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DEVELOPING SAFETY PERFORMANCE FUNCTIONS FOR UTAH ROADWAYS AND INTERSECTIONS

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RESEARCH
UDOT
Keeping Utah Moving
Utah Department of Transportation - Research Division
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DISCLAIMER

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16. Abstract
The Highway Safety Manual (HSM), published by the American Association of State Highway and Transportation Officials (AASHTO) provides guidance as to the development of predictive models used to estimate the predicated average crash frequency for a particular site using regression models developed from data for similar sites across a network. These regression models are called safety performance functions (SPFs) and are introduced in the HSM for base conditions and base geometry. Although the HSM Part C includes SPFs for base conditions of a variety of roadway types, the HSM recommends developing jurisdiction-specific SPFs whenever possible to provide the most accurate models for crash prediction. To provide a more accurate representation of crashes across the state of Utah, the purpose of this project was to use existing crash data to develop state-specific SPFs. These SPFs will be incorporated into the Numetric (AASHTOWare Safety) tool. The data were modeled using a negative binomial distribution with parameters for the expected number of crashes and the overdispersion parameter. Coefficients for the segment model included terms for the intercept, the alignment average annual daily traffic (AADT), and the overdispersion parameter. Coefficients for the intersection model included terms for the intercept, the major street AADT, the minor street AADT, and the overdispersion parameter. The research team developed models for both segments and intersections using these inputs. SPFs were developed for most of the segment and intersection categories in the AASHTOWare Safety tool. Some categories did not have a sufficient sample size to develop an SPF. For many of these categories, a hierarchical model was developed to generate SPFs. Not all the categories with small sample sizes could be analyzed hierarchically due to a lack of compatibility with other categories. In this case, the categories were reported with no SPF.

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LIST OF ACRONYMS

AADT	Average Annual Daily Traffic
AASHTO	American Association of State Highway and Transportation Officials
CMF	Crash Modification Factor
CURE	CUmulative REsidual
EB	Empirical Bayes
FHWA	Federal Highway Administration
HOV	High Occupancy Vehicle
HSM	Highway Safety Manual
SPF	Safety Performance Function
SPUI	Single Point Urban Interchange
TAC	Technical Advisory Committee
UDOT	Utah Department of Transportation

EXECUTIVE SUMMARY

The Highway Safety Manual (HSM), published by the American Association of State Highway and Transportation Officials (AASHTO) provides guidance as to the development of predictive models used to estimate the predicted average crash frequency for a particular site using regression models developed from data for similar sites across a network. These regression models are called safety performance functions (SPFs) and are introduced in the HSM for base conditions and base geometry. Although the HSM Part C includes base condition SPFs for a variety of roadway types, the HSM recommends developing jurisdiction-specific SPFs whenever possible to provide the most accurate models for crash prediction.

To provide a more accurate representation of crashes across the state of Utah, the purpose of this project was to use existing crash data to develop state-specific SPFs. These SPFs will be incorporated into the Numetric (AASHTOWare Safety) tool.

To obtain SPF results, two primary research methods were followed. First, the data were cleaned and second, base SPF equations were developed. To begin the research, the Utah Department of Transportation (UDOT) Traffic and Safety Division provided the research team with segment and intersection segmentation files as well as the 2016 to 2021 crash data. The research team then combined the datasets and prepared the data for modeling. The first phase involved combining the crash dataset with the segment and intersection datasets provided by UDOT. To do this, the research team first determined if each crash was a segment or intersection-related crash. This was done using both the "intersection related" attribute and the area of influence for each intersection type. If a crash was categorized as "intersection related" and fell within the area of influence for the intersection type, it was considered an intersection crash. If it did not meet both criteria, it was considered a segment-related crash. The second phase involved combining roadway characteristics and forming categories that mimic the segmentation and intersection categories found in the AASHTOWare Safety tool. The overall data preparations varied slightly between segment and intersection crashes; however, most of the procedure was the same for both. A seven-step procedure and a six-step procedure for segments and intersections, respectively, were executed.

The data were modeled using a negative binomial distribution with parameters for the expected number of crashes and the overdispersion parameter. Coefficients for the segment model included terms for the intercept, the alignment AADT, and the overdispersion parameter. Coefficients for the intersection model included terms for the intercept, the major street AADT, the minor street AADT, and the overdispersion parameter. The research team then developed models for both segments and intersections based on these base model forms.

SPFs were developed for most of the segment and intersection categories in the AASHTOWare Safety tool. Some categories did not have a sufficient sample size to develop an SPF. For many of these categories, a hierarchical model was developed to generate SPFs. Not all the categories with small sample sizes could be analyzed hierarchically due to a lack of compatibility with other categories. In this case, the categories were reported with no SPF.

The primary limitations of the research findings relate to the categorization of the data. Although many categories had sufficient data to develop SPFs, several categories failed to meet the data requirements to develop a robust statistical model. These categories should be evaluated further to determine if some categories should be aggregated to develop a more robust dataset. The other limitation noted was that in several instances the CURE plots showed variability in the residuals as a function of AADT. In these instances, the categories should be evaluated to determine if the data should be disaggregated by AADT. This would require future research to evaluate the data and to refine the SPFs developed.

