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Estimation of Average Daily Traffic on Local Roads in Kentucky

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Research Report
KTC-16-13/FRT201-15-1F

Estimation of Average Daily Traffic on Local Roads in Kentucky

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16. Abstract <p>Kentucky Transportation Cabinet (KYTC) officials use annual average daily traffic (AADT) to estimate intersection performance across the state maintained highway system. KYTC currently collects AADTs for state maintained roads but frequently lacks this information on local roads. A method is needed to estimate local road AADTs in a cost-effective and reasonable manner. Kentucky Transportation Center (KTC) researchers conducted a literature review on U.S. AADT models but found that none of them were suitable to Kentucky. Therefore, KTC developed an AADT model using non-linear regression to estimate AADTs on approaches to those intersections.</p> <p>KTC developed a Poisson distributed, non-linear regression model to estimate AADT. This model divided the state into three regions encompassing all of the highway districts: West (Districts 1, 2, 3, and 4), North Central (Districts 5, 6, and 7), and East (Districts 8, 9, 10, 11, and 12). This partitioning accounted for geographic and socioeconomic variability across the state. Each regional model relied upon three independent variables: probe count, residential vehicle registration, and curve rating. HERE proprietary probe counts—indicative of vehicle movements—provide tracking visibility on a select portion of vehicles moving across Kentucky highways. Residential vehicle registrations can be used to estimate trip generation information. Finally, the curve rating partially indicates accessibility.</p> <p>Model results were adjusted to KYTC daily vehicle miles traveled (DVMT) county control totals for local roads. Sensitivity analysis was conducted to examine the impact of model errors for use in intersection safety analysis. Results indicate that the estimates generated can be effectively used for safety assessment and countermeasure prioritization.</p>			
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Executive Summary

Kentucky Transportation Cabinet (KYTC) officials use annual average daily traffic (AADT) to estimate intersection performance across the state maintained highway system, particularly with regard to safety. AADT is an estimate of the number of vehicles passing a point on a roadway in a given day. KYTC currently collects AADTs for state maintained roads. Yet, state maintained roads represent only a fraction of Kentucky's total roadway network. At many intersections, state maintained roads cross local roads with unknown AADTs. Determining actual AADTs at these locations proves difficult due to the prohibitive costs associated with data collection. A method is needed to estimate local road AADTs in a cost-effective and reasonable manner. The Kentucky Transportation Center (KTC) has developed an AADT model using non-linear regression to estimate AADTs on approaches to those intersections and therefore, better predict crash rates associated with them.

Previously conducted studies in the U.S. estimated AADT as a means to compensate for data shortfalls along non-major roadways. These studies used various modeling techniques to derive AADT including ordinary linear regression, geographically weighted regression, Kriging interpolation, and travel demand modeling, among others. However, none of these studies displayed the needed triad of performance, feasibility, and compatibility required for a Kentucky local road model. Therefore, a new model approach would be required.

KTC researchers developed a technique to estimate AADT for local roads in Kentucky incorporating various facets from the previous studies. First, KTC divided the state into three regions encompassing all of the highway districts: West (districts 1, 2, 3, and 4), North Central (districts 5, 6, and 7), and East (districts 8, 9, 10, 11, and 12). This partitioning accounted for geographic and socioeconomic variability across the state. Next, KTC developed the model using Poisson distributed non-linear regression with a log link function in JMP 12.1, a statistical software package. KYTC provided known state owned locally classified road AADTs, derived from traffic counts and other means, to KTC in order to calibrate and validate the developed models. KTC used 75 percent of the regional AADT dataset for calibration and the remaining 25 percent for model validation.

Each regional model relied upon three independent variables: probe counts, residential vehicle registrations, and curve rating. Probe counts—synonymous with vehicle movements—provide tracking visibility on a select portion of vehicles moving across Kentucky highways. The HERE corporation collects probe counts, or pings, from smartphones, personal navigation devices, and vehicle fleets to track vehicle movements. Probe count data includes latitudes, longitudes, speeds, and directions. KTC acquired this proprietary data as an explanatory variable for AADT. It cannot be substituted explicitly with AADT since not all vehicles are tracked via this method, and because vehicles with multiple devices are counted more than once. KYTC collects vehicle registration information through their Automated Vehicle Information System (AVIS). KTC used this database to plot residential addresses along the state's roadway network using GIS. This served as a second explanatory variable in determining potential trips generated for each road segment. Finally, the curve rating assessed the roadway's geometry using Highway Information System (HIS) attributes. This rating was derived by dividing the actual roadway length by the straight distance between its beginning and end points. In essence, the curve rating measured a road's curvature. KTC included this variable since it assumed the curve rating would have a measurable effect on AADTs.

Each regional model produced AADT estimates on local roads for each county in Kentucky. These models performed best when AADT values ranged between 100 and 400, as evidenced by the low errors across

this interval. Daily vehicle miles traveled (DVMT) were computed by multiplying local road segment lengths by their AADTs. Model results were then adjusted with KYTC provided county control totals.

Finally, KTC performed a sensitivity analysis to assess how the model's estimated local road AADT values potentially impact safety performance functions (SPFs) when accounting for errors. SPFs use AASHTO-developed regression equations to estimate crashes within a roadway segment or an intersection, primarily using AADT as an input variable. The sensitivity analysis used the models' maximum and minimum percent errors to estimate their impact on estimated AADTs. In this process, each AADT estimate was recalculated using both error measures and analyzed for its effect on its corresponding SPF. The sensitivity analysis showed the model sometimes underestimated the number of crashes expected at an intersection. However, SPF functions rely on both historical crash records as well as crash estimates derived by models in determining predicted crash rates. Results indicate that errors do not significantly impact safety assessment and prioritization.

Chapter 1: Background

1.1 Introduction

Annual average daily traffic (AADT) provides transportation planners and safety engineers with critical roadway information to estimate performance, but limitations in data collection have left much of Kentucky’s highway network unevaluated. The Federal Highway Administration (FHWA) defines AADT as the “total volume of vehicle traffic of a highway or road for a year divided by 365 days” (1). Transportation planners and policy decision-makers rely heavily on AADT metrics to assess highway performance and guide their future planning and funding decisions. For instance, AADT assists in the calculation of vehicle miles travelled (VMT) which, in turn, establishes the basis for distributing highway funds related to maintenance and safety. Furthermore, AADT serves as the framework for estimating other transportation planning factors including crash rate predictions, vehicle emissions, and forecasting future travel demand. For these reasons, state department of transportation (DOT) planners and other affected stakeholders often take great efforts to collect and utilize this data.

Through its Traffic Monitoring System, the Kentucky Transportation Cabinet (KYTC) collects highway traffic data to develop AADTs on all state-maintained roads and local roads functionally classified as Collector or above. This generally involves segmenting the entire roadway system and using Automatic Data Recorders (ADRs) placed in each segment to collect data for a minimum of 48 hours every three years. Factors are derived from sites that collect data continuously – Automatic Traffic Recorders (ATRs) – and used to annualize these short duration counts into AADTs.

Currently, Kentucky has significant gaps in collecting traffic data across its non-state maintained transportation network. The collection of traffic data to develop AADTs on non-state roads—also referred to as local roads—is optional for county and city agencies. Metropolitan Planning Organizations (MPOs) and Area Development Districts (ADDs) may also collect data. These agencies may also employ the use of ADR equipment to determine their respective AADT. However, many local agencies struggle in their traffic data collection efforts due to their limited fiscal resources, labor shortages, and in some cases, the lack of expertise and/or political will. For these reasons, AADT across many of these local roads remains unknown. To date, KYTC has obtained AADT for approximately 1,200 miles of local roadways across the entire state. This study will hereafter refer to KYTC-provided AADT as “known” AADT, subsequently used to develop and validate the AADT models. This represents only 2 percent of the state’s 52,000 miles of local roadways. Consequently, approximately 98 percent of the local roadways in Kentucky currently lack AADT thereby posing planning and funding challenges to highway officials.

1.2 Problem Statement

KYTC and other highway agencies rely heavily on the use of AADT in safety analysis. This research provides a method of estimating AADTs and supports KYTC’s ability to plan and prioritize safety mitigations.

1.3 Objectives

This report describes the development of a model to estimate AADT for local roads in Kentucky. To achieve this objective, the following tasks were completed:

- a. Research available AADT transportation models in use or previously developed by other state DOTs, universities, or other research organizations, and determine capabilities, requirements, and accuracy of selected models
- b. Select an AADT transportation model that can be successfully applied to Kentucky's local roadway network
- c. Revise and adjust model to fit the data available for Kentucky and produce relevant, accurate, and precise model outputs
- d. Validate and calibrate developed model using known local roadway data

Chapter 2: Literature Review

2.1 AADT Methodologies

The Kentucky Transportation Center (KTC) research team investigated various methodologies that have been used across the United States to estimate AADTs. The research team selected methodologies based upon a wide range of peer-reviewed scientific articles published by practitioners and researchers within the transportation planning community. This comprehensive approach to AADT estimation provided the research team with a rigorous overview of best practices currently being used as well as those methods which may be best suited to Kentucky’s roadway network. Academic universities and state DOTs developed the majority of the methods described in this section. In Table 1 below, AADT methodologies, corresponding sources, and facilities of interest are shown.

Methodology	Source	Facilities of Interest
Ordinary Linear regression	Pan (2)	All roads in Florida
	Shen et al. (3)	Off-system roads in Florida
	Zhao and Chung (4)	County roads in Florida
	Lowry and Dixon (5)	Streets in an urban area
	Mohammad et al. (6)	County roads in Indiana
Geographically weighted regression	Zhao and Park (7)	County roads
Kriging interpolation	Selby and Kockelman (8)	All roads in Texas
	Eom et al. (9)	Non-freeway roads in a county
	Shamo et al. (10)	Roadways with ATR data
	Wang and Kockelman (11)	All roads in Texas
Artificial Neural Network	Sharma et al. (12)	Rural roads
Travel demand modeling	Wang et al. (13)	All roads in Florida
	Wang (14)	All roads in Florida
	Zhong and Hanson (15)	Low-class roads
Origin-Destination centrality based Method	Lowry (16)	Community roads
Florida Turnpike state model	Florida DOT (17, 18)	Roads without traffic counts

Table 1: AADT Methodologies

The following sections provide brief descriptions of each methodology. This discussion includes an outline of the modeling equations, data input requirements, and an examination of select source models.

2.1.1 Ordinary Linear Regression Model

Ordinary linear regression (OLR) identifies the statistical relationship that exists between a dependent variable and one or more independent variables. In this case, OLR describes the relationship between AADT and its explanatory factors. OLR minimizes the sum of errors between estimated values and known values. The equation is as follows:

$$Y = \beta_0 + \beta_1x_1 + \beta_2x_2 + \dots + \beta_ix_i + \varepsilon$$

Where

- Y is the dependent variable
- x_i are the selected explanatory variables
- β_i are the coefficients estimated from the model
- ε is the random error term

The research team's literature review indicated OLR is the most frequently used method to estimate AADT due to its proven ability to assess relationships in multiple situations while maintaining simplicity and ease of use.

In one study, Mohamad et al. applied OLR to estimate AADT for county roads in Indiana (6). The study's authors collected standard 48-hour traffic counts across 40 counties from February through August in 1996. These traffic counts were used to determine AADTs along the selected county roads. The final regression model included four explanatory variables (down from the 11 the researchers began with). The final OLR model equation was:

$$\text{Log}_{10}(\text{AADT}) = 4.82 + 0.81X1 + 0.84X2 + 0.24\text{Log}(X4) - 0.46\text{Log}(X10) \quad (R^2 = 0.751)$$

Where

- $X1$: 1 if urban, 0 if rural
- $X2$: 1 if easy access or close to state highways, 0 otherwise
- $X4$: county population
- $X10$: total arterial mileage of a county

Estimation errors ranged from 1.56 percent to 34.18 percent when the model's estimated AADT output was compared with existing AADT data from eight selected counties.

In another study, Shen et al. estimated AADTs for Florida "off-system" roadways lacking them (3). The research authors developed various regression models to assess different types of areas in Florida. In each model, AADT served as the dependent variable. The regression models examined included:

- Statewide model
- Rural model
- Small-medium urban model
- Large metropolitan area model

In particular, this "rural" based model incorporated data from eight counties. The final regression equation was:

$$ADT = 4853.49 + 0.12 \text{ Pop} + 0.26 \text{ Labor} - 18.93 \text{ Lanemile} - 0.0032338 \text{ Vehicles}$$

Where

- *Pop* is a county's total population;
- *Labor* is a county's total labor force;
- *Lanemile* is the total lane miles of county roads in a county;
- *Vehicles* is the number of automobiles registered in a county;

Upon initial examination, this model seemed to show promise for assessing rural roads, a primary element of Kentucky's local roadway network. However, the model's coefficient of determination, or R-squared, was only 0.25. The R-squared value can be translated as the percentage of variance in "Y" (or ADT) that is explained by the dependent variables. This means the model only explained 25 percent of the ADT value using its explanatory variables. Consequently, the model's overall usefulness is limited in estimating ADT values in Kentucky.

Similarly, Zhao and Chung used regression modeling to assess various factors and their ability to estimate AADTs (4). The researchers examined four unique regression models to estimate AADTs in Broward County, Florida. This yielded the following regression equations:

$$\text{Model 1: } AADT = -9.520386 + 8.480001 \text{ FCLASS} + 3.428939 \text{ LANE} + 0.596752 \text{ REACCESS} + 2.991573 \text{ DIRECTAC} + 0.069086 \text{ EMPBUFF}$$

$$\text{Model 2: } AADT = -6.15742 + 6.55471 \text{ LANE} + 0.61433 \text{ REACCESS} + 7.88344 \text{ DIRECTAC} - 0.34494 \text{ DPOPCNTR}$$

$$\text{Model 3: } AADT = -4.66034 + 4.95341 \text{ LANE} + 0.51119 \text{ REACCESS} + 4.52713 \text{ DIRECTAC} - 0.10689 \text{ DPOPCNTR} + 0.00112 \text{ POPBUFF}$$

$$\text{Model 4: } AADT = -4.26565 + 4.86271 \text{ LANE} + 0.47286 \text{ REACCESS} + 4.34780 \text{ DIRECTAC} - 0.10197 \text{ DPOPCNTR} + 0.00104 \text{ POPBUFF} + 0.00022820 \text{ EMPBUFF}$$

Where

- *FCLASS* is functional classification of roadway
- *LANE* is the number of lanes in both directions
- *REACCESS* is the access to regional employment
- *DIRECTAC* is direct access (or connection) to an expressway
- *EMPBUFF* is the number of people employed along a roadway segment
- *DPOPCNTR* is the distance to a population center
- *POPBUFF* is the number of people living along a roadway segment

These regression models produced R-squared values ranging from 0.66 to 0.82, a significantly higher precision over other regression models. In addition, these models examined a larger set of variables than regression models developed by other researchers, thus leading to a more comprehensive approach in determining AADT. For these reasons, these regression models exhibited the greatest initial promise for inclusion into a Kentucky-based model. Therefore, KTC researchers selected the variables used in these regression models for further study and analysis.

2.1.2 Geographically Weighted Regression Model

Geographically weighted regression (GWR) models account for transportation network spatial variation. Unlike OLR models, GWR generates equations locally for each observation. For this reason, a GWR model is generally considered more capable in accurately estimating results than comparable OLR models. The basic equation is as follows:

$$Y_i = \beta_0(u_i, v_i) + \beta_1(u_i, v_i)x_{i1} + \beta_2(u_i, v_i)x_{i2} + \dots + \beta_k(u_i, v_i)x_{ik} + \varepsilon_i$$

Where

- Y_i is the AADT
- i is the i^{th} observation
- $\beta_k(u_i, v_i)$ is the coefficient of local model to be estimated
- x_{ik} is the k^{th} variable from i^{th} observation
- ε_i is the random (model) error

The GWR model examines each observation and then selects those observations found in close proximity to a selected geospatial area for further consideration. In those instances, the model estimates the coefficient using a weighted factor which, in turn, relies upon a weighting function for its calculation. Simply put, locations found closer to the roadway of interest will receive higher weighted values on their explanatory factors. This is because those nearby areas are considered to have proportionately larger impacts on the travel demands of the geographical area of interest.

Zhao and Park applied this concept to develop two distinct GWR models used in estimating AADTs and utilized data from Zhao and Chung's OLR model (4). While more difficult to implement, both GWR models showed improvements in performance over the previous OLR model, with higher R-squared values and smaller estimation errors.

2.1.3 Kriging Interpolation Model

The Kriging model uses spatial interpolation to estimate unknown values at locations or points based on known values at nearby locations or points (19). This method assumes that observations are spatially correlated. It subsequently generates a function based on this spatial relationship. In this manner, Kriging generates a prediction surface from existing points to estimate values of a parameter at unknown locations. The model equation is as follows:

$$\hat{Z}(S_0) = \sum_{i=1}^n \lambda_i Z(S_i)$$

Where

- $\hat{Z}(S_0)$ is the value to be estimated
- S_0 is the location to be estimated
- $Z(S_i)$ is the measured value at location i
- λ_i is the weight assigned to the value at measured location i
- n is the number of measured locations included in the calculation

To use the model, a semivariogram that reflects the spatial relationship between data points must be created. Several mathematical functions assist in identifying spatial relationships, including exponential, spherical, and Gaussian, among others. Next, the weights for measured locations to estimate values at unknown locations are derived from the semivariogram.

Selby and Kockelman applied the Kriging method to estimate AADTs for Texas roadways lacking them (8). In this study, the following source data served as the initial input into this analysis:

- Existing traffic counts from ATRs across different functional classifications in Texas (including large metropolitan and local rural areas)
- Roadway network
- Block-level census data
- Employment data

Based upon these input data, the authors incorporated the following variables to refine the model:

- 2005 AADTs
- Speed limits
- Lanes
- Persons/Acre
- Jobs/Sq Mile
- Rural Interstate
- Rural Major road
- Urban Interstate
- Urban Principal Arterial
- Local/collector road

In general, the model reduced estimation errors commonly associated with conventional OLR models. However, the model's estimation errors often increased when applied to low-volume roads. For this reason, the model's limitations make it less useful in estimating unknown AADT on local roads across Kentucky, many of which are rural.

2.1.4 Artificial Neural Network

Artificial neural networks (ANN) encompass a consortium of neuron-based models and have been widely used across a number of transportation studies. ANN models have a pronounced advantage in modeling nonlinear relationships due to their rapid adaptive capabilities in responding to data input characteristics. Unlike many of the other models, ANN models are not defined by a specific mathematical equation. Instead, they share the common trait of using neurons to capture and learn relationships between inputs and outputs. A wide array of unique neural networks has been developed for transportation research. The diversity of ANN technology provides a range of options for the transportation planner but must be balanced with limitations unique to its development, such as the need for large sets of data.

In Canada, Sharma et al. adopted a multilayered, forward-feeding, and back-propagating neural network to estimate AADTs on low-volume roads inside a chosen province (12). Researchers used samples of hourly volume and AADT data obtained from 55 ATR sites to train the neural network. The model yielded

an approximate 25 percent error at the 95th confidence interval. As one would expect, increased counts over multiple time periods improved the model’s performance, as evidenced by the lower errors associated with a second model simulation which used two 48-hour counts over two months.

2.1.5 Travel Demand Modeling

Travel demand models estimate travel patterns and demand over time based on select, independent variables. Many state DOTs, metropolitan planning organizations, and other transportation planning organizations use these models to predict future traffic patterns and volumes in their areas. Using this approach, Wang et al. developed a four-step, parcel-level travel demand model to estimate AADTs on local roads within a select county in Florida (14). The four main steps used to construct this model included the following:

1. *Network Modeling*: The network model was developed using original and processed data from a range of sources. Centroids and centroid connectors were placed in each parcel to provide access to adjacent roads.
2. *Trip Generation*: The model used regression equations from the Institute of Transportation Engineers (ITE) Trip Generation manual to estimate trips generated (20). Land-use types corresponding to each parcel in the model area informed the regression equation selection process.
3. *Trip Distribution*: The model distributed trips through the gravity model method. This method distributes trips produced in one zone to other zones in the model (21). The model assumed each parcel only produced trips but did not attract trips in relation to other parcels.
4. *Trip Assignment*: Each vehicle traveling on local roads within the model area received trip assignments prescribing the chosen travel path. The model assumed travelers would choose paths that minimized free-flow travel times.

The model utilized ArcGIS and Cube. The final model's results compared favorably with known AADTs extracted from short-term traffic counts. The model generated mean absolute errors of 52 percent, considerably lower than the 211 percent from the Zhao and Chung OLR model.

