Louisiana Transportation Research Center

Final Report 548

Developing a Method for Estimating AADT on All Louisiana Roads

by

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Traffic flow volumes present key information needed for making transportation engineering and planning decisions. Accurate traffic volume count has many applications including: roadway planning, design, air quality compliance, travel model validation, and administrative purposes. Traffic counts also serve as an important input in highway safety performance evaluation. However, collecting traffic volume on all rural non-state roads has been very limited for various reasons, although these roads constitute a great portion (60 to 70%) of road mileage in the roadway network of any state in the U.S. For example, out of 61,335 miles of roadway in Louisiana, 73% of the roadways are non-state roads. Due to limited resources, traffic volume information on non-state roadways has not been systematically collected in Louisiana. Generally, traffic volumes on these roads are fairly low, and VMT on these roads is much less compared with that on interstate or arterial roads. Thus, regularly conducting traffic count is not economically feasible for non-state roadways. This study develops an AADT estimation methodology by using modern statistical and pattern recognition methods. By using available traffic counts on non-state roadway and four variables (namely: population, job, and distance to intersection and to major state highways at block level), a training set to estimate roadway AADT for eight parishes were obtained by a modified support vector regression (SVR) method. This pattern recognition method yields better AADT estimates than the conventional parametric statistical methods. Sensitivity analyses were also conducted in this study, which indicates a parish-specific model works better than an aggregated single model.

With the estimated AADT, the DOTD and local government agencies can make better decisions on funding allocations for safety improvement projects and pavement maintenance actions. The estimated parish-specific AADT on non-state roads can also improve statewide travel demand forecasting models and air quality assessment.

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ABSTRACT

Annual average daily traffic (AADT) is a critical input to many key components of transportation activities. Accurate AADT data are vital to the calibration and validation of travel demand models, roadway improvement funding allocations, and safety performance evaluations. Non-state roads constitute a large percentage (60 to 70%) of the total mileage of a state's roadway network. In Louisiana, nearly 73% of the highways are non-state roadways, meaning they are not under DOTD roadway network. Traffic volumes on these roads are generally fairly low, and vehicle-miles-traveled (VMT) on these roads is much less compared with that on interstate or arterial roads. Thus, regularly conducting traffic count is not economically feasible for non-state roadways. This study develops an AADT estimation methodology by using modern statistical and pattern recognition methods. By using available traffic counts on non-state roadways and four variables (namely: population, job, distance to intersection and to major state highways at block level), a training set to estimate roadway AADT for eight parishes were obtained by a modified support vector regression (SVR) method. This pattern recognition method yields better AADT estimates than the conventional parametric statistical methods. Sensitivity analyses were also conducted in this study, which indicates a parish-specific model works better than an aggregated single model.

With the estimated AADT, the DOTD and local government agencies can make better decisions on funding allocations for safety improvement projects and pavement maintenance actions. The estimated parish-specific AADT on non-state roads can also improve statewide travel demand forecasting models and air quality assessment.

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IMPLEMENTATION STATEMENT

Louisiana has about 44,814 miles of non-state roadways. Collecting traffic counts on these roadways is not economically and administratively feasible. The methodology developed by this study can be used to develop parish-specific models for all 64 parishes to estimate AADT on all non-state roadways in rural and small urban areas in Louisiana. The recommendations made at the end of this project should help the Louisiana Department of Transportation and Development's (DOTD) future plan on AADT prediction on all non-state roadways.

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INTRODUCTION

Annual average daily traffic (AADT) is the average 24 hour traffic volume at a roadway segment over an entire year. AADT is a key input to many activities of the State Departments of Transportation (DOT), such as roadway planning, design, traffic operation, pavement maintenance, air quality assessment, revenues from the roadway user fees, and last but not the least, roadway safety evaluations. Accurate AADT data are vital to the calibration and validation of travel demand models. AADT is also used to estimate state-wide vehicle miles traveled on all of the roadways and is used by governments and the environmental protection agencies to determine compliance with the 1990 Clean Air Act Amendment. Additionally, AADT is reported annually by the state DOTs to the Federal Highway Administration (FHWA).

The DOTs and local transportation agencies traditionally use AADT count programs to collect traffic information. The focus of these traffic count programs is on higher classes of roadways, which consists mainly of interstates and arterials. Due to the budgetary and administrative constraints, regular traffic counting is only conducted on the state highway network (generally every three years). The traffic counting for non-state roadways is highly selective and irregular. Most of the major cities in Louisiana, such as New Orleans, Baton Rouge, Lafayette, Lake Charles etc., have the traffic volume data collected or estimated by their respective Metropolitan Planning Organization (MPO). Other non-state roadways in rural and small urban areas do not have an AADT collection or estimation program. Since approximately three-fourths of all roadway mileage in Louisiana is non-state maintained by local governments (parishes and municipalities), estimating AADT on non-state roadways is important. Oftentimes, the AADT estimation is made based on comparisons to similar types of roadways. This rough estimation results in a major discrepancy due to a variety of reasons, such as false assumptions, and may not be repeated often enough to remain current. FHWA's Highway Performance Monitoring System (HPMS) does not require any explicit procedure for the sampling of non-state road traffic volumes. The procedure to be used for estimating vehicle miles traveled (VMT) on these roads is expected to be selected by respective DOTs, and, in many cases, they use archaic or erratic traffic volume data on non-state roadways.

Non-state roadways constitute a large percentage (60 to 70%) of the total mileage of a state's roadway network. Traffic volumes on these roads are fairly low, leading to much smaller VMT compared with that on interstate or arterial roads. Usually the VMT from non-state roadways only consists of 10% to 20% total state VMT. In recent years, more attention has been given to non-state roadway VMT because it is a significant component of air quality emissions from mobile sources. With increased emphasis on non-state roadway safety and publication of the Highway Safety Manual (HSM), AADT is becoming a "must-have" element in roadway safety evaluation. Lack of AADT information hinders roadway safety assessment and makes it hard to develop cost-effective safety improvement projects. Out of 61,335 miles of roadways in Louisiana, 44,814 miles of the roadways (73%) are non-state roads *[1]*. Difficulty in collecting traffic data for all non-state roadways makes the AADT estimation the only option for the DOTD.

Literature Review

The information on estimating AADT for roads that do not have traffic counts has been reviewed, which can be summarized in the following two aspects.

- State of the practice
- State of the art in modeling techniques

Due to the strategic importance of AADT, many state DOTs have established methods to estimate AADT for roadways that do not have regular traffic counts. The state of the practice on the AADT estimation is summarized in the following table for the interest of this research. Table 1 lists the summary of most noteworthy state practices.

Table 1

Summary of most noteworthy state practices

State	Analysis Unit	Scope	Method
Alaska	Densities of built tax parcels	Local urban roadways	GIS based linear regression model and parcel data analysis
Florida	Block level data and densities of built tax parcels.	Urban and rural locations with a permanent traffic monitoring site in Florida	Linear regression analyses to identify possible factors contributing to the seasonal fluctuations in traffic volumes
Kentucky	By functionally classified collector roads and local roads, minimizing the level of effort required to estimate traffic volumes on local roads	Collector roads and local roads	Random sampling procedure
Pennsylvania	Stratification of locally-owned roads for traffic data collection	Local roads owned by municipalities	Sampling method
Texas	Selected traffic count sites randomly on local streets, resulting in a statistically valid estimation of local street vehicle miles traveled	Local roads	Random count site selection
New York	Sample-based count program representing geographic distribution, functional classification, and volume group	Local-owned, non-Federal-aid Highways	Sampling method

The literature review on the state of the modeling techniques reveals that two methods are widely used in estimating AADT: statistical model and pattern recognition. Statistical models can be developed through the use of linear regression, parcel-level trip generation, and spatial grids with the latter two being more related to this study. Although statistical models are relatively easier to establish, these models can only be used at an aggregated level. Machine learning or pattern recognition approaches like artificial neural network, decision trees, clustering, support vector machines (SVM), and fuzzy algorithms are also widely used in estimating AADT.

Among the statistical methods, regression analysis has been widely used. Xia *et al.* developed regression models to estimate the AADT in Broward County, Florida *[2]*. A modified and improved follow-up study was conducted by Shen *et al [3]*. Zhao and Chung improved the same study by using of a larger data set (including all the AADTs for state roads) and replacing the old state roadway function classification system with the new federal function classification system, and performed more extensive analysis of land use and accessibility variables *[4]*. Based on the preliminary analyses, six independent variables were used to generate four regression models, and all four models showed a strong relationship between the explanatory variables and AADT as well as having no multi-collinearity among the explanatory variables. The final results from this study showed that the more explanatory variables used, the better a model would perform, and the choice of a model would likely be based on the data processing cost, though this data is generally available and easy to process. This study did realize that the current models may not be adequate in meeting the need of engineering design or the calibration of travel demand models, but the performances of the models have shown improvements. A more recent attempt to estimate AADTs for non-state roads in Florida was performed by Lu *et al.* to improve upon Xia *et al.*'s study *[5]*. However, the estimation errors from their models were found to be quite high. Another recent study using Florida non-state roadways utilized a parcel-level travel demand analysis model as an improved approach *[6]*. The method applied travel demand modeling techniques at the tax parcel level. The parcel-level demand analysis incorporated four steps based on standard trip generation and trip assignment: network modeling defining the boundaries of the study area, parcel-level trip generation estimating the number of vehicle trips generated by each parcel, parcel-level trip distribution determining where each generated trip by each parcel will do, and parcel-level trip assignment predicting the routes the travelers will take to reach the traffic count sites on major roads which results in the estimated AADTs on non-state roads in the study area. One advantage of using tax parcel data is that the data are updated at least annually; this aspect makes it possible to update the AADTs in response to land use changes.

Seaver *et al*. developed a method to determine traffic volumes on non-state roads in Georgia through the use of alternative methods for estimating AADT to the traditional sampling approach that is currently used for FHWA's Highway Performance Monitoring System (HPMS) *[7]*. Four road types (Non-Atlanta urban areas, small urban areas, and all rural roads-paved or otherwise) and their characteristics were analyzed within 80 of the 159 counties in Georgia. The initial models, with a total of 45 variables considered, were poor in predictability, but a stratification of counties based on their location within or outside a Metropolitan area was used to anticipate differences in the amount of rural traffic. The developed models can be used to estimate AADT in counties in Georgia that were not included in this study, thus reducing the need for resources to collect AADT on rural roads within the state.

Selby and Kockelman conducted a study by using Universal kriging for spatial prediction of AADT in unmeasured locations in Texas *[8]*. Universal kriging is a geostatistical technique used to harness known non-state conditions influencing count and road network spatial information about measured locations; this technique involves spatial interpolation as well as making use of non-state information (lane count, population, etc.) and drawing on residuals in prediction from nearby sites. The models developed used data from the year 2005 in Texas, which includes both large metropolitan areas (Houston and Dallas-Fort Worth) as well as sparsely populated lands (primarily West Texas), and the sample counts, obtained from the Texas Department of Transportation (TxDOT) came from all types of roads in the state. Results based on Euclidean distances were compared to those using network distances, and both allow for strategic spatial interpolation of count values while controlling for each roadway's functional classification, lane count, speed limit, and other site attributes.

In his study, Dixon used the classification and regression tree (CART) method to reduce the variability in the AADT annual growth rate *[9]*. The finding showed that the CART method performed well in classifying the automatic traffic recorder (ATR) stations into groups with similar characteristics while reducing the variability of the AADT annual growth rates. Using a stratified sample of portable count locations validated the method. The CART method is considered to be more promising due to its ease, the small amount of data in the calibration data sets, and the potential to update the growth factors more frequently.

A study in Tennessee by Castero-Neto *et al.* used support vector regression (SVR) with data-dependent parameters to predict AADT within the state of Tennessee *[10].* The objective of the research was to evaluate the performance of a modified version of the SVR technique for forecasting AADT one year into the future without use of any external, or predictor, variables. The attention of SVR has been increasing due to its remarkable characteristics, good generalization performance, absence of non-state minima, and sparse representation of solution; however, the computation of adequate SVR parameters is crucial to the quality of SVR models developed. Using 20 years of AADT for both rural and urban roads in 25 counties in Tennessee, the performance of the SVR was compared with those of Holt exponential smoothing (Holt-ES) and of ordinary least square linear regression (OLS-regression). SVR performed better than both methods, although the Holt-ES also presented good results.

A study of Gecchele *et al.* focused on a comparative analysis of cluster analysis methods *[11].* It can be adopted for the definition of groups of roads with similar traffic patterns in FHWA factor approach procedure for AADT estimation. Differently from conventional traffic count studies, factors were calculated separately for passenger and truck vehicles, allowing for a deeper understanding of factor approach use and differences in temporal traffic patterns of vehicles.

The study of Gastaldi *et al.* presented an approach of estimating AADT from a one-week seasonal traffic count (STC) of a road section in the Province of Venice, Italy *[12].* The objective was to improve the interpretability of results with measures of non-specificity and discord. The proposed method used fuzzy set theory to represent the fuzzy boundaries of road groups and measures of uncertainty. Neural networks were used to assign a road segment to one or more predefined road groups. The approach was tested with data for the period of the year in which STCs are taken. The method was found to produce accurate results.

A summary of the state of the art of the methods of AADT estimation is listed in Table 2.

Table 2

Summary of important research on AADT estimation of local roadways

Division	Methods	Advantages	Disadvantages	Reference
Parametric Statistical methods	Regression method	Easy to group, highly aggregated, and easy in application	Ignoring the difference among roadways in the save classification group	2-5
	Travel demand modeling method at tax parcel level	Update of data at least annually which makes possible to update the AADTs in response to lane use changes	Need number of parcels to be preprocessed to improve the model's efficiency	6
	Stratification method	Better results than the traditional sampling methods	Not useful when the population cannot be exhaustively partitioned into disjoint subgroups	7
	Kriging methods	Less error and statistically significant	Ignoring the difference within each roadway classification	8
Pattern Recognition Methods	Clustering and regression trees	Analyzing AADT for roadways with similar characteristics	No specific models	9, 11
	Support vector regression with data dependent parameters	Highly aggregated at county by rural and urban with good results	Ignoring the difference inside a large geographic area or roadway class	10
	Fuzzy theory and neural network	Consideration of uncertainty	Pre-defined aggregated roadway group	12

This study introduces a modified SVR technique to estimate AADT in non-state roadways. DOTD maintains traffic counts in a few count stations in non-state roadways throughout the state. The available count station traffic count is used as parish-specific training data. This method predicts parish-specific block level AADT based on the distribution of the training data and performs better than conventional statistical methods.

OBJECTIVE

The goal of this project is to develop a methodology for estimating AADT on all Louisiana roadways with an emphasis on non-state rural roadways. Exploring different AADT estimating procedures established previously and new data collection technologies will do this. Specifically, the objectives of the proposed project are to:

- Review existing (permanent and mobile) traffic counts and identify roadways currently without traffic counts on the entire Louisiana roadway network.
- Identify variables influential to AADT estimation such as population, demographic characteristics, distance to permanent counts, and number of jobs.
- Select the representative parishes to develop models.
- Develop the AADT estimation models for non-state roadways in rural areas.
- Explore AADT estimation methods for non-state roadways in small urban areas.

SCOPE

The research aims to develop an appropriate method for estimating AADT on non-state roadways in Louisiana. The study has developed the AADT estimation models using the SVR method for eight parishes at the census block level.

METHODOLOGY

The methodology developed in this study can be divided into four major tasks: 1) Selection of the parishes, 2) Data collection, 3) Data processing, and 4) AADT model development.