It is important to note that several of the SPFs developed should be used with caution based on the statistical diagnostic tools used to evaluate the model fit.

1.0 INTRODUCTION

1.1 Problem Statement

The Highway Safety Manual (HSM), published by the American Association of State Highway and Transportation Officials (AASHTO) provides guidance as to the development of predictive models used to estimate the predicted average crash frequency for a particular site using regression models developed from data for similar sites across a network. These regression models are called safety performance functions (SPFs) and are introduced in the HSM for base conditions and base geometry (AASHTO, 2010). Although the HSM Part C includes base condition SPFs for a variety of roadway types, the HSM recommends developing jurisdiction-specific SPFs whenever possible to provide the most accurate models for crash prediction using the *Safety Performance Function Development Guide: Developing Jurisdiction-Specific SPFs* (Srinivasan and Bauer, 2013).

The Utah Department of Transportation (UDOT) has contracted with Numetric (AASHTOWare Safety) to provide a data-driven platform for the analysis of crash data in the state. The AASHTOWare Safety tool provides a suite of apps that can be used to evaluate crash data and trends, as well as to estimate traffic crashes using SPFs (numetric.com). The SPFs in the AASHTOWare Safety tool currently are generic SPFs for base conditions and base geometry.

To provide a more accurate representation of crashes across the state of Utah, the purpose of this project was to use existing crash data to develop state-specific SPFs. These SPFs will be incorporated into the AASHTOWare Safety tool.

1.2 Objectives

The primary objective of this research was to utilize state-specific data to develop SPFs for predetermined segment and intersection groupings in the AASHTOWare Safety tool for Utah. These SPFs have been developed such that they are compatible with the AASHTOWare Safety tool and will be input into AASHTOWare Safety for use across the state.

1.3 Scope

To meet the objectives of the research, a scope of work was developed that included tasks evaluated and approved by the Technical Advisory Committee (TAC). Task 1 involved holding a kick-off meeting with the TAC and solidifying the goals and objectives for the research project. Regular TAC meetings were held throughout the course of the project to provide input and data for project completion. Task 2 was to conduct a brief literature review related to SPF development. Task 3 included the bulk of the research where the research team worked with the TAC members to identify segment and intersection groupings in the AASHTOWare Safety tool and to then develop SPFs for each of the groupings. Task 4 included the development of recommendations and conclusions, including the preparation of this report. The final task of the research will be to incorporate the SPFs in the AASHTOWare Safety tool.

1.4 Outline of Report

This report is organized into the following chapters:

1. Introduction
2. Literature Review
3. Research Methods
4. Data Evaluation
5. Conclusions
6. Recommendations and Implementation

2.0 LITERATURE REVIEW

2.1 Overview

A literature review was conducted to gain insights into the general topic of safety, focusing on the development of SPFs, safety analysis procedures, and providing a general overview of the AASHTOWare Safety tool. The first section of this chapter provides a basic definition of safety. The second section focuses on the fundamental aspects of SPFs, exploring their functional form, utilization, derivation methods, and steps involved to develop SPFs. The next section examines the safety procedures outlined in the HSM, with specific emphasis on crash-related aspects. The final section addressed the general purpose and functionality of the AASHTOWare Safety tool.

2.2 Safety Definition

Within the HSM, the term “safety” is fundamentally used to indicate crash frequency (crashes per year) for the evaluations and estimation methods presented. The HSM describes two types of safety: subjective safety and objective safety. Subjective safety is qualitative data gathered from roadway users that focuses on how safe they feel on the road. Objective safety is based on quantitative measures which are independent from the observer’s interpretation. These are measures such as crash frequency, crash severity, collision type, crash location, roadway geometry, roadway conditions, etc. (AASHTO, 2010).

According to the definitions outlined in the HSM, a crash entails a series of incidents resulting in injury or property damage originating from the collision of at least one motorized vehicle. This definition considers various contributing factors to road incidents. Crash frequency, as defined by the HSM, represents the tally of crashes at a specific location, facility, or network within a one-year period. This straightforward metric offers a clear snapshot of the frequency of crashes. For example, if a particular intersection experiences three crashes in a year, its crash frequency is recorded as three, exemplifying the practical application of this metric in assessing and addressing road safety (AASHTO, 2010).

Crash severity is an indicator of the magnitude of the crash as it relates to the people involved in the crash. Regarding the severity rating, the HSM focuses primarily on the KABCO scale. KABCO is an acronym with each letter denoting the magnitude, or level of a specific crash event: K: Fatal injury, A: suspected serious injury, B: suspected minor injury, C: possible injury, and O: no apparent injury (AASHTO, 2010). UDOT has mapped the KABCO scale to an integer range from 1 to 5 in descending order in their internal database as summarized in Table 2.1.