2.1.6 Origin-Destination (OD) Centrality-based Method

Typical origin-destination models attempt to predict travel behavior with respect to a vehicle’s starting point (origin) and end point (destination). Lowry built upon this conventional method by incorporating the concept of centrality into this framework (16). The Lowry model spatially interpolated AADT for local streets found in the model area. It used the following equation to describe this relationship:

$$OD\ centrality_e = \sum_{i \in I, j \in J} \sigma_{ij}(e) M_i M_j$$

Where

- i and j are origin and destination nodes
- σ_{ij} is the shortest path from origin i to destination j
- $\sigma_{ij}(e)$ is equal to 1 if link e is on the path of σ_{ij} , and 0 otherwise
- M_i and M_j are the corresponding multipliers for origin i and destination j

The model used multipliers for specific land-use types, as shown in the ITE Trip Generation manual. Furthermore, it calculated trip production and attraction rates in a manner similar to conventional travel demand models. The following inputs were required for this process:

- The street network
- The known AADTs
- Land use parcels
- Boundary locations on the street network

Lastly, this model calculated three different origin-destination (OD) centrality measures, including internal-internal OD centrality, internal-external OD centrality, and external-external OD centrality. These measures are used as explanatory variables in accompanying OLR models. The Lowry model produced the highest R-squared values and lowest median absolute percent errors, respectively, in relation to the models evaluated for this literature review.

2.1.7 Florida Turnpike Model

The Florida Department of Transportation uses a statewide transportation model — the FDOT Turnpike Model — to determine AADTs along its roadways. This model estimates AADT on all roads including local roads. The model uses the following data as inputs:

- Statewide parcel shapefile
- Known AADT data shapefile
- Employment data from InfoUSA
- Selection of Traffic Analysis Zones
- HERE Street Network

Once collected, the Turnpike Model divides the roadways found in the HERE street network into different tiers based on the roadway's functional levels (22). Next, the model assigns housing and employment units to routes. Housing and employment units (in terms of number of employees) are converted into trips generated. Finally, trips are assigned travel routes within the network. Transportation planners can then estimate AADTs based upon the model's predicted output.

2.2 Discussion and Recommendation

The KTC research team selected the Zhao and Chung OLR method as the modeling approach for identifying local roadway AADT due to: availability of data, ability to replicate the process, and availability of resources (chiefly time). Specifically, KTC researchers used the explanatory variables found in this model to derive their own Kentucky-based model, hereafter referred to as the Broward County model. The research team selected this model for several reasons. First, it displayed positive results in estimating local roadway AADT within Broward County, Florida. Second, it was compatible with existing data KTC researchers had access to across various KYTC and county databases, thereby eliminating additional time and resource demands needed in data collection. Finally, the model achieved an optimal balance between roadway modeling accuracy, user friendliness, and resource requirements, to achieve the desired effect within reasonable demands (4). Other models were excluded from further analysis because they were either prone to excessive errors, had limited compatibility with Kentucky's roadway network, or imposed too many resource (e.g., data and time) demands.

Chapter 3: AADT Model

3.1 Model Development

Building upon the state of practice, the KTC research team developed six unique models to estimate local roadway traffic volumes in Kentucky. The team assessed each model's capacity to produce reliable and accurate AADT estimates as well as its ability to use readily available data. The developed models included two variations on the original Broward County model (with and without Property Valuation Administrator (PVA) data), a Rooftop model, a 911 model, and two variations of an AVIS-HERE model (linear and non-linear regressions). Each model had specific advantages as well as limitations. Ultimately, KTC researchers selected the non-linear regression AVIS-HERE model as the final Kentucky model for estimating local road traffic counts based upon its accuracy, low error associations, and availability of data. Section 3.3 describes this model in detail. The other investigated models are described briefly below and in greater detail in Appendices A - E.

Initially, the Broward County model required modification to align its explanatory variables with those most closely associated with Kentucky's local roadway characteristics. This model was tested on data from Boyd, Clark, Franklin, Green, and Henry counties. However, the estimative attributes of this model were limited. A graph comparing estimated AADT with known AADT demonstrated the model's high error rate. Thus, the model required additional modifications to improve its effectiveness.

In an effort to enhance the Broward County model, KTC added another component to it —PVA data. County governments routinely collect PVA data for residential and commercial properties within the county limits. PVA data may include information on property owners, sizes, and addresses, among others. PVA data were incorporated to determine the number and type of properties located along local roadways and analyze their potential impacts on AADT. This model demonstrated improvement over the original Broward County version, with reductions in the magnitude of errors corresponding to the deviation between known and estimated AADTs. Nonetheless, the errors still exceeded acceptable ranges (100 – 300 percent), thereby excluding it from further consideration.

Next, KTC researchers attempted to improve the identification of properties located near local roadways through the Rooftop model. Properties located along local roads were assumed to serve as potential traffic generators. To locate properties, ArcGIS was used to identify rooftops—and by extension, their associated properties—throughout Meade County. Properties were classified as small, medium, or large, depending on their use. For example, individual houses were classified as small, while an industrial complex was considered large. Furthermore, a connectivity rating was assigned to individual roads within the county. Connectivity ratings ranged from one to six. Higher values indicated greater connectivity between the individual road and the overall roadway network. The Rooftop model used these variables to estimate AADT values. However, it did not produce a measurable improvement in errors over the previous two models. The combination of high errors along with time constraints imposed by the model's visual identification methodology ultimately excluded it as a viable alternative.

The 911 model estimated AADT based on the number and location of residential and commercial properties in Meade County, which were identified in its emergency services, or 911, database. This approach was similar to the Broward County with PVA model, given that it leveraged known property addresses. The model assigned residential and commercial properties to the nearest local roadway, with each property type serving as a type of trip generator. Testing this model revealed it represented an

improvement over previously developed models, with lower errors found between known and estimated AADT. Unfortunately, statewide county-level 911 data proved difficult to obtain. Therefore, this model ended up relying on only a single county for its development and could not be practically extrapolated to model all counties in Kentucky. A more robust dataset was needed to provide statewide coverage of properties.

KTC researchers adapted regression techniques originally used in the 911 model to develop two versions of the AVIS-HERE model. Both models relied on a combination of KYTC statewide data and proprietary HERE data to successfully estimate AADTs. The AVIS-HERE model has two multivariable forms, ordinary linear regression and non-linear regression. In the former, the model estimates AADTs as a single statewide model and does not make the distinction between different regions or districts. Two lane roads classified as local roads were used to calibrate and validate the models based on known traffic counts. Additional details on this model's performance and derivation can be found in Appendix E. The second AVIS-HERE model used non-linear regression to estimate AADT. This model outperformed all models in the study with the exception of the 911 model. However, 911 model data was not readily accessible for all counties in Kentucky. Therefore, KTC researchers selected the non-linear regression AVIS-HERE model as the Kentucky local roadway AADT model due to its combined high performance and data availability.

Two sets of models were developed for Kentucky using non-linear regression, one for rural local roads and one for urban local roads. A separation was made for these road types to account for the difference in traffic characteristics in these two settings. Section 3.3 includes a detailed discussion of these models and their characteristics.

3.2 Data Collection

KTC researchers used several data types as input into the AVIS-HERE model. The data collected included: short duration traffic counts, Highway Information System (HIS) variables, AVIS, and HERE. Short duration traffic counts track the number of vehicles passing a roadway segment through mechanical means. HIS is a database maintained by KYTC that includes various characteristics on the highway network including functional classification, number of lanes, etc. KYTC also provided access to their AVIS database, a collection of state registration records on all private and commercial vehicles. Finally, KTC acquired use of the HERE corporation's probe count data, which tracks select smartphones, personal navigation devices, and vehicle fleets. Each data category is discussed in greater detail below.

3.2.1 Short Duration Traffic Counts

KYTC strategically and periodically places automatic data recorders (ADRs) along select roadway segments across the state to collect traffic counts. ADRs typically stay in place for a minimum of 48 hours (although sometimes longer), but nearly always less than a week. KYTC primarily uses ADRs to collect data on state roadways directly under its jurisdiction, but they sometimes capture information on local roads as well. KYTC's Division of Planning performs these actions as part of its Traffic Monitoring System in an effort to better understand the traffic demands and constraints existing along its transportation network. This information is available to the public through KYTC's Interactive Statewide Traffic Counts Map (Figure A).

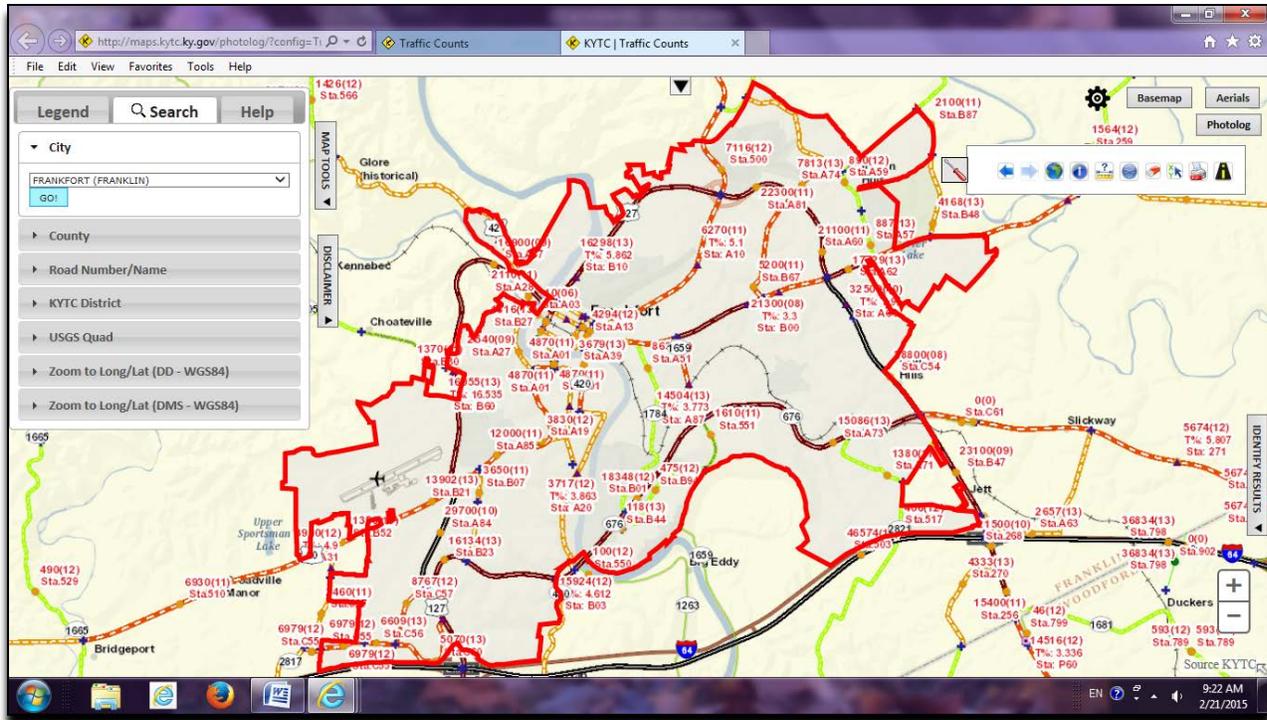


Figure A: KYTC Traffic Counts, Franklin Co.

Once traffic counts are known, KYTC transportation planners calculate the AADT for each location. The Division of Planning provided known AADTs to the KTC research team along selected local roadways of interest. Portions of this data were used to validate and calibrate the AADT model through comparison between estimated and known AADTs.

3.2.2 KYTC AADT Data

KYTC uses Automatic Traffic Recorders (ADRs) to collect data continuously in order to develop factors to annualize short duration coverage counts. Planners use this information to better inform its transportation planning activities as well as meet federal guidelines such as data collection requirements used for the Highway Performance Monitoring System (HPMS). KYTC AADT data used in this study consisted of their most recent traffic count cycle of data compiled over the years 2010 through 2013. KYTC AADTs were used to test and calibrate models.

3.2.3 AVIS Data

KYTC assesses the values and collects taxes on all vehicles across the state. Each year, Kentucky vehicle owners must file for continued vehicle registration and provide required, predetermined information to KYTC along with a fee. KYTC collects and manages this information through its Automated Vehicle Information System (AVIS). AVIS is an automated information technology support system used to collect, maintain, and process motor vehicle registration data. Each County Clerk office initially enters these data into AVIS through a computer interface. From each of these locations, the data move across the network into the centralized AVIS mainframe, located in Frankfort, and provides the KYTC with motor vehicle registration records from across the state.

AVIS data include information related to the vehicle, owner, and the county of record. Specifically, AVIS data used in this analysis include: vehicle identification number (VIN), county of registration, year of registration, registration type, and the owner’s address. The registration type is categorized as official, commercial, or non-commercial. Vehicles registered as official include those owned by state agencies and organizations, such as police departments or universities. Commercial vehicles indicate ownership by registered businesses while non-commercial vehicles are those owned by private citizens (23). A small sample of AVIS data is shown in Table 2. All vehicle identification numbers (VINs) and address listings have been replaced with generic identifiers to maintain confidentiality of the data.

VIN	CNTY_REG	YEAR_REG	REGISTRATION_TYPE	ADDR_STREET	ADDR_CITY	ADDR_STATE	ADDR_ZIP
VIN #1	MEAD	15	Non-Commercial Registration	ADDRESS #1	EKRON	KY	401170000
VIN #2	MEAD	15	Non-Commercial Registration	ADDRESS #2	BRANDENBURG	KY	401080000
VIN #3	MEAD	15	Commercial Registration	ADDRESS #3	BRANDENBURG	KY	401080000
VIN #4	MEAD	15	Commercial Registration	ADDRESS #4	VINE GROVE	KY	401750000
VIN #5	MEAD	15	Commercial Registration	ADDRESS #5	BRANDENBURG	KY	401080000
VIN #6	MEAD	15	Non-Commercial Registration	ADDRESS #6	BRANDENBURG	KY	401080000
VIN #7	MEAD	15	Non-Commercial Registration	ADDRESS #7	BATTLETOWN	KY	401040000
VIN #8	MEAD	15	Non-Commercial Registration	ADDRESS #8	BRANDENBURG	KY	401080000
VIN #10	MEAD	15	Non-Commercial Registration	ADDRESS #10	GUSTON	KY	401420000
VIN #11	MEAD	15	Official Registration	ADDRESS #11	EKRON	KY	401170000
VIN #12	MEAD	15	Non-Commercial Registration	ADDRESS #12	VINE GROVE	KY	401750000
VIN #13	MEAD	15	Official Registration	ADDRESS #13	BRANDENBURG	KY	401080000
VIN #14	MEAD	15	Non-Commercial Registration	ADDRESS #14	EKRON	KY	401170000
VIN #15	MEAD	15	Commercial Registration	ADDRESS #15	BATTLETOWN	KY	401040000

Table 2: AVIS Data

3.2.4 HERE Data

The HERE corporation, formerly known as NAVTEQ, is an industry leader in geospatial products, including digital maps. Various digital platforms incorporate this mapping technology into their consumer products, including cell phones and GPS devices. HERE uses mapping technology to track vehicle movements through the same cell phones and GPS devices. The tracking process relies upon cellular towers and antennas located across much of the nation to collect and monitor cell phone data and GPS signals.

HERE uses vehicle tracking data to calculate and monitor vehicular speeds across roadways. This is accomplished by monitoring the time it takes a vehicle to move along a predetermined roadway segment. HERE partitions existing roadways into a series of discrete segments defined by an origin (starting point) and destination (finish point). Each individual segment corresponds to a distinct “probe” area. Along with calculating average speeds, HERE collects probe counts from select smartphones, personal navigation devices, and vehicle delivery transponders (24). These counts, however, do not entirely represent the traffic on segments. Limitations exist because not every vehicle on the roadway contains an applicable HERE probe device, and some contain more than one.

HERE probe counts are available in 15-minute intervals for any given day of the week. HERE initially aggregates its probe data for each day in the month, which produces a daily count. Next, daily averages are determined for each day of the week. This methodology combines daily counts across a given month and calculates probe count averages for each day of the week. For example, a typical June may have four Thursdays. Probe counts are obtained for each Thursday and averaged into a single Thursday probe count for June. This single count is subsequently divided into 15-minute intervals. This same methodology is used for each month of the year. Consequently, a Thursday probe count average in June might differ from

the Thursday probe count average occurring in another month. KTC researchers acquired probe count data from the HERE corporation for the 2012 calendar year (22).

3.3 Kentucky AADT Model

3.3.1 AVIS-HERE Non-Linear Regression Model

KTC selected the AVIS-HERE non-linear regression model as the best overall modeling method due to its ability to accurately estimate AADTs for Kentucky's local roads while drawing from accessible and comprehensive data sources. This model relied on property records contained in the KYTC-sponsored AVIS database as well as the HERE corporation's probe counts. As discussed previously, the AVIS database is a motor vehicle registration database that contains address information on people, commercial businesses, and governmental agencies that own one or more vehicles registered in the state of Kentucky. This vehicle registration database allowed researchers to use AVIS records as a proxy for residential and commercial properties located in Kentucky. For instance, all addresses of non-commercial registration records were considered private residences and used to determine residential properties in this model. Similarly, addresses of commercially-owned vehicles were designated as commercial properties. A limitation of this model is that it did not take into account residential and commercial properties owning a vehicle registered outside of Kentucky. In some instances, KTC researchers noted that a small number of vehicles were registered in Indiana, Tennessee, and other states. Nevertheless, this model should capture the large majority of passenger car vehicles traveling in Kentucky.

KYTC categorizes AVIS data as proprietary and sensitive due to its ability to match vehicle identification numbers and addresses to specific individuals and businesses. Therefore, KTC agreed to implement appropriate safeguards and protocols when handling this data to ensure confidentiality and prevent its release. The second data source included probe count tabulations from the 2012 HERE data set. This data set identifies traffic counts along roadway segments across the state. The factors used to formulate this model also included properties, commercial properties, vehicle probe counts, and road curvature. Each factor used is discussed in more detail below.

3.3.1.1 Residential Properties

All properties, residential or otherwise, were plotted in ArcMap. ArcMap displays GIS data on a planar map and allows users to overlay multiple layers of data on the map's layout (25). Each layer of data corresponded to a unique dataset (e.g., roadway locations, property addresses). Figure B illustrates this concept through a listing of residential and commercial addresses, which have been plotted along local roadways in Meade County.

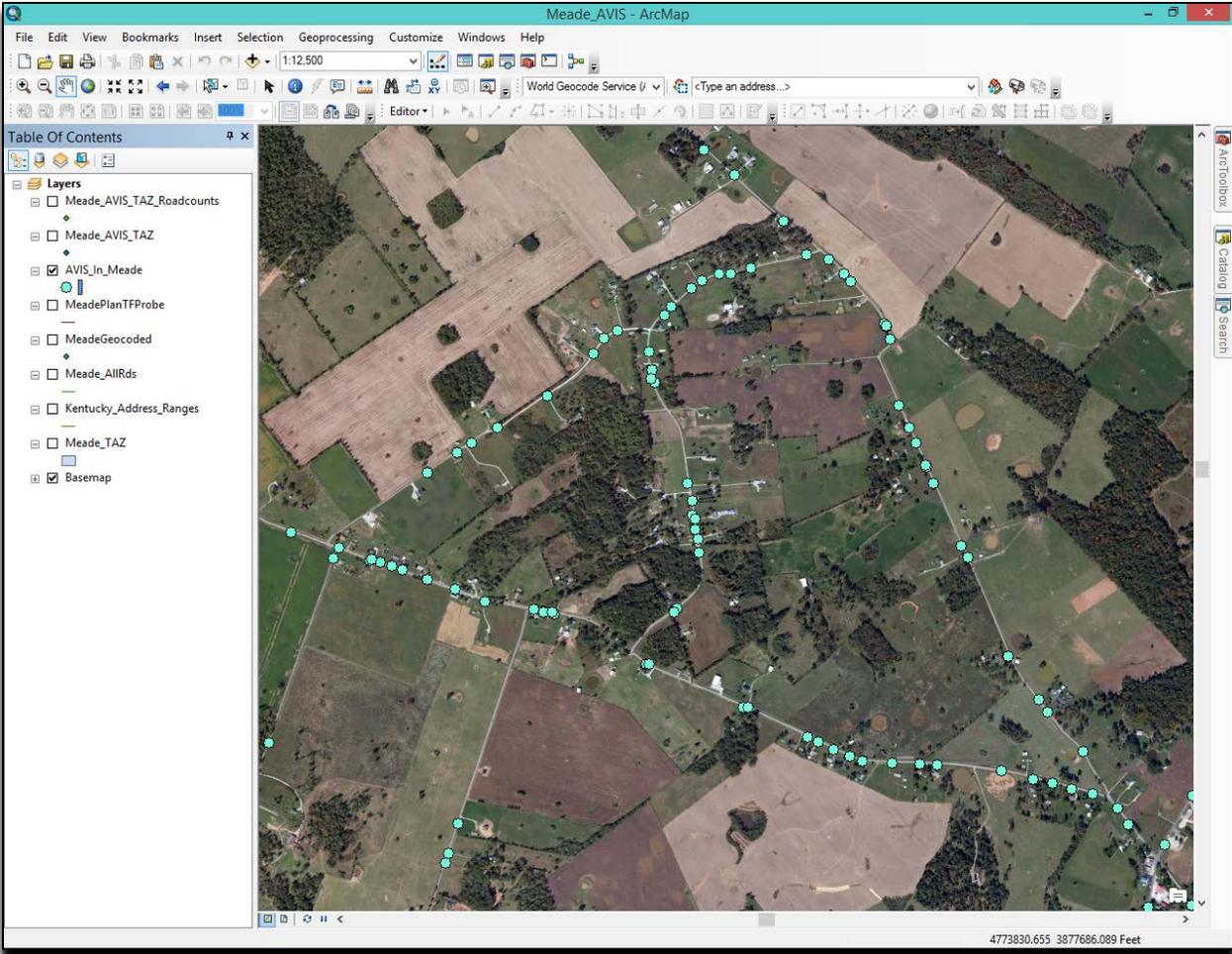


Figure B: AVIS Residential and Commercial Properties, Meade County

In ArcMap, known addresses were plotted using geocoding, which locates addresses as GPS coordinates. Geocoding relies on the use of a preexisting address network to determine locations. In this case, ArcMap used the World Geocode Service — an online ArcGIS feature — to locate addresses.

