4%	0.4%
US9_15	16	Urban Minor	NJ 166 to Garden State Pkwy	NJ 166	89.84000	89.84	91.05			209	77	20374	0.0%	1.0%	0.4%
US9_16	14	Urban Major	Garden State PKWY to NJ 70	Garden State PKWY	91.05000	91.05	98.71			1799	764	24884	0.0%	7.2%	3.1%
US9_17	14	Urban Major	NJ 70 to NJ 88	NJ 70	98.71000	98.71	101.7			1361	807	42942	0.0%	3.2%	1.9%
US9_18	2	Rural Interstate	NJ 88 to I 195	NJ 88	101.71000	101.71	107.1			255	1073	49686	0.0%	0.5%	2.2%
US9_19	2	Rural Interstate	I 195 to NJ 33	I 195	107.05000	107.05	112.9	54532	888	-9749	1368	45130	2.0%	-21.6%	3.0%
US9_20	14	Urban Major	NJ 33 to NJ 33B	NJ 33	112.91000	112.91	114.3			1222	1025	52948	0.0%	2.3%	1.9%
US9_21	14	Urban Major	NJ 33B to NJ 18	NJ 33B	114.33000	114.33	122.1			-82	1023	60632	0.0%	-0.1%	1.7%
US9_22	14	Urban Major	NJ 18 to NJ 34	NJ 18	122.10000	122.1	126.9			1267	732	62483	0.0%	2.0%	1.2%
US9_23	14	Urban Major	NJ 34 to NJ 35	NJ 34	126.88000	126.88	129.8			1644	438	75680	0.0%	2.2%	0.6%
US9_24	14	Urban Major	NJ 35 to NJ 440	NJ 35	129.82000	129.82	133			1769	1162	60977	0.0%	2.9%	1.9%
US9_25	14	Urban Major	NJ 440 to NJ 184	NJ 440	132.99000	132.99	134.1			1444	1096	70687	0.0%	2.0%	1.5%
US9_26	14	Urban Major	NJ 184 to US 1	NJ 184	134.07000	134.07	136.4			1683	1443	68938	0.0%	2.4%	2.1%