Table 2.1 Crash Severity Scales

KABCO	DATABASE	Severity
K	5	Fatal injury
A	4	Suspected serious injury
B	3	Suspected minor injury
C	2	Possible injury
O	1	Property damage only

2.3 Safety Performance Functions

SPFs are mathematical equations that relate the number of crashes to specific site characteristics. They are derived using crash data from similar roadway networks, and they take inputs including average annual daily traffic (AADT) and segment length to determine the expected crash frequency on a specific roadway (Srinivasan and Bauer, 2013). The HSM defines the expected average crash frequency as “the estimate of long-term expected average crash frequency of a site, facility, or network under a given set of geometric conditions and traffic volumes (AADT) in a given period of years. In the Empirical Bayes (EB) methodology, this frequency is calculated from observed crash frequency at the site and predicted crash frequency at the site based on crash frequency estimates at other similar sites” (AASHTO, 2010). This differs from the predicted average crash frequency, defined by the HSM as “the estimate of long-term average crash frequency which is forecast to occur at a site using a predictive model found in Part C of the HSM. The predictive models in the HSM involve the use of regression models, known as Safety Performance Functions [SPFs], in combination with Crash Modification Factors [CMFs] and calibration factors to adjust the model to site-specific and local conditions” (AASHTO, 2010).

According to the HSM (AASHTO, 2010) and Farid et al. (2016), sometimes it is valid to derive SPFs for one state from SPFs used by another state. For example, the SPFs listed in the HSM were determined using crash data from Washington and California, but these can be applied to other states using calibration factors. This is a useful method for transportation agencies that lack the resources to develop their own SPFs. However, the HSM (AASHTO, 2010), Borsos et al. (2016), and Cafiso et al. (2018) also discuss methods used to generate SPFs from local crash data for more accurate results. This process is explained in more detail in the source material, but it is mostly the same as the predictive method used in the HSM. It is important to note that previously derived SPFs usually aren't the most accurate performance measure for network screening, but they are a reasonable alternative to use in determining the expected crash frequency for a site. The following subsections describe the functional form of SPFs, utilization of SPFs, the derivation methods for SPFs, and the steps involved in developing SPFs.

2.3.1 Functional Form of Safety Performance Functions

The HSM explains the functional form of SPFs as regression equations geared toward estimating the average predicted crash frequency for specific site types under defined base conditions. For network screening purposes (HSM Part B) these equations incorporate AADT and, in the context of roadway segments, segment length as they are the two most significant variables for crash prediction. For more detailed design-level analysis (HSM Part C), SPFs are coupled with base conditions, unique to each SPF, which encompass factors such as lane width, lighting presence, and turn lanes. This detailed specification allows for a more context-specific estimation of crash frequencies, enhancing the accuracy and applicability of the analysis.

The predictive aspect of SPFs, as outlined in the HSM Part C, goes beyond estimating overall crash frequency. Instead, it provides methodologies to dissect the estimated crash frequency into components based on severity levels and collision types, such as run-off-road or rear-end crashes. Default distributions are often employed for these breakdowns, recognizing that variations in crash severity and collision types exist across jurisdictions. The HSM emphasizes the importance of updating these default distributions based on local data, allowing for a more tailored and region-specific application of SPFs.

The HSM further acknowledges the potential for agencies with substantial experience to employ advanced statistical approaches for predicting changes in crash frequency by severity levels. This highlights the flexibility of the SPF framework and its adaptability to different analytical methods, showcasing a commitment to precision and refinement in safety analysis. Overall, the HSM provides a comprehensive overview of the functional form of SPFs, emphasizing their versatility, reliance on specific variables, and the methodologies involved in predicting and categorizing crash frequencies (AASHTO, 2010).

Equation 2.1 illustrates an example function provided in the HSM to display the components of an SPF (AASHTO 2010).

$$N_{spf,rs} = AADT \times L \times 365 \times 10^{-6} \times e^{-0.4865} \quad (2.1)$$

where: $N_{spf,rs}$ = estimate of predicted average crash frequency for SPF base conditions for a rural two-lane two-way roadway segment (crashes/year),

AADT = average annual daily traffic volume (veh/day) on roadway segment, and

L = length of roadway segment (miles).

2.3.2 Utilization of Safety Performance Functions

Derived from historical crash data large sample sizes for intersections or roadway segments, SPFs serve as crash prediction models that yield the expected average crash frequency at a specific site type (AASHTO, 2010).

The SPF development guide published by the Federal Highway Administration (FHWA) determines the three main applications of SPFs: to act as network screening for potential improvement, to determine the safety impacts of design changes, and to determine the safety effects of engineering treatments. The document provides both discussion and examples for each application, aiding in a comprehensive grasp of the mechanics of using SPFs (Srinivasan and Bauer, 2013).

It is important to note that the literature describes network-screening-level SPFs *may* not account for site-specific conditions such as poor lighting, worn pavement markings, bike lanes, etc. Crash modification factors (CMFs) representing site-specific conditions may be used in conjunction with SPFs to account for various roadway features which may affect the overall number of crashes. These factors are used to adjust the crash prediction and to assess the effectiveness of safety treatments and inform decision-making in roadway design and management (AASHTO, 2010). This research will not investigate the development or use of site-specific CMFs but will focus exclusively on network-screening-level SPFs.