The assignment of residential properties used non-commercial addresses shown in AVIS, which are linked to private citizens’ vehicle registrations. Non-commercial, vehicle registration addresses functioned as a proxy for residential properties since statewide property use data was not available for this project. The following fields were entered into the Geocode tool (Figure C) before it was run:

- Input Table – AVIS data
- Input Address Locator – comprehensive address book for residential, commercial, and industrial properties shown in ArcMap and known as the World Geocode Service
- Input Address Field – variables used include ADDR_STREET, ADDR_CITY, ADDR_STATE, and ADDR_ZIP
- Output Feature Class – final file name and its location for data as shown in ArcMap

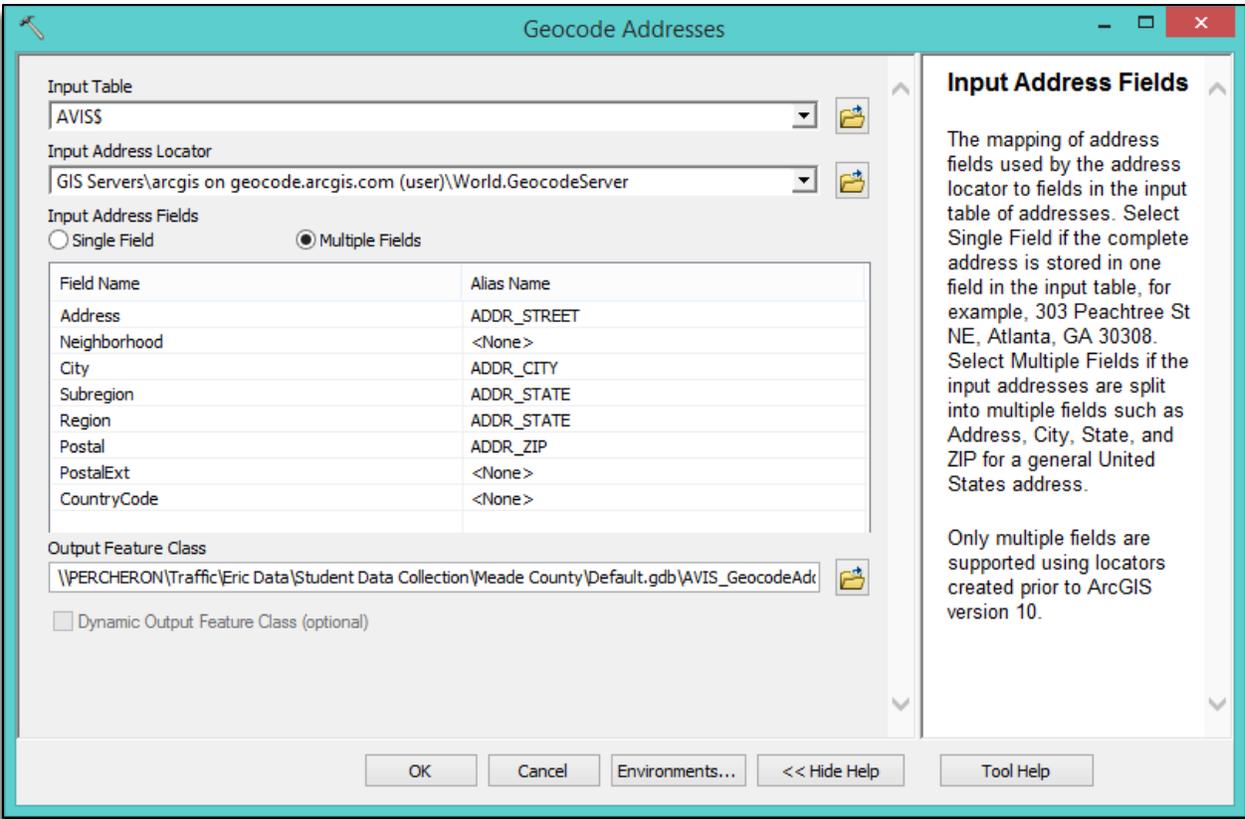


Figure C: ArcMap Geocoding Inputs

3.3.1.2 Commercial Properties

KTC researchers located commercial properties using their designated commercial and official property classifications within the AVIS database. Commercial, vehicle registration addresses in AVIS were used as proxies for commercial property addresses. In this case, any business owning a business-registered vehicle showed up as a commercial property. However, this method does overlook commercial businesses which have a vehicle registered under an individual's name or businesses that do not own a vehicle. Official vehicles are those assigned to any branch of government, and which operate within the boundaries of Kentucky. These vehicles were also designated as commercial properties due to their ability to generate higher traffic volumes along assigned roadways. The total number of official properties is much lower than the number of commercial properties and does not warrant assignment of an individual variable in this model.

3.3.1.3 Probe Counts

The 2012 HERE probe counts were aggregated for the entire year to produce an annual traffic count for each roadway segment. The traffic count was then divided by 365 (the total number of days in a year) to calculate AADT. However, this measure is not a true AADT because it does not account for all vehicles using the roadway network. HERE only counts probes from select smartphones, personal navigation devices, and vehicle delivery fleets. Next, the highway segmentation of the HERE roadway network, which does not use the same segmentation as the KYTC's HIS files, was adapted to map the values of HERE probe

counts in ArcMap. The HERE segmentation was then overlaid using the join feature in ArcMap, which produced an average value of the probe counts for each roadway segment from the KYTC HIS files.

3.3.1.4 Roadway Curvature

A value to describe the curvature of each road segment was calculated by determining the actual length of the road segment and the straight length between the end points of the road segment. The ratio of the actual length to the straight length of the road is the curve rating, and it was used as an input variable for the model. The research team included the curve rating in the model because roads designed with low anticipated AADTs would not have the adequate funding needed to make roads straight. Thus, low-volume roadways tend to be more sinuous than high-volume ones. Researchers expected an inverse relationship between a road segment's curve rating and its AADT.

KTC researchers developed two separate AVIS-HERE non-linear regression models in this effort, including a rural- and an urban-based models. Developing two distinct models allowed for differentiation between conditions typically associated with rural and urban areas, respectively. The urban and rural models, their development, and underlying results are described in greater detail in the following sections.

3.3.2 Rural Model Development

KTC researchers developed the rural model using short duration traffic counts, residential and commercial property locations, and HERE probe counts. Each variable required assignment to a defined roadway segment. In the initial step, researchers obtained defined roadway segments from KYTC's HIS database via the ArcMap-based *Traffic Flow* (TF) file. (26) This file contains roadway segments for all-type roads across the state, totaling 152,388 segments. The complete list of roadway segments includes state-maintained and non-state maintained roads (typically local routes). Small, black dots divided the roadway into its partitioned segments. To illustrate, Figure D displays a small area within Franklin County, including U.S. Route 127, County Route 1036, and County Route 1039, and their corresponding delineated segments. This figure includes five labels identifying the segments.

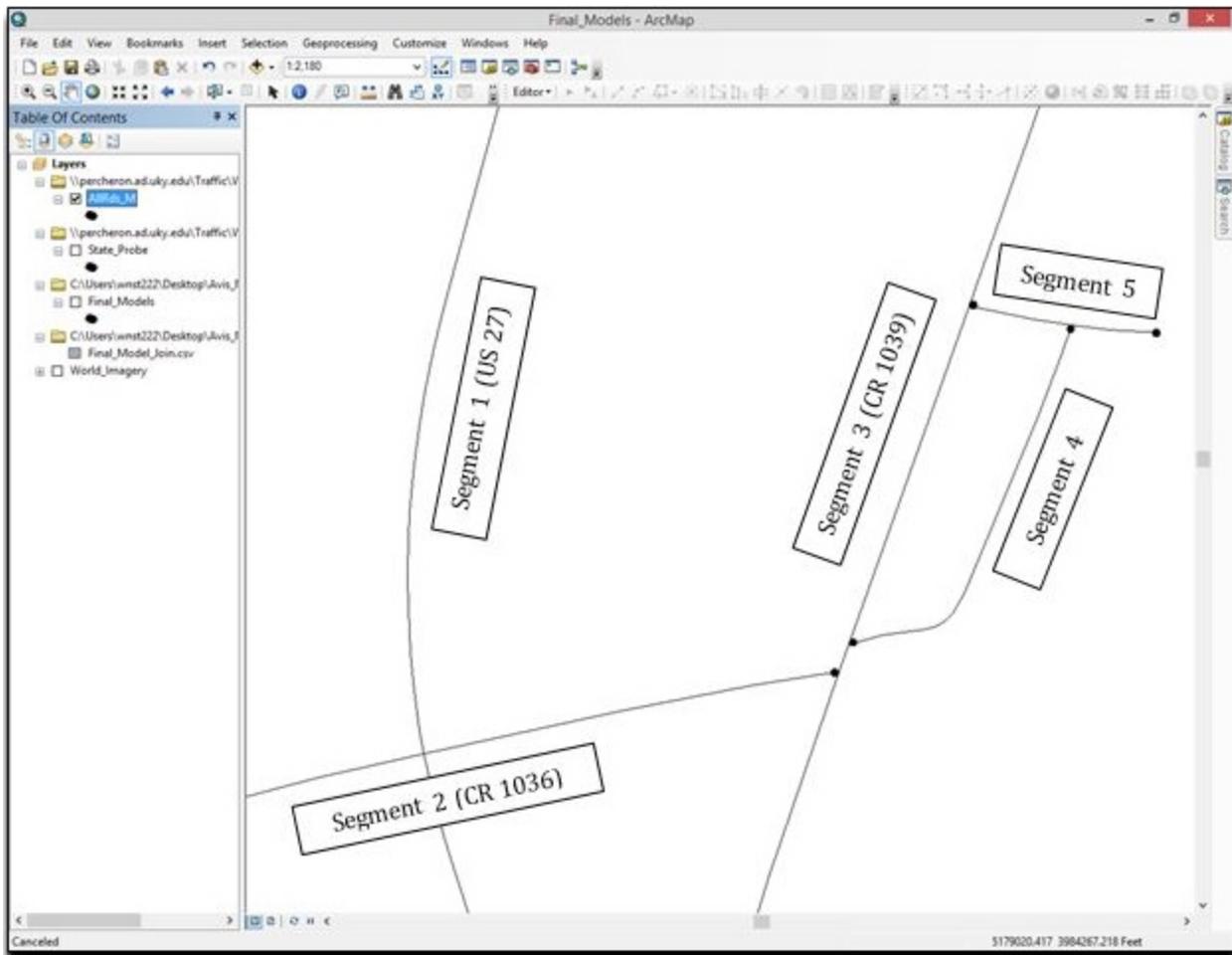


Figure D: KYTC Roadway Segments

KTC researchers performed additional modifications to the original KYTC roadway segment file to better differentiate between state-maintained and local roadway segments. This added segmentation step employed the “planarized lines” function in ArcMap to divide local roadways into a larger number of segments. Local roadways were divided into two distinct segments where they intersect with state-maintained roadways (previously it was a single, continuous segment). This step improved the accuracy of the model as it assigned discrete AADTs to both sides of the partitioned local roadway. This process resulted in a total of 167,236 roadway segments in Kentucky, an increase of nearly 10 percent over the original KYTC file count. Figure E illustrates the same area of Franklin County depicted in Figure D, but using the modified segmentation process. The map now captures six distinct segments, or one more than the previously employed segmentation process.

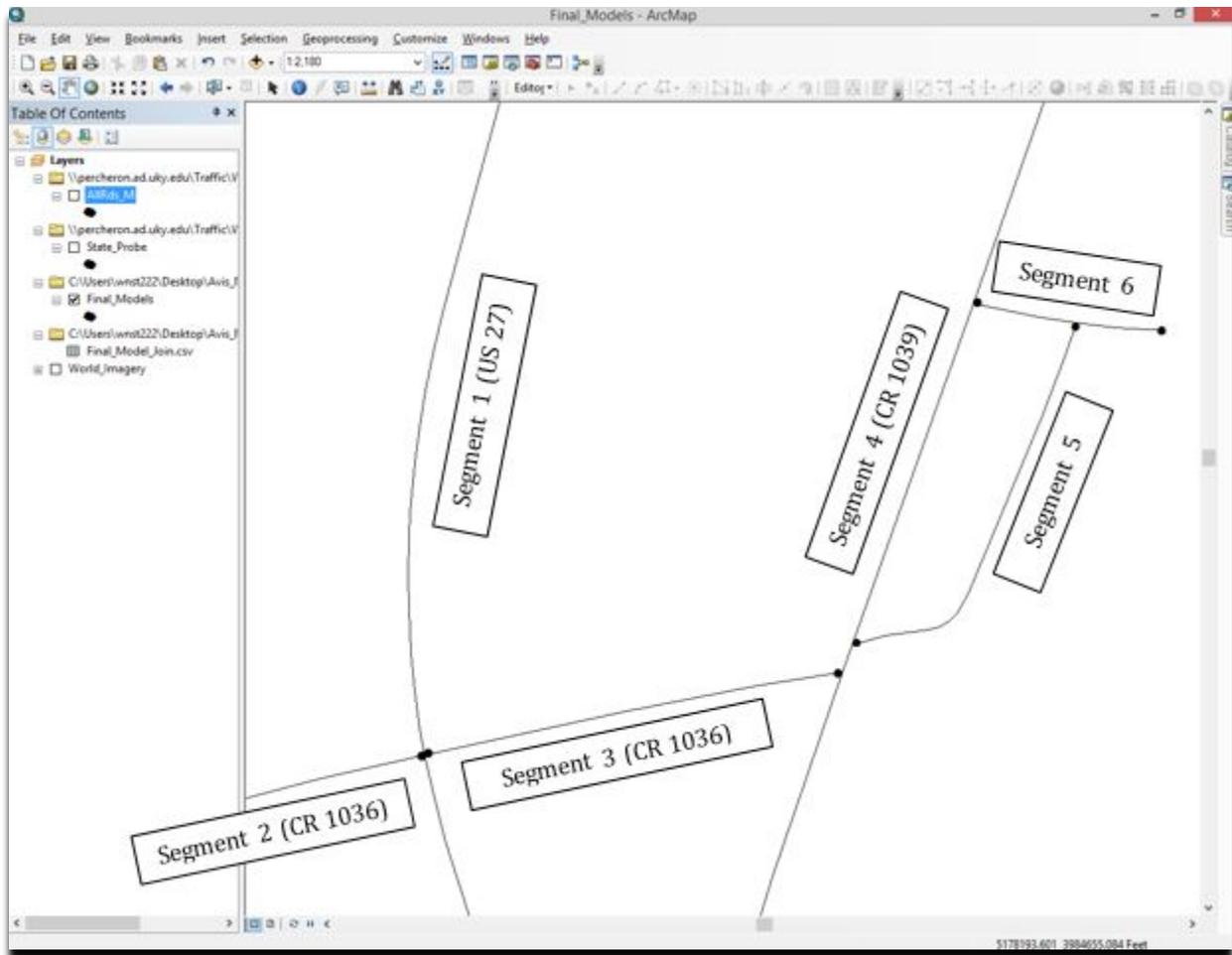


Figure E: KTC Modified Roadway Segments

In the final step, HERE probe counts were incorporated into the segmentation process. HERE has delineated their own unique roadway segments across the state, which correspond with their probe counts (see Section 3.2.4 for a description of this process). HERE's number of roadway segments vastly exceeds the counts of KYTC's original model and the KTC modified version, with a total of 514,293 segments. In Figure F, the number of roadway segments identified through probe counts is displayed for the same area as shown in Figures D and E. The number of segments increased to 11 for this map.

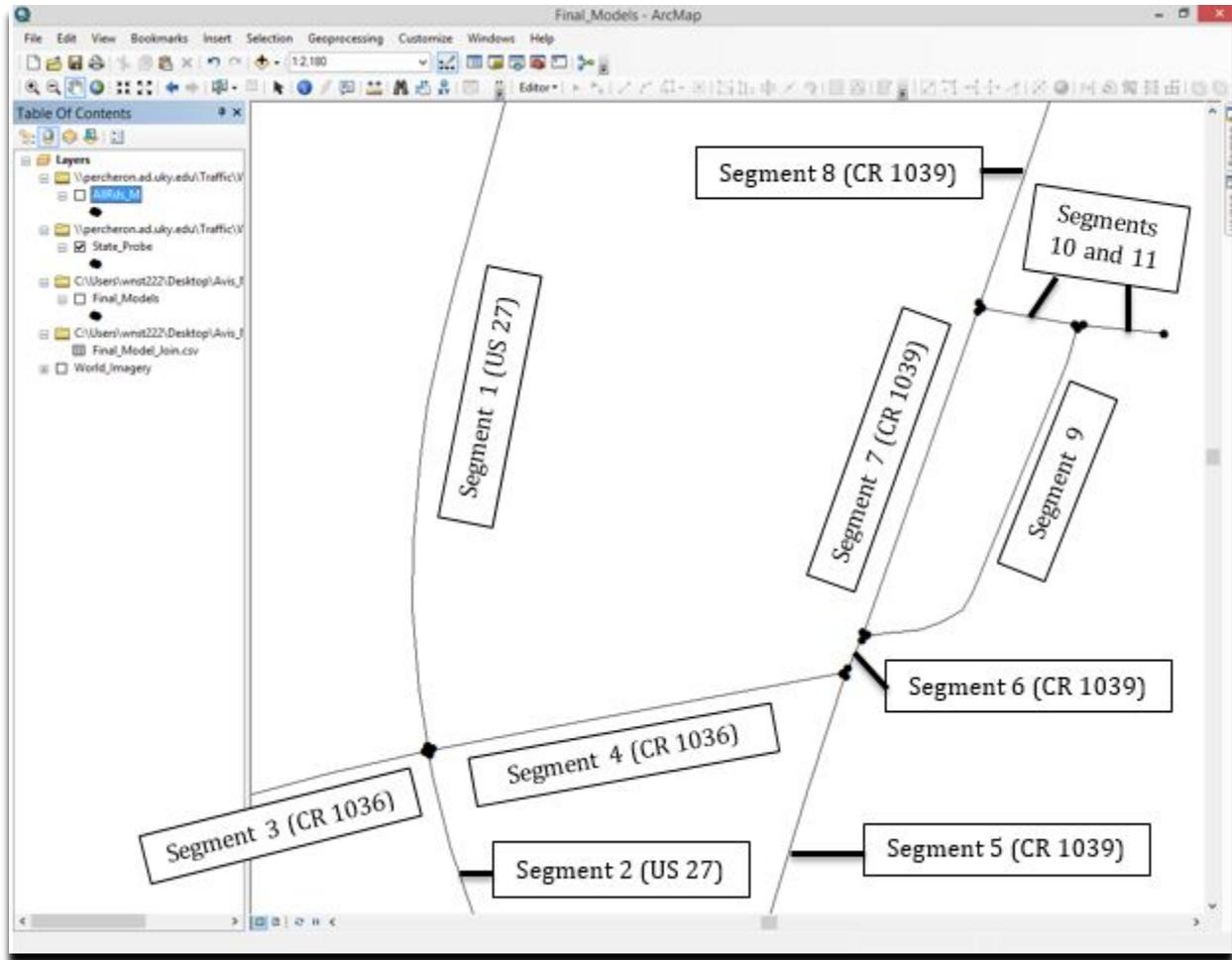


Figure F: HERE Probe Data Segments

The geocoding process converts a table of addresses into a set of coordinates that can be mapped in ArcMap. Once mapped, they are treated as distinct entities (e.g., individual properties). Points maintain attributes from the AVIS database. Therefore, each point is also categorized as official, commercial, or non-commercial.