Selection of the Parishes

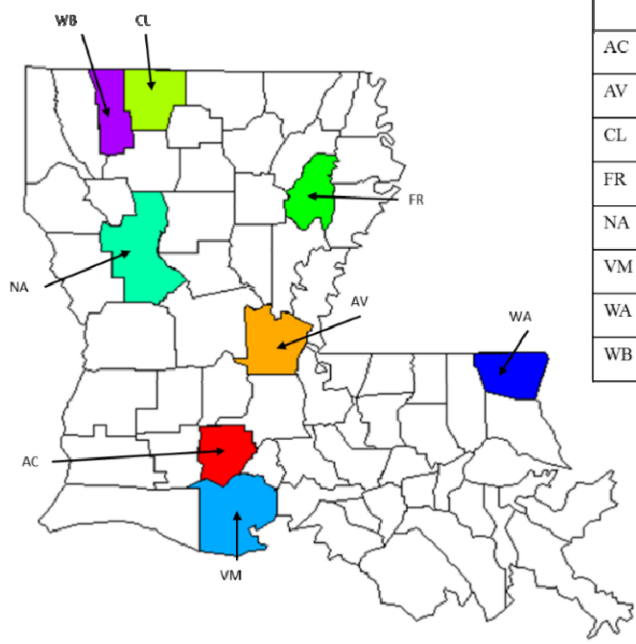
Due to the time and budgetary constraints, it is not possible to use all 64 parishes for the AADT estimation model development. To select the representative parishes, the following factors are considered:

- Type of parish (urban, suburban, or rural)
  - Parish population
  - Existence of small urban area
- Geographic location of the parish in Louisiana (north and south Louisiana)
- Accessibility to Interstate and U.S. Highways
- The number of traffic count stations

No parishes with major cities were selected, as the AADTs are collected or estimated regularly for roadways in the large urbanized areas by either DOTD or local MPOs. The eight parishes selected were:

- Parishes with direct access to an Interstate
  - Acadia
  - Avoyelles
  - Natchitoches
  - Webster
- Parishes without direct access to an Interstate
  - Claiborne
  - Franklin
  - Vermilion
  - Washington

Of the four parishes selected with direct access to an interstate, Acadia has I-10, Webster has I-20, and Avoyelles and Natchitoches have I-49. Washington Parish is the only parish that does not have direct access to either interstates or U. S. Highways. Figure 1 illustrates the eight selected parishes.



CODE	PARISH	POPULATION (2010)	NUMBER OF COUNT STATIONS
AC	Acadia	61.773	1227
AV	Avoyelles	42.073	923
CL	Claiborne	17,195	681
FR	Franklin	20.767	810
NA	Natchitoches	39,566	895
VM	Vermilion	57.999	987
WA	Washington	47.168	1177
WB	Webster	41.207	970

Figure 1

Location, population, and number of AADT count stations for the eight selected parishes in Louisiana

More information on the selected parishes is given in Table 3.

Table 3

Information on selected parishes

Average Population (2010)	40,970
Average Number of Count Stations	959
DOTD Districts Selected and Number of Parishes within District	Dist. 03: 2 (Acadia, Vermilion) Dist. 04: 2 (Claiborne, Webster) Dist. 08: 2 (Avoyelles, Natchitoches) Dist. 58: 1 (Franklin) Dist. 62: 1 (Washington)

As shown in Figure 1, no parishes were selected from the more populated urban/suburban southeastern Louisiana. Several parishes in this area have the population (2010 Census) exceeding 100,000 (East Baton Rouge, Jefferson, Orleans, St. Tammany, Livingston, Ascension, and Terrebonne). The number of available traffic counts in parishes with smaller populations is considerably smaller than the numbers in parishes with large populations.

Appendix A lists all parish populations based on the 2010 Census and number of AADT counts in Louisiana.

Data Collection

A preliminary data exploration was first conducted to examine the important factors that may contribute to crash occurrence. After investigating the collected variables, a few key variables were selected for final data preparation. The variables were collected from different sources: (1) DOTD collected AADT data on non-state roadways, (2) U.S. Census block level data (population, household), (3) Employment data from Longitudinal Employer-Household Dynamics (LEHD), and (4) Shortest distance measurement from ArcGIS shape files *[13]*.

Available AADT Count

The DOTD collects traffic counts at 5,067 permanent or portable count locations on the state-maintained highways and has provided 43,755 counts on non-state roads throughout the past 40 years. These are the updated counts on the state highways since these counts are repeated every three years. The data obtained for non-state highway traffic counts are before 2011. The non-state traffic count data is provided in a non-state dataset provided by DOTD, and Appendix B describes the attributes of this table. Figure 2 demonstrates the locations of non-state AADT count stations within Acadia Parish.

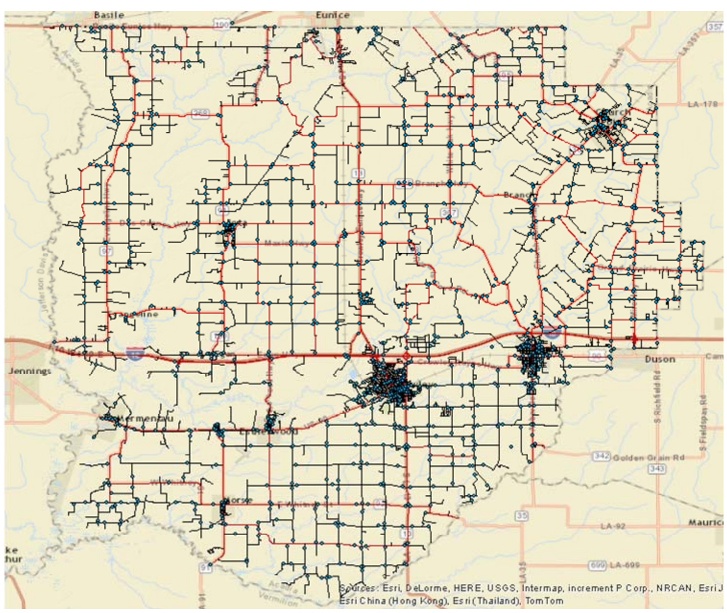


Figure 2

Locations of AADT count stations in Acadia Parish

U.S. Census Data

All Census demographic and geographic data, updated as of the most recent Census in 2010, was obtained from two sources: the demographic information from the American FactFinder, and the block shapefiles from the Topologically Integrated Geographic Encoding and Referencing (TIGER) database. Census data is subdivided into three units within each parish: Tracts, Block Groups, and Blocks. Each of these units is further detailed below:

- Tract: The highest-level geographic unit, relatively permanent statistical subdivisions of a parish, generally defined to contain 1,200 to 8,000 people, identified with an integer number of up to four digits, and special codes exist for special land-use tracts with little or no population (9800s) or to cover large bodies of water (9900s).
- Block Group: The intermediate-level geographic unit, the division of tracts and clusters of blocks, generally defined to contain 600 to 3,000 people, identified as first digit of the block code (for example, if a particular tract has blocks 2000, 2001, 2002, etc., then those blocks belong to *block group 2* of that particular tract).
- Block: The lowest-level geographic unit, the division of block groups, generally small statistical areas bounded by visible features such as roads, streets, small bodies of water, or railroad tracts, all blocks are numbered between 0000 and 9999, and blocks beginning with zero are water-only blocks (i.e. 0XXX).

A map comparing two of the census geographic subdivisions for Acadia Parish is shown in Figure 3.

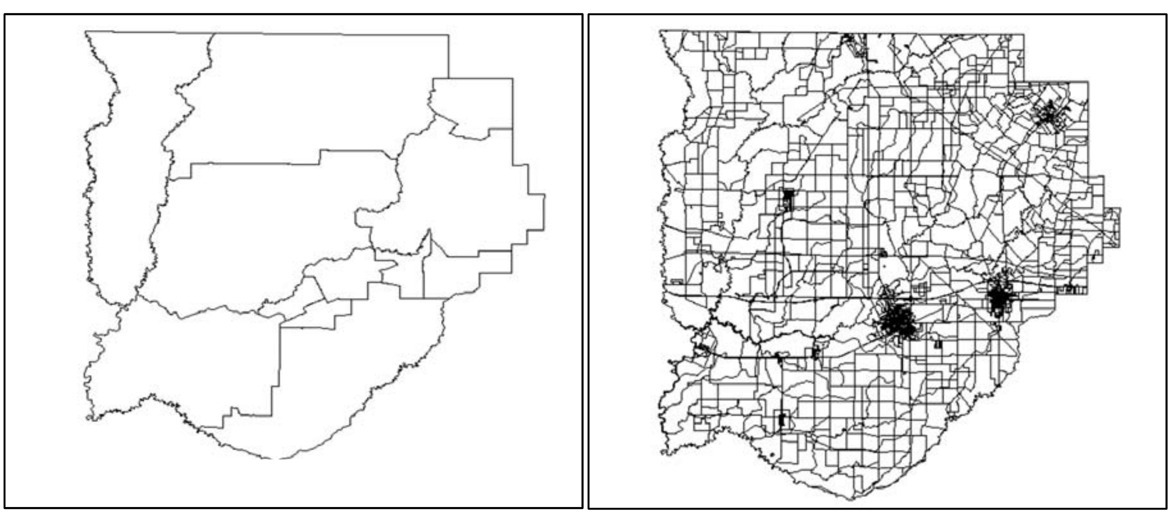


Figure 3

Census tracts (left) and census blocks (right) for Acadia Parish

The amount of available demographic and economic data from the census website is based on the geographic unit. More data are readily available at the tract level. While data at the census block level is more accurate than the data at the tract level due to its small spatial size, the number of data items at the bock level is considerably limited. The GIS obtained from *TIGER* show the shape of each census spatial unit and its geographic attributes. The attributes codes are given in Appendix C.

LEHD Data

The Longitudinal Employer-Household Dynamics (LEHD) program is part of the Center for Economic Studies at the U.S. Census Bureau that produces new, cost effective, public-use information combining federal, state, and Census Bureau data on employers and employees under the Local Employment Dynamics Partnership. The partnership works to fill critical data gaps and provide indicators needed by state and local authorities. Under the partnership, states agree to share unemployment insurance earnings data and the Quarterly Census of Employment and Wages data with the Census Bureau. The LEHD program combines these administrative data, additional administrative data and data from censuses and surveys. From these data, the program creates statistics on employment, earnings, and job flows at a detailed level such as the block.

Several employment-related data and residential area characteristics data were downloaded from LEHD for the eight selected parishes at the block level, which was later used in the AADT estimation model.

Shortest Distance Measurement

Non-state roadways in rural areas basically function as collectors and a few of them may serve as minor arterials carrying traffic from local connector roads to major arterials. Thus, it is expected that AADT on rural non-state roadways should have something to do with the distance to interstates and or major highways. To derive the shortest path from a non-state roadway point to the closest interstate or major highway, the following data and steps are involved.

Roadway Network. The Louisiana highway network consists of 61,335 miles, including state-maintained highways and non-state roadway (parish roads and city streets), shown in Figure 4.

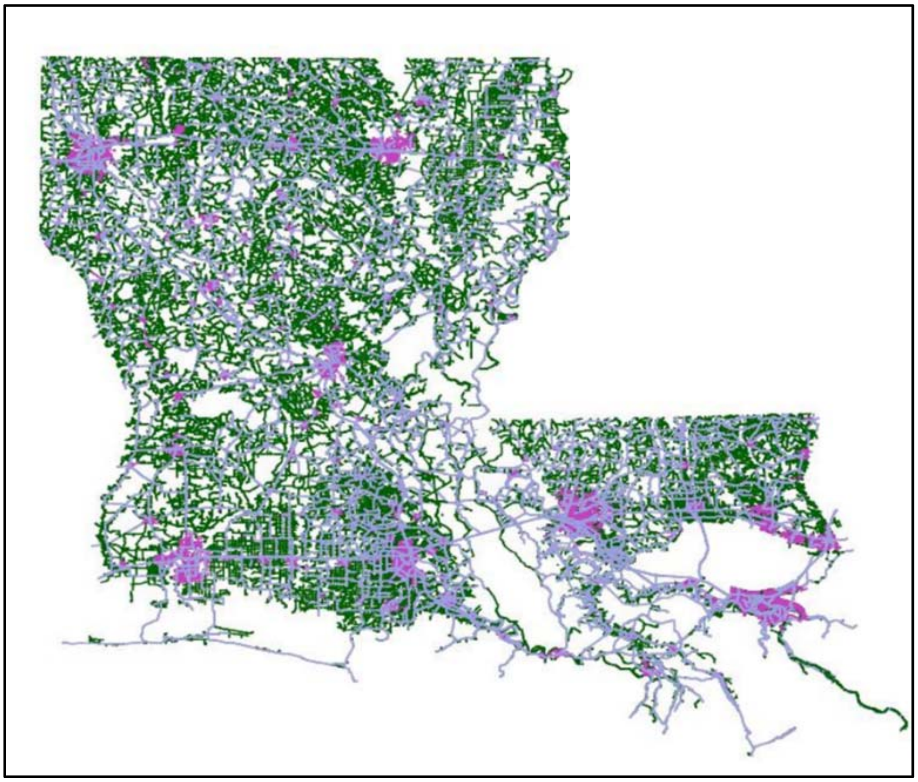


Figure 4

Louisiana roadway network

In Figure 4, state-maintained highways are depicted in blue, non-state roadways in rural areas are depicted in green and municipal areas are depicted in purple. Non-state roadways account for approximately 73 percent of all roadway mileage in Louisiana, totaling over 44,814 miles. Appendix C details the attributes for the statewide roadway network dataset. Louisiana ranks tenth in the U.S. in the proportion of roadways that are state-maintained.

Interstates and Major Highways. To derive the shortest path, it is important to identify the interstates and major highways. Figure 5 shows the interstates that pass through Louisiana.

Figure 5

Interstates within Louisiana [image courtesy of Louisiana DOTD]

Although six major interstates and six Loop/Spur interstates exist within Louisiana, only three interstates were considered in the study, including:

- Interstate 10, the East-West interstate through south Louisiana from the Sabine River at the Texas state border to the Pearl River, part of the state border line with Mississippi. I-10 passes through Lake Charles, Lafayette, Baton Rouge and New Orleans in its 274 mile-long segment through Louisiana.
- Interstate 20, the East-West interstate through north Louisiana between Texas and Mississippi. It passes through Shreveport/Bossier City and Monroe in its 190 mile-long stretch in the state.
- Interstate 49, the state's major North-South interstate, with its southern terminus in Lafayette and passing through Alexandria and Shreveport before entering Arkansas.

Other interstates such as I-12, I-55, and I-59, and the Loop and Spur interstates are not in any of the selected parishes. Future interstates in Louisiana include the north and south extensions of Interstate 49 and an all-new Interstate 69 in northwestern Louisiana.

For four selected parishes without direct access to interstates, distance to major highways is derived as a measurement of highway network accessibility. Most parishes in Louisiana without interstate access are located in the northeastern part of the state and south-central Louisiana. All parishes have major highway access. The majority of the parishes in the state without interstate access have access to multiple-lane major highways, including:

- United States Highway 90 (U.S.90) between Lafayette and New Orleans (future Interstate 49 South corridor), with controlled-access on portions of the highway around New Iberia, western St. Mary Parish, and from Morgan City to Raceland bypassing Houma-Thibodaux areas
- United States Highway165 (U.S. 165) between Iowa and the Arkansas state lines; passing through Alexandria and Monroe
- United States Highway167 (U.S. 167) from Alexandria to the Arkansas state line; passing through Ruston
- United States Highway 171 (U.S. 171) from Lake Charles to Shreveport; passing through DeRidder, Leesville, and Fort Polk
- United States Highway 425 (U.S. 425) from the Mississippi State Line near Natchez, Mississippi to the Arkansas state line
- United States Highway 71 (U.S. 71), the main north-south United States highway through western Louisiana, passing through Alexandria and Shreveport
- United States Highway (U.S. 79) from Minden to the Arkansas state line, passing through Homer
- United States Highway 80 (U.S. 80), north Louisiana's primary east-west United States highway
- Louisiana Highway 1 (LA 1), the state's longest highway in any highway classification, from Grand Isle to the Texas state line in far northwestern Louisiana
- Louisiana Highway 2 (LA 2), north Louisiana's primary east-west state highway
- Louisiana Highway 9 (LA 9), from Natchitoches Parish to Homer in Claiborne Parish

- Louisiana Highway 14 (LA 14), from Lake Charles to New Iberia passing through eastern Calcasieu, Jefferson Davis, Cameron, Vermilion, and Iberia parishes

The following highways are considered a major highway in the *shortest distance* analysis:

- United States Highways (e.g., U.S. 90), the highest highway class in parishes without interstate access.
- Trans-Parish (i.e., parish line to parish line), State Highways that serve as a relatively direct connection to the neighboring parishes, which is considered an important link, especially in parishes without either interstate or United States highway access.
- State Highways with a terminus (end point) within the study parish and serving as the main route to the parish seat of a neighboring parish.

Most of the state highways considered for analysis are numbered as one or two-digit highways (e.g., LA 1 or LA 14), since the majority of these highways carry more traffic than other state highways. The types of highways that were considered as major highways are listed in Appendix C.

Measurement Procedure. The shortest path from a point of the investigated roadway to closest interstate or a major highway is determined by a procedure in ArcGIS called the *Closest Facility Analysis* that starts with defining the following locations:

- Incidents- location of the count stations
- Facilities- either where an on-ramp merges with the interstate main lanes or at an intersection of a non-state road with a major highway.