2.3.3 Derivation Methods for Safety Performance Functions

Appendix 3B of the HSM outlines the process of deriving SPFs. One of the concepts discussed in this process is that of data visualization to aid in the understanding of analysis results. In SPF derivation, visualizations play an instrumental role, serving as key tools in unraveling complex safety data. These graphical representations help uncover patterns and outliers that might otherwise remain hidden within the raw data. Beyond this, graphics act as litmus tests, allowing researchers to evaluate the alignment of developed SPFs with observed crash data. These visualizations ensure the SPF derivation has well-defined markers and fewer blind spots (AASHTO, 2010).

One of the common visualization tools to use in evaluating SPFs are cumulative residual (CURE) plots. Hauer (2004) recommends the use of CURE plots to obtain further insights into whether the SPF was reasonable. CURE plots illustrate the relationship between the cumulative residuals and AADT as illustrated in Figure 2.1.

CURE plots generally include confidence limits ($\pm 2\sigma$) beyond which the plot should rarely extend. If the data regularly extends beyond the confidence limits, caution should be exercised regarding the developed SPF. The data in a CURE plot are expected to oscillate around 0. If the cumulative residuals are consistently drifting up/downward within a particular range of AADT, the CURE plot would imply that there were more/less observed than predicted crashes generated by the SPF within that range. These “drifts” from the cumulative residuals signal that there may be other things influencing crashes that are not accounted for with the selected SPF. (Srinivasan and Bauer, 2013).

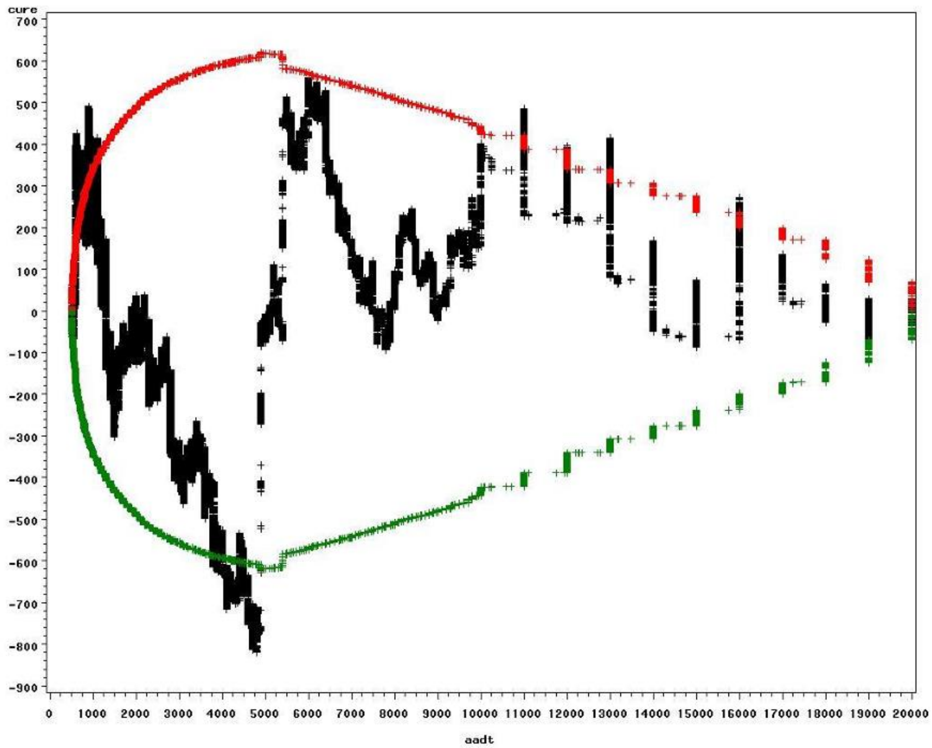

Figure 2.1 Sample CURE plot (Srinivasan and Bauer, 2013).

2.3.4 Steps Involved in Developing Safety Performance Functions

The *Safety Performance Function Development Guide: Developing Jurisdiction-Specific SPFs* outlines eight steps for the development of SPFs. These steps include the following, the details of which can be found in the guide (Srinivasan and Bauer, 2013):

Step 1: Determine use of the SPF – SPFs are generally developed for network screening, project-level analysis, deriving CMFs, or before-after evaluation.

Step 2: Identify facility type – In order to generate an applicable SPF, the user needs to select the facility type to which the SPF will be applied.

Step 3: Compile necessary data – The base data to collect for the model development includes AADT and segment length for segments, as well as major and minor AADT for intersections. Additional data can also be collected and used to develop the SPF.

Step 4: Prepare and clean up database – The databases used for the model must be assembled and cleaned for use in the SPF development models.

Step 5: Develop the SPF – This step includes the use of statistical modeling tools to estimate the regression coefficients of the model for each desired crash type.

Step 6: Develop the SPF for the base condition – The SPF for the given base condition is obtained by substituting the value of the desired base conditions in the SPF.

Step 7: Develop CMFs for specific treatments – If the SPF is to be used for a specific treatment, CMFs should be developed for consideration with the SPF.