The roadway network file containing the HERE probe count averages was joined to the Traffic Flow (TF) file from the KYTC HIS database. This created a new shapefile comprising all roadway along with the average probe count and known traffic counts. At this point the straight length of each road segment was calculated using the coordinates of the beginning and end points of each road segment. Actual road segment lengths were also calculated. Both calculations were performed using ArcMAP's "calculate geometry" tool. The ratio of actual road length to the straight length was calculated for each segment.

Each address coordinate then had information about the nearest roadway segment joined to it, creating a shapefile of points with the following information:

- AVIS registration type: official, commercial, or non-commercial
- Unique ID of the roadway segment nearest to the point
- Average probe count associated with the nearest roadway segment

- State traffic count (the count was 0 for local roads)
- Curve rating

The shapefile of points with associated roadway segment information was exported into Excel to convert the data from point format to a polyline format. Each road segment, along with its associated traffic and probe count, was placed in a separate sheet. To populate the Residential variable for each roadway segment, the “countifs” function in Excel was executed such that it only counted the points for each road segment that were registered as non-commercial and had the nearest road segment with same unique ID as the segment in question. The Commercial variable was calculated in a similar manner, except it counted points registered as commercial or official.

Several types of regression were attempted with four variables (commercial and residential registrations, probe count and curve rating), including ordinary multiple linear regression, log transformed multiple linear regression, and generalized linear regression. During model development, researchers observed that many commercial properties had no vehicles registered to those locations. As such, the commercial variable was excluded from the model. After comparing errors among the different regression types, researchers decided that a generalized linear model with a Poisson distribution and a log link function best fit the data. This type of model has the following format:

$$Y = e^{\alpha + \beta_1 X_1 + \dots + \beta_n X_n}$$

Where

- Y is the dependent variable
- e is Euler’s number
- α is the calibrated constant
- β_n are the calibrated coefficients
- X_n are the explanatory variables
- n is the number of variables

To account for the spatial and socioeconomic variations across Kentucky, the state was divided into three regions based on the highway districts. The regions and their respective highway districts were:

- West: 1, 2, 3, 4
- North Central: 5, 6, 7
- East: 8, 9, 10, 11, 12

One model was calibrated for each region. Certain restrictions were placed on the data used to calibrate each region to ensure that the calibration data closely matched the characteristics of the roads for which the models would be used to estimate AADT. The data used to calibrate the models were known traffic counts conducted by KYTC on rural, state-maintained roads that were functionally classified as local roads. Only roads with traffic counts between 20 and 1000 were included in the analysis. Several roads with known traffic counts from KYTC had AADT values ranging from 6 to 19, which appeared inconsistent with numbers reported on an official traffic count. There may have been some errors in the collection or reporting of these counts. Because of this, they were left out of the model calibration to avoid introducing bias toward low AADT estimates. The upper limit of 1000 was established because the researchers assumed that no rural local roads in Kentucky lacking a known count would have daily traffic volumes

exceeding 1000, given that the standard definition of a local road is one with an AADT of 400 or fewer. Of the road segments in each region that fit these criteria, 75 percent were used to calibrate the model. The remaining 25 percent in each region were used to validate the model.

3.3.3 Rural Model Results

Researchers developed the rural models using Poisson distributed non-linear regression with a log link function in JMP 12.1, a statistical software package. The three model variables included probe count (Probe), curve rating (Curve), and residential AVIS registrations (Residential). Seventy-five percent of each region’s data set was randomly selected to calibrate the model. Table 3 shows the calibrated coefficients for each model, with the model taking the following form:

$$AADT = e^{\alpha + \beta_1 Probe + \beta_2 Curve + \beta_3 Residential}$$

Model	α	β_1 , Probe	β_2 , Curve	β_3 , Residential
West	5.7696115	0.0058785	-0.529959	0.0040769
North-Central	5.2644224	0.0057724	-0.077597	0.0055012
East	5.5054758	0.0056975	-0.015072	0.0023554

Table 3: Rural Regional Model Coefficients

Each regional model, and its explanatory variables, was statistically significant at the 0.01 percent confidence level. Hence, regional explanatory variables were useful in accounting for the variation in AADT. Coefficient signs (positive or negative) for each model were calibrated as expected. Both Probe and Residential variables have positive coefficients. This meant an increased probe count or residential vehicle registration along a road segment would produce a higher AADT estimate. The Curve coefficient is negative, which indicates curvier roads have lower AADTs. Researchers anticipated the Curve variable would have this effect when they decided to incorporate it into the model.

Next, researchers tested each model’s AADT estimative capability by using the remaining 25 percent of the data set for validation. This step compared estimated AADTs within each calibrated model with their respective known AADTs, as contained in the regional validation data sets. This occurred for each highway segment and generated several error measures. Table 4 summarizes the error measures from the regional models’ validation data.

	West	North-Central	East
N (sample size)	194	45	150
Mean Absolute Error	133	152	158
St. Dev. Absolute Error	128	125	121
MAPE (%)	102	123	97
Max % Error	801	790	1104
Min % Error	-76	-75	-73

Table 4: Rural Regional Model Errors

Where

- **Mean Absolute Error** is the mean absolute value of the difference between the estimated AADT and the known AADT for every sample used in the validation process
- **Standard Deviation of Absolute Error** is the standard deviation of the absolute difference between the known AADT and the estimated AADT

- **Mean Absolute Percent Error (MAPE)** is the average absolute value of the percent error for every sample used in the validation process
- **Maximum Positive Error** is the highest positive error observed during model validation
- **Maximum Negative Error** is the highest negative error observed during model validation

The measures of error were calculated using the following equations:

- Mean Absolute Error = $\sum_{i=1}^n \frac{|Estimated\ AADT_i - Actual\ AADT_i|}{n}$
- Standard Deviation of Absolute Error = $\sqrt{\frac{\sum_{i=1}^n (Average\ Absolute\ Error - Absolute\ Error_i)^2}{n-1}}$
- Mean Absolute Percent Error = $\frac{\sum_{i=1}^n \frac{|Estimated\ AADT_i - Actual\ AADT_i|}{Actual\ AADT_1}}{n}$
- Maximum Positive Error = $\max_n \frac{Estimated\ AADT_i - Actual\ AADT_i}{Actual\ AADT_1}$
- Maximum Negative Error = $\min_n \frac{Estimated\ AADT_i - Actual\ AADT_i}{Actual\ AADT_1}$

Each regional model showed standard deviations of the absolute error that were nearly the same magnitude as the mean absolute error. Assuming errors are normally distributed, this means the model produced a wide range of errors, which is not ideal, but it does not necessarily diminish the model’s ability to estimate AADT. The MAPE for each model was around 100 percent, meaning the estimated AADT — on average — differs by a factor of two. However, the purpose of an estimate is to identify locations suitable for safety improvements so errors of this magnitude should not interfere with this purpose. The sensitivity analysis discusses this further.

Figure G shows the geographical distribution of the error (Model AADT – Known AADT) for the calibrated and validated data sets. The creation of three regional models compensated for geographical and socioeconomic variability typically absent in a single statewide model. The figure shows only rural, local roads with known AADTs between 20 and 1,000. Blue lines represent segments where the model underestimated AADT; gray lines indicate close alignment between known and estimated AADTs; and red lines represent segments where the model overestimated AADT. Geographical bias in AADT estimation is limited because the under- and overestimates on road segments are evenly distributed across the state. Therefore, this result supports the research team’s decision to create three regional models rather than a single statewide model.

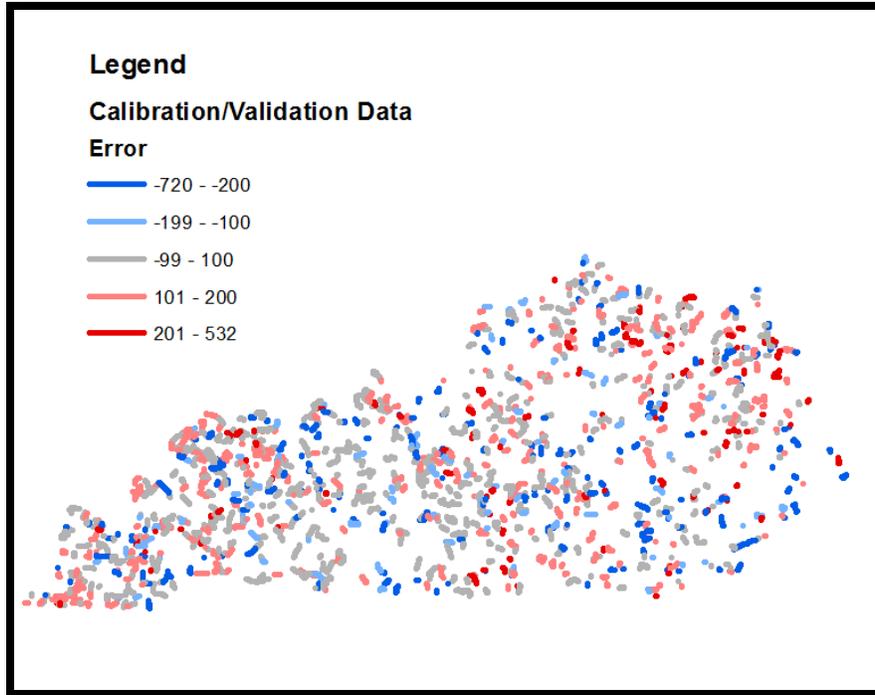


Figure G: Geographical Distribution of Errors

Figure H displays the difference (represented as error) between the AADT estimates for the three models' validation datasets and their known AADTs on the y-axis. The x-axis includes known AADTs. The models underestimated high AADTs and overestimated low AADTs. Consequently, the three regional models produced the lowest errors on road segments between the AADT range of 100 to 400. KTC researchers estimated that most Kentucky rural, local roads also fall in this AADT range so this estimate should prove beneficial. Researchers selected this model due to its increased performance over the original AVIS-HERE OLR model (shown in Appendix E).

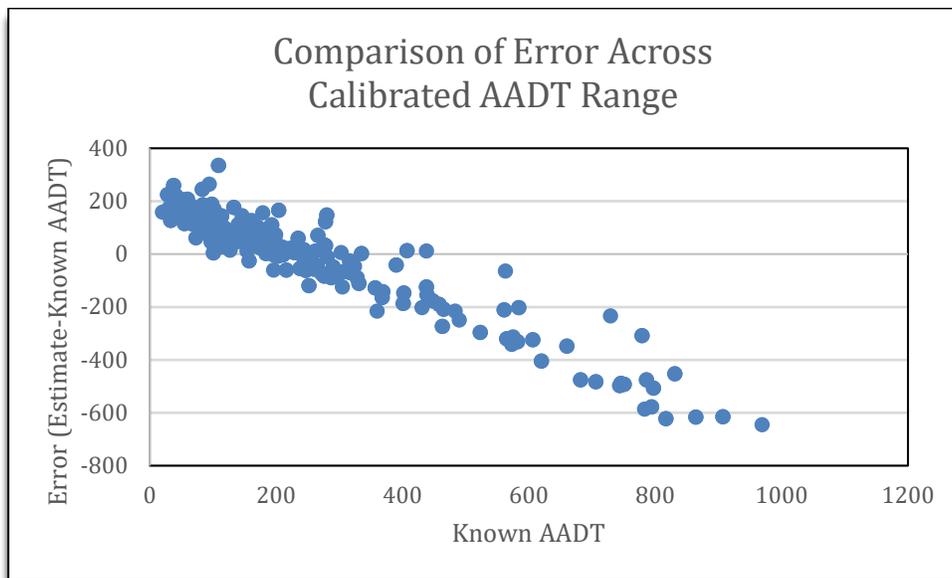


Figure H: Validation Errors in Three Regional Models

Figures I, J, and K display known versus estimated AADTs for each Kentucky region. An ideal estimate would form a 45-degree line demonstrating alignment between known and estimated AADTs. This hypothetical line is shown in each figure. Data points above the line represent segments where the model overestimated AADT and points below the line represent segments where the model underestimated AADT. Greater distances between the points and the line represent greater errors.

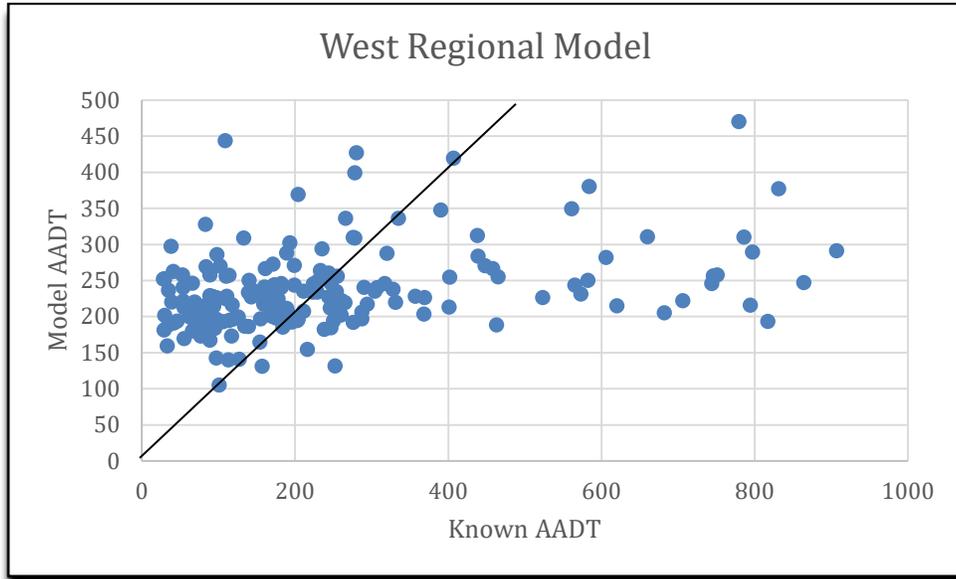


Figure I: West Regional Model, Known vs. Model AADT

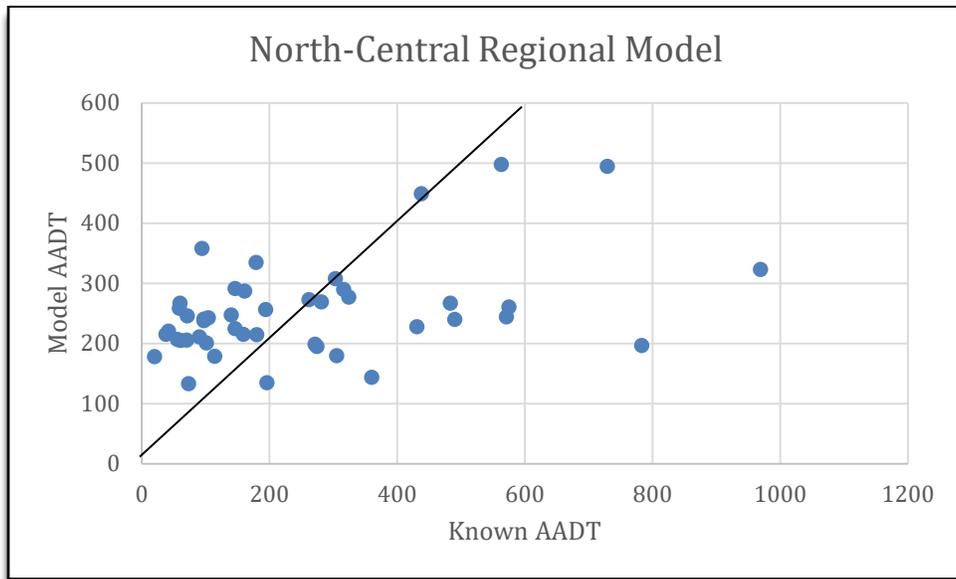


Figure J: North-Central Regional Model, Known vs. Model AADT

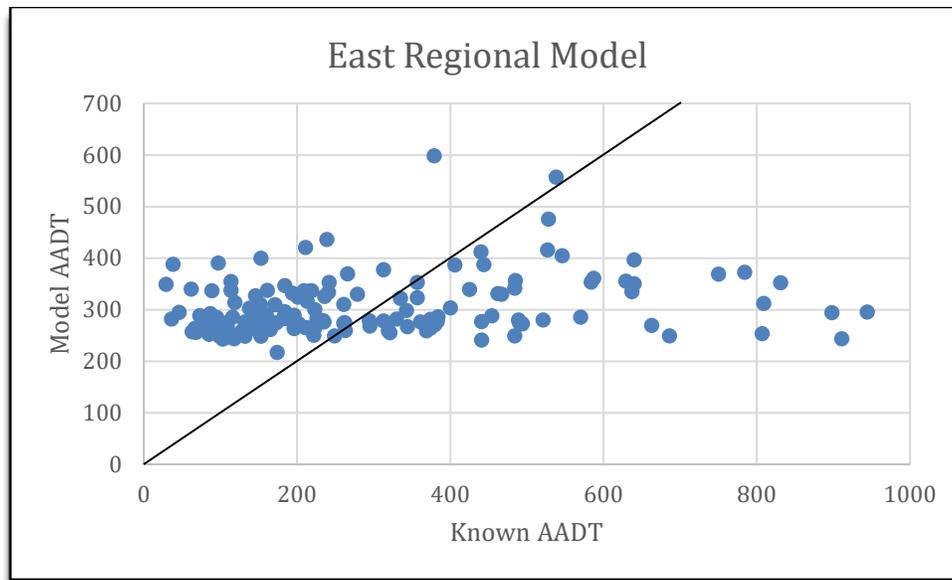


Figure K: East Regional Model, Known vs. Model AADT

Each model contained a baseline AADT which represented the minimum value the model could estimate. This baseline was approximately 100 for the West and North-Central models and approximately 200 for the East model. The calibrated constant α was responsible for this baseline since it remained constant as other explanatory variables moved to zero. Each model produced higher errors as AADT estimates increase. Nevertheless, these regional models focused on rural, local roadways – which typically have lower AADTs—so the higher range AADT errors were not cause for concern.

Next, researchers collected KYTC’s daily vehicle miles traveled (DVMT) estimate for rural, local roads and compared those values to each model’s AADT estimates. DVMT is determined by multiplying a local road segment’s distance (in miles) with its AADT and represents the total number of vehicle miles traveled along a given roadway segment daily. KYTC employs a power function to estimate DVMT for rural, local roads. County collector AADTs serve as explanatory variables in this model which can be described as follows (27):

$$Local\ DVMT = Local\ Miles * Local\ AADT, \text{ where } Local\ AADT = 3.3439 * (Collector\ AADT)^{0.6248}$$

Each rural, local DVMT estimate was calculated at the roadway segment level and aggregated county-wide to produce a county-level DVMT value, the same scale used in the regional models. The DVMT values served as a basis of comparison with the regional model AADT estimates. In most instances, the models produced higher DVMT values than the KYTC DVMT estimates. Ratios by county of the KYTC DVMT estimated values to the model’s estimated AADTs is shown in Figure L. A brief discussion of this adjustment methodology is described in the subsequent paragraphs.