To prevent accessing the interstate where no actual access exists (i.e., a street crossing an interstate at a grade-separated non-interchange), *point barriers* were implemented along an interstate where a non-state road crosses the interstate or where the route would have a possibility of traveling the wrong way on a divided major highway. This was done to prevent wrong-way traveling and accessing an interstate improperly. Because the route from the count stations to the nearest major state highway will not include any major highways (divided or undivided) or interstates, point barriers were not needed for the *shortest distance to major highway* analysis. The step-by-step process in calculating the shortest distance from the count station to an interstate or major highway involves:

1. Loading all count stations as Incidents
2. Loading all access points to the Interstate as Facilities
3. Executing the program by clicking SOLVE, which gives the shortest paths to an intersection with major highway or Interstate on-ramp as “routes.”

The *point barriers* must be loaded for the *shortest distance to interstate* analysis due to the aforementioned possibilities that the “route” will access the interstate at a location where access to the interstate is not allowed or the “route” travels the wrong-way to an interstate access point. An example of the shortest route between a count station and interstate or major highway access is shown in Figure 6 and Figure 7.

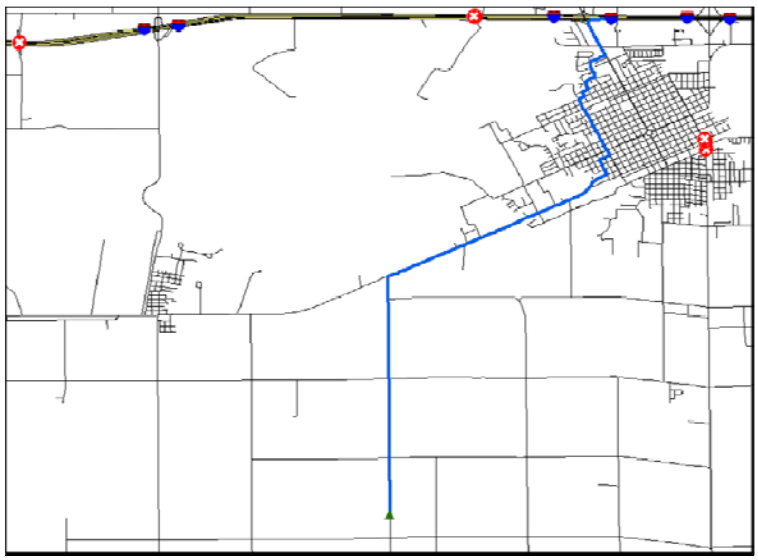


Figure 6

Example of measuring shortest distance to interstate in Acadia Parish

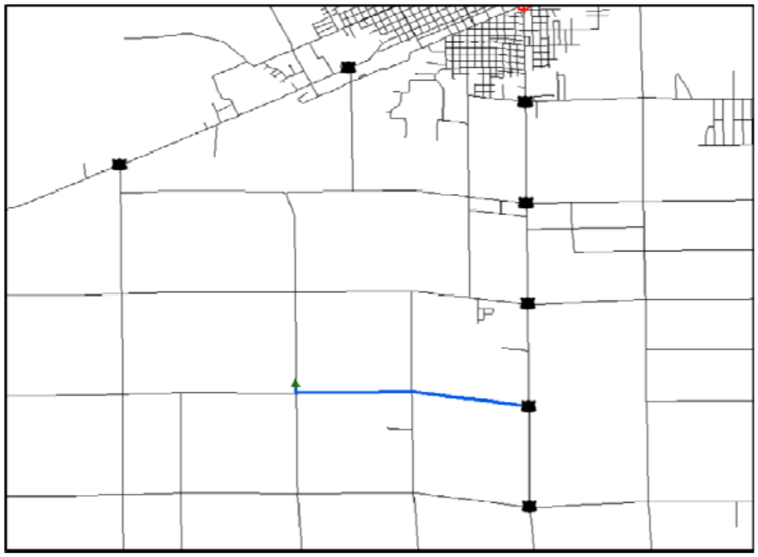


Figure 7

Example of measuring shortest distance to major highway in Acadia Parish

In both of the above figures, the routes from the count station (green triangles) to an interstate/major highway access point (red circles) are depicted in blue along the roadway network. The *point barrier* feature is shown as with a white "X" inside a red circle, as shown in Figure 6. However, a few shortest paths between the count station and interstate/major highway access may not have been determined due to: the location of the count station not locking to the roadway network or the count station is located along a segment of disconnected network, typically near parish lines. In such cases, manual measurement must be utilized, i.e., manually identifying and estimating the distance from the problematic count location to a major highway or interstate access.

Data Processing

To prepare the final dataset with the selected variables, datasets from different sources needed to be merged: (1) DOTD collected AADT data on non-state roadways, (2) U.S. Census block level data (population, household), (3) Shortest distance measurement from ArcGIS shape files, and (4) Employment data from Longitudinal Employer-Household Dynamics (LEHD). The data merging involved the following step:

- Merging the block level data from U.S. census and traffic count data from DOTD for a selected parish by the common GEOid. It is important to note that DOTD does not have traffic counts for all of the blocks in a parish. The number of blocks with the traffic counts thus trims the dataset.

- Merging the shortest path data with the trimmed dataset developed above based on the GEOids.
- Merging the employment data from LEHD at block level with the previously merged dataset as the final dataset. It's important to note that LEHD doesn't have employment information for all blocks in a parish. The dataset is thus trimmed again according number of blocks with the LEHD employment data.

The flowchart of the data merging process is illustrated in Figure 8.

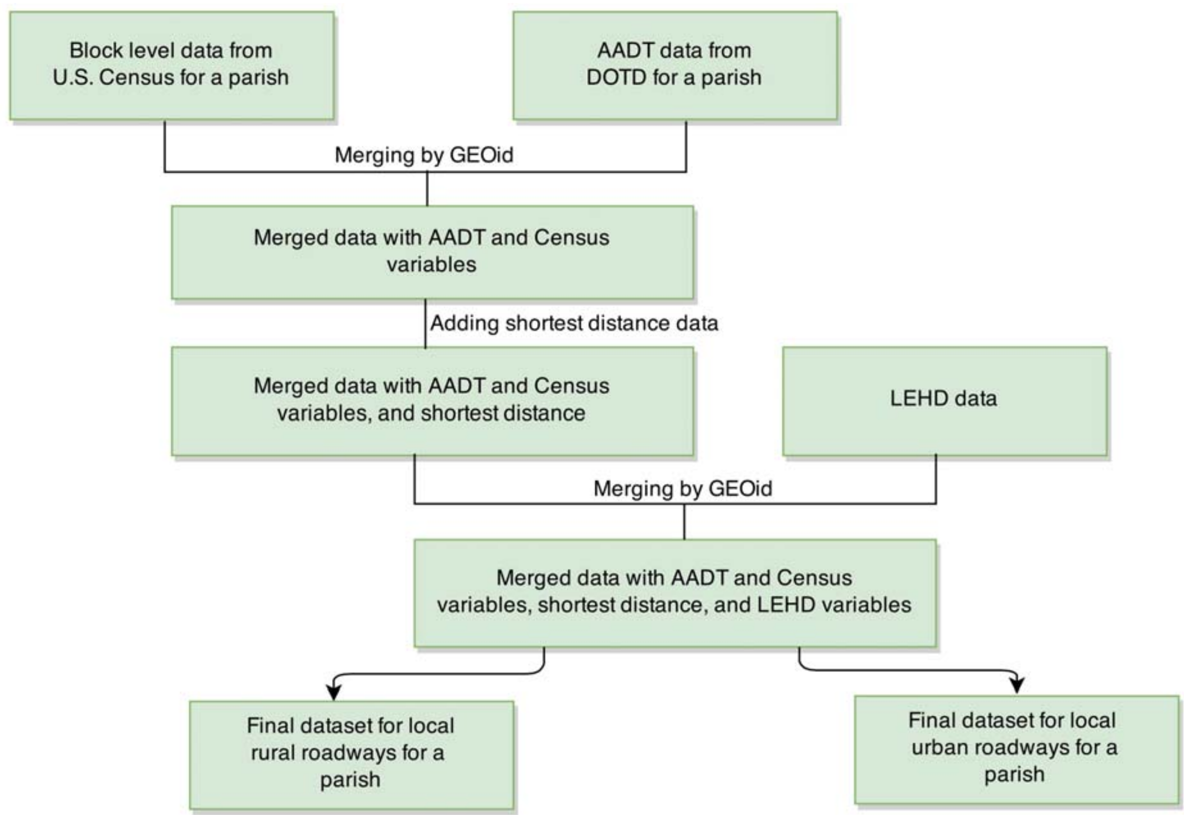


Figure 8

Data merging process

An example of the data processing is illustrated in Figure 9 for Acadia Parish. Initially, the geographic dataset includes information on all blocks within Acadia Parish (3,105), while the AADT dataset includes all non-state and some state counts in Acadia Parish (1,154 counts).

Because some counts in the non-state traffic count database are on major state highways or interstates, those counts are removed (1,154 counts remaining). In the next step, merging the economic datasets collected from the LEHD datasets would further reduce the dataset (554 counts remaining). The final dataset contains roadway, demographic, and socioeconomic information in 464 records.

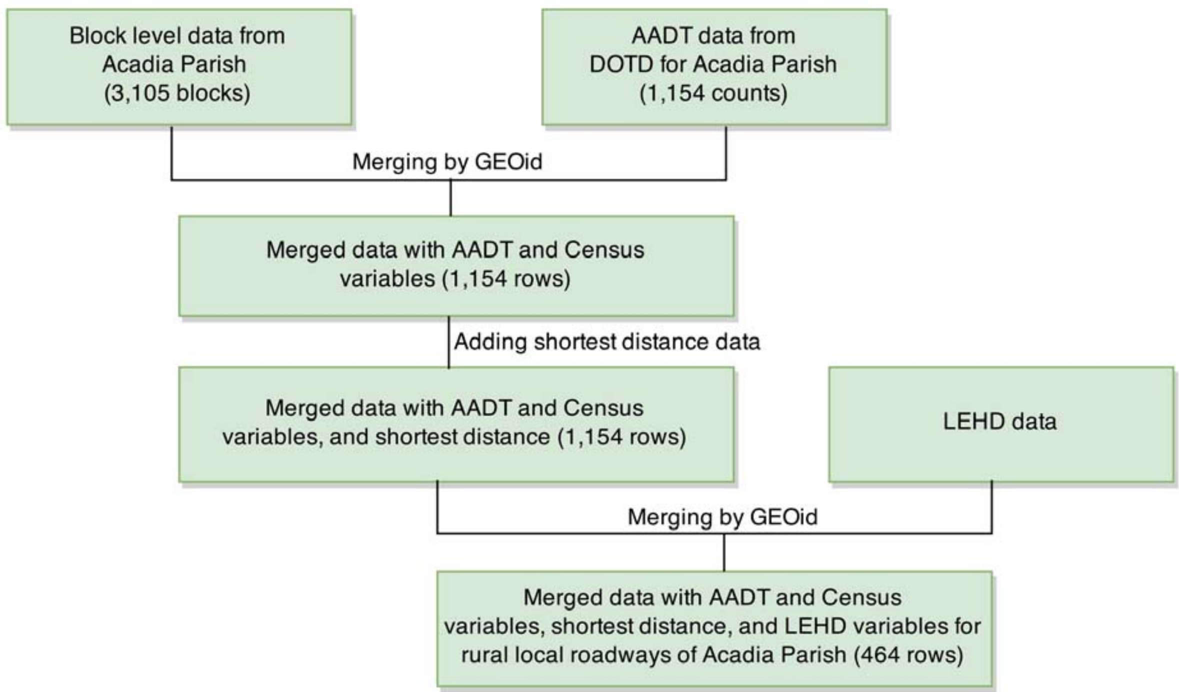


Figure 9

Example of data merging process for Acadia Parish

SVR Model Development

Theory of SVR

Support Vector Machines (SVM) are learning machines executing the structural risk minimization inductive principle to attain good generalization on a limited number of learning patterns. Vapnik *et al.* originally developed this theory on a basis of a separable bipartition problem at the AT & T Bell Laboratories in 1992. The basic idea of SVM is to map the data x into a high-dimensional feature space F via a nonlinear mapping and to perform linear regression in this space. The SV algorithm can also be applied to regression, maintaining all the main features that characterize the maximal margin algorithm: a non-linear function is learned by a linear learning machine in a kernel-induced feature space while the capacity of the system is controlled by a parameter that does not depend on the dimensionality of the space. An overview of the basic conception underlying SVR and function estimation has been given in two papers *[14, 15]*.

Support Vector Regression (SVR) is one of the most common application forms of SVMs. First, we consider a training dataset $\{(x_1, y_1)\ldots\ldots(x_n, y_n) \subset \aleph \times \Re\}$, where $\aleph$ denotes the space of the input patterns (e.g., $\aleph = \Re^d$). In ε-SV regression, the target is usually to find a function *f(x)* that has at most ε deviation from the actually obtained targets y_i for all of the training dataset. The other target is to make it as flat as possible. So, errors less than ε are acceptable, but no deviations larger than this. The linear function *f(x)* can be described as follows:

$$f(x) = \langle w, x \rangle + b \text{ with } \omega \in \aleph,\ b \in \Re \tag{1}$$

where, $\langle \ldots \rangle$ denotes the dot product in $\aleph$. Flatness in equation (1) means smaller ω. To obtain this we need to minimize the Euclidean norm $\|\omega\|^2$. Formally, this can be considered as a convex optimization problem by fulfilling the condition

$$\text{minimize } \frac{1}{2}\|\omega\|^2$$

$$\text{subject to } y_i - \langle w, x_i \rangle - b \le \varepsilon \text{ and } \langle w, x_i \rangle + b - y_i \le \varepsilon \tag{2}$$

The convex optimization in equation (2) is feasible in cases where *f* actually exists and approximates all pairs (x_i , y_i) with ε precision. At times, some errors are usually allowed. The slack variables ξ_i, ξ_i^* can be introduced to handle otherwise infeasible constraints of the optimization problem in equation (2), the formulation will be

$$\text{minimize } \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*)$$

$$\text{subject to } \begin{cases} y_i - \langle w, x_i \rangle - b \le \varepsilon + \xi_i \\ \langle w, x_i \rangle + b - y_i \le \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \ge 0 \end{cases} \tag{3}$$

The constant $C > 0$ defines the tradeoff between the flatness of *f* and tolerance of deviations larger than ε. The ε -intensive loss function $|\xi|_\varepsilon$ can be described as

$$|\xi|_{\varepsilon} = \begin{cases} 0 & if |\xi < \varepsilon| \\ |\xi| - \varepsilon & otherwise \end{cases} \tag{4}$$

The dual formulation provides the key for extending SVM to nonlinear functions. The standard dualization method utilizing Lagrange multipliers can be equated as follows:

$$L = \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*) - \sum_{i=1}^{n}(\alpha + \xi_i - y_i + \langle \omega, x_i \rangle + b) - \sum_{i=1}^{n}\alpha_i^*(\varepsilon + \xi_i^* + y_i - \langle \omega, x_i \rangle - b) -$$
$$-\sum_{i=1}^{n}(n_i\xi_i + n_i^*\xi_i^*) \tag{5}$$

The dual variables in equation (5) is needed to satisfy positivity constraints i.e. $\alpha_i, \alpha_i^*, \eta_i, \eta_i^* \geq 0$. It follows from saddle point condition that the partial derivatives of *L* with respect to the primal variables $(\omega, b, \xi_i, \xi_i^*)$ have to vanish for the optimality condition.

$$\frac{\partial N}{\partial b} = \sum_{i=1}^{n}(\alpha_i^* - \alpha_i) = 0 \tag{6}$$

$$\frac{\partial N}{\partial \omega} = \omega - \sum_{i=1}^{n}(\alpha_i^* - \alpha_i)x_i = 0 \tag{7}$$

$$\frac{\partial N}{\partial \xi_i^*} = C - \alpha_i^{(*)} - \eta_i^{(*)} = 0 \tag{8}$$

The dual optimization problem after using equations (6), (7), and (8), by maximizing

$$-\frac{1}{2}\sum_{i,j=1}(\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*)\langle x_i, x_j \rangle - \varepsilon\sum_{i=1}^{n}(\alpha_i + \alpha_i^*) + \sum_{i=1}^{n}y_i(\alpha_i - \alpha_i^*) \tag{9}$$

The equation (9) subjects to $\sum_{i=1}^{n}(\alpha_i - \alpha_i^*) = 0, \quad and \quad \alpha_i, \alpha_i^* \in [0, C]$

Dual variables η_i, η_i^* through condition (8) have been eliminated for deriving (9). Equation (7) can be rewritten as follows:

$$\omega = \sum_{i=1}^{n}(\alpha_i^* - \alpha_i)x_i \Rightarrow f(x) = \sum_{i=1}^{n}(\alpha_i - \alpha_i^*)\langle x_i, x \rangle + b \tag{10}$$