Step 8: Document the SPFs – After the SPFs are estimated, it is important to document them so that they can be used by other analysts and researchers in the future.

This research addresses steps one through five. Future research could be conducted to address the three remaining steps (six through eight).

2.4 Safety Analysis Procedures in the Highway Safety Manual

The Predictive Method holds a central position in the safety analysis procedure outlined in the HSM, relying primarily on SPFs for its predictive modeling. For instance, SPFs are employed to estimate average crash frequency for specific site types, leveraging factors such as AADT and segment length. Complementing this, CMFs play a pivotal role in adjusting crash frequencies by considering the effectiveness of safety treatments. This may involve modifying crash frequencies to account for the impact of improved lighting conditions at a specific intersection (as an example), offering a nuanced approach to safety enhancement (AASHTO, 2010).

Network screening is an integral aspect of the safety analysis procedure, employing systematic screening across the entire roadway network to identify areas with potential safety improvements. This involves identifying specific road segments or intersections with consistently higher observed crash frequencies than expected, facilitating targeted safety enhancements. The procedure also encompasses evaluation of safety impacts of design changes, which involves a rigorous assessment of the safety implications of proposed design alterations to roadway infrastructure. An example could involve evaluating how the introduction of shoulder rumble strips along a rural two-lane roadway may impact the expected crash frequency (AASHTO, 2010).

Altogether, the safety analysis procedure in the HSM provides a structured and comprehensive framework for enhancing roadway safety, integrating predictive modeling, evaluation of design changes, and engineering treatments (AASHTO, 2010).

2.5 AASHTOWare Safety Tool

The AASHTOWare Safety tool is a webtool that provides data for reviewing crash data and comparing predictive analysis results with observed data. It is a database that stores information regarding crash location, crash severity, and the various defining factors associated with each crash (e.g., geometry, weather, etc.). AASHTOWare Safety includes a webtool that focuses on predictive analysis that has the capability of incorporating the results of jurisdictional SPFs.

2.6 Summary

This literature review provides a brief overview of SPFs and safety analysis procedures within the HSM. It highlights the role of SPFs in predictive modeling, design change evaluations, and engineering treatments, as well as their integration into a structured safety analysis procedure. The significance of the AASHTOWare Safety tool in facilitating predictive crash analysis is emphasized. Overall, the review reinforces the foundational role of SPFs and the safety analysis procedure of the HSM in advancing the general understanding of transportation safety and emphasizing the tools and methodologies essential for effective decision-making and road safety enhancement.

3.0 RESEARCH METHODS

3.1 Overview

To obtain SPF results, several research methods were utilized and are discussed in this chapter. The first section summarizes the data cleaning methods employed including combining datasets and data preparation for modeling. The second section focuses on the base form for the SPF equations for both segments and intersections.

3.2 Data Cleaning

During this project, UDOT provided the research team with several key data files. These included one segment and one intersection file that summarized the segment and intersection segmentation, respectively, with information specific to each segment or intersection, and a shapefile to add an urban or rural designation to the intersection file. It is important to note that segmentation was not part of the research effort, rather the network was segmented by UDOT, and the segmented files were provided to the research team. These files were initially cleaned by UDOT, but to perform the analysis, the files needed some additional cleaning by the research team. In addition, the segment and intersection data provided by UDOT did not contain crash data, so the research team retrieved the 2016 to 2021 crash data from a separate file provided by UDOT Traffic and Safety.

There were two phases of cleaning performed by the research team: combining datasets and data preparations for modeling. The first phase involved combining the crash dataset to the segment and intersection datasets. The second involved combining roadway characteristics and forming categories that mimic the segmentation and intersection categories found in AASHTOWare Safety, in addition to further data preparation necessary to develop SPFs. Each of these topics are discussed in the following subsections.

3.2.1 Phase 1: Combining Datasets

The crash data obtained from UDOT Traffic and Safety required cleaning and preparation before it was ready for modeling. The file had most of the necessary fields to be joined with the other datasets, so all that needed to be done was to change field names and check data types. The next step was to combine the crash datasets with the segmentation datasets provided by UDOT. To do this, each crash had to be designated as either segment or intersection related. To make this determination the research team focused on intersection-related crashes first. If crashes were not designated as intersections, they would automatically become part of the segments file.

The first criterion for an intersection-related crash was that the crash needed to be marked as “intersection related” in the crash database. This field of data is a rollup summary field based on whether the reporting officer identified the crash as being related to an intersection as opposed to a driveway or roadway. The second criterion was that the crash needed to be within the area of influence detailed in Table 3.1 for the intersection type. For example, any crash that occurs within 100 feet of an All-Way Stop Control intersection would be assigned to that intersection. To determine if a crash is within the area of influence, a spatial analysis was performed using the “rgis” package in R. If a crash is marked “intersection related” and falls within the intersection area of influence, then that crash must be assigned to an intersection. Crashes that are not marked “intersection related” but fall within this area of influence are not assigned to intersections but are assigned to the segment in which they occur. Crashes that are marked “intersection related” but do not fall within the area of influence of an intersection are assigned to segments. Using a spatial join with the area of influence serving as a buffer, crashes that have the “intersection related” attribute are assigned to intersections. The remaining crashes were assigned to segments. No crashes were removed from the database.