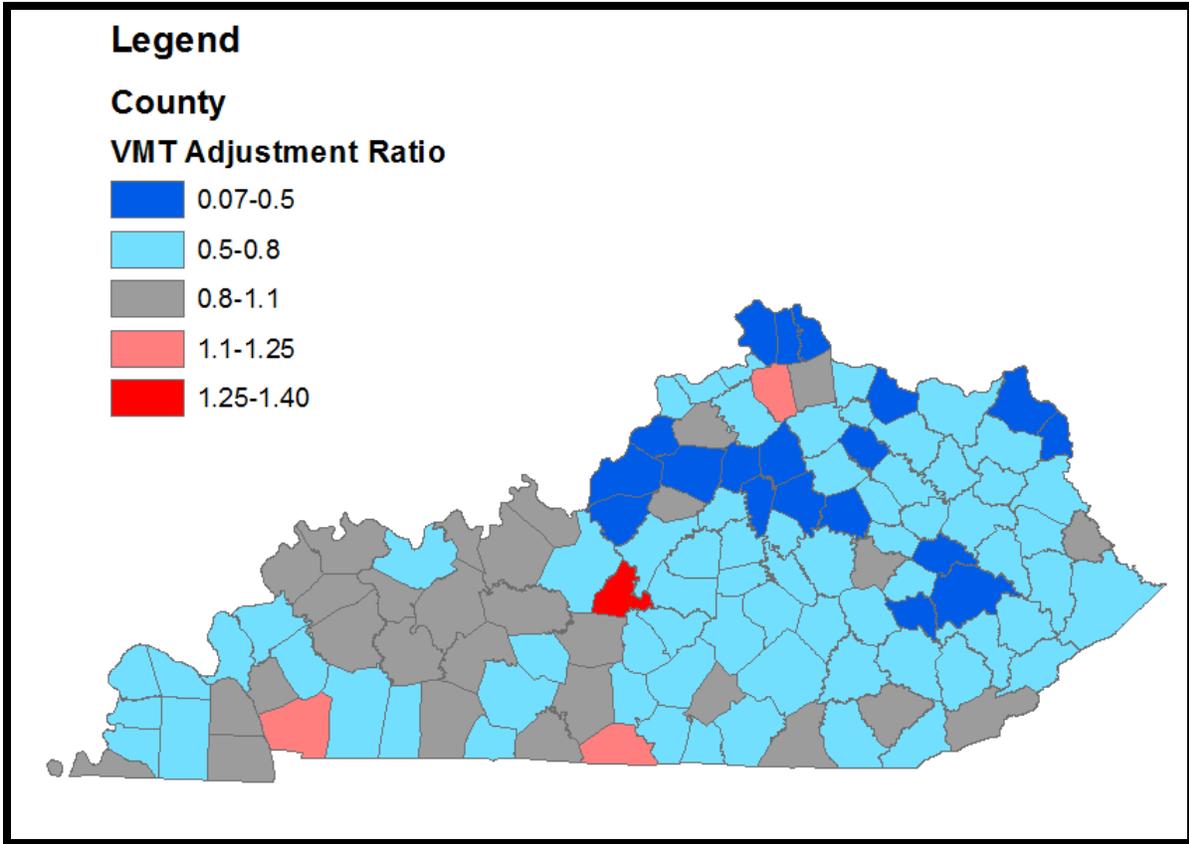


Figure L: VMT Adjustment Ratio by County

The KYTC DVMT to model DVMT ratio was used as an adjustment factor in the model’s AADT estimates. For example, a ratio of 0.75 would be multiplied by the estimated AADT to further refine the estimate. The majority of adjustment factors were found to be less than one. This meant that the model DVMT estimates tended to exceed KYTC DVMT values. The lowest adjustment ratios were found in population and urban areas, such as northern Kentucky. These regions typically have increased cell phone coverage which leads to an increase in vehicle probe counts (HERE data). The increased population density and proximity to local roads also contributed to higher residential variable values. Therefore, the rural, local AADT road estimates in these counties typically exceeded rural, local AADT road estimates in less populated counties. This, in turn, produced higher DVMT values for the model estimates compared to the KYTC DVMT values. In Figure L, counties in pink and red show counties where the KYTC DVMT values exceeded the model’s DVMT estimates; conversely, blue counties show locations where the KYTC DVMT values fell below the model’s estimates. The latter case represented the majority of counties fitting this description.

Each individual county adjustment factor was multiplied by its respective county AADT estimate to produce a revised AADT estimate. This revised estimate provided additional weighting from the KYTC DVMT data. The different error measures were recalculated from these revised estimates as shown in Table 5.

	West	North-Central	East
N (sample size)	194	45	150
Mean Absolute Error	129	172	149
St. Dev. Absolute Error	142	184	159
MAPE (%)	87	85	61
Max % Error	797	519	702
Min % Error	-80	-94	-85

Table 5: Rural Regional Model Errors with DVMT Adjustment Factor

Various error measures changed—in some cases substantially—from the original error measures shown in Table 4. The MAPE improved the most as evidenced by a 15 percent or more reduction in each region. Similarly, the maximum percent error decreased in each region, particularly for the East and North Central regions. The mean absolute error experienced minor improvements in the West and East regions but increased slightly in the North Central region. However, this measure was less useful than the other error measures since it lacked normalized distribution across its AADT data.

Adopting the adjustment factor, Figure M displays the difference (represented as error) between the revised AADT estimates for the three models’ validation datasets and their known AADTs on the y-axis. The x-axis shows known AADTs. The models underestimated high AADTs and overestimated low AADTs. In this adjusted model, the three regional models produced the lowest errors on road segments between the AADT range of 100 to 300. The actual AADTs are compared to the estimated AADTs in Figure N, O, and P. In most instances, the DVMT adjustment factors reduced AADT estimates.

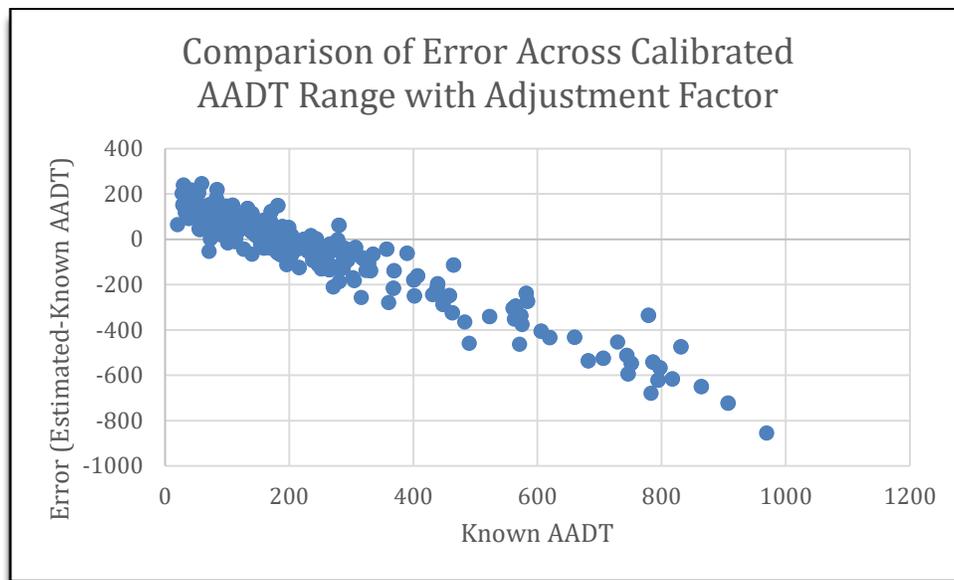


Figure M: Validation Errors in Three Regional Models (w/ Adjustment Factor)

The combined errors graph for the three models (Figure M) displays a similar trend as previously shown in Figure H. Recall, the previous error graph did not account for the adjustment factor per the KYTC DVMT data. Nevertheless, the newly revised errors were nearly zero in the 100 to 300 AADT range, an ideal parameter for the rural, local roads. The revised model continued to underestimate AADTs for roads with higher known AADTs but these roads typically lie outside the AADT range expected for rural, local roads. Therefore, improving model errors across the lower AADT ranges remained the focus as achieved here.

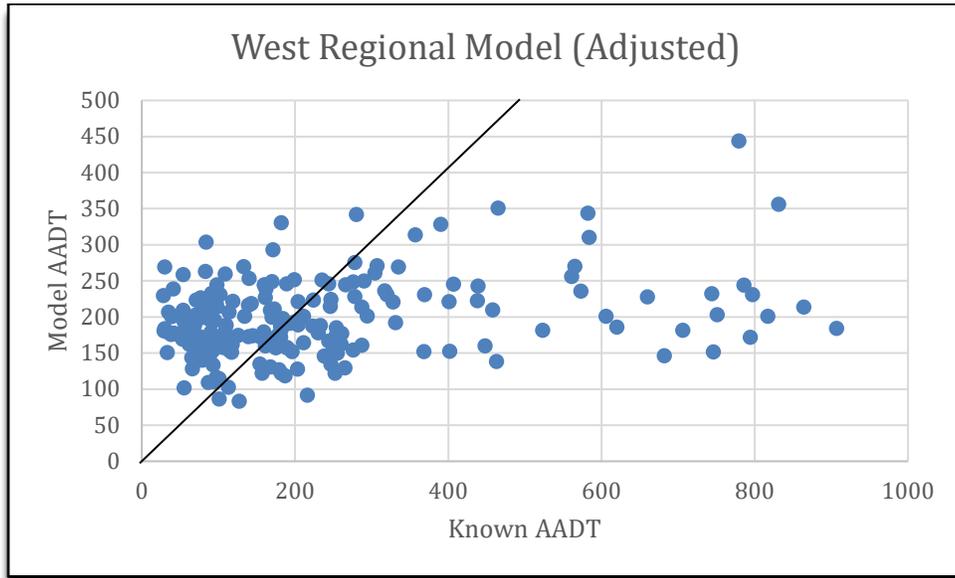


Figure N: West Regional Model, Known vs Model AADT (w/ Adjustment)

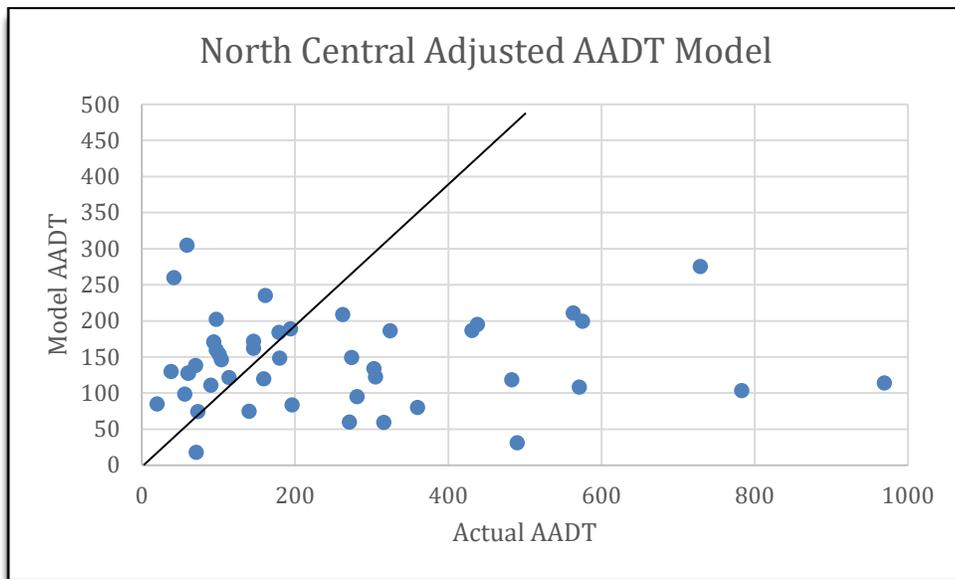


Figure O: North-Central Regional Model, Known vs Model AADT (w/ Adjustment)

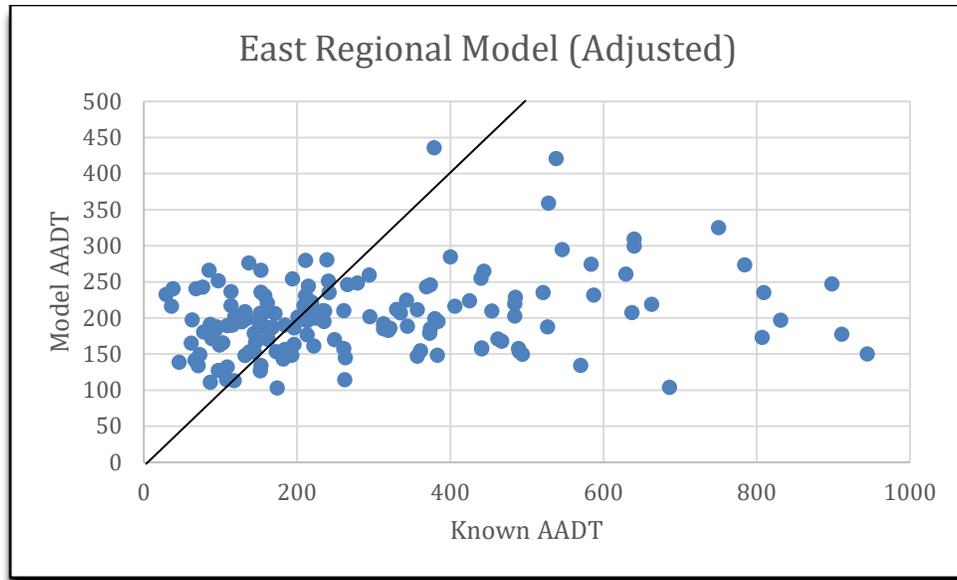


Figure P: East Regional Model, Known vs Model AADT (w/ Adjustment)

Next, known AADTs were graphed against estimated AADTs for each of the regional models (Figures N, O, P). The minimum estimated AADT decreased by a factor of two for each model. Thus, these regional models improved the alignment between known and estimated AADTs, as represented by an increased number of points moving closer to the 45 degree graph line. Each county possessed a unique adjustment factor and therefore, was adjusted independently from other counties. This led to increased variation in the model AADT estimates. This can be seen by an increase in scatter between points amongst Figures N, O, and P compared to Figures I, J, and K.

3.3.4 Urban Model Development

KTC researchers developed the urban AADT model using a similar methodology as employed in the rural AADT models development. To this extent, the urban models used the same segmentation process for subdividing roadways as described in detail in section 3.3.2. The urban model consisted of the same three variables (probe count, curve rating, and residential AVIS registrations) derived from the same data sets. Once again, this model split the state into three separate geographical regions (West, North-Central, and East) using the same procedures shown in developing the rural model. KTC researchers used 75% of the AADT data in each region to calibrate the model and the remaining 25% of data to validate the model. However, there was one major methodological difference between the rural and urban model development. The original rural AADT model required road segments with a known AADT between 20 and 1,000, while no such limitation was placed on the calibration data set for the urban model. In fact, urban traffic counts span a wide range of values and limitations on the calibrated datasets were not deemed necessary.

3.3.5 Urban Model Results

Researchers developed the urban models using Poisson distributed non-linear regression with a log link function in JMP 12.1, in a similar fashion to the rural models. The three model variables included probe

count (Probe), curve rating (Curve), and residential AVIS registrations (Residential). Table 6 shows the calibrated coefficients for each model, with the model taking the following form:

$$AADT = e^{\alpha + \beta_1 Probe + \beta_2 Curve + \beta_3 Residential}$$

Model	α	β_1 , Probe	β_2 , Curve	β_3 , Residential
West	6.470643	0.0064529	-0.125808	0.0028887
North-Central	5.8138784	0.0112211	0.2191382	0.0115388
East	7.0093157	0.0072614	-0.079176	0.0002173

Table 6: Urban Regional Model Coefficients

Each regional model, and its explanatory variables, was statistically significant at the 0.01 percent confidence level. Hence, regional explanatory variables were useful in accounting for the variation in AADT. Coefficient signs (positive or negative) for each model performed as expected for all but one coefficient. Both Probe and Residential variables had positive coefficients. This meant an increased probe count or residential vehicle registration along a road segment produced a higher AADT estimate. The Curve coefficient was negative for the West and East models, which indicated curvier roads have lower AADTs. However, the Curve coefficient in the North-Central model was positive, which ran contrary to the results of the West and East models. Nonetheless, dividing the state into three regions limited the overall effect this positive coefficient had on the cumulative urban AADT estimates for the state.

Researchers calculated the same model errors as before as suitable measures of effectiveness. Table 7 summarizes these error types and their associated valuations from the urban regional models' validation data.

	West	North-Central	East
N (sample size)	16	24	35
Mean Absolute Error	916	892	1048
St. Dev. Absolute Error	750	613	1393
MAPE (%)	1956	1828	354
Max % Error	16878	11070	8278
Min % Error	-79	-63	-81

Table 7: Urban Regional Models Errors

The Table 7 summary results demonstrate the urban models had much higher errors when compared to the rural models. One possible explanation for this may be the higher variability of AADT values used to calibrate the urban models. Also, the urban model relied upon a smaller available dataset to calibrate each regional model which likely impacted the model's effectiveness.

KTC researchers used KYTC-provided DVMT values as control totals to develop adjustment factors and modify the urban models' AADT estimates. However the calculations used to derive control totals differed between the urban models and the rural models. In the rural models, the DVMT adjustment factor represented the ratio between KYTC-derived rural DVMT values for a county and rural DVMT model estimates for the same county. This adjustment factor was applied to each rural local road segment in the county. In the urban models, adjustment factors were calculated differently based on the following two scenarios: the model-derived DVMT was less than the KYTC-derived DVMT or the model-derived

DVMT was greater than the KYTC-derived DVMT. For the first scenario, researchers adjusted urban local roads found to intersect state roads when the county’s model-derived DVMT was less than the KYTC-derived DVMT using an adjustment factor that increased AADT on roads that intersect state roads. With the second the urban local roads that do not intersect state roads received DVMT adjustments if the county’s model DVMT exceeded the Cabinet’s DVMT value, thereby reducing the urban local road AADT values.

The purpose of creating adjustment factors in this manner was to avoid assigning additional AADT on neighborhood roads that only connect to other local roads while assigning increased AADT on roads that contribute more heavily to state roads. An example adjustment factor calculation for each described case scenarios shown below (and based on the DVMT data in Table 8).

County	DVMT do not intersect state	DVMT intersect state	KYTC DVMT	Adjustment Factor
Anderson	7361	6529	55000	7.30
Pike	14367	28707	37000	0.58

Table 8: Urban DVMT Control Total Data

The urban AADT model estimated AADT values that lead to a lower DVMT (combined intersect and do not intersect) in Anderson County than estimated by KYTC in 2014. Therefore, an adjustment factor was needed to increase AADT on the urban, local roads that intersect state roads. The adjustment factor was calculated as follows:

$$\text{Adjustment Factor} = \frac{\text{Cabinet DVMT} - \text{DVMT not intersecting state roads}}{\text{DVMT intersecting state roads}} = \frac{(55000 - 7361)}{6529} = 7.30$$

This factor holds constant the AADT on local roads that do not intersect state roads while increasing AADT on local roads that intersect state roads to 47662.

In another example, Pike County had a larger model DVMT value than the KYTC DVMT, thus requiring an adjustment factor to reduce the AADT on urban, local roads that only intersect other local roads. The adjustment factor was calculated as follows:

$$\text{Adjustment Factor} = \frac{\text{Cabinet DVMT} - \text{DVMT intersecting state roads}}{\text{DVMT not intersecting state roads}} = \frac{(37000 - 28707)}{14367} = 0.58$$

This factor holds constant the AADT on local roads that intersect state roads while only decreasing AADT on local roads that do not intersect state roads to 8333.

Applying the DVMT adjustment factors to the individual road segments in the validation datasets and recalculating the selected measures of effectiveness resulted in the errors displayed in Table 9.

	West	North-Central	East
N (sample size)	16	24	35
Mean Absolute Error	915	764	1063
St. Dev. Absolute Error	751	591	1178
MAPE (%)	1923	1145	313
Max % Error	16878	6268	8278
Min % Error	-79	-63	-81

Table 9: Errors from Urban Regional Models after DVMT Adjustment

The greatest impact found in using DVMT adjustment factors was seen in the associated MAPE value reductions shown in each region. The minimum errors did not change and the maximum error was only reduced for the North-Central model. The DVMT adjustment factors improved the model performance and therefore, the adjustments were applied to the final urban local road AADT estimates.

Chapter 4: Sensitivity Analysis

4.1 Sensitivity Analysis

Estimative models inherently rely on engineering judgment and analytical assumptions. These are incorporated into the models' algorithms to compute the desired outputs. In some cases, however, a model may estimate values that do not align with expected empirical solutions. This requires the model developer to perform additional checks and/or validation procedures to further improve its performance. Sensitivity analysis is one procedure that can be used to improve results. A sensitivity analysis measures how a model's output (or dependent variable) is expected to change based upon the explanatory factors (or independent variables) used to develop it. This process provides an additional check on uncertainty or the model's assumptions and determines how they might impact the predicted solutions. One of the key goals of a sensitivity analysis is to minimize any unexpected or adverse outcomes stemming from a less-than-satisfactory output. This process helps ensure that the model's inaccuracies do not have an overly adverse impact on the output. Following this process, KTC researchers developed a sensitivity analysis to analyze the selected AADT traffic model and its expected range of impacts on crash predictions, including their severity.