This is known as the support vector expansion, i.e. ω can be completely described as a linear combination of the training patterns x_i. Even for evaluating *f(x)*, it is not needed to compute ω explicitly (although this may be computationally more efficient in the linear setting). Computation of *b* is done by exploiting Karush-Kuhn-Tucker (KKT) conditions that states that at the optimal solution the product between dual variables and constraints has to vanish. This can be written as follows:

$$\begin{aligned} &\alpha_i(\varepsilon+\xi_i-y_i+\langle\omega,x_i\rangle+b)=0 \\ &\alpha_i^*(\varepsilon+\xi_i^*+y_i-\langle\omega,x_i\rangle-b)=0 \end{aligned} \tag{11}$$

$$\begin{aligned} &(C-\alpha_i)\xi_i=0 \\ &(C-\alpha_i^*)\xi_i^*=0 \end{aligned} \tag{12}$$

The following conclusions can be made: (i) only samples (x_i , y_i) with corresponding $\alpha_i^*=C$ lie outside the ε- insensitive tube around *f,* (ii) α_i,α_i^* , i.e. there can never be a set of dual variables which are both simultaneously nonzero as this would require nonzero slacks in both of the directions. At last, for $\alpha_i^*\in(0,C), \xi_i^*=0$ and moreover the second factor in equation (11) has to vanish. So, b can be computed as follows

$$\begin{aligned} &b=y_i-\langle\omega,x_i\rangle-\varepsilon \quad \text{for } \alpha_i\in(0,C) \\ &b=y_i-\langle\omega,x_i\rangle+\varepsilon \quad \text{for } \alpha_i\in(0,C) \end{aligned} \tag{13}$$

From equation (11), it follows that only for $|f(x_i)-y_i|\geq\varepsilon$ the Lagrange multipliers may be nonzero. For all samples inside the ε -tube, the $\alpha_i^*=C$ vanish: for the second factor in equation (11) is nonzero, hence α_i,α_i^* has to be zero such that the KKT conditions are satisfied. Therefore, a sparse expansion of ω exists in terms of x_i (i.e., all x_i are not needed to describe ω). The examples that come with non-vanishing coefficients are called Support Vectors. SV algorithms can be turned into nonlinear by simply preprocessing the training patterns x_i , by a map $\phi: X\rightarrow\zeta$, into some feature space ζ and then applying the standard SV regression algorithm. The expansion in equation (10) will be

$$\omega=\sum_{i=1}^{n}(\alpha_i-\alpha_i^*)\phi(x_i) \text{ and}$$

$$f(x)=\sum_{i=1}^{n}(\alpha_i-\alpha_i^*)k(x_i,x)+b \tag{14}$$

The difference with the linear case is that ω is no longer explicitly given. In the nonlinear setting, the optimization problem corresponds to finding the flattest function in feature space, not in input space. The standard SVR to solve approximation problem is

$$f(x)=\sum_{i=1}^{N}(\alpha^{*}{}_{i}-\alpha_{i})k(x_{i},x)+b \qquad (15)$$

where, α_i, and α_i^* are Lagrange multipliers.

Development of AADT Estimation Models

Model variables. After the initial data exploration, the following variables were selected for the model development:

- Total Population: the total population of a census block with traffic count
- Total Jobs: the number of jobs in a census block with traffic count
- Distance from Interstate: the shortest distance (in miles) between the count and Interstate access point (on-ramp merge with mainlines)
- Distance from a major (US) highways: the shortest distance (in miles) between the traffic count location and the intersection with a major highway

Because of the variations in each selected variable and in the characteristics of the parish (e.g. demographic, interstate access), parish-specific models and integrated parish models were developed. The integrated parish models were for all parishes with and without direct interstate access.

Parish specific SVR Models. The open source called the "*e1071 library in R*" was used to develop the AADT estimation models with the support vector regression techniques [17]. The "*e1071 library*" contains implementations for a number of statistical learning methods. A cost argument allows specifying the cost of a violation to the margin. When the cost argument is small, the margins will be wide and many support vectors will be on the margin or will violate the margin. When the cost argument is large, the margins will be narrow and there will be few support vectors on the margin or violating the margin. The *svm() function* was used to fit the support vector classifier for a given value of the cost parameter. In order to fit an SVM by using a non-linear kernel, we once again use the svm() function. To fit an SVM with a radial kernel, *kernel="radial"* was used. To specify a value for the radial basis kernel, gamma is used. In the AADT estimation, the following parameters were used (after performing several trial and error runs to get the best prediction):

- *SVM-Type= eps-regression*

- *SVM-Kernel= radial in this study*
- *Cost =100*
- *Gamma= 1*
- *Epsilon=0.1*

SVR can enhance prediction accuracy and provides an efficient way to compute parameters. The quality and performance of the SVR models depend on the setting of three parameters: kernel type, value of the penalty for excess deviation during training (C), and error-term value for the ε-insensitive loss function (ε). In addition, the number of support vectors is determined before running the SVR analysis. Once all parameters are determined, R is used to run the SVR analysis. Also, the values can be graphically summarized to better analyze the results since the initial estimated values are not shown in the script window in R.

DISCUSSIONS OF RESULTS

Results for Non-state Roadway in Rural Areas

Figure 10 and Figure 11 show the estimated AADT vs. traffic counts for eight parishes. The points on the diagonal line indicate a perfect match between the predicted and observed. Two lines placed on each side of the diagonal line represent the difference between the predicted and observed in the 100 and 200 ranges. Compared to the models explored initially such as the Poisson and Negative Binomial models, the SVR model yields much better results.

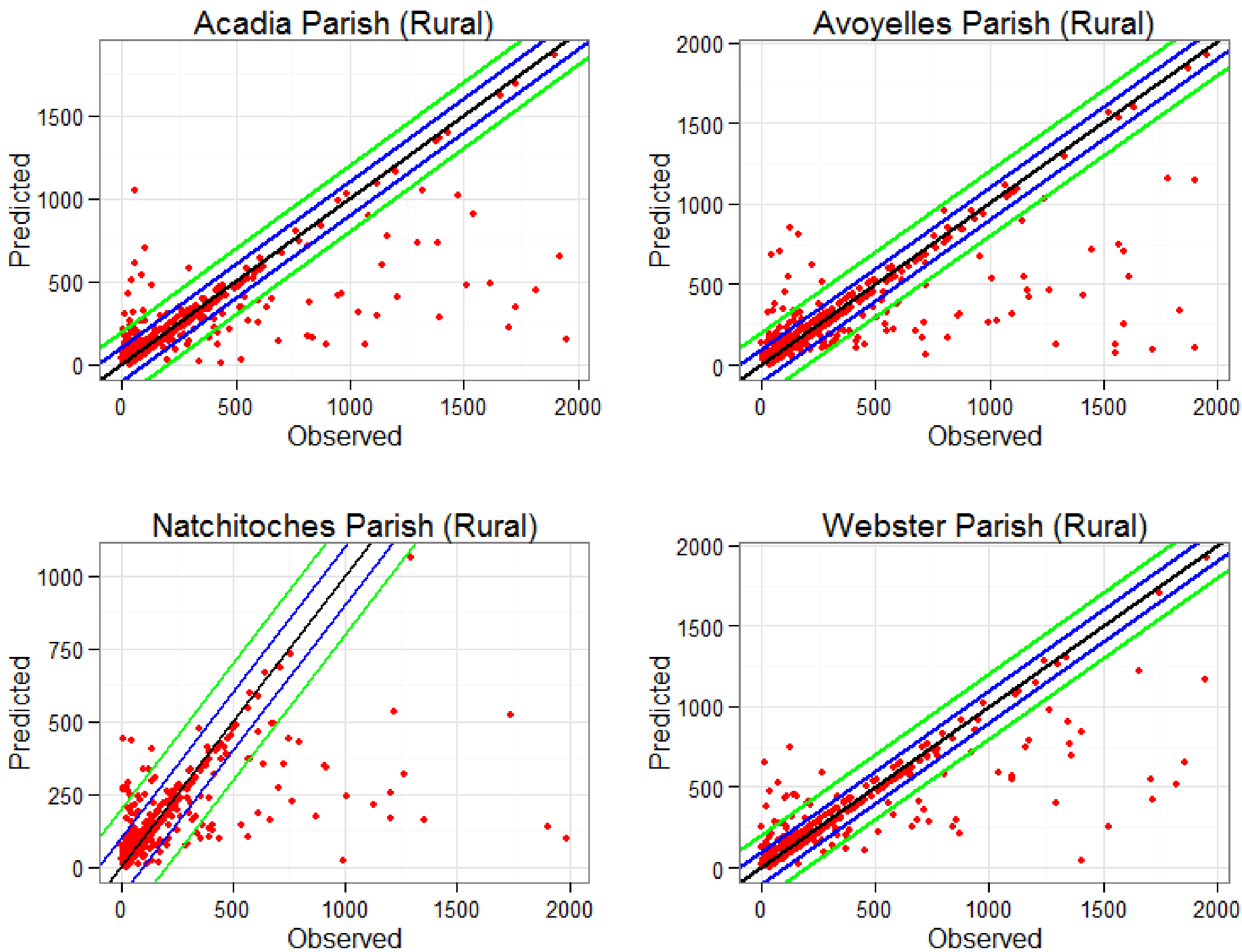


Figure 10

Predicted AADT vs. observed AADT for parishes with direct interstate access in rural areas

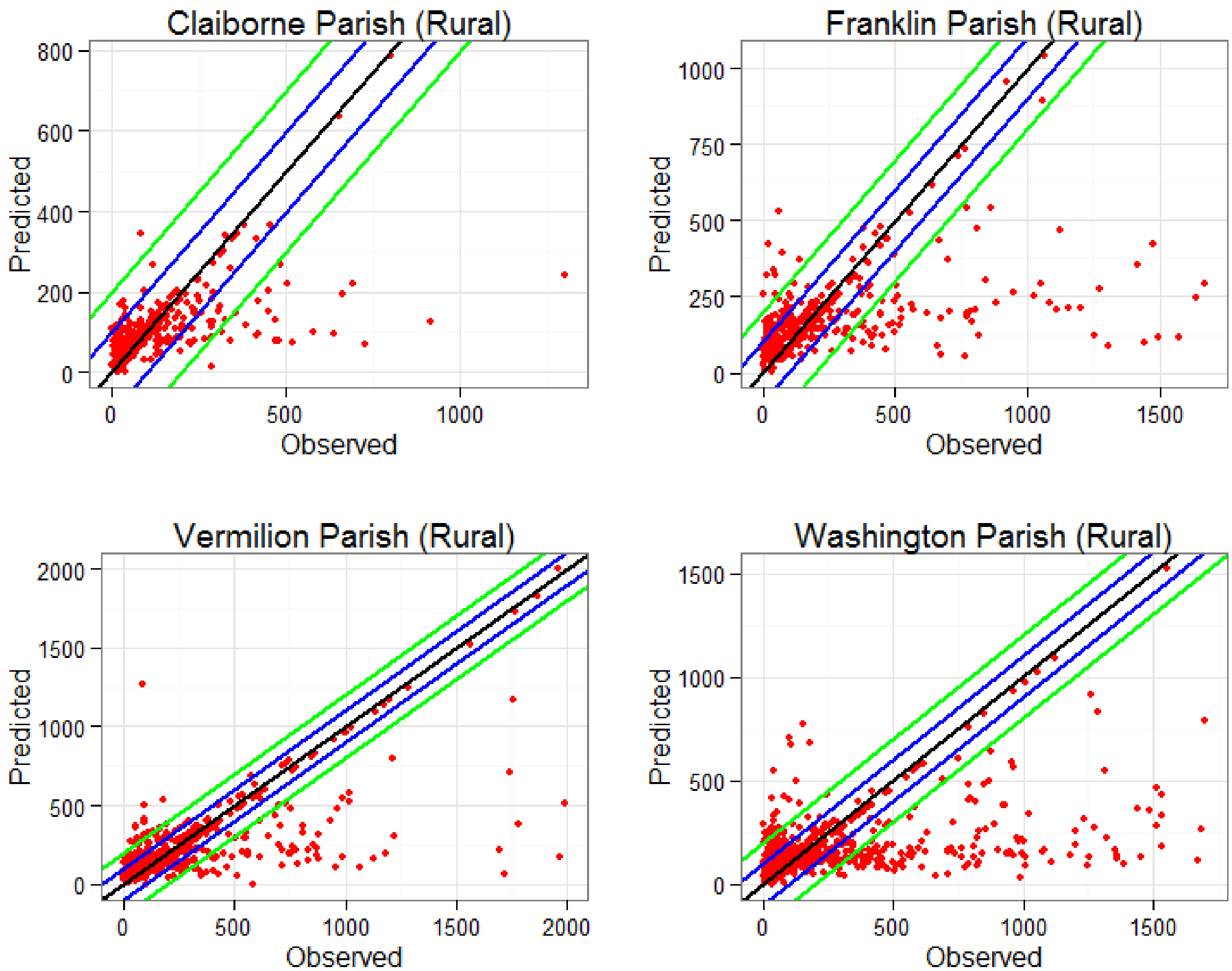


Figure 11

Predicted AADT vs. observed AADT for parishes without direct interstate access in rural areas

It is clear that the SVR model tends to underestimate the AADT at higher observed traffic count values, and somewhat overestimate the AADT at lower traffic count values. However the SVR model does capture the majority of traffic counts as shown in Table 4.

Within the ±100 bandwidth, the coverage runs from the minimum 64% to the highest 82%. Within the ±200 bandwidth, the coverage runs from the lowest 78% to the highest 91%. This close match is more than sufficient for the intended applications in transportation planning and traffic management, as well as roadway safety evaluation with the HSM. All other models explored can only research the 30%-40% match. No previous studies on the AADT estimation revealed such results at the disaggregated level. Again, the majority of the previous studies estimated AADT at much aggregated levels such as by roadway functional classification.

Table 4

Results evaluation for non-state rural highways

				Within ±100 boundary		Within ±200 boundary	
Parish		Sample size	Support vectors	Count	Percent	Count	Percent
Interstate	Acadia	464	419	380	82%	413	89%
	Avoyelles	481	422	391	81%	425	88%
	Natchitoches	453	378	373	82%	406	90%
	Webster	380	344	310	82%	333	88%
Non-Interstate	Claiborne	335	295	283	84%	310	93%
	Franklin	431	376	304	71%	357	83%
	Vermilion	447	401	298	67%	368	82%
	Washington	740	634	477	64%	581	79%

To investigate the results sensitivity to each variable with SVR modeling techniques, a sensitivity analysis was conducted for the parishes with and without direct interstate access. The objective of the sensitivity analysis was to see if the parish specific model is necessary and how sensitive each variable is to the result. The variable basic information for each parish is listed in Table 5 and Table 6.