To assign segment identification, linear referencing was used instead of spatial analysis. Linear referencing uses mile marker measurements on the roadways as contained in the segment file. The crash file has mile points associated with the location of the crash that were then used to determine which segment the crash fell within so that the corresponding segment ID could be assigned. The crash dataset and the segment dataset were joined together and the total number of crashes for each segment was added up.

Table 3.1 Intersection Area of Influence

Intersection Type	Area of Influence (ft.)
Signal Control	300
Minor Leg Stop Control	150
All-Way Stop Control	100
Yield Control	100
Uncontrolled	100
Roundabout	300
Offset Left-Turn (CFI)	400
Median Thru-U Turn	400
R-Cut	400
SPUI	500
DDI	400
Active Transportation Only	100
Railroad Crossing	100

3.2.2 Phase 2: Data Preparation for Modeling

The major tasks associated with data preparation for modeling are outlined in this section separated by segments and then intersections. Data preparation for both segments and intersections have some similarities, but due to different SPF models being used for each, there are some distinct differences that will be discussed.

3.2.2.1 Data Preparation for Modeling Segments

Each category for segments needed to have approximately 10 observations for every parameter estimated. In the case of segments, approximately 30 observations were needed for each category, since there are three parameters being estimated: the y-intercept (β_0); the coefficient for the AADT for each unique alignment (divided in half where there are two alignments) referred to as the alignment AADT (β_1), and the overdispersion parameter (ϕ). Categories with fewer than 30 parameters would need to be modeled using a hierarchal model based on similar characteristics.

The following steps were employed for segment model data preparation:

Step 1: In the “Median Urban” field, change “Urban Cluster” and “Urbanized Area” to “Urban.”

Step 2: Combine the “Median Urban,” “Lanes,” and “Interstate” fields into a new field that mimics the segmentation categories found in the AASHTOWare Safety tool.

Step 3: Create five additional categories by adding a high-occupancy vehicle (HOV) designation implemented according to the following conditions:
- Freeway segments on I-15 northbound between MP 257.8 and 330.5.
- Freeway segments on I-15 southbound between MP 259.3 and 331.0.

Step 4: Sum the number of crashes for all years.

Step 5: Ensure that each segment category has approximately 30 distinct roadways (10 for every parameter estimated as outlined previously).

Step 6: Separate categories and extract crash counts and alignment AADT.

Step 7: Order the data in ascending order based on alignment AADT.

3.2.2.2 Data Preparation for Modeling Intersections

Like segments, each category for intersections needed to have approximately 10 observations for every parameter estimated. In the case of intersections, approximately 40 observations were needed for each category, since there are four parameters being estimated: the y-intercept (β_0), the coefficient for major AADT (β_1), the coefficient for minor AADT (β_2), and the overdispersion parameter (ϕ). Additionally, the UDOT Traffic and Safety Division requested that a few specific categories be analyzed regardless of sample size and whether there was minor AADT. These included railroad crossings and active transportation crossings. Additionally, it was requested that SPFs be created for yield control intersections, single point urban interchange (SPUI) intersections, and all-way stop control intersections regardless of sample size.

The following steps were employed for intersection model data preparation:

Step 1: Ensure that the urban or rural designations are categorized as “Urban” and “Rural.”

Step 2: Combine the “Intersection Description” field and the “Urban Rural” field into a new field that mimics the intersection categorization that is found in the AASHTOWare Safety tool.

Step 3: Create two different datasets, one with the AASHTOWare Safety categories that do not include minor leg data and the other that excludes all data points that have zero minor AADT and zero major AADT.

Step 4: Ensure that each intersection category has approximately 40 distinct locations (10 for every parameter estimated as outlined previously) for the dataset that excludes zero major and minor AADT.

Step 5: Separate categories and record crash counts, major AADT, and minor AADT for each intersection and year for both datasets.

Step 6: Order the data in ascending order based on major AADT for both datasets.

3.3 Safety Performance Function Equations for Segments and Intersections

The data are modeled using a negative binomial distribution with two parameters: the expected number of crashes (η) and ϕ. For a particular roadway type, the general form of the negative binomial probability mass function is outlined in Equation 3.1 (Hauer, 2001).

$$P(\mathrm{Y} = \mathrm{y}) = \frac{\Gamma(\mathrm{y}+\phi)}{\Gamma(\phi)\mathrm{y}!}\left(\frac{\phi}{\eta+\phi}\right)^{\phi}\left(\frac{\eta}{\eta+\phi}\right)^{\mathrm{y}} \tag{3.1}$$

where: y = crash observations from the data,

η = the expected number of crashes, and

ϕ = the overdispersion parameter.

The segment data provided by UDOT only had one AADT value for the crash data from 2016 to 2021. Due to this limitation, all 6 years were modeled together. Thus, the number of crashes for all 6 years was summed up and the AADT was multiplied by 6, resulting in an SPF for 6 years rather than an SPF per year. This approach adds some uncertainty into the data to guard against overconfidence of imputing the alignment AADT values for the years 2016 to 2020.