4.1.1 KYTC Crashes and Associated Costs

KYTC seeks the use of an AADT traffic model to estimate traffic counts on local roads across the state. These values are critical to KYTC for a number of reasons, including providing a means to predict crashes along a roadway segment or at an intersection. KYTC uses crash data to evaluate safety measure installations. Roadway segments or intersections experiencing a large number of crashes warrant additional scrutiny to decide whether increased funding might reduce crash frequency. In some cases, the installation of safety measures at an appropriate roadway segment or intersection may significantly lower the number of crashes within that area. In other cases, the installation of the safety measures may have a negligible impact and therefore provide little benefit at a potentially high financial cost. Intuitively, it is in KYTC's interest to prioritize locations where treatments will provide the greatest return on investment while avoiding areas where treatments will yield minimal benefits at a significant cost. State DOTs take their lead from the U.S. DOT to provide safe roadways to all their citizens. In fact, a significant percentage of overall federal highway funding is dedicated exclusively to reducing crashes. This aligns with the U.S. DOT's 2012-2016 Strategic Plan "*Transportation for a New Generation*" and their goal to "improve public health and safety by reducing transportation-related fatalities and injuries." (28)

KYTC leaders and decision-makers must rely on sound estimates and projections whenever determining which roadways or intersections need safety treatments. Likewise, roadway sites receive a prioritization ranking based on the expected benefits of installing a safety measure. To compare the effects of measures at different sites, the FHWA has developed crash costs, which are estimated based on the crash severity in terms of human life and property damage. The categories or types of crash severity are: fatal, disabling injury, evident injury, possible injury, and property damage only. Each of these categories is assigned a corresponding monetary value (in dollars), which quantifies impacts financially. Along with the crash types, the crash costs are further delineated according to human capital crash costs and comprehensive crash costs. The human capital crash costs category only includes financial losses directly associated with the crash, such as vehicle repair and medical treatment, among others. The comprehensive crash costs category takes this a step further and assigns a monetary value to the burdens imposed on the individual's

quality of life due to time lost during recovery or potential physical limitations attributable to the crash. Table 10 lists the FHWA’s crash cost estimates.

Crash Type	Human Capital Crash Costs	Comprehensive Crash Costs
Fatal (K)	\$1,245,600	\$4,008,900
Disabling Injury (A)	\$111,400	\$216,000
Evident Injury (B)	\$41,900	\$79,000
Possible Injury (C)	\$28,400	\$44,900
Property Damage Only (O)	\$6,400	\$7,400

Table 10: FHWA Crash Cost Estimates by Crash Severity

4.1.2 Sensitivity Analysis Methodology

KTC researchers developed a sensitivity analysis to assess how the model’s estimated local road AADT values potentially impact crash estimates when accounting for errors. Safety performance functions (SPFs) are used to estimate crashes, and for this project, were taken from the Highway Safety Manual (HSM). SPF equations rely upon AADTs as input variables, in our case, a known AADT for the state road and an estimated AADT for the local road. This sensitivity analysis used the models’ maximum and minimum percent errors to estimate AADT estimation error impact on predicted crashes.

First, researchers located all intersections in Kentucky via the GIS platform. Intersections were selected so they would match the data set used in the AADT model. The types of intersections were subsequently categorized into three groups, including:

- State-maintained roadways intersecting state-maintained roadways (State-State)
- State-maintained roadways intersecting local roadways (State-Local)
- Local roadways intersecting local roadways (Local-Local)

All intersections forming a state-to-local roadway crossing (State-Local) formed the basis of the sensitivity analysis. Intersections were then classified based on their characteristics. These were used to determine the appropriate HSM regression equations used in the analysis. For intersections, the factors considered included:

- Rural or urban roads
- Number of intersection approaches (three versus four)
- Unsignalized or signalized
- Number of lanes in each direction

Roadway characteristics provide transportation planners the details required when selecting the appropriate regression equations to use. Furthermore, each regression equation is only suitable for a specified range of traffic volumes. In this sensitivity analysis, all of the traffic volumes on the major and minor roadways approaching intersections fell within the acceptable ranges. Therefore, no additional modifications to the regression equations were required.

Next, the AADTs were used in the sensitivity analysis. Known AADT is available from HIS for the major crossing or state road. Conversely, the AADT for the local intersecting roadway is estimated from the AVIS-HERE model. Once the AADTs and roadway characteristics are known, the SPF can be evaluated and crash estimates produced.

4.1.3 Rural Model Sensitivity Analysis

Most rural two-lane state-local road intersections are stop controlled on the minor approach. SPF regression equations from the Highway Safety Manual for 3 and 4 leg intersections are shown below (29):

Rural Two-Lane, Two-Way Roads

1. Three-Leg Stop Sign-Controlled Intersections

$$N_{spf,3SSC} = \exp[-9.86 + 0.79 \times \ln(AADT_{maj}) + 0.49 \times \ln(AADT_{min})]$$

Where:

- $N_{spf,3SSC}$ = estimate of intersection-related predicted crash average crash frequency for base conditions for three-leg stop-controlled intersections
- $AADT_{maj}$ = AADT (vehicles per day) on the major road
- $AADT_{min}$ = AADT (vehicles per day) on the minor road
- *Overdispersion parameter* = 0.46

2. Four-Leg Stop-Sign Controlled Intersections

$$N_{spf,4SSC} = \exp[-8.56 + 0.60 \times \ln(AADT_{maj}) + 0.61 \times \ln(AADT_{min})]$$

Where:

- $N_{spf,4SSC}$ = estimate of intersection-related predicted crash average crash frequency for base conditions for four-leg stop-controlled intersections
- $AADT_{maj}$ = AADT (vehicles per day) on the major road
- $AADT_{min}$ = AADT (vehicles per day) on the minor road
- *Overdispersion parameter* = 0.494

A crash frequency estimate at a select intersection is determined using the intersection regression SPF equations and their corresponding AADT values¹. The Empirical Bayes method is then used to refine this estimate by incorporating known crash data. It adjusts the estimate for future predicted crashes using the overdispersion parameter calculated during the development of the SPF equations. The Empirical Bayes formula is as follows:

¹ In many instances, KYTC does not know the AADT of a minor road, typically a rural, local road. This becomes problematic since the minor road AADT is a key input into the regression equations described above. Therefore, KYTC currently estimates an AADT of 300 on minor roads where the AADT is unknown.

Expected Crashes in X years

$= \text{Overdispersion parameter} * N * CMF * X + (1 - \text{Overdispersion parameter})$
 $* \text{Previous crashes}$

Where:

- Overdispersion parameter is calibrated for each SPF and is obtained from the Highway Safety Manual
- N is the number of crashes predicted by the SPF
- CMF is a crash modification factor (from Highway Safety Manual or CMF Clearinghouse)
- X is the number of years
- Previous crashes is the number of crashes at the intersection in the past X years

The overdispersion parameter determines the SPF's weighted contribution to the overall crash estimate. In this case, the SPF predictions for three- and four-leg rural, state-local intersections contributed 46 percent and 49.4 percent, respectively, to the weighted analysis. Known, historical crash frequencies contributed the majority. Consequently, the errors stemming from AADT estimates in this model will be minimized due to their reduced influence on predicting expected crashes through Empirical Bayes.

A sensitivity analysis assesses the impact an estimated AADT's error has on a decision-maker's selection process in implementing appropriate countermeasures at intersections. AADT estimate errors influence the crash frequency predicted by SPFs which, in turn, influences the Empirical Bays crash frequency prediction. Safety countermeasures can be based on a cost-benefit ratio whereby the benefits received (e.g., crash reduction) exceed the costs (e.g., countermeasure expense) as quantified in monetary terms.

This sensitivity analysis compared the model's estimated AADTs with estimated AADTs adjusted for errors. It then determined how "sensitive" the determinant variable (i.e., expected crashes) is to variations in error. In this case, the estimated AADTs adjusted for errors included the following: maximum percent error (797%), average positive error (134%), minimum percent error (-94%), and average negative error (-38%). The maximum percent error and minimum percent error represent the extreme outliers for AADT estimates and evaluate the maximum extent to which the model may over- or underestimate crashes. Likewise, the average positive error and average negative error represent the average AADT error effect on over- or underestimating crashes. AADTs were adjusted using the following equation:

$$\text{Adjusted AADT} = \text{Estimated AADT} / (1 + \text{Percent Error})$$

Where:

- Estimated AADT is the AADT generated by the model
- Percent Error is either maximum percent error, minimum percent error, average positive error, or average negative error

As seen in the previous equation, positive errors arise when overestimating AADT and negative results arise when underestimating AADT. Researchers used the adjusted AADT estimates to determine revised SPF values. The Empirical Bayes method incorporated these updates and used crash data over the previous 10 years assuming a crash modification factor (CMF) of 0.15. A weighted crash cost average of \$54,051 was calculated using the cost figures in Table 10 and applied to projected crashes over the next 10 years. Then, a benefit-to-cost ratio equal to five was used to assess maximum safety countermeasure costs for each intersection. Five iterations of this process were conducted to include the estimated AADT and its error-induced derivatives. Those determined most cost-effective were deemed feasible.

Next, percent errors were calculated for maximum countermeasure costs between the original, estimated AADT and its adjusted AADTs. This range of errors described the association of intersection crash predictions based on differences in errors. AADT estimates ranged in error from a 134 percent overestimate to a 33 percent underestimate. However, applying these same AADT estimates to crash predictions resulted in a significant drop in errors as evidenced by their 28 percent overestimate and 22 percent underestimate. The most extreme errors in AADT estimation included a 797 percent overestimate and a 94 percent underestimate. Yet, these corresponding errors translated into a 54 percent overestimate and 253 percent underestimate on predicting crashes. However, the AADT errors have only a limited impact on the final crash predictions for rural, local roads. This is because the local road AADT only influences the number of crashes predicted by SPFs. Intersection crash predictions must take into account both SPFs and historical crash rates, with the latter weighted proportionately higher.

A sensitivity analysis helps identify possible locations for Type I and Type II errors. A Type I error overestimates the number of crashes occurring at an intersection. Type I errors can lead decision-makers to implement safety countermeasures which may not be needed. Essentially, this error can lead to unneeded expenditures on safety countermeasure but would not have a measurable impact on crash risk. Conversely, a Type II error underestimates the number of crashes expected at an intersection. In this instance, decision-makers may not fully realize an intersection's crash risk and therefore, choose not to fund it for safety countermeasures. Type II errors are considered more severe because they may result in higher than anticipated crash frequency or severity.

Oftentimes, the model estimated Type II errors at intersections lacking a historical record of known crashes. These locations relied solely on AADT estimates since they lacked historical crash data. Consequently, the errors associated with these AADT estimates regularly underestimated AADT and by extension, underestimated crashes. Still, intersections previously not experiencing a crash would probably not warrant consideration of safety countermeasure treatment anyway. Rather, intersections identified as high crash rate locations based on historical crash data garner increased interest from transportation planners. In these instances, the historical crash data controls overestimated crashes. This greatly diminished AADT estimate errors' ability to adversely impact the calculated crash rate.

In summary, AADT estimate errors did not significantly impact the model as a tool in prioritizing safety countermeasures. The controlling variable in crash prediction is historical crash data. AADT estimates may lead to Type II errors but the sensitivity analysis demonstrated this primarily occurs at intersections lacking historical crashes. These locations are unlikely to receive consideration for safety countermeasures anyway. Most intersection locations have a history of crashes and would find this method suitable for further analysis.

4.1.4 Urban Model Sensitivity Analysis

Researchers performed a sensitivity analysis for the urban AADT estimates that paralleled the sensitivity analysis performed for the rural AADT estimates. Intersection crashes were predicted following SPFs from the Highway Safety Manual and utilizing the Empirical Bayes method to evaluate the impact of the models' errors on the selection of intersections for the implementation of safety countermeasures. Crashes were predicted using the base AADT estimates from the urban models and AADTs adjusted using the following four errors associated with the models: maximum percent error (16878%), average positive error (1533%), minimum percent error (-81%), and average negative error (-44%). The four intersection SPFs used in this analysis are summarized below.

Urban Intersection SPFs

1. Three-Leg Stop-SignControlled Intersections

$$N_{spf,3SSC} = \exp[-13.36 + 1.11x \ln(AADT_{maj}) + 0.41 x \ln(AADT_{min})]$$

Where:

- $N_{spf,3SST}$ = estimate of intersection-related predicted crash average crash frequency for base conditions for three-leg stop-sign controlled intersections
- $AADT_{maj}$ = AADT (vehicles per day) on the major road
- $AADT_{min}$ = AADT (vehicles per day) on the minor road
- *Overdispersion parameter* = 0.80

2. Four-Leg Stop-SignControlled Intersections

$$N_{spf,4SSC} = \exp[-12.13 + 1.11 x \ln(AADT_{maj}) + 0.26 x \ln(AADT_{min})]$$

Where:

- $N_{spf,4SSC}$ = estimate of intersection-related predicted crash average crash frequency for base conditions for four-leg stop-sign controlled intersections
- $AADT_{maj}$ = AADT (vehicles per day) on the major road
- $AADT_{min}$ = AADT (vehicles per day) on the minor road
- *Overdispersion parameter* = 0.33

3. Three-Leg Signal-Controlled Intersections

$$N_{spf,3SC} = \exp[-8.90 + 0.82 x \ln(AADT_{maj}) + 0.25 x \ln(AADT_{min})]$$

Where:

- $N_{spf,3SC}$ = estimate of intersection-related predicted crash average crash frequency for base conditions for three-leg signal-controlled intersections
- $AADT_{maj}$ = AADT (vehicles per day) on the major road
- $AADT_{min}$ = AADT (vehicles per day) on the minor road
- *Overdispersion parameter* = 0.40

4. Four-Leg signal-Controlled Intersections

$$N_{spf,4SC} = \exp[-10.99+ 1.07 x \ln(AADT_{maj}) + 0.23 x \ln(AADT_{min})]$$

Where:

- $N_{spf,4SC}$ = estimate of intersection-related predicted crash average crash frequency for base conditions for four-leg signal-controlled intersections
- $AADT_{maj}$ = AADT (vehicles per day) on the major road
- $AADT_{min}$ = AADT (vehicles per day) on the minor road
- *Overdispersion parameter* = 0.39

After propagating the urban models' errors through the SPFs and Empirical Bayes formula as described in Section 4.1.3, it was found that the errors associated with the AADT estimates were significantly reduced through the inclusion of overdispersion parameters and historical crash data. The maximum errors from the AADT model validation translated into errors ranging from overestimating by 49% to underestimating by 53%. The maximum errors associated with the predicted crashes were significantly lower than the maximum errors associated with AADT estimates which lead to the conclusion that crashes at urban intersections are not overly sensitive to changes in AADT on the minor roads. A similar trend was seen when the average errors were propagated through the crash prediction equations. They translated to an average range of overestimating crashes by 37% to underestimating by 15%. Therefore the impact of the errors from the AADT estimations was reduced meaning the AADT estimates can be used as a tool to prioritize intersections for safety countermeasure implementation.

The urban intersection analysis showed less sensitivity to model error than did the rural intersection analysis, due to calibration and overdispersion parameters in the urban SPFs which place less weight on local road AADT.

Chapter 5: Conclusion

5.1 Findings

KTC researchers conducted a literature review and developed multiple AADT estimation models for estimating local road AADTs in Kentucky. In the selected AADT models, researchers combined two sets (urban and rural) of three regression-based models to estimate AADT across three regions in Kentucky including the West (highway districts 1, 2, 3 and 4), North Central (highway districts 5, 6, and 7), and East (highway districts 8, 9, 10, 11, and 12). The models were calibrated using generalized linear regression with a Poisson distribution and log link function. Each model contained three variables including probe counts, residential vehicle registrations, and roadway curvature. KTC acquired probe counts from the HERE corporation, which tracked vehicle movements through its proprietary data. KYTC provided residential vehicle registration information obtained through its AVIS database to the research team. Curvature variables were calculated based on road segment geometry.

The data was combined and analyzed to estimate AADT for local roads in Kentucky. KYTC provided DVMT estimates on local roads in Kentucky to assist in further refinement of the model. A DVMT ratio (KYTC DVMT estimate to the model's estimated DVMT) led to the development of an adjustment factor, which was applied to corresponding road segments. The adjustment factor increased model performance by reducing MAPE and maximum percent errors.

Researchers subsequently analyzed model estimates using a sensitivity analysis to understand how AADT error adjustments may impact safety countermeasure selection. The sensitivity analysis showed that intersection crash predictions were dominated by historical crash data, thereby reducing the impact from AADT estimate errors. Local intersections experiencing average- to above-average crash rates would be ideally suited for this model since historical crash data is used in conjunction with SPF crash estimates. Intersection locations with minimal crash rates may underestimate crashes and should be used prudently. Nevertheless, the estimates still provide a reasonable basis for estimating intersection crashes absent this information. In summary, the AADT model provides KYTC with a tool to better approximate local intersection AADTs and subsequently prioritize those intersections warranting closer examination for crash estimates.

5.2 Recommendations

The HERE-AVIS non-linear regression model demonstrated a reasonable basis for estimating local road AADTs in the absence of known traffic counts. Still, the model may be improved further with additional data sources as explanatory variables. The 911 model initially displayed the greatest potential in estimating AADTs but data constraints prevented its development at the statewide level. AVIS vehicle registration addresses served as a proxy for commercial and residential properties in lieu of the 911 database. However, vehicle registration addresses do not fully incorporate all commercial and residential properties in Kentucky. Further refinements to the model should be made if 911 datasets become available in the future for Kentucky counties.

HERE probe counts represent an emerging method in determining traffic volumes but may presently lack satisfactory vehicular or area coverage. For example, rural areas in Kentucky sometimes experience gaps in cell phone tower coverage further diminishing the ability to track vehicles. Continued advances in GPS technologies and increased adoption of those devices by the public should provide additional

opportunities to estimate AADTs. Moreover, cellular coverage should continue its expansion across the U.S. and increased coverage across rural regions should enhance tracking capabilities. However, HERE recently discontinued the option to provide vehicle counts in probe count datasets they offer commercially. Rather, HERE will focus solely on selling datasets containing vehicle speeds and associated confidence intervals. This means that any future model iterations can no longer rely on probe counts as an explanatory variable, potentially impacting model estimates. A new model approach would be required. One such approach might involve disaggregating the Statewide Transportation Model into smaller analysis zones. Then, trip generation rates could be applied to each zone to develop a zone-by-zone trip estimate. This approach would substitute HERE probe counts with generated trips.

The HERE-AVIS non-linear regression model provides empirically based AADT estimates and should not be used as a substitute for actual AADTs acquired from traffic counts. Rather, these estimates provide initial insights into intersections potentially requiring safety improvements. It is recommended that actual traffic counts occur on approaches at selected intersections prior to implementing safety countermeasures. In some instances, preexisting regional models developed for urban areas in Kentucky may be more appropriate for estimating AADT on local, urban roadways because they have been calibrated for better defined regions of the state. AADT estimates from these urban regional models should be used alongside or in place of the estimates discussed in this report to ensure greater accuracy. Furthermore, future AADT models could follow the 911 model (Appendix D) should statewide data become available.

Appendix A: Broward County Model

KTC’s researchers collected a wide range of transportation data across six Kentucky counties to develop the Broward County model. They initially selected Boyd, Clark, Franklin, Green, Henry, and Meade Counties due to data availability (see figure Q). Data collection occurred prior to and in conjunction with model development activities as data input requirements were identified for the model development process. KTC researchers coordinated with various state and county transportation officials to collect data in the selected counties. KYTC, as well as select county offices, supplied the team with data. Select data sets were then used to populate and determine the AADT model variable requirements, whereas others served as validation sets to compare estimated AADTs with known AADTs.