Table 5

Summary of variables for parishes with direct access to interstates in rural areas

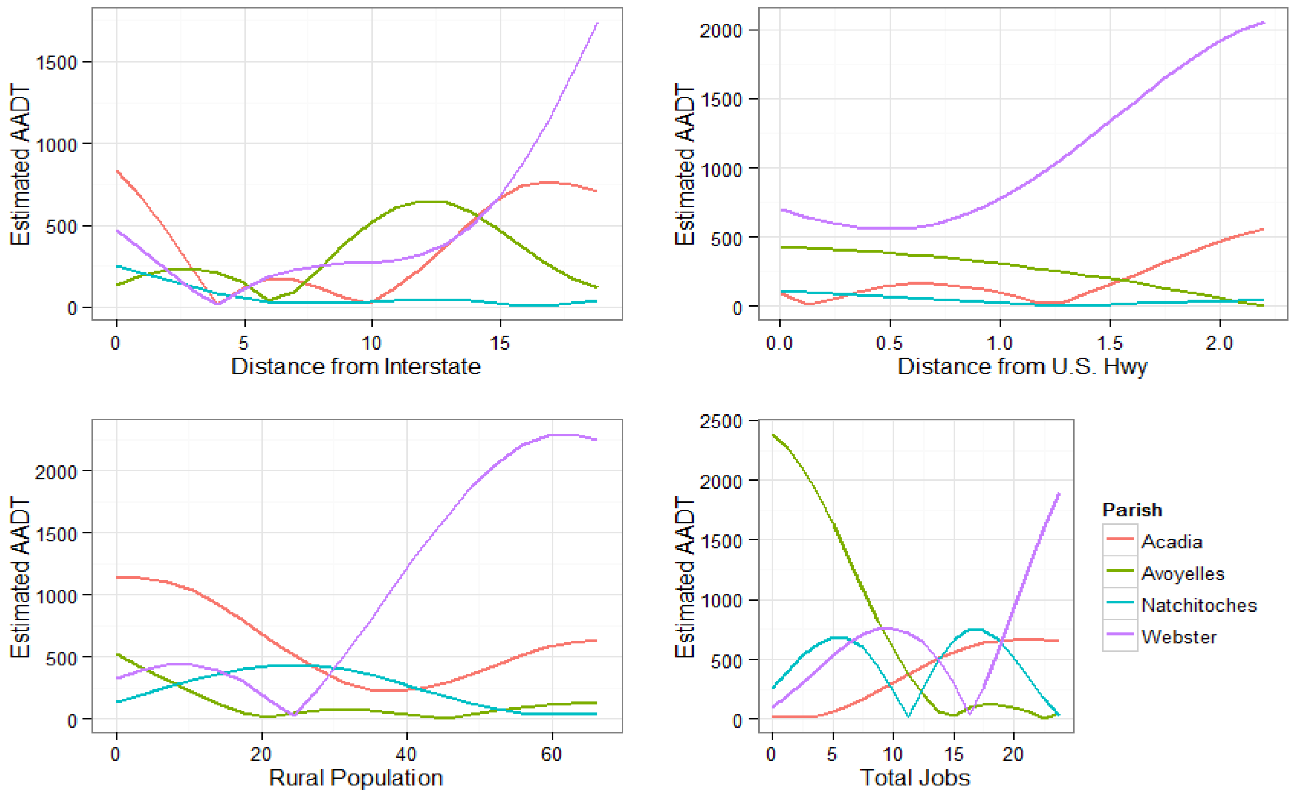
	Distance from Interstate	Distance from Major Highway	Rural Population	Total Jobs
Acadia				
Maximum	26.11	3.97	135	49
Minimum	0.46	0.10	1	1
Average	10.03	1.37	34	13
Median	9.52	1.18	26	9
Avoyelles				
Maximum	41.11	16.9	151	57
Minimum	2.71	0.10	1	1
Average	25.83	5.29	50	16
Median	26.03	3.87	45	13
Natchitoches				
Maximum	39.92	24.19	119	39
Minimum	0.61	0.10	1	1
Average	14.50	8.10	28	10
Median	12.06	6.52	21	8
Webster				
Maximum	36.14	7.77	116	54
Minimum	0.32	0.10	1	1
Average	15.54	2.44	34	14
Median	12.81	2.11	26	11

Table 6

Summary of variable for parishes without direct access to interstates in rural areas

	Distance from Major Highways	Rural Population	Total Jobs
Claiborne			
Maximum	6.88	116	37
Minimum	0.10	1	1
Average	2.23	22	8
Median	1.98	16	7
Franklin			
Maximum	10.79	108	34
Minimum	0.10	1	1
Average	3.75	29	10
Median	3.31	22	7
Vermilion			
Maximum	6.97	139	52
Minimum	0.10	1	1
Average	2.25	37	13
Median	2.05	28	11
Washington			
Maximum	11.50	160	56
Minimum	0.10	1	1
Average	3.83	45	16
Median	3.32	36	13

The results of the sensitivity analysis are plotted in Figure 12 and Figure 13 for the parishes with and without direct access to interstate, respectively. No clear relationship is found in the plots. Unlike parametric models (i.e., statistical models), there is no clear trend (increasing or decreasing) appearing on either figure. But the “plateau” on several curves are observed, which may be caused by the variables exceeding the maximum values in a particular parish before reaching the overall maximum values for all four parishes. A possible explanation for this untrendy relationship is that the variation of variable values in each parish is different. It is clear that the difference among parishes is significant, which validates the parish-specific modeling direction.



(c) (d)

Figure 12

Sensitivity analysis for parishes with direct interstate access in rural areas

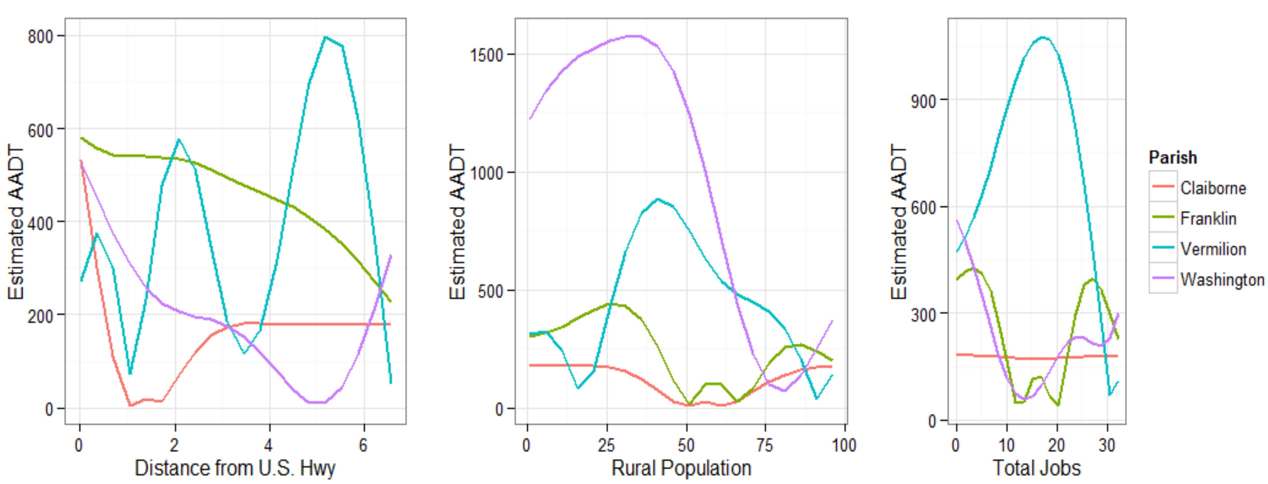


Figure 13

Sensitivity analysis for parishes without direct interstate access in rural areas

Results for Non-State Roadway in Small Urban Areas

Figure 14 and Figure 15 show the estimated AADT vs. traffic counts for non-state roadways in small urban areas. Similarly, the points on the diagonal line indicate a perfect match between the predicted and observed. Two lines placed on each side of the diagonal line represent the difference between the predicted and observed in the 100 and 200 ranges. Compared to the models explored initially such as the Poisson and Negative Binomial models, the SVR model yields better results. However, comparing with the results for the rural areas, the predicted results for the small urban areas are as good as the predicted AADT for the rural roadways. As shown in Table 7, the percentage match between the observed and predicted is given. Within the ±100 bandwidth, the coverage runs from the minimum 63% to the highest 100%. Within the ±200 bandwidth, the coverage runs from the lowest 74% to the highest 100%.

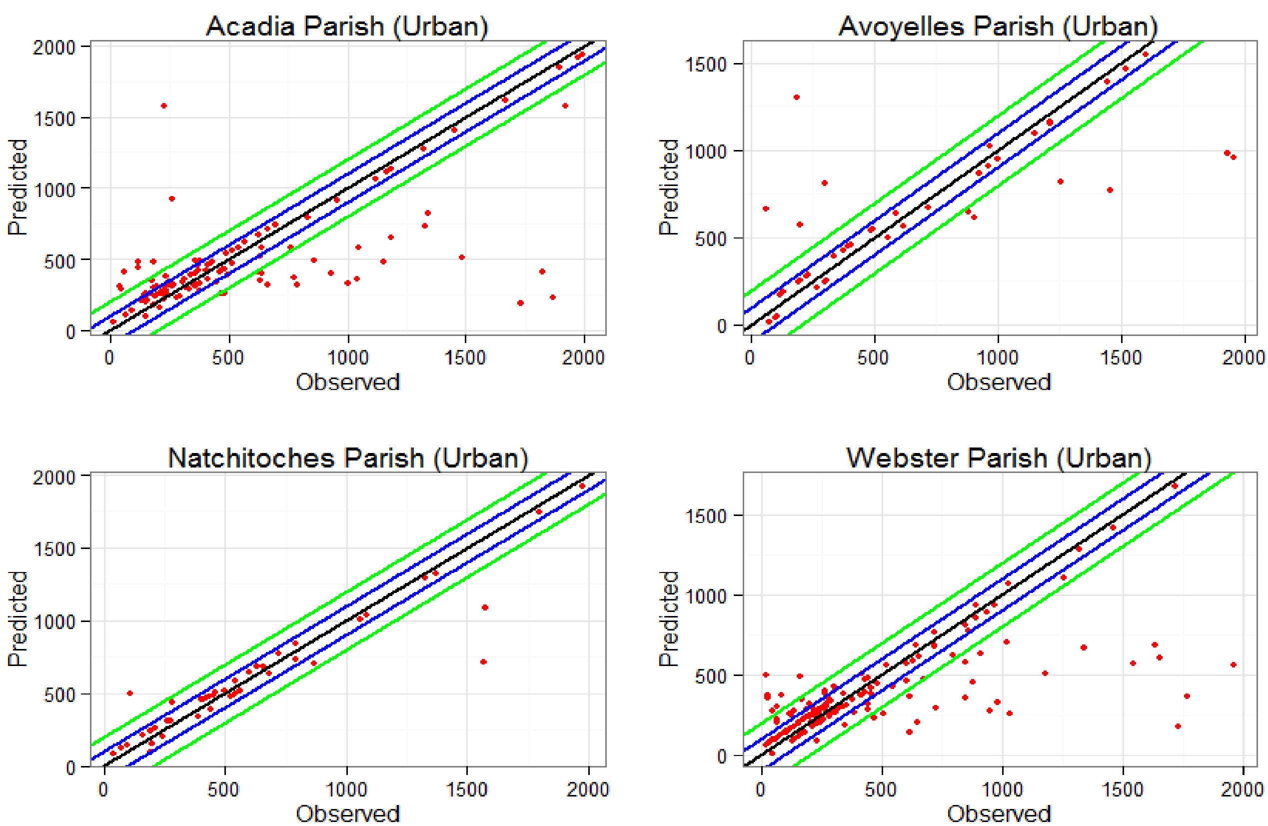


Figure 14

Predicted AADT vs. observed AADT for parishes with direct interstate access in small urban areas

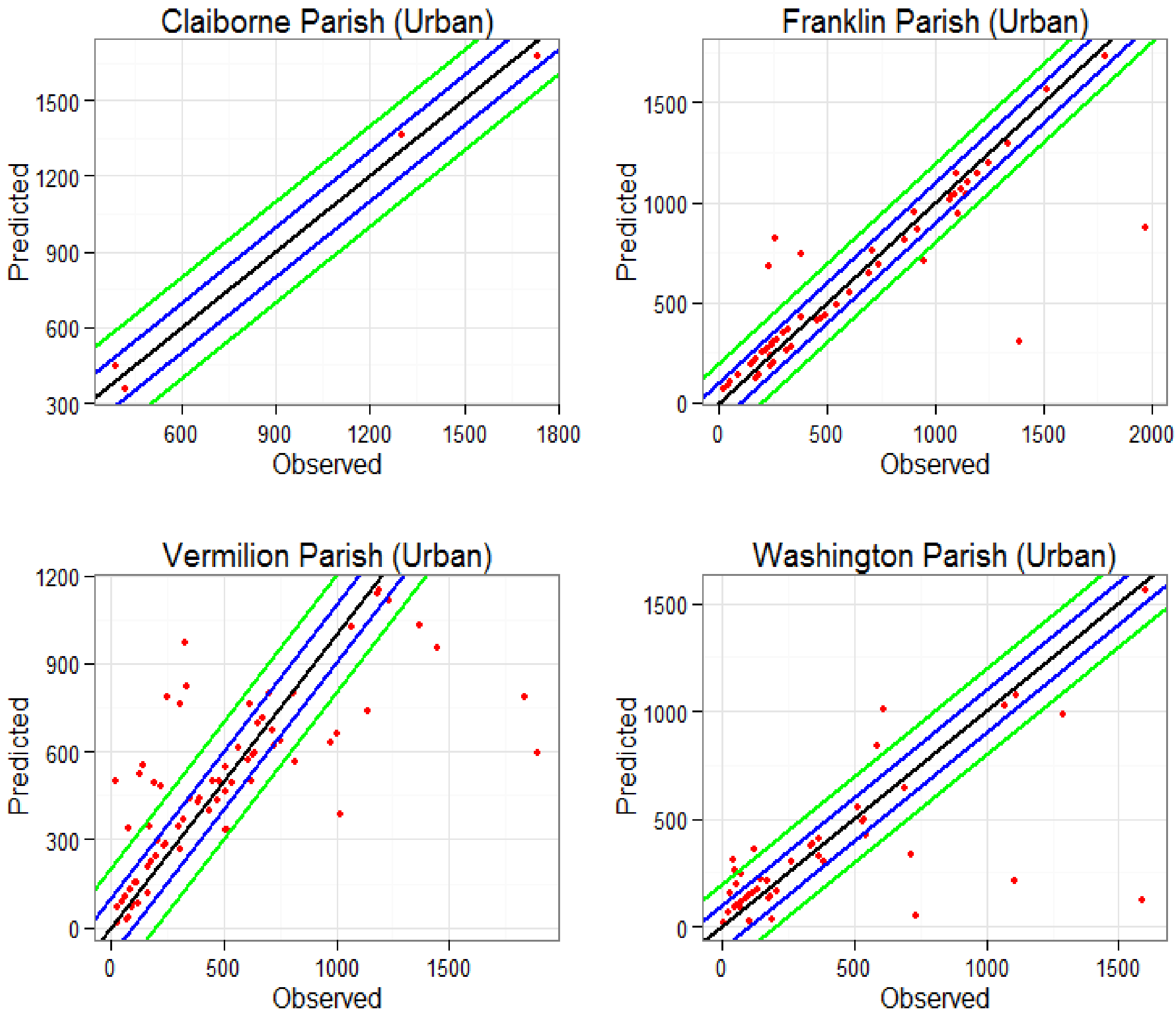


Figure 15

Predicted AADT vs. observed AADT for parishes without direct interstate access in small urban areas

Table 7

Results evaluation for non-state roadways in small urban areas

				Within ±100 boundary		Within ±200 boundary	
Parish		Sample size	Support vectors	Count	Percent	Count	Percent
Interstate	Acadia	114	104	72	63.16%	84	73.68%
	Avoyelles	46	46	36	78.26%	36	78.26%
	Natchitoches	44	38	39	88.64%	41	93.18%
	Webster	167	153	118	70.66%	137	82.04%
Non-Interstate	Claiborne	5	5	5	100.00%	5	100.00%
	Franklin	55	54	47	85.45%	49	89.09%
	Vermilion	73	69	46	63.01%	54	73.97%
	Washington	49	47	34	69.39%	39	79.59%

CONCLUSIONS

This study developed an AADT estimation model using an SVR modeling method for non-state roadways in rural and small urban areas in eight Louisiana parishes. Summarizing the model development process, the following conclusions are made:

- Among all potential modeling techniques, the SVR, a so-called machine learning or pattern recognition method, works the best in capturing the complicated AADT generation in rural and small urban areas.
- The estimated AADT are sufficiently accurate for transportation planning and roadway safety evaluation purposes.
- The developed method tends to underestimate AADT for roadways observed with traffic count higher than 1,500 per day.
- There are significant differences in the estimated AADT among the parishes, thus parish-specific models should be developed.
- AADT estimation by nature is highly stochastic. Lack of probability estimation of the results is the main drawback of SVR and all machine learning methods.
- AADT estimation for non-state roadway in small urban areas also yield satisfactory results

RECOMMENDATIONS

This project recommends DOTD develop parish-specific models for all 64 parishes in the state to estimate AADT on non-state roadways in rural and small urban areas, and repeat the estimation procedure every 10 years in general and at small time intervals for specific roadways of interest in particular.