To convert the results to an SPF per year, the SPF is divided by 6. Or equivalently, the parameter β_0 is adjusted by the natural logarithm of 6, as outlined in Equation 3.2. The segment SPF model equation for expected number of crashes for 6 years with the adjusted parameter results in a per year model.

$$\eta = SegLength\, e^{\beta_0 - \ln(6)} AlignAADT^{\beta_1} \tag{3.2}$$

where: η = the expected number of crashes,

β_0 = the y-intercept,

ln = the natural logarithm,

β_1 = the coefficient for alignment AADT, and

AlignAADT and *SegLength* are the covariates of the roadway for the 6-year period.

For intersections, the expected number of crashes for 1 year is expressed as outlined in Equation 3.3. The intersection analysis did not need to model all 6 years together because the intersection data had unique AADT values for each year.

$$\eta = e^{\beta_0} MajorAADT^{\beta_1} MinorAADT^{\beta_2} \tag{3.3}$$

where: η = the expected number of crashes,

β_0 = the y-intercept,

β_1 = the coefficient for major AADT,

β_2 = the coefficient for minor AADT, and

MajorAADT and *MinorAADT* are the covariates for the intersection and year.

Typically, built-in R functions are readily available to run these models in a computational setting. Professor Eric Green from the University of Kentucky developed the R code to simplify the process of SPF development. This code is called SPF-R and has an online tool associated with it (Green et al., 2022). The research team used SPF-R initially, but to generalize the method to find SPFs for roadway types with smaller amounts of data, a more generalized model was developed. The generalization developed produces very similar results to SPF-R if there is sufficient data, and when there isn't sufficient data, it uses a Bayesian hierarchical modeling framework to "inform" similar roadway types while still allowing them to have distinct SPFs.

3.4 Summary

To obtain SPF results, two primary research methods were followed. First, the data were cleaned and then the base SPF equations were developed. To clean the data for analysis, the research team combined datasets and prepared the data for modeling. The first phase involved combining the crash dataset to the segment and intersection datasets provided by UDOT. The second phase involved combining roadway characteristics and forming categories that mimic the segmentation and intersection categories found in the AASHTOWare Safety tool. The data are modeled using a negative binomial distribution as outlined in this chapter. The cleaned data will be evaluated using statistical methods described in the next chapter.

4.0 DATA EVALUATION

4.1 Overview

This chapter summarizes information on how the data were evaluated to calculate SPFs. First, the statistical model is outlined. Next, the hierarchical modeling used to combine categories is explained. Finally, the overdispersion parameter is defined.

4.2 Statistical Model

The research team used a Bayesian approach to develop SPFs to be able to analyze smaller data groups hierarchically. When sufficient data are available, this approach yields very similar results to SPF-R (Green et al., 2022). The slight differences arise by using a prior distribution (required by a Bayesian framework) and some Monte Carlo error introduced in the posterior sampling. The non-hierarchical Bayesian model is equivalent to SPF-R with the choice of diffuse priors. This can be illustrated with the segment and intersection Bayesian SPF model implementations for the expected number of crashes.

For segments, the Bayesian segment SPF model implementation is summarized by the relationships outlined in Equation 4.1.

$$\begin{aligned}
&y \sim NegBinom(\eta, \phi) \\
&\eta = e^{\beta_0 - \ln(6)} DivAADT^{\beta_1} SegLength \\
&\phi \sim Gamma(1, 0.1) \\
&\beta_0 \sim Normal(0, 0.0001) \\
&\beta_1 \sim Normal(0, 0.0001).
\end{aligned} \tag{4.1}$$

The Bayesian model requires a prior distribution for parameters that capture the prior belief or knowledge of what the parameters are. In this scenario, ϕ follows a gamma distribution with mean 10. The variables β_0 and β_1 each follow a Normal distribution with mean 1 and precision 0.0001, where precision is defined to be the reciprocal of the variance. The resulting SPFs are summarized in Appendix A.

For intersections, a similar Bayesian implementation is used with different covariates. The intersection SPF model is summarized by the relationships outlined in Equation 4.2.

$$\begin{aligned}
&y \sim NB(\eta, \phi) \\
&\eta = e^{\beta_0} MinorAADT^{\beta_1} MajorAADT^{\beta_2} \\
&\phi \sim G(1, 0.1) \\
&\beta_0 \sim N(0, 0.0001) \\
&\beta_1 \sim N(0, 0.0001) \\
&\beta_2 \sim N(0, 0.0001).
\end{aligned} \tag{4.2}$$

Here ϕ follows a gamma distribution with mean 10. The variables β_0, β_1, β_2 each follow a Normal distribution with mean 0 and precision 0.0001. The resulting SPFs are summarized in Appendix B.