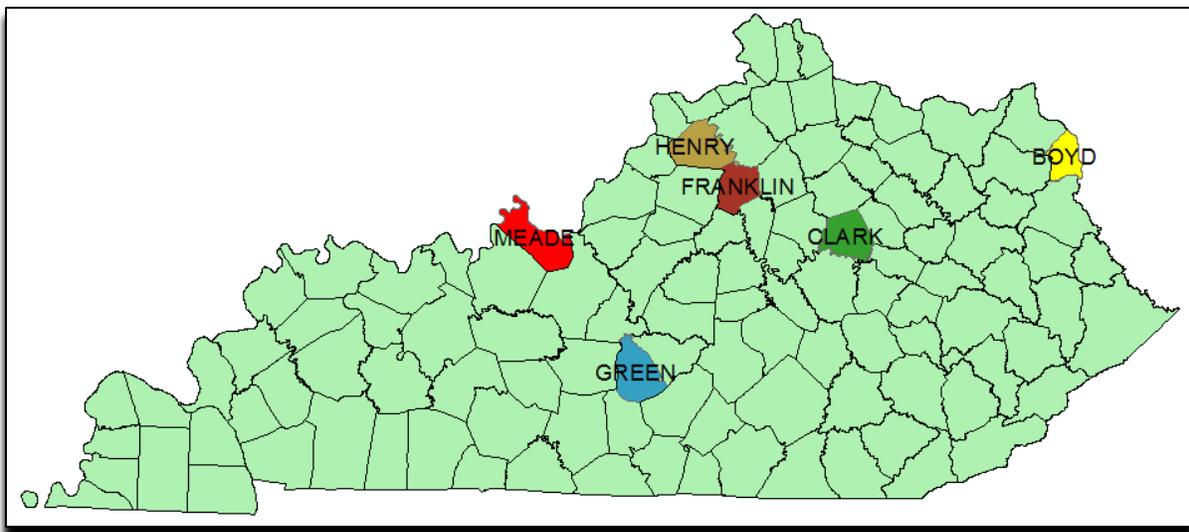


Figure Q: AADT Test Counties

Initially, KTC researchers developed this model based upon the Zhao and Chung AADT model developed at the Lehman Center for Transportation Research, Florida International University (4). This model estimated AADTs based upon ordinary linear regression analysis. This model included the following regression variables: functional classification, number of lanes, direct access to an expressway, employment buffer, population buffer, distance to population center, and accessibility to regional employment centers. However, the characteristics of Florida’s transportation network differ from Kentucky’s transportation network and the model needed to be adjusted accordingly. Therefore, KTC researchers modified the Zhao and Chung model to better fit the characteristics found within Kentucky. A description of this process, including variables, are discussed further below:

Functional Classification: The functional classification (FCLASS) describes a roadway’s intended purpose and inherent characteristics within the transportation network. This variable assigns numerical values to roads across the following categories: urban principal arterial, urban minor arterial, urban collectors, and unclassified roads. However, these categories confront limitations in their relevance and usefulness when applied to the Kentucky AADT model. The majority of local roads within Kentucky are rural and low-volume in nature and do not fall into any one of these select categories. Therefore, the KTC research team excluded the use of this variable in the proposed Kentucky AADT model due to the lack of variation among the local roads in Kentucky with respect to functional classification. Furthermore, roadway traffic volume is one of the factors used to determine a roadway’s functional classification. Since this model intended to

estimate traffic volumes, the use of functional classification was not mutually exclusive from the output of the model and may have negatively impacted the estimated AADTs.

Number of Lanes: The number of lanes (LANES) variable measures the number of roadway travel lanes in both directions along a given segment of roadway. This variable has a strong correlation to AADT due to its direct impact on roadway capacity, or how many vehicles a roadway is designed to accommodate over time. The model contained all types of roads—not just local—and subsequently represented a wide range of travel lanes. KTC researchers similarly used all types of roads for development of the model but narrowed their output focus to only estimating local road AADTs. During this data collection phase, KTC researchers determined that only 25 percent of the roads located in the sample county data had a known number of lanes. Local roads frequently received less travel and were duly classified as unlisted. Many of these same roads also typically had two lanes or one lane carrying traffic in both directions as shown through aerial inspection methods, such as ArcMap. Therefore, the research team assigned all roads lacking this information a value of two lanes which was exceedingly common for this data.

Direct Access to an Expressway: Any road connected to an expressway through the use of adjoining entrance and exit ramps is considered to have direct access. The model labeled this variable as “direct access to an expressway” (DIRECTAC). Expressways—also known as interstates or freeways—represent limited access, high-volume major roadways and serve as common use connectors between large population and employment centers. To this extent, expressways typically have higher AADT values than most other categories of roads. It stands to reason that nearby roads with direct access to these expressways will similarly have higher AADTs. The model accounted for increased AADTs due to their abundance of expressways. On the other hand, Kentucky has fewer expressways than Florida so the variable was modified to capture any potential roadway lying within a defined buffer distance from an expressway access point. The assumption being, in these instances, that readily available expressway access for nearby roads would result in increased AADTs along these same roads. In Figure R below, an expressway direct access buffer zone is shown for Interstate 64 in Franklin County. By extension, all roads contained within the red circle were designated as meeting direct access to expressway requirements.

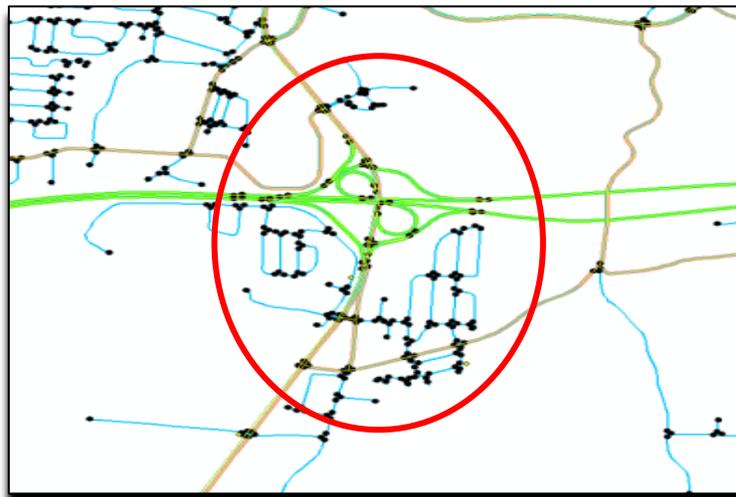


Figure R: Direct Access to Expressway Radius, Franklin County

The DIRECTAC variable was categorized as a binary variable. In other words, roads with direct access to an expressway were given a value of one while all other roads received a value of zero. KTC researchers used the ArcGIS mapping function to identify all roadways meeting these direct access criteria. First,

shapefiles containing all roads in Kentucky were obtained from the KYTC and opened with ArcGIS. Next, a data table was generated for determining direct access to an expressway and assigned all Kentucky roads an initial value of zero. Expressways were then assigned to display in green and other roads as blue within the map. Buffer zones with radii of approximately 0.5 miles around each expressway access point were placed. Finally, all roads within these buffer zones received a newly assigned value of one in the previously generated data table and were subsequently identified as having direct access to an expressway.

Employment Buffer: The employment buffer (EMPBUFF) variable captured the distribution of people employed along a given roadway. An increase in this variable reflects strong employment for that roadway segment and attracts an increased number of travel destinations. Consequently, roads with higher employment buffers should similarly display higher AADTs. The model generated employment buffer variables at a given location based upon both the roadway's functional classification as well as its location. The Kentucky model did not incorporate the use of functional classification into its regression equations so buffers were instead based on a road's rural or urban classification. This classification process sought to prevent the overlapping of buffers and avoid assigning the same employees to more than one road. This methodology generated urban roads with smaller buffer distances due to their close proximity to one another while rural roads often maintained larger buffer distances between each other (30).

KYTC provided employment data contained in the form of TAZ files for use in calculating the employment buffer. This data relied upon results found from the U.S. Census Bureau 2010 census. A TAZ, or Traffic Analysis Zone, is a small land unit area shown on a transportation map with a defined geographical boundary and used for the purpose of collecting and analyzing data. These units usually aggregate multiple census blocks and typically contain less than 3,000 people. Essentially, a traffic analysis zone serves to break down a large transportation network map into smaller, more manageable study areas. In most cases, the boundaries for a TAZ will lie upon existing topographical or roadway boundaries such as along rivers or major highways. In Figure S, each TAZ boundary is shown in red for Boyd County and its surrounding areas. Each county normally contains many traffic analysis zones within its boundaries.

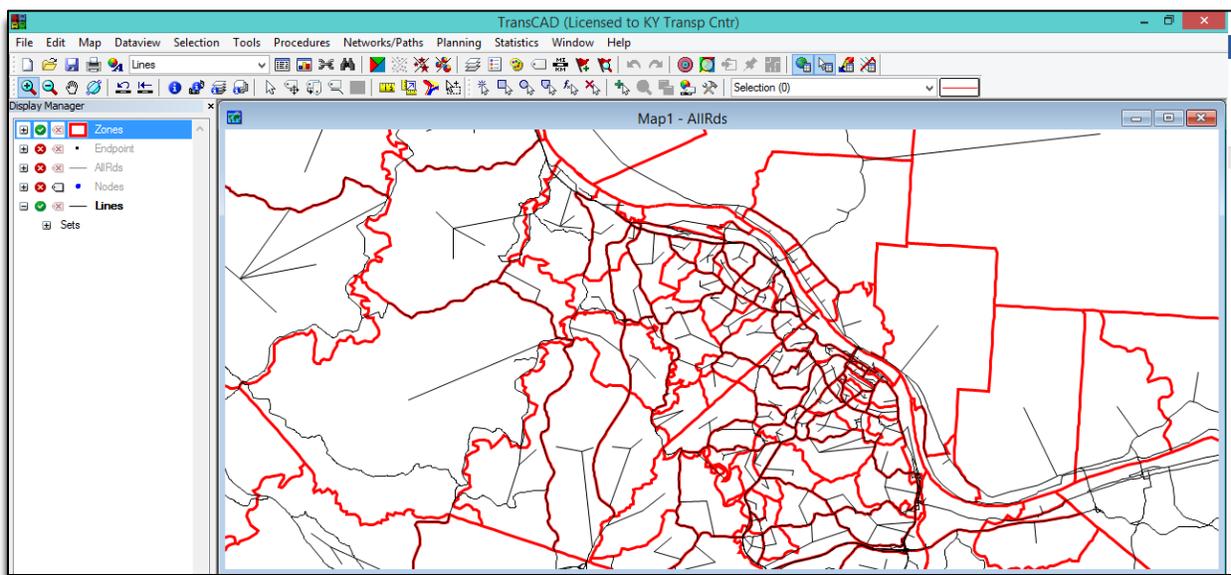


Figure S: KYTC Statewide Transportation Model, Boyd County TAZ Boundaries

Using ArcMap, KTC researchers opened all road files and their respective traffic analysis zones and calculated midpoints along each roadway. Next, the entire roadway was assigned to a single TAZ based upon which TAZ contained the determined midpoint location. Each TAZ was further classified as either rural or urban and each assigned roadway was thereby given its respective TAZ's urban or rural designation. Buffer distances of 400 feet and 0.25 miles were established for urban and rural roads, respectively, and visual inspections performed to prevent areas with overlapping boundaries. The employment buffer was then calculated as shown in the equation below:

$$EMPBUFFER_i = TAZ \text{ Employment} * \frac{RoadBufferArea_i}{Total \ TAZ \ Area}$$

The weighted average method assigned every employee to a single roadway while preventing potential omissions or double-counting.

Population Buffer: The population buffer (POPBUFF) measured the population assigned to a given roadway. It followed the same methodology for calculation as the employment buffer described previously. Roads with a high population density were presumed to experience higher AADTs due to their ability to increase potential trip generations as measured by origins. Population buffers were assigned distances of 400 feet and 0.25 miles for urban and rural roads, respectively. The population buffer equation is shown below:

$$POPBUFFER_i = TAZ \text{ Population} * \frac{RoadBufferArea_i}{Total \ TAZ \ Area}$$

Distance to Population Center: The distance to the population center (DPOPCNTR) measured the travel times from the centroid for an individual TAZ to the centroids of other TAZs located in Kentucky. This variable considered each TAZ to be a population center. The KYTC maintains a travel time matrix that provides travel times between the centroids of every TAZ in the state. Using this approach, KTC researchers used the defined centroid for each TAZ as the spatial location of assignment for all roads within that TAZ and successively calculated travel times between that select centroid and the centroid locations for all TAZs across the state. This streamlined the calculation process by eliminating the need for calculations between every roadway midpoint within the study area and all TAZ centroids located across the state. This resulted in every roadway located within a select TAZ having the same value for DPOPCNTR. However, most TAZs contained a minimal number of roads (typically less than 25) so this proxy approach remained viable.

Regional Employment Access: The regional employment access (REACCESS) variable accounted for trip distance and total employment at a given destination. The calculation for determining this variable is seen below:

$$REACCESS_k = \sum_{j=1}^{N_E} E_j * e^{-0.0954 * t_{kj}}$$

Where

- j is the TAZ centroid;
- k is the TAZ that REACCESS is being calculated for
- N_E is the total number of TAZs

- E_j is the total employment of TAZ j
- t_{kj} is the time from TAZ k to TAZ j

This model considered every TAZ to be a regional employment center. Similar to the DPOPCNTR variable, this methodology determined travel times between centroids for every respective TAZ within the state. In this equation, employment centers with increased levels of employment coupled with short distances to roadways created a larger trip distribution attraction and resulted in larger REACCESS values for those nearby roadways. Finally, a query within Microsoft Access calculated REACCESS for every single TAZ within Kentucky to produce the variables of interest.

Based upon these variables, KTC researchers developed a Kentucky model using five of the original Zhao and Chung model variables including: direct access to an expressway, employment buffer, population buffer, distance to population center, and accessibility to regional employment centers. The model drew upon obtained data from Boyd, Clark, Franklin, Green, and Henry counties. The final regression equation used in this model was:

$$AADT = 357.23 * DIRECTAC + 0.02 * REACCESS - 0.63 * POPBUFFER - 0.05 * EMPBUFFER + 0.09 * DISPOPCNTR$$

Using this regression equation, data were plotted to compare actual AADTs collected from local traffic authorities to the estimated AADTs from the model. The results of this plot are shown in Figure T.

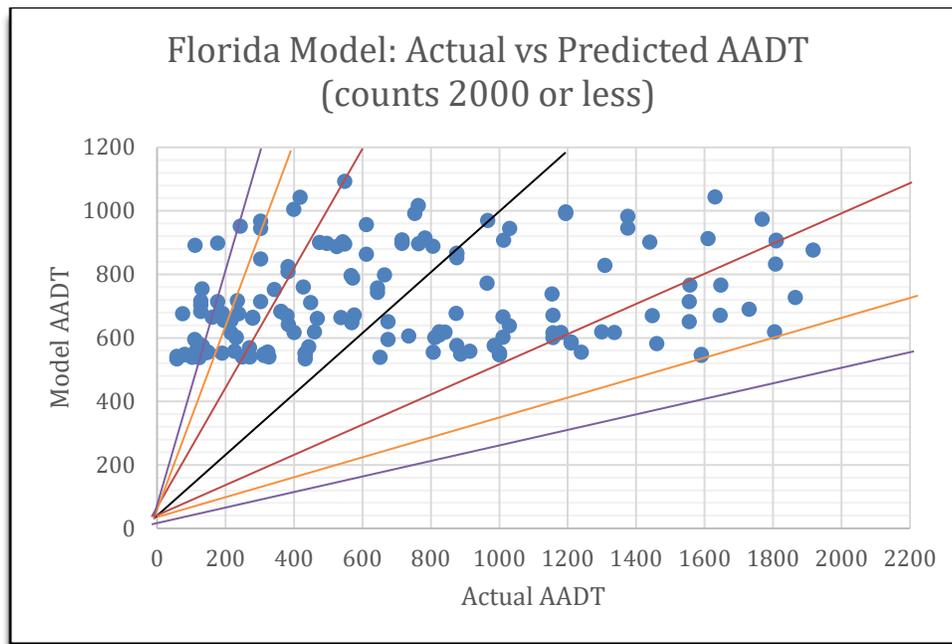


Figure T: Broward County Model; Boyd, Clark, Franklin, Green, and Henry Counties

In general, the estimative attributes of this model were limited. The large variation of data scattered across the plot indicated excessive errors associated with this model. The errors represented the deviations between AADTs the model estimated for a local roadway and the actual AADTs known to occur based upon previously collected traffic counts. Each distinctly colored line represents a different magnitude of error from the “true” value represented by the black line within the middle portion of the graph. A 100 percent accurate model would display all estimated data points along the black line so that

the estimated AADT would entirely match the actual AADT at any given traffic volume. Intuitively, no model can achieve this degree of precision so the key is to optimize the model to the highest performance possible. Following this framework, the red lines form an upper and lower boundary showing a 100 percent error deviation between the estimated value and the actual value. Correspondingly, an estimated AADT placed along the upper redline would be exactly twice the value of the actual AADT. For example, an actual AADT of 600 intersects the upper redline at an estimated AADT of 1200. In this context, errors provided a window into the accuracy of the model to perform as intended and provide valid results. The Broward County model graph remained limited in this regard due to the wide variation of data spread across multiple error ranges (e.g., 100%, 200%, 300%).

The results of this model’s regression function can be partly explained through the use of the Broward County model itself. The state of Florida possesses unique transportation attributes in relation to Kentucky. In particular, the majority of Florida’s local roadways are urban in nature. This contrasts with Kentucky’s local roadways which tend to be rural and occupied by lower traffic volumes. Due to these initial results and seemingly limited applicability, KTC researchers decided to exclude the use of this particular model going forward. The errors associated with this model and their descriptions are shown in Table 11.

Measure of Effectiveness	Broward County Model
MAPE (%)	125
Average Absolute Error	417
Maximum Positive Error (%)	833
Maximum Negative Error (%)	-66

Table 11: Broward County Model Errors

Appendix B: Broward County with PVA Model

This model version built upon select variables contained within the Zhao and Chung Broward County model described in Appendix A and sought to enhance it by incorporating property valuation administrator (PVA) data into the analysis. KTC researchers extracted the most relevant variables from the previously discussed Broward County model for use in this enhanced model. The variables selected for inclusion were *REACCESS*, *DISPOPCNTR*, *POPBUFFER*, and *EMPBUFFER*. To this extent, the variables *DIRECTAC* and *LANES* were subsequently removed for use in this model due to lack of statistical significance. Each of these two variables displayed little variation between different roadways within the model thereby limiting their usefulness in estimating AADTs.

Next, KTC researchers used PVA data as additional input into the regression model. Each county government within Kentucky is responsible for determining and assessing taxes on its residential and commercial properties. County governments perform these actions through their internal or PVA office. In this effort, each PVA office collects and maintains data on its jurisdictional properties including property owners, sizes, and addresses, among others. KTC researchers sought the use of PVA data as a tool to determine the number and type of properties located along a local roadway.

The number of residential and commercial properties located adjacent to local roadways is a determining factor for several AADT model variables such as trip generation and trip distribution. The research team contacted two of the county governments (Franklin and Meade) participating in this study in an effort to collect this information. The Franklin County PVA provided use of their address database detailing the addresses of all properties—both residential and commercial—known to exist along their local roads. Furthermore, the Meade County road department also made their 911 emergency address database available for use in this study. Similarly, this 911 database contained known addresses for every residential or commercial property residing within its county borders.

This data—contained within the form of a shapefile—was merged using the route overlay function in ArcMap and used to form the boundaries for each assessed property or parcel of land in Franklin County. The Franklin County PVA classifies all of its properties into one of 12 distinct categories. Within these categories, KTC researchers identified four as displaying the most utility to this model including *RESIDENTIAL*, *COMMERCIAL*, *AGRICULTURAL*, and *EDUCATIONAL*. Each parcel was subsequently assigned to the nearest roadway. Researchers aggregated the number of parcels assigned to each roadway and used this information in the follow-on regression analysis. The regression equation for this model consisted of the following:

$$\text{AADT} = 4622.68 - 0.01 * \text{REACCESS} - 0.75 * \text{DISPOPCNTR} + 0.35 * \text{POPBUFFER} - 0.92 * \text{EMPBUFFER} - 0.56 * \text{RESIDENTIAL} - 0.47 * \text{AGRICULTURAL} + 17.92 * \text{COMMERCIAL} - 3.81 * \text{EDUCATIONAL}$$

This regression model represented incremental improvement over the previous and original Broward County regression model. As can be seen below, the data more closely fit the intended regression function as depicted by the black line located within the middle portion of the graph (Figure U).

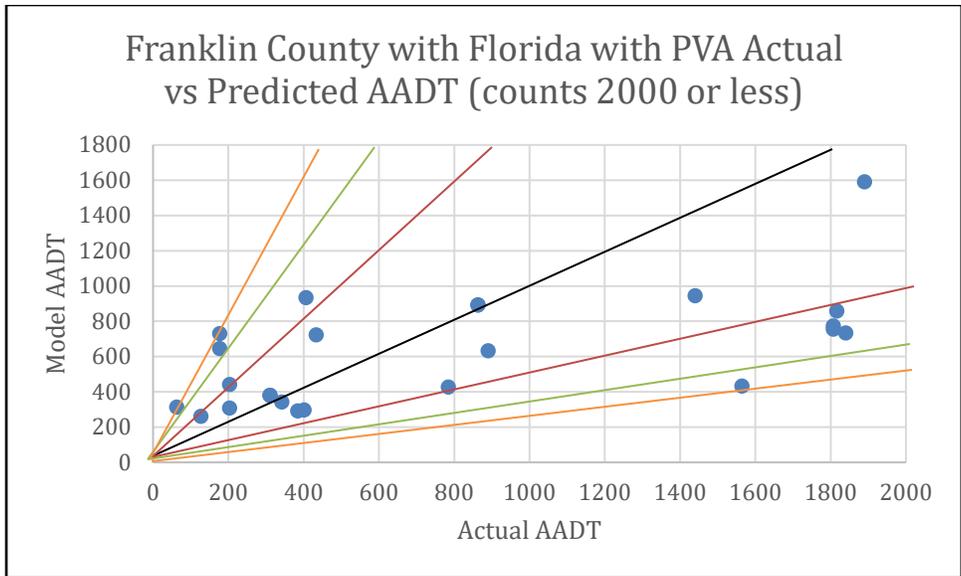


Figure U: Broward County with PVA Model, Franklin County

This model demonstrated improvement over the previous Broward County model across three of the four error categories. The magnitude of the errors decreased for the MAPE, average absolute error, and maximum positive error categories.