ACRONYMS, ABBREVIATIONS, AND SYMBOLS

AADT	Annual Average Daily Traffic
ADT	Average Daily Traffic
AASHTO	American Association of State Highway and Transportation Officials
ATR	Automatic Traffic Recorder
CART	Classification and Regression Tree
DOT	Department of Transportation
FHWA	Federal Highway Administration
HPMS	Highway Performance Monitoring System
Hwy	Highway
LADOTD	Louisiana Department of Transportation and Development
LEHD	Longitudinal Employer-Household Dynamics
LTRC	Louisiana Transportation Research Center
MPO	Metropolitan Planning Organization
STC	Seasonal Traffic Count
SVM	Support Vector Machine
SVR	Support Vector Regression
TxDOT	Texas Department of Transportation
U.S. Hwy	United States Highways
VMT	Vehicle Mile Traveled
vpd	Vehicles Per Day

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APPENDIX A

Table 8

List of all parishes with population (Census 2010) and number of AADT count stations

District	Parish Name	# Count Stations	Population (Census 2010)	District	Parish Name	# Count Stations	Population (Census 2010)
02	Jefferson	877	31,594	07	Beauregard	859	35,654
02	Lafourche	1017	96,318	07	Calcasieu	1257	192,768
02	Orleans	139	343,829	07	Cameron	364	6,839
02	Plaquemines	319	23,042	07	Jefferson Davis	328	432,552
02	St. Bernard	195	35,897	08	Avoyelles	923	42,073
02	St. Charles	364	52,780	08	Grant	724	22,309
02	Terrebonne	563	111,860	08	Natchitoches	895	39,566
03	Acadia	1227	61,773	08	Rapides	1241	131,613
03	Evangeline	1025	33,984	08	Sabine	755	24,233
03	Iberia	719	73,240	08	Vernon	862	52,334
03	Lafayette	1107	221,578	08	Winn	747	15,313
03	St. Landry	1104	83,384	58	Caldwell	512	10,132
03	St. Martin	735	52,160	58	Catahoula	467	10,407
03	St. Mary	671	54,650	58	Concordia	294	20,822
03	Vermillion	987	57,999	58	Franklin	810	20,767
04	Beinville	803	14,353	58	Lasalle	600	14,890
04	Bossier	699	116,979	58	Tensas	275	5,252
04	Caddo	1083	254,969	61	Ascension	791	107,215
04	Claiborne	681	17,195	61	Assumption	165	23,421
04	Desoto	708	26,656	61	East Baton Rouge	815	440,171
04	Red River	321	9,091	61	East Feliciana	409	20,267
04	Webster	970	41,207	61	Iberville	428	33,387
05	East Carroll	343	7,759	61	Point Coupee	304	22,802
05	Jackson	498	16,274	61	St. James	293	22,102
05	Lincoln	760	46,735	61	West Baton Rouge	317	23,788
05	Madison	287	12,093	61	West Feliciana	61	15,625
05	Morehouse	698	27,979	62	Livingston	939	128,026
05	Ouachita	894	153,720	62	St. Helena	433	11,203
05	Richland	726	20,725	62	St. John The Baptist	284	45,924
05	Union	1072	22,721	62	St. Tammany	1433	233,740
05	West Carroll	509	11,604	62	Tangipahoa	1199	121,097
07	Allen	690	25,764	62	Washington	1177	47,168

APPENDIX B

Attributes of the Non-state AADT Dataset from the Louisiana Department of Transportation and Development

The attributes for each non-state (non-state) count station (location and observed AADT in a particular year) in Louisiana is detailed below:

- **STATION:** The five or six digit ID for the count station, with the first digit or two digits being the Parish code
- **DISTRICT:** The DOTD District the count station is located in (Appendix D gives further explanation on the Districts)
- **PARISH CODE:** The parish the count station is located in. The code starts with the value of *1*, being Acadia Parish, the first parish in alphabetical order, and increases by 1 for each successive Parish in alphabetical order
- **STREET NAME:** The name of the street the count station is located on
- **LRS ID:** The state-issued ID for a particular roadway segment, which is in the format PPP-X-NNNNNN-TTT-S-F-LL and is described below:
  - PPP- Parish FIPS
  - X- Prefix Code (N, S, E, or W)
  - T- Type Code (Ave., Blvd., St., etc.)
  - S- Suffix (N, S, E, or W)
  - F- Feature Type Code (Main direction, Frontage Road, or Ramp)
  - L- Sequential Occurrence.
- **LRS LOGMILE:** Logmile on the roadway segment where the count station is located
- **YEAR 1, YEAR 2, … YEAR 6:** The year when the AADT was recorded; not all stations have data for six different years. Year 1 is the most recent year the AADT was recorded, and no stations have more than six different years of recorded data
- **ADT 1, ADT 2, …, ADT 6:** The recorded AADT for a particular year (For example, if year 1 was in 2007, then the ADT 1 that is given is what was recorded in 2007)
- **LATITUDE:** The coordinate detailing the Y-Axis component of the location of the count station
- **LONGITUDE:** The coordinate detailing the X-Axis component of the location of the count station.

Since some count stations have more than one year of count data available for non-state roads, only the data recorded for the most recent year (YEAR 1) is to be used as the dependent variable in model determination. The latitude and longitude of the count station is to be used in ESRI's ArcGIS program to locate where the count station is on the State roadway network.

APPENDIX C

Statewide Roadway Network Attributes

The attributes of the Louisiana statewide roadway network, which includes a roadway segment's descriptive characteristics (name of road, length of roadway segment, etc.) is detailed below:

- **NAME**, the street name (e.g. Main)
- **STREET_CATEGORY**, the type of street (Ave., St., Blvd., Rd., etc.)
- **SUFFIX**, if the roadway has a directional identifier (e.g. North)
- **FULL_NAME**, the full name of the roadway (e.g. North Main Street)
- **DOTD_DISTRICT**, the DOTD District the road segment is located in
- **PARISH_FIPS**, the Census Parish code
- **CONTROL_SECTION**, the State-identified code for a roadway
- **LRS_ID**, based on the Control Section and additional information to distinguish between roadway segments (the state LRS_ID is in the XXX-XX-F-LLL format where XXX-XX is the control section, F is the feature type code, and LLL is the sequential occurrence)
- **BEGIN AND END LOGMILE**, the beginning and ending logmile from the Control Section of the roadway segment
- **SHAPE_LENGTH (MILES)**, the length of the roadway segment
- **STATE_ROUTE**, if the roadway segment is on a state-maintained roadway
- **ROADWAY_CATEGORY**, the type of roadway (main road, frontage road, etc.)
- **OWNERSHIP**, the owner of the road (State, Parish, or Municipal).

APPENDIX D

Louisiana Department of Transportation and Development Districts

DOTD operates nine districts throughout the state that are responsible for operations and highway maintenance in a particular region of the state, which include:

- District 02: Southeastern Louisiana south of Lake Pontchartrain (headquarters in Bridge City just west of New Orleans)
- District 03: Acadiana (headquarters in Lafayette)
- District 04: Northwestern Louisiana (headquarters in Bossier City immediately east of Shreveport)
- District 05: Northeastern Louisiana (headquarters in Monroe)
- District 07: Southwestern Louisiana (headquarters in Lake Charles)
- District 08: Central Louisiana (headquarters in Alexandria)
- District 58: East-Central Louisiana (headquarters in Chase)
- District 61: South-Central Louisiana and Capitol Area (headquarters in Baton Rouge)
- District 62: Northshore of Lake Pontchartrain (headquarters in Hammond)

Figure 16 shows the location of each district within Louisiana, including the District number and the location of the headquarters of the District.

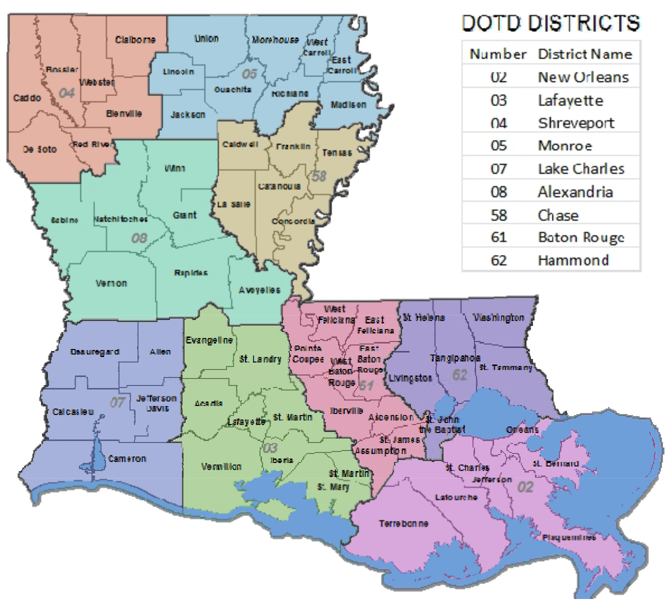

Figure 16

Louisiana DOTD districts [image courtesy of Louisiana DOTD]

APPENDIX E

Major Highways in Louisiana

United States Highways

United States Highways (i.e., "US Highways") are generally state-maintained highways that are interstate in nature (serving more than one state) but do not typically meet Interstate Highway standards. In many locations where interstates are nearby (e.g., Interstate 10 paralleling United States Hwy. 90 from the Texas State Line to Lafayette and New Orleans to the Mississippi State Line), these highways serve predominately non-state traffic; however, these highways can still be major thoroughfares in other locations where interstates are not nearby (e.g., United States Highway 90 between Lafayette and New Orleans).

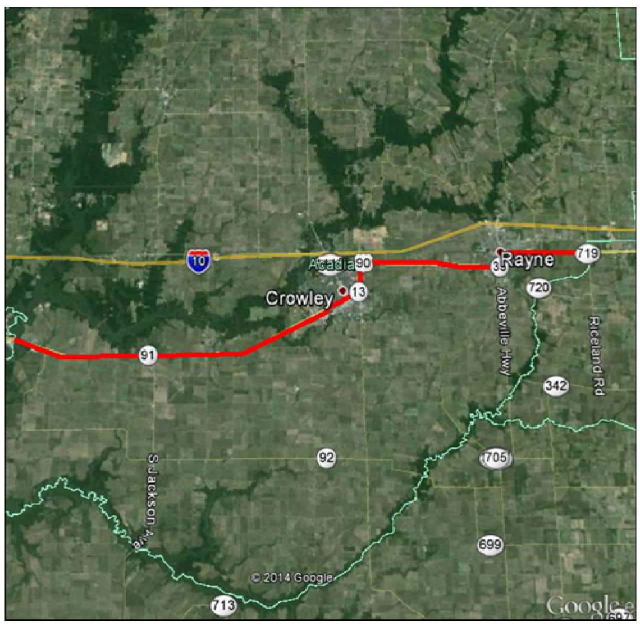

Figure 17

U.S. Highway 90 in Acadia Parish

Trans Parish Direct Highways

These highways are the direct route between two parish lines. The figure below shows Louisiana Highway 13 in Acadia Parish serving as the direct route between Vermilion Parish to the south (particularly between Gueydan, Kaplan, and Abbeville) and St. Landry Parish (Eunice) to the north. Especially in coastal areas, the north-south Trans-Parish highways serve as Hurricane Evacuation Routes from the coastal communities in the south towards north Louisiana.

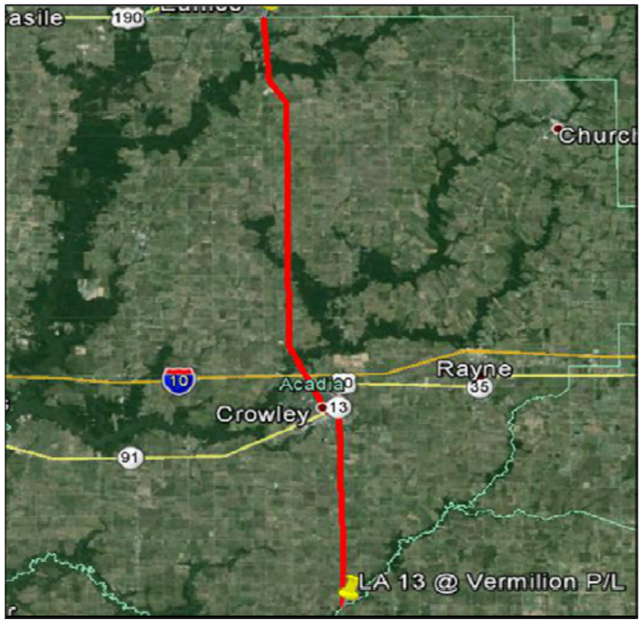

Figure 18

Louisiana highway 13 in Acadia Parish from Vermilion Parish to St. Landry Parish

Main Highway to Parish Seat in Neighboring Parish

Some major highways have a terminus within a particular parish, but serve as the main route to a major population center such as a Parish Seat in the neighboring parish. The example figure below shows that the southern terminus of Louisiana Highway 9 is in Natchitoches Parish, and this highway serves as the direct route to the seat in Bienville Parish-Arcadia; in this particular example, this highway is more direct, especially for Natchitoches Parish, to reach Arcadia (and Interstate 20 Eastbound) versus using United States Hwy. 71 or Interstate 49 towards Shreveport to reach Interstate 20 Eastbound.

Figure 19

Louisiana highway 9 in Natchitoches Parish connecting to Acadia in neighboring Bienville Parish

APPENDIX F

Census Geographic Attributes

The Census geographic dataset includes these attributes, regardless of whether the geographic subdivision is a Tract, Block Group, or Block:

- **FID**, which is the numerical order of the Census geographic subdivision
- **STATEFP10**, the Census's code for each state (The **STATEFP10** for Louisiana is 22.)
- **COUNTYFP10**, the Census's code for each parish (The code follows a *2n-1* formula where *n* is the parish's number in alphabetical order; for example, Avoyelles Parish's **COUNTYFP10** is *7* since this parish is the fourth parish in alphabetical order in Louisiana; this is related to the Parish_FIPS code in Appendix D)
- **GEOID10,** the numerical designation of the Census geography, given in the format USSSCCCTTTTTTBBBB
    - SS-STATEFP10
    - CCC-COUNTYFP10
    - TTTTTT-Census Tract
    - BBBB-Block Number
- **NAME10**, the number of the Census geography which is in the format- *Block GBBB, Block Group G, Census Tract TTTT, (Parish Name), Louisiana*
- **NAMELSAD10**, the full name of the Census geography (e.g. *Census Tract 2*)
- **ALAND10**, the land area of the Census geography, in square meters
- **AWATER10**, the water area of the Census geography, in square meters
- **INTPLAT10**, the latitude of the centroid of the Census geography
- **INTPTLON10**, the longitude of the centroid of the Census geography. Since the area of a particular Census geographic subdivision (both land and water) is in square meters, a conversion to square miles is necessary to calculate the geographic subdivision's population density, which is shown in this formula:

$$AREA_{Square\ Miles} = \frac{\sum AREA_{\ Square\ Meters}}{(\ 1000\ \times 1.609)^2}$$

Dividing by $1{,}000^2$ (or 1,000,000) converts the area from square meters to square kilometers while dividing by 1.609^2 (or 2.588) converts the area from square kilometers to square miles.