When implementing Markov Chain Monte Carlo methods in a Bayesian model, the posterior samples should be representative of the posterior distribution (i.e., the chain converged). To check this, the Gelman diagnostic (Gelman and Rubin, 1992) provides some assurance that the samples are representative of the posterior distribution. For segments and intersections, after burn-in, two chains of each model were run with 20,000 posterior draws. The Gelman diagnostic for each model and variable were less than 1.1 (which indicates good convergence). However, the hierarchical models needed more computation. For these models, two chains each with 900,000 posterior draws (after burn-in) were run. The Gelman diagnostic for these variables in each of these models were also less than 1.1, indicating good convergence.

4.3 Hierarchical Modeling

Although there are many roadway types with less than 30 or 40 data points, it would still be very useful to have an SPF for them. Due to a lack of data, these are not analyzed individually using the developed Bayesian model. However, an SPF for these categories using a hierarchical approach was undertaken by the research team. Hierarchical modeling provides an opportunity to borrow information from other categories with similar characteristics and use that information to create an SPF even for those categories with a small sample size, if enough roadway types are available to share information. With input and approval from the UDOT TAC members, approximately 30 hierarchical groupings were developed for segment roadway types. The following general criteria were used when proposing these hierarchical groupings:

1. Categories must have the same median type, urban designation, and interstate designation.

2. Categories must have a similar number of lanes in addition to Criterion 1.

3. Categories that do not meet Criteria 1 and 2 but have less than 30 or 40 data points will not have an SPF developed.

The list of approved hierarchical groupings for segments is included in Appendix A. For those roadway types that could not be adequately matched with others and did not have sufficient data, no SPFs were developed. A list of the roadway types in which an SPF was not developed are listed at the end of Appendix A. It is important to note that hierarchical modeling was not used for intersections. Unlike the segments, there were only a few intersections that did not have enough data to generate an SPF. These intersections with few observations did not have “natural” groupings that could be used to create hierarchical models. Thus, no hierarchical models were developed for intersections.

4.4 Overdispersion Parameter

The overdispersion parameter (ϕ) is an important parameter when modeling SPFs. In this section, the purpose of the overdispersion parameter is discussed along with recommendations for the use of the overdispersion parameter in SPFs.

Typically, when using count data, such as crash counts, the Poisson distribution is used to model the data. However, one assumption of the Poisson distribution is that the variance and the mean (i.e., expected value) are equal. Often, in practice, this assumption is not true, and frequently the variance exceeds the mean. When the variance exceeds the mean, the counts are reported as over dispersed, or that there is overdispersion in the data.

In the case of crash data, since it is known that the data are typically over dispersed, the negative binomial distribution is used to represent the data (Hauer, 2001). The negative binomial distribution accommodates over dispersed data. Additionally, when SPFs are calculated, there may be some confusion regarding what is termed "the overdispersion parameter." The HSM typically refers to $1/\phi$ as the overdispersion parameter, whereas in other literature, and in this document, ϕ is used as the overdispersion parameter. The variance of the data (Y) is related to the overdispersion parameter as outlined in Equation 4.3.

$$Var(Y) = \eta\left(1 + \frac{\eta}{\phi}\right) \quad (4.3)$$

where: Y = crash data,

η = the expected number of crashes, and

ϕ = the overdispersion parameter.

Frequently, the HSM uses the overdispersion parameter as a goodness-of-fit measure, indicating lower values of $1/\phi$ to be more favorable. While in general, a smaller quantity is better, from a statistical perspective, in this research the parameter is interpreted differently. Specifically, this research advocates the use of the overdispersion parameter as a measure of how much variability one might encounter. If $1/\phi$ is high (or ϕ is low), it is less likely that the observed value will be "close" to the predicted value than for lower values. This is not to say that the model does not fit well, it is just that there is more noise in the data that the model must account for. The HSM uses the overdispersion parameter in the Empirical Bayes method to determine the "relative weights given to the model prediction and the [crash] record" (Hauer, 2001).

The overdispersion parameter relates more to variability in the model than it does model fitting. There appears to be a misconception that when there is a lot of variability in a model, the model itself does not fit well. One reason why this misconception exists is because SPFs are being used to estimate the average crash frequency for a certain group of roadway characteristics. If there is more variability being accounted for in a model, the observed value will (on average) be further from the true population mean. A high value of $1/\phi$ does not mean that the model is bad. It is *desirable* for the model to take the variability into account. The overdispersion parameter is a way to quantify how far, on average, the observed values will be from the predicted values. Thus, models with high or low overdispersion parameters can still fit data well and, conversely, models that fit the data poorly can have high or low overdispersion parameters. Because there are other means of determining model goodness-of-fit, using these methods is often recommended over the use of the overdispersion parameter.

In this research, it is recommended that the p-value percentage metric, given by the Bayesian chi-square (χ^2) goodness-of-fit test (Johnson, 2004), along with the CURE plots, be used to determine how well the model fits the data. In Bayesian modeling, many different (posterior) models are probable and form the basis of the final model results. Each of these models are evaluated to determine overall model fit. The p-value percentage metric from the model is the proportion of the posterior sampled models that do not fit the data well. For example, if the p-value percentage metric is 0.1, 10 percent of the posterior models did not fit the data well. The p-value percentage metric provides a quantitative value to reference from a statistical modeling point of view, while the CURE plot