Measure of Effectiveness	Broward County with PVA Model
MAPE (%)	82
Average Absolute Error	402
Maximum Positive Error (%)	399
Maximum Negative Error (%)	-72

Table 12: Broward County with PVA Model Errors

Nevertheless, the degree of improvement in relation to the original Broward County model remained limited. Errors still occurred frequently across all three ranges of errors, or at the 100, 200, and 300 percent levels. To this extent, this model did not represent a significant upgrade in estimating local road AADTs in relation to the original Broward County model. Further study of the two remaining models was warranted.

Appendix C: Rooftop Model

In the “Rooftop” model, KTC researchers used a GIS map to visually determine the number of properties through rooftop identification along local roadways. This approach utilized Highway Information System data to populate roadway information within ArcGIS. KTC researchers incorporated this approach by visually identifying the number of rooftops adjacent to roadways on this map using Google Earth. Each rooftop was thereby assigned to the nearest roadway. In addition, rooftops were classified as small, medium, and large and categorized according to the following attributes:

- *SMALL* – Individual Houses
- *MEDIUM* – Small Apartment Complex (e.g., Single Building), Minor Buildings (e.g., small retail)
- *LARGE* – Major Apartment Complex (e.g., Multiple Buildings), Major Buildings (e.g., large retail), Industrial Complex or Facility

Next, KTC researchers established a connectivity rating for roads within this “Rooftop” model by rating roads from one to six based on their *CONNECTIVITY* to other roads. The ranking system ranged from a low rank assigned to dead end roads to the highest rank corresponding with urban roads in a grid pattern. Visual inspection in ArcMap delineated the existence of dead end roads. Mid-range rankings typically included the existence of minor collectors or major through roads. It was possible to distinguish through roads and urban grid roads based on the functional classifications found within the KYTC “All Roads” shapefile. The purpose of the connectivity rating was to provide a variable that would account for the presence of traffic on roadways that may not have any adjacent properties, thereby allowing the regression model to have an intercept of zero.

The connectivity rating was used in conjunction with the three rooftop count variables to run a regression for Meade County. The regression equation for this model was:

$$AADT = 113.8*CONNECTIVITY + 2.1*SMALL + 49.3*MEDIUM + 138.8*LARGE$$

KTC used Meade County data for this model in order to compare the results from this regression analysis with that of the 911 model detailed in Appendix D. The 911 model only used data from Meade County since KTC researchers did not have 911 data from other Kentucky counties. In general, the results from this model estimated higher than expected AADTs for low-volume, local roads in comparison with actual traffic counts and lower than expected AADTs for high-volume, local roads. The approximate range at which the regression model moved from overestimating to underestimating actual AADTs occurred around the 700 count threshold for the actual AADT. A graphic depicting the results from this linear regression model is shown in Figure V.

Appendix C: Rooftop Model

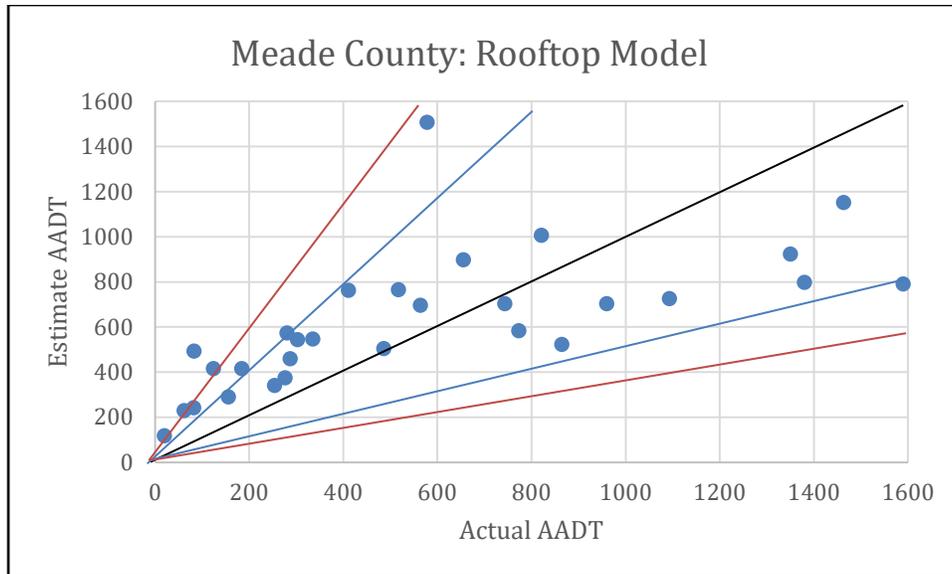


Figure V: Rooftop Model, Meade County

The Rooftop model produced an increase in errors when compared to the previous Florida with PVA model and therefore, did not improve upon the previous model. Furthermore, this model represented the most time intensive methodology of the studied models. Due to these reasons, KTC researchers decided to exclude this model for further analysis. The errors associated with this model were as follows:

Measure of Effectiveness	Rooftop Model
MAPE (%)	93
Absolute Error (AADT)	332
Maximum Positive Error (%)	494
Maximum Negative Error (%)	-60

Table 13: Rooftop Model Errors

Appendix D: 911 Model

The “911” model version utilized a similar approach to the PVA version by determining residential and commercial property types through the use of 911 data. In this approach, KTC researchers coordinated with the Meade County Planning and Zoning Office for use of their 911 database. This database contains listings of all known residential and commercial properties within the county. Meade County provided this data to KTC in the form of a shapefile, which can be used in ArcMap. KTC researchers merged this data with the KYTC Highway Information System (HIS) database. The HIS database is a KYTC maintained system containing the elements of the roadway network such as roadway types, locations, and other attributes across the state of Kentucky. The merging of this data allowed researchers to locate each 911 address and determine its proximity to nearby roadways. Properties were subsequently assigned to the nearest roadway. Finally, the total number of properties assigned to each roadway were aggregated and used in the follow-on regression analysis. The regression equation for this model was:

$$AADT = 565.93 + 6.99*RESIDENTIAL + 6.73*COMMERCIAL$$

However, this formula produced 565 vehicles per day on a road with no residential or commercial properties alongside. Consequently, KTC researchers modified the formula and changed the intercept to zero. The formula for this equation was as follows:

$$AADT = 43.5*RESIDENTIAL + 16.4*COMMERCIAL$$

However, forcing the model to go through zero does not allow for accurate estimations of through trips. Therefore, an intercept greater than zero but less than the number estimated by the regression may be more appropriate.

In this model, estimated AADTs tended to underestimate actual AADTs across much of the traffic volume range from low to high traffic counts. The model results are shown graphically in Figure W.

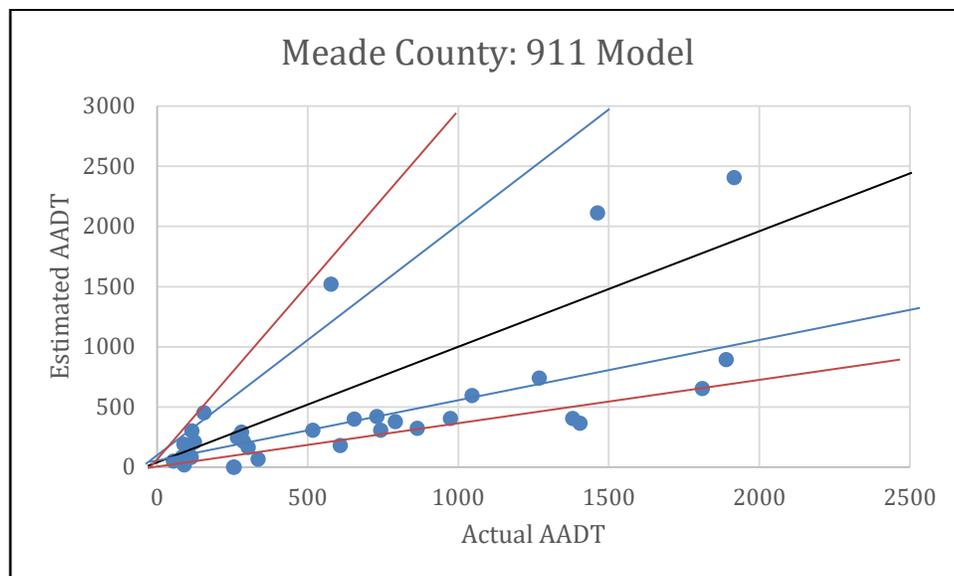


Figure W: 911 Model, Meade County

Appendix E: AVIS-HERE Model (OLR)

The errors contained within this model are shown in the table below.

Measure of Effectiveness	911 Model
MAPE (%)	61
Absolute Error (AADT)	352
Maximum Positive Error (%)	190
Maximum Negative Error (%)	-100

Table 14: 911 Model Errors

On average, the 911 model provided the best combination of results across the aggregated error categories. It contained the lowest error values among all the models for the Mean Absolute Percent Error (MAPE) and the Maximum Error as well as the second lowest Absolute Error value. It happened to contain the highest minimum error value but this did not differ significantly from the other model minimum error values. Aggregating the overall errors, KTC researchers identified the 911 model as the overall best performing model thus warranting additional research efforts. However, researchers discovered this data was not accessible at the statewide level and therefore, this model was excluded for further analysis.

Appendix E: AVIS-HERE Model, Ordinary Linear Regression

The AVIS-HERE ordinary linear regression (OLR) model used two variables, probe counts (HERE) and residential vehicle registrations (AVIS). This model preceded the generalized linear model developed in the selected AVIS-HERE non-linear regression model. This model spatially represented the entire state as one closed system, instead of the subsequent three regional models later developed. The road segments used in data calibration and validation included rural, two lane roads with known traffic counts and functionally classified as local. Researchers imposed an upper AADT boundary of 1000 on the dataset. 75 percent of the segments that met the criteria were randomly selected to calibrate the model, and the remaining 25 percent were used to validate the model.

Excel performed the ordinary linear regression. The model used the following equation:

$$ADT = 168.32 + 2.06 * Probe + 1.04 * Residential$$

The calibrated constant inferred that the model will not estimate a road AADT less than 168. This assumption introduced bias into the model's estimative capability. Figure X illustrates a plot of the actual AADT versus the model's estimated AADT. The graph's 45° line represents the ideal case where model AADT estimates equal actual AADTs. The graph demonstrates the model overestimated AADT in the low range and underestimated AADT in the high ranges.

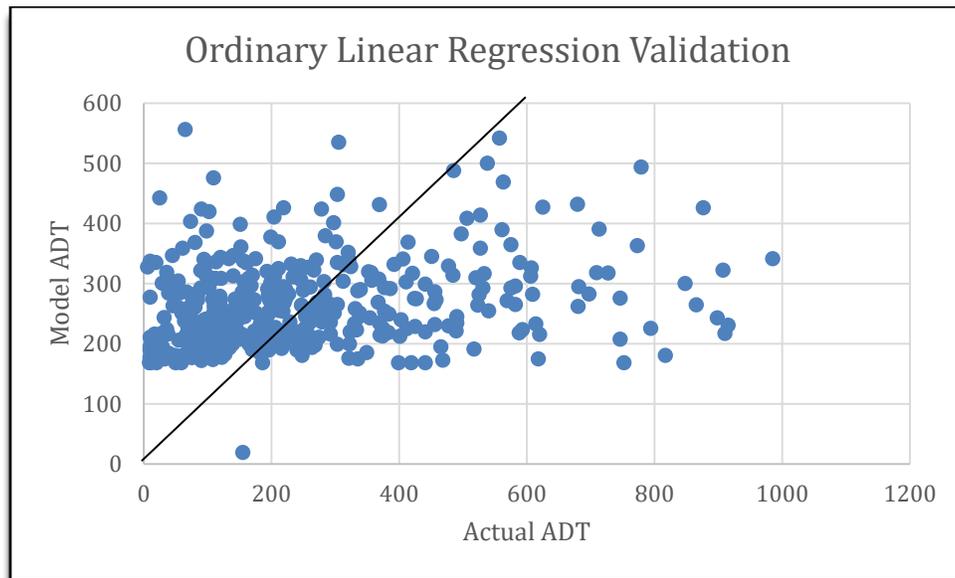


Figure X: Actual versus Model AADT

Table 15 summarizes errors associated with the AVIS-HERE OLR model. The mean absolute error was the lowest value amongst the derived models, but the MAPE and maximum percent errors were among the highest. The high percent errors caused the MAPE to be higher than anticipated. Road segments with low AADTs were the segments with the highest percent error. In one example, a road had a known AADT of 6, yet the model is estimated 168 based on the calibrated constant. This, in turn, created high errors. Another method warranting additional investigation would be establishing a lower AADT boundary on the calibration dataset and requiring exclusion for very low AADT road segments.

Appendix E: AVIS-HERE Model (OLR)

	Model
N (sample size)	401
Mean Absolute Error	153
St. Dev. Absolute Error	124
MAPE (%)	192
Max % Error	5359
Min % Error	-78

Table 15: OLR Model Errors

Table 16 summarizes errors for all studied models. On average, the 911 model provided the best combination of results across the aggregated error categories. It contained the lowest Mean Absolute Percent Error (MAPE) and Maximum Error values for all models and the third lowest Absolute Error value. Its minimum error value exceeded other models but not significantly. Aggregating the overall errors, KTC researchers identified the 911 model as the overall best performing model. However, the 911 data used to develop this model was not readily available statewide. Therefore, researchers selected the AVIS-HERE model because it demonstrated the best overall combination of performance and data availability.

Measure of Effectiveness	Florida	Florida with PVA	Rooftop	911	AVIS-HERE OLR
MAPE (%)	125	82	93	61	192
Absolute Error (AADT)	417	402	332	352	153
Maximum Positive Error (%)	833	399	494	190	5359
Maximum Negative Error (%)	-66	-72	-60	-100	-78

Table 16: Summary of Model Errors

Bibliography

Bibliography

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- ¹ Federal Highway Administration (FHWA), Traffic Monitoring Guide, September 2013, pg. 1-5
 - ² Pan, T. Assignment of estimated average annual daily traffic on all roads in Florida. In Civil Engineering, No. Thesis, University of South Florida, 2008. p. 100.
 - ³ Shen, L. D., F. Zhao, and D. I. Ospina. Estimation of Annual Average Daily Traffic for Off-System Roads in Florida. In, 1999. p. 86 p.
 - ⁴ Zhao, F., and S. Chung. Contributing Factors of Annual Average Daily Traffic in a Florida County: Exploration with Geographic Information System and Regression Models. Transportation Research Record, No. 1769, 2001, pp. p. 113-122.
 - ⁵ Lowry, M., and M. Dixon. GIS Tools to Estimate Average Annual Daily Traffic. In, 2012. p. 33p.
 - ⁶ Mohamad, D., K. Sinha, T. Kuczek, and C. Scholer. Annual Average Daily Traffic Prediction Model for County Roads. Transportation Research Record: Journal of the Transportation Research Board, Vol. 1617, No. -1, 1998, pp. 69-77.
 - ⁷ Zhao, F., and N. Park. Using Geographically Weighted Regression Models to Estimate Annual Average Daily Traffic. Transportation Research Record, No. 1879, 2004, pp. p. 99-107.
 - ⁸ Selby, B., and K. Kockelman. Spatial Prediction of AADT in Unmeasured Locations by Universal Kriging. In, 2011. p. 21p.
 - ⁹ Eom, J. K., M. S. Park, T.-Y. Heo, and L. F. Huntsinger. Improving the Prediction of Annual Average Daily Traffic for Nonfreeway Facilities by Applying a Spatial Statistical Method. Transportation Research Record: Journal of the Transportation Research Board, No. 1968, 2006, pp. pp 20-29.
 - ¹⁰ Shamo, B., E. Asa, and J. Membah. Linear Spatial Interpolation and Analysis of Annual Average Daily Traffic Data. Journal of Computing in Civil Engineering, Vol. 0, No. 0, p. 04014022.
 - ¹¹ Wang, X., and K. M. Kockelman. Forecasting Network Data: Spatial Interpolation of Traffic Counts from Texas Data. Transportation Research Record: Journal of the Transportation Research Board, No. 2105, 2009, pp. pp 100-108.
 - ¹² Sharma, S., P. Lingras, F. Xu, and P. Kilburn. Application of Neural Networks to Estimate AADT on Low-Volume Roads. Journal of Transportation Engineering, Vol. 127, No. 5, 2001, pp. p. 426-432.
 - ¹³ Wang, T., A. Gan, and P. Alluri. Estimating Annual Average Daily Traffic for Local Roads for Highway Safety Analysis. Transportation Research Record: Journal of the Transportation Research Board, No. 2398, 2013, pp. pp 60-66.
 - ¹⁴ Wang, T. Improved Annual Average Daily Traffic (AADT) Estimation for Local Roads using Parcel level Travel Demand Modeling. In, Florida International University, FIU Electronic Theses and Dissertations, 2012. p. 135.
 - ¹⁵ Zhong, M., and B. L. Hanson. GIS-based travel demand modeling for estimating traffic on low-class roads. Transportation Planning and Technology, Vol. 32, No. 5, 2009, pp. 423-439.
 - ¹⁶ Lowry, M. Spatial interpolation of traffic counts based on origin-destination centrality. Journal of Transport Geography, Vol. 36, No. 0, 2014, pp. 98-105.
 - ¹⁷ Adler, T. J., Y. Dehghani, M. Doherty, and W. Olsen. Florida's Turnpike State Model: Development and Validation of an Integrated Land Use and Travel Forecasting Model. TRB 86th Annual Meeting Compendium of Papers CD-ROM 2007. p. 14p.
 - ¹⁸ Florida Department of Transportation. AADT Methodology for All Roads. http://www2.dot.state.fl.us/trafficsafetywebportal/post/Post_332_Allocator%20Process.pdf. Accessed December 13, 2014.
 - ¹⁹ Arcgis Resource Center. How Kriging works. <http://help.arcgis.com/en/arcgisdesktop/10.0/help/index.html#/009z00000076000000.htm>. Accessed on December 13, 2014.
 - ²⁰ Trip Generation Manual, Institute of Transportation Engineers (ITE). 9th edition. <http://www.ite.org/tripgeneration/trippubs.asp>. Accessed on February 19, 2015.
 - ²¹ National Highway Institute, Federal Highway Administration. Introduction to Travel Demand Forecasting CD-ROM (FHWA-NHI-152054). Accessed on February 23, 2015
 - ²² NAVMART. HERE Traffic Patterns. *HERE*. <http://www.navmart.com/here-traffic-patterns.php>. Accessed June 18, 2015.

Bibliography

- ²³ Jefferson County PVA. Motor Vehicle Assessment. Jefferson County Property Valuation Assessment. <https://jeffersonpva.ky.gov/property-assessment/motor-vehicle-assessment>. Accessed June 18, 2015.
- ²⁴ Slash Gear. "Nokia HERE Research: We talk Smart Cities, ethical tracking & self-driving cars". <http://www.slashgear.com/nokia-here-research-we-talk-smart-cities-ethical-tracking-self-driving-cars-21294397/>. Obtained on December 21, 2015.
- ²⁵ ArcGIS Resource Center, Desktop 10. <http://help.arcgis.com/en/arcgisdesktop/10.0/help/index.html#//00660000001000000>. Accessed June 29, 2015
- ²⁶ Kentucky Transportation Cabinet, Division of Planning. Highway Information System GIS Extracts. <http://transportation.ky.gov/Planning/Pages/HIS-Extracts.aspx>.
- ²⁷ Kentucky Transportation Cabinet, Division of Planning. Planning Highway Information (HIS Database). Daily Vehicle Miles Traveled (DVMT) and Mileage Reports. Accessed November 05, 2015.
- ²⁸ U.S. Department of Transportation. Transportation for a New Generation Strategic Plan, 2012-2016. Pg. 9
- ²⁹ American Association of State and Highway Transportation Officials (AASHTO). Highway Safety Manual, 1st ed., Vol. 2. 2010.
- ³⁰ Green, Eric R. and Agent, Kenneth R. Crash Rates at Intersections. Kentucky Transportation Center, KTC-03-21/SPR258-03-2I. August 2003.