APPENDIX G

R Codes

```
###### Data attachment and preparation for analysis [Rural
###### blocks]

setwd("C:/Users/…")              ## setting up the directory
all_a <- read.csv("All_a_bp.csv") ## data attaching
all_b <- read.csv("All_b_bp.csv")

head(all_a)
  Adt Dist_Int   Dist_US Rur_Pop Total_Jobs Par
1  54 14.99544 2.8997012      50         35 Aca
2   5 14.12065 2.0249073      50         35 Aca
3  42 14.62432 0.2712610      44         14 Aca
4 871 16.28147 1.0886676      15         11 Aca
5 158 15.57282 0.6166764      15         11 Aca
6 341 14.28677 0.5771938      35         17 Aca

head(all_b)
  Adt    Dist_US Rur_Pop Total_Jobs Par
1 238 0.17429243      11          2 Cla
2 245 2.80198120      66         28 Cla
3  15 4.18712486       5          8 Cla
4 187 2.19418858      65         26 Cla
5 143 0.10349450      26         10 Cla
6  81 0.01776988       7          6 Cla

#### Number of rows in each Parish
table(all_a$Par)

Aca Avo Nat Web
464 481 453 380

table(all_b$Par)

Cla Fra Ver Was
335 431 447 740

#### Data preparation for each Parish [Rural Blocks]
aca <- subset(all_a, Par=="Aca")
avo <- subset(all_a, Par=="Avo")
nat <- subset(all_a, Par=="Nat")
web <- subset(all_a, Par=="Web")
cla <- subset(all_b, Par=="Cla")
fra <- subset(all_b, Par=="Fra")
```

```
ver <- subset(all_b, Par=="Ver")
was <- subset(all_b, Par=="Was")

#### calling e1071 library for svm() function
library(e1071)

###### SVM Model development [Parish wise (Rural blocks)]

#### Acadia Parish
svm.model <- svm(Adt~ Dist_Int+   Dist_US+ Rur_Pop+ Total_Jobs ,
data=aca,cost=100,gamma=1)
svm.pred <- predict(svm.model, aca[2:5])
m1 <- cbind(obs= aca$Adt, pred=abs(round(svm.pred,0)))

#### Avoyelles Parish
svm.model <- svm(Adt~ Dist_Int+   Dist_US+ Rur_Pop+ Total_Jobs ,
data=avo,cost=100,gamma=1)
svm.pred <- predict(svm.model, avo[2:5])
m2 <- cbind(obs= avo$Adt, pred=abs(round(svm.pred,0)))

#### Natchitoches Parish
svm.model <- svm(Adt~ Dist_Int+   Dist_US+ Rur_Pop+ Total_Jobs ,
data=nat,cost=100,gamma=1)
svm.pred <- predict(svm.model, nat[2:5])
m3 <- cbind(obs= nat$Adt, pred=abs(round(svm.pred,0)))

#### Webster Parish
svm.model <- svm(Adt~ Dist_Int+   Dist_US+ Rur_Pop+ Total_Jobs ,
data=web,cost=100,gamma=1)
svm.pred <- predict(svm.model, web[2:5])
m4 <- cbind(obs= web$Adt, pred=abs(round(svm.pred,0)))

#### Claiborne Parish
svm.model <- svm(Adt~   Dist_US+ Rur_Pop+ Total_Jobs ,
data=cla,cost=100,gamma=1)
svm.pred <- predict(svm.model, cla[2:4])
m5 <- cbind(obs= cla$Adt, pred=abs(round(svm.pred,0)))

#### Franklin Parish
svm.model <- svm(Adt~   Dist_US+ Rur_Pop+ Total_Jobs ,
data=fra,cost=100,gamma=1)
svm.pred <- predict(svm.model, fra[2:4])
m6 <- cbind(obs= fra$Adt, pred=abs(round(svm.pred,0)))

#### Vermilion Parish
svm.model <- svm(Adt~   Dist_US+ Rur_Pop+ Total_Jobs ,
data=ver,cost=100,gamma=1)
```

```
svm.pred <- predict(svm.model, ver[2:4])
m7 <- cbind(obs= ver$Adt, pred=abs(round(svm.pred,0)))

#### Washington Parish
svm.model <- svm(Adt~   Dist_US+ Rur_Pop+ Total_Jobs ,
data=was,cost=100,gamma=1)
svm.pred <- predict(svm.model, was[2:4])
m8 <- cbind(obs= was$Adt, pred=abs(round(svm.pred,0)))

###### Visualization of observed versus predicted plots

#### Interstate Parishes
library(ggplot2)
p1 <- ggplot(m1, aes(obs, pred))
p1a <- p1 + geom_point(colour = "red", size = 1.5)+ theme_bw()+
geom_abline(slope=1,size = 1)+ geom_abline(intercept=100,
slope=1, color="blue",size = 1)+
geom_abline(intercept=-100, slope=1, color="blue",size =
1)+geom_abline(intercept=200, slope=1, color="green",size = 1)+
geom_abline(intercept=-200, slope=1, color="green",size = 1)+
labs(title = "Acadia Parish (Rural)")+labs(x = "Observed",
y="Predicted")

p2 <- ggplot(m2, aes(obs, pred))
p2a <- p2 + geom_point(colour = "red", size = 1.5)+ theme_bw()+
geom_abline(slope=1,size = 1)+ geom_abline(intercept=100,
slope=1, color="blue",size = 1)+
geom_abline(intercept=-100, slope=1, color="blue",size =
1)+geom_abline(intercept=200, slope=1, color="green",size = 1)+
geom_abline(intercept=-200, slope=1, color="green",size = 1)+
labs(title = "Avoyelles Parish (Rural)")+labs(x = "Observed",
y="Predicted")

p3 <- ggplot(m3, aes(obs, pred))
p3a <- p2 + geom_point(colour = "red", size = 1.5)+ theme_bw()+
geom_abline(slope=1,size = 1)+ geom_abline(intercept=100,
slope=1, color="blue",size = 1)+
geom_abline(intercept=-100, slope=1, color="blue",size =
1)+geom_abline(intercept=200, slope=1, color="green",size = 1)+
geom_abline(intercept=-200, slope=1, color="green",size = 1)+
labs(title = "Natchitoches Parish (Rural)")+labs(x = "Observed",
y="Predicted")

p4 <- ggplot(m4, aes(obs, pred))
p4a <- p4 + geom_point(colour = "red", size = 1.5)+ theme_bw()+
geom_abline(slope=1,size = 1)+ geom_abline(intercept=100,
slope=1, color="blue",size = 1)+
```

```
geom_abline(intercept=-100, slope=1, color="blue",size =
1)+geom_abline(intercept=200, slope=1, color="green",size = 1)+
geom_abline(intercept=-200, slope=1, color="green",size = 1)+
labs(title = "Webster Parish (Rural)")+labs(x = "Observed",
y="Predicted")

#### Merging of four figures for Interstate Parishes
library(ggplot2)
library(grid)
grid.newpage()
pushViewport(viewport(layout = grid.layout(2, 2)))
vplayout <- function(x, y)
  viewport(layout.pos.row = x, layout.pos.col = y)
print(p1a, vp = vplayout(1, 1))
print(p2a, vp = vplayout(1, 2))
print(p3a, vp = vplayout(2, 1))
print(p4a, vp = vplayout(2, 2))

#### Non-Interstate Parishes
p1 <- ggplot(m5, aes(obs, pred))
p1b <- p1 + geom_point(colour = "red", size = 1.5)+ theme_bw()+
geom_abline(slope=1,size = 1)+ geom_abline(intercept=100,
slope=1, color="blue",size = 1)+
geom_abline(intercept=-100, slope=1, color="blue",size =
1)+geom_abline(intercept=200, slope=1, color="green",size = 1)+
geom_abline(intercept=-200, slope=1, color="green",size = 1)+
labs(title = "Claiborne Parish (Rural)")+labs(x = "Observed",
y="Predicted")

p2 <- ggplot(m6, aes(obs, pred))
p2b <- p2 + geom_point(colour = "red", size = 1.5)+ theme_bw()+
geom_abline(slope=1,size = 1)+ geom_abline(intercept=100,
slope=1, color="blue",size = 1)+
geom_abline(intercept=-100, slope=1, color="blue",size =
1)+geom_abline(intercept=200, slope=1, color="green",size = 1)+
geom_abline(intercept=-200, slope=1, color="green",size = 1)+
labs(title = "Franklin Parish (Rural)")+labs(x = "Observed",
y="Predicted")

p3 <- ggplot(m7, aes(obs, pred))
p3b <- p2 + geom_point(colour = "red", size = 1.5)+ theme_bw()+
geom_abline(slope=1,size = 1)+ geom_abline(intercept=100,
slope=1, color="blue",size = 1)+
geom_abline(intercept=-100, slope=1, color="blue",size =
1)+geom_abline(intercept=200, slope=1, color="green",size = 1)+
geom_abline(intercept=-200, slope=1, color="green",size = 1)+
labs(title = "Vermilion Parish (Rural)")+labs(x = "Observed",
```

```
y="Predicted")

p4 <- ggplot(m8, aes(obs, pred))
p4b <- p4 + geom_point(colour = "red", size = 1.5)+ theme_bw()+
geom_abline(slope=1,size = 1)+ geom_abline(intercept=100,
slope=1, color="blue",size = 1)+
geom_abline(intercept=-100, slope=1, color="blue",size =
1)+geom_abline(intercept=200, slope=1, color="green",size = 1)+
geom_abline(intercept=-200, slope=1, color="green",size = 1)+
labs(title = "Washington Parish (Rural)")+labs(x = "Observed",
y="Predicted")

#### Merging of four figures for Non-interstate Parishes
library(ggplot2)
library(grid)
grid.newpage()
pushViewport(viewport(layout = grid.layout(2, 2)))
vplayout <- function(x, y)
  viewport(layout.pos.row = x, layout.pos.col = y)
print(p1b, vp = vplayout(1, 1))
print(p2b, vp = vplayout(1, 2))
print(p3b, vp = vplayout(2, 1))
print(p4b, vp = vplayout(2, 2))

###### Data attachment and preparation for analysis [Urban
###### blocks]

setwd("C:/Users/…")               ## setting up the directory
all_a <- read.csv("All_a_urb.csv")## data attaching
all_b <- read.csv("All_b_urb.csv")

head(all_a)
   Adt Dist_Int    Dist_US Urb_Pop Total_Jobs Par
1  570 12.96919 0.13607160     207         66 aca
2 3763 12.66319 0.00000000      77         35 aca
3 4396 12.66418 0.00000000      77         35 aca
4  428 12.84323 0.21304169      40         27 aca
5  630 12.89067 0.26048324      40         27 aca
6 4760 12.69522 0.03754325     115         71 aca

head(all_b)
   Adt    Dist_US Urb_Pop Total_Jobs Par
1 1736 0.12283667      32         14 cla
2 1672 0.09965565       9          2 cla
3  389 0.19781251      16          6 cla
4 2788 0.00000000      51         12 cla
5  417 0.30937902       4          2 cla
```

```
6 1303 0.67421925     167         60 cla

table(all_a$Par)

aca avo nat web
114  46  44 167

table(all_b$Par)

cla fra ver was
  5  55  73  49

#### Data preparation for each Parish [Rural Blocks]
aca <- subset(all_a, Par=="Aca")
avo <- subset(all_a, Par=="Avo")
nat <- subset(all_a, Par=="Nat")
web <- subset(all_a, Par=="Web")
cla <- subset(all_b, Par=="Cla")
fra <- subset(all_b, Par=="Fra")
ver <- subset(all_b, Par=="Ver")
was <- subset(all_b, Par=="Was")



###### SVM Model development [Parish wise (Urban blocks)]

#### Acadia Parish
svm.model <- svm(Adt~ Dist_Int+   Dist_US+ Urb_Pop+ Total_Jobs ,
data=aca,cost=100,gamma=1)
svm.pred <- predict(svm.model, aca[2:5])
m1 <- cbind(obs= aca$Adt, pred=abs(round(svm.pred,0)))

#### Avoyelles Parish
svm.model <- svm(Adt~ Dist_Int+   Dist_US+ Urb_Pop+ Total_Jobs ,
data=avo,cost=100,gamma=1)
svm.pred <- predict(svm.model, avo[2:5])
m2 <- cbind(obs= avo$Adt, pred=abs(round(svm.pred,0)))

#### Natchitoches Parish
svm.model <- svm(Adt~ Dist_Int+   Dist_US+ Urb_Pop+ Total_Jobs ,
data=nat,cost=100,gamma=1)
svm.pred <- predict(svm.model, nat[2:5])
m3 <- cbind(obs= nat$Adt, pred=abs(round(svm.pred,0)))

#### Webster Parish
svm.model <- svm(Adt~ Dist_Int+   Dist_US+ Urb_Pop+ Total_Jobs ,
data=web,cost=100,gamma=1)
```

```
svm.pred <- predict(svm.model, web[2:5])
m4 <- cbind(obs= web$Adt, pred=abs(round(svm.pred,0)))

#### Claiborne Parish
svm.model <- svm(Adt~   Dist_US+ Urb_Pop+ Total_Jobs ,
data=cla,cost=100,gamma=1)
svm.pred <- predict(svm.model, cla[2:4])
m5 <- cbind(obs= cla$Adt, pred=abs(round(svm.pred,0)))

#### Franklin Parish
svm.model <- svm(Adt~   Dist_US+ Urb_Pop+ Total_Jobs ,
data=fra,cost=100,gamma=1)
svm.pred <- predict(svm.model, fra[2:4])
m6 <- cbind(obs= fra$Adt, pred=abs(round(svm.pred,0)))

#### Vermilion Parish
svm.model <- svm(Adt~   Dist_US+ Urb_Pop+ Total_Jobs ,
data=ver,cost=100,gamma=1)
svm.pred <- predict(svm.model, ver[2:4])
m7 <- cbind(obs= ver$Adt, pred=abs(round(svm.pred,0)))

#### Washington Parish
svm.model <- svm(Adt~   Dist_US+ Urb_Pop+ Total_Jobs ,
data=was,cost=100,gamma=1)
svm.pred <- predict(svm.model, was[2:4])
m8 <- cbind(obs= was$Adt, pred=abs(round(svm.pred,0)))

###### Visualization of observed versus predicted plots

#### Interstate Parishes
library(ggplot2)
p1 <- ggplot(m1, aes(obs, pred))
p1a <- p1 + geom_point(colour = "red", size = 1.5)+ theme_bw()+
geom_abline(slope=1,size = 1)+ geom_abline(intercept=100,
slope=1, color="blue",size = 1)+
geom_abline(intercept=-100, slope=1, color="blue",size =
1)+geom_abline(intercept=200, slope=1, color="green",size = 1)+
geom_abline(intercept=-200, slope=1, color="green",size = 1)+
labs(title = "Acadia Parish (Urban)")+labs(x = "Observed",
y="Predicted")

p2 <- ggplot(m2, aes(obs, pred))
p2a <- p2 + geom_point(colour = "red", size = 1.5)+ theme_bw()+
geom_abline(slope=1,size = 1)+ geom_abline(intercept=100,
slope=1, color="blue",size = 1)+
geom_abline(intercept=-100, slope=1, color="blue",size =
1)+geom_abline(intercept=200, slope=1, color="green",size = 1)+
```

```
geom_abline(intercept=-200, slope=1, color="green",size = 1)+
labs(title = "Avoyelles Parish (Urban)")+labs(x = "Observed",
y="Predicted")

p3 <- ggplot(m3, aes(obs, pred))
p3a <- p2 + geom_point(colour = "red", size = 1.5)+ theme_bw()+
geom_abline(slope=1,size = 1)+ geom_abline(intercept=100,
slope=1, color="blue",size = 1)+
geom_abline(intercept=-100, slope=1, color="blue",size =
1)+geom_abline(intercept=200, slope=1, color="green",size = 1)+
geom_abline(intercept=-200, slope=1, color="green",size = 1)+
labs(title = "Natchitoches Parish (Urban)")+labs(x = "Observed",
y="Predicted")

p4 <- ggplot(m4, aes(obs, pred))
p4a <- p4 + geom_point(colour = "red", size = 1.5)+ theme_bw()+
geom_abline(slope=1,size = 1)+ geom_abline(intercept=100,
slope=1, color="blue",size = 1)+
geom_abline(intercept=-100, slope=1, color="blue",size =
1)+geom_abline(intercept=200, slope=1, color="green",size = 1)+
geom_abline(intercept=-200, slope=1, color="green",size = 1)+
labs(title = "Webster Parish (Urban)")+labs(x = "Observed",
y="Predicted")

#### Merging of four figures for Interstate Parishes
library(ggplot2)
library(grid)
grid.newpage()
pushViewport(viewport(layout = grid.layout(2, 2)))
vplayout <- function(x, y)
  viewport(layout.pos.row = x, layout.pos.col = y)
print(p1a, vp = vplayout(1, 1))
print(p2a, vp = vplayout(1, 2))
print(p3a, vp = vplayout(2, 1))
print(p4a, vp = vplayout(2, 2))

#### Non-Interstate Parishes
p1 <- ggplot(m5, aes(obs, pred))
p1b <- p1 + geom_point(colour = "red", size = 1.5)+ theme_bw()+
geom_abline(slope=1,size = 1)+ geom_abline(intercept=100,
slope=1, color="blue",size = 1)+
geom_abline(intercept=-100, slope=1, color="blue",size =
1)+geom_abline(intercept=200, slope=1, color="green",size = 1)+
geom_abline(intercept=-200, slope=1, color="green",size = 1)+
labs(title = "Claiborne Parish (Urban)")+labs(x = "Observed",
y="Predicted")
```

```
p2 <- ggplot(m6, aes(obs, pred))
p2b <- p2 + geom_point(colour = "red", size = 1.5)+ theme_bw()+
geom_abline(slope=1,size = 1)+ geom_abline(intercept=100,
slope=1, color="blue",size = 1)+
geom_abline(intercept=-100, slope=1, color="blue",size =
1)+geom_abline(intercept=200, slope=1, color="green",size = 1)+
geom_abline(intercept=-200, slope=1, color="green",size = 1)+
labs(title = "Franklin Parish (Urban)")+labs(x = "Observed",
y="Predicted")

p3 <- ggplot(m7, aes(obs, pred))
p3b <- p2 + geom_point(colour = "red", size = 1.5)+ theme_bw()+
geom_abline(slope=1,size = 1)+ geom_abline(intercept=100,
slope=1, color="blue",size = 1)+
geom_abline(intercept=-100, slope=1, color="blue",size =
1)+geom_abline(intercept=200, slope=1, color="green",size = 1)+
geom_abline(intercept=-200, slope=1, color="green",size = 1)+
labs(title = "Vermilion Parish (Urban)")+labs(x = "Observed",
y="Predicted")

p4 <- ggplot(m8, aes(obs, pred))
p4b <- p4 + geom_point(colour = "red", size = 1.5)+ theme_bw()+
geom_abline(slope=1,size = 1)+ geom_abline(intercept=100,
slope=1, color="blue",size = 1)+
geom_abline(intercept=-100, slope=1, color="blue",size =
1)+geom_abline(intercept=200, slope=1, color="green",size = 1)+
geom_abline(intercept=-200, slope=1, color="green",size = 1)+
labs(title = "Washington Parish (Urban)")+labs(x = "Observed",
y="Predicted")

#### Merging of four figures for Non-interstate Parishes
library(ggplot2)
library(grid)
grid.newpage()
pushViewport(viewport(layout = grid.layout(2, 2)))
vplayout <- function(x, y)
  viewport(layout.pos.row = x, layout.pos.col = y)
print(p1b, vp = vplayout(1, 1))
print(p2b, vp = vplayout(1, 2))
print(p3b, vp = vplayout(2, 1))
print(p4b, vp = vplayout(2, 1))


###### Sensitivity analysis

#### Two set of test data preparation
test1 <- read.csv("test1_all.csv")
```

```
test2 <- read.csv("test2_all.csv")

#### Interstate Parishes
test1_dist_int <- subset(test1, Change=="dist_int")
test1_dist_us <- subset(test1, Change=="dist_us")
test1_pop <- subset(test1, Change=="pop")
test1_job <- subset(test1, Change=="job")

#### Distance from Interstate

svm.model <- svm(Adt~ Dist_Int+   Dist_US+ Rur_Pop+ Total_Jobs ,
data=aca,cost=100,gamma=1)
svm.pred <- predict(svm.model, test1_dist_int[1:4])
pl <- cbind(test1_dist_int[1:4],
Pred_Aca=abs(round(svm.pred,0)))
pl1 <- data.frame(pl)

svm.model <- svm(Adt~ Dist_Int+   Dist_US+ Rur_Pop+ Total_Jobs ,
data=avo,cost=100,gamma=1)
svm.pred <- predict(svm.model, test1_dist_int[1:4])
pl <- cbind(test1_dist_int[1:4],
Pred_Avo=abs(round(svm.pred,0)))
pl2 <- data.frame(pl)

svm.model <- svm(Adt~ Dist_Int+   Dist_US+ Rur_Pop+ Total_Jobs ,
data=nat,cost=100,gamma=1)
svm.pred <- predict(svm.model, test1_dist_int[1:4])
pl <- cbind(test1_dist_int[1:4],
Pred_Nat=abs(round(svm.pred,0)))
pl3 <- data.frame(pl)

svm.model <- svm(Adt~ Dist_Int+   Dist_US+ Rur_Pop+ Total_Jobs ,
data=web,cost=100,gamma=1)
svm.pred <- predict(svm.model, test1_dist_int[1:4])
pl <- cbind(test1_dist_int[1:4],
Pred_Web=abs(round(svm.pred,0)))
pl4 <- data.frame(pl)

m <- cbind(test1_dist_int[1:4], Aca=pl1$Pred_Aca,
Avo=pl2$Pred_Avo, Nat=pl3$Pred_Nat, Web=pl4$Pred_Web)
head(m)
m1 <- m[c(1, 5:8)]
m2 <- read.csv("test1_distINTpred1.csv")

p <- ggplot(m2, aes(x=Dist_Int, y=Pred, group=Parish,
colour=Parish))
p1 <- p + geom_line(size=1)+theme_bw()+xlab("Distance from
```

```
Interstate")+ylab("Estimated AADT") +scale_colour_discrete(guide
= FALSE)

#### Distance from US Highways
svm.model <- svm(Adt~ Dist_Int+   Dist_US+ Rur_Pop+ Total_Jobs ,
data=aca,cost=100,gamma=1)
svm.pred <- predict(svm.model, test1_dist_us[1:4])
pl <- cbind(test1_dist_int[1:4],
Pred_Aca=abs(round(svm.pred,0)))
pl1 <- data.frame(pl)

svm.model <- svm(Adt~ Dist_Int+   Dist_US+ Rur_Pop+ Total_Jobs ,
data=avo,cost=100,gamma=1)
svm.pred <- predict(svm.model, test1_dist_us[1:4])
pl <- cbind(test1_dist_int[1:4],
Pred_Avo=abs(round(svm.pred,0)))
pl2 <- data.frame(pl)

svm.model <- svm(Adt~ Dist_Int+   Dist_US+ Rur_Pop+ Total_Jobs ,
data=nat,cost=100,gamma=1)
svm.pred <- predict(svm.model, test1_dist_us[1:4])
pl <- cbind(test1_dist_int[1:4],
Pred_Nat=abs(round(svm.pred,0)))
pl3 <- data.frame(pl)

svm.model <- svm(Adt~ Dist_Int+   Dist_US+ Rur_Pop+ Total_Jobs ,
data=web,cost=100,gamma=1)
svm.pred <- predict(svm.model, test1_dist_us[1:4])
pl <- cbind(test1_dist_int[1:4],
Pred_Web=abs(round(svm.pred,0)))
pl4 <- data.frame(pl)


m <- cbind(test1_dist_us[1:4], Aca=pl1$Pred_Aca,
Avo=pl2$Pred_Avo, Nat=pl3$Pred_Nat, Web=pl4$Pred_Web)
head(m)
m1 <- m[c(2, 5:8)]
m2 <- read.csv("test1_distuspred1.csv")

p <- ggplot(m2, aes(x=Dist_US, y=Pred, group=Parish,
colour=Parish))
p2 <- p + geom_line(size=1)+theme_bw()+xlab("Distance from U.S.
Hwy")+ylab("Estimated AADT")+scale_colour_discrete(guide =
FALSE)


#### Rural Population
```

```
svm.model <- svm(Adt~ Dist_Int+   Dist_US+ Rur_Pop+ Total_Jobs ,
data=aca,cost=100,gamma=1)
svm.pred <- predict(svm.model, test1_pop[1:4])
pl <- cbind(test1_dist_int[1:4],
Pred_Aca=abs(round(svm.pred,0)))
pl1 <- data.frame(pl)

svm.model <- svm(Adt~ Dist_Int+   Dist_US+ Rur_Pop+ Total_Jobs ,
data=avo,cost=100,gamma=1)
svm.pred <- predict(svm.model, test1_pop[1:4])
pl <- cbind(test1_dist_int[1:4],
Pred_Avo=abs(round(svm.pred,0)))

svm.model <- svm(Adt~ Dist_Int+   Dist_US+ Rur_Pop+ Total_Jobs ,
data=nat,cost=100,gamma=1)
svm.pred <- predict(svm.model, test1_pop[1:4])
pl <- cbind(test1_dist_int[1:4],
Pred_Nat=abs(round(svm.pred,0)))
pl3 <- data.frame(pl)

svm.model <- svm(Adt~ Dist_Int+   Dist_US+ Rur_Pop+ Total_Jobs ,
data=web,cost=100,gamma=1)
svm.pred <- predict(svm.model, test1_pop[1:4])
pl <- cbind(test1_dist_int[1:4],
Pred_Web=abs(round(svm.pred,0)))
pl4 <- data.frame(pl)

m <- cbind(test1_pop[1:4], Aca=pl1$Pred_Aca, Avo=pl2$Pred_Avo,
Nat=pl3$Pred_Nat, Web=pl4$Pred_Web)
head(m)
m1 <- m[c(3, 5:8)]
m2 <- read.csv("test1_poppred1.csv")
head(m2)

p <- ggplot(m2, aes(x=Rur_Pop, y=Pred, group=Parish,
colour=Parish))
p3 <- p + geom_line(size=1)+theme_bw()+xlab("Rural
Population")+ylab("Estimated AADT")+scale_colour_discrete(guide
= FALSE)

#### Total Jobs
svm.model <- svm(Adt~ Dist_Int+   Dist_US+ Rur_Pop+ Total_Jobs ,
data=aca,cost=100,gamma=1)
svm.pred <- predict(svm.model, test1_job[1:4])
pl <- cbind(test1_dist_int[1:4],
Pred_Aca=abs(round(svm.pred,0)))
pl1 <- data.frame(pl)
```

```
svm.model <- svm(Adt~ Dist_Int+   Dist_US+ Rur_Pop+ Total_Jobs ,
data=avo,cost=100,gamma=1)
svm.pred <- predict(svm.model, test1_job[1:4])
pl <- cbind(test1_dist_int[1:4],
Pred_Avo=abs(round(svm.pred,0)))
pl2 <- data.frame(pl)



svm.model <- svm(Adt~ Dist_Int+   Dist_US+ Rur_Pop+ Total_Jobs ,
data=nat,cost=100,gamma=1)
svm.pred <- predict(svm.model, test1_job[1:4])
pl <- cbind(test1_dist_int[1:4],
Pred_Nat=abs(round(svm.pred,0)))
pl3 <- data.frame(pl)

svm.model <- svm(Adt~ Dist_Int+   Dist_US+ Rur_Pop+ Total_Jobs ,
data=web,cost=100,gamma=1)
svm.pred <- predict(svm.model, test1_job[1:4])
pl <- cbind(test1_dist_int[1:4],
Pred_Web=abs(round(svm.pred,0)))
pl4 <- data.frame(pl)

m <- cbind(test1_job[1:4], Aca=pl1$Pred_Aca, Avo=pl2$Pred_Avo,
Nat=pl3$Pred_Nat, Web=pl4$Pred_Web)
head(m)
m1 <- m[c(4, 5:8)]
m2 <- read.csv("test1_jobpred1.csv")

p <- ggplot(m2, aes(x=Total_Jobs, y=Pred, group=Parish,
colour=Parish))
p4 <- p + geom_line(size=1)+theme_bw()+xlab("Total
Jobs")+ylab("Estimated AADT")

### Merging of four figures for Interstate Parishes
grid.newpage()
pushViewport(viewport(layout = grid.layout(2, 2)))
vplayout <- function(x, y)
  viewport(layout.pos.row = x, layout.pos.col = y)
print(p1, vp = vplayout(1, 1))
print(p2, vp = vplayout(1, 2))
print(p3, vp = vplayout(2, 1))
print(p4, vp = vplayout(2, 2))


#### Non-interstate Parishes
```

```
test2_dist_us <- subset(test2, Change=="dist")
test2_pop <- subset(test2, Change=="pop")
test2_job <- subset(test2, Change=="job")

#### Distance from US Highways
svm.model <- svm(Adt~ Dist_US+ Rur_Pop+ Total_Jobs ,
data=cla,cost=100,gamma=1)
svm.pred <- predict(svm.model, test2_dist_us[1:3])
pl <- cbind(test2_dist_us[1:3], Pred_Cla=abs(round(svm.pred,0)))
pl1 <- data.frame(pl)


svm.model <- svm(Adt~Dist_US+ Rur_Pop+ Total_Jobs ,
data=fra,cost=100,gamma=1)
svm.pred <- predict(svm.model,  test2_dist_us[1:3])
pl <- cbind(test2_dist_us[1:3], Pred_Fra=abs(round(svm.pred,0)))
pl2 <- data.frame(pl)

svm.model <- svm(Adt~ Dist_US+ Rur_Pop+ Total_Jobs ,
data=ver,cost=100,gamma=1)
svm.pred <- predict(svm.model,  test2_dist_us[1:3])
pl <- cbind(test2_dist_us[1:3],
Pred_Ver=abs(round(svm.pred,0)))
pl3 <- data.frame(pl)

svm.model <- svm(Adt~ Dist_US+ Rur_Pop+ Total_Jobs ,
data=was,cost=100,gamma=1)
svm.pred <- predict(svm.model,  test2_dist_us[1:3])
pl <- cbind(test2_dist_us[1:3],
Pred_Was=abs(round(svm.pred,0)))
pl4 <- data.frame(pl)

m <- cbind(test2_dist_us[1:3], Cla=pl1$Pred_Cla,
Fra=pl2$Pred_Fra, Ver=pl3$Pred_Ver, Was=pl4$Pred_Was)
head(m)
m1 <- m[c(1, 4:7)]
m2 <- read.csv("test2_distuspred1.csv")

p <- ggplot(m2, aes(x=Dist_US, y=Pred, group=Parish,
colour=Parish))
p2 <- p + geom_line(size=1)+theme_bw()+xlab("Distance from U.S.
Hwy")+ylab("Estimated AADT")+scale_colour_discrete(guide =
FALSE)

#### Rural Population
svm.model <- svm(Adt~ Dist_US+ Rur_Pop+ Total_Jobs ,
data=cla,cost=100,gamma=1)
```

```
svm.pred <- predict(svm.model, test2_pop[1:3])
pl <- cbind(test2_pop[1:3], Pred_Cla=abs(round(svm.pred,0)))
pl1 <- data.frame(pl)

svm.model <- svm(Adt~Dist_US+ Rur_Pop+ Total_Jobs ,
data=fra,cost=100,gamma=1)
svm.pred <- predict(svm.model,  test2_pop[1:3])
pl <- cbind(test2_pop[1:3], Pred_Fra=abs(round(svm.pred,0)))
pl2 <- data.frame(pl)

svm.model <- svm(Adt~ Dist_US+ Rur_Pop+ Total_Jobs ,
data=ver,cost=100,gamma=1)
svm.pred <- predict(svm.model,  test2_pop[1:3])
pl <- cbind(test2_pop[1:3],  Pred_Ver=abs(round(svm.pred,0)))
pl3 <- data.frame(pl)

svm.model <- svm(Adt~ Dist_US+ Rur_Pop+ Total_Jobs ,
data=was,cost=100,gamma=1)
svm.pred <- predict(svm.model,  test2_pop[1:3])
pl <- cbind(test2_pop[1:3],  Pred_Was=abs(round(svm.pred,0)))
pl4 <- data.frame(pl)

m <- cbind(test2_pop[1:3], Cla=pl1$Pred_Cla, Fra=pl2$Pred_Fra,
Ver=pl3$Pred_Ver, Was=pl4$Pred_Was)
head(m)
m1 <- m[c(2, 4:7)]
m2 <- read.csv("test2_poppred1.csv")

p <- ggplot(m2, aes(x=Rur_Pop, y=Pred, group=Parish,
colour=Parish))
p3 <- p + geom_line(size=1)+theme_bw()+xlab("Rural
Population")+ylab("Estimated AADT")+scale_colour_discrete(guide
= FALSE)

#### Total Jobs
svm.model <- svm(Adt~ Dist_US+ Rur_Pop+ Total_Jobs ,
data=cla,cost=100,gamma=1)
svm.pred <- predict(svm.model, test2_job[1:3])
pl <- cbind(test2_job[1:3], Pred_Cla=abs(round(svm.pred,0)))
pl1 <- data.frame(pl)

svm.model <- svm(Adt~Dist_US+ Rur_Pop+ Total_Jobs ,
data=fra,cost=100,gamma=1)
svm.pred <- predict(svm.model,  test2_job[1:3])
pl <- cbind(test2_job[1:3], Pred_Fra=abs(round(svm.pred,0)))
pl2 <- data.frame(pl)
```

```
svm.model <- svm(Adt~ Dist_US+ Rur_Pop+ Total_Jobs ,
data=ver,cost=100,gamma=1)
svm.pred <- predict(svm.model,  test2_job[1:3])
pl <- cbind(test2_job[1:3],  Pred_Ver=abs(round(svm.pred,0)))
pl3 <- data.frame(pl)

svm.model <- svm(Adt~ Dist_US+ Rur_Pop+ Total_Jobs ,
data=was,cost=100,gamma=1)
svm.pred <- predict(svm.model,  test2_job[1:3])
pl <- cbind(test2_job[1:3],  Pred_Was=abs(round(svm.pred,0)))
pl4 <- data.frame(pl)

m <- cbind(test2_job[1:3], Cla=pl1$Pred_Cla, Fra=pl2$Pred_Fra,
Ver=pl3$Pred_Ver, Was=pl4$Pred_Was)
head(m)
m1 <- m[c(3, 4:7)]
m2 <- read.csv("test2_jobpred1.csv")
head(m2)

p <- ggplot(m2, aes(x=Total_Jobs, y=Pred, group=Parish,
colour=Parish))
p4 <- p + geom_line(size=1)+theme_bw()+xlab("Total
Jobs")+ylab("Estimated AADT")


### Merging of three figures for Non-interstate Parishes
grid.newpage()
pushViewport(viewport(layout = grid.layout(1, 3)))
vplayout <- function(x, y)
  viewport(layout.pos.row = x, layout.pos.col = y)
print(p2, vp = vplayout(1, 1))
print(p3, vp = vplayout(1, 2))
print(p4, vp = vplayout(1, 3))
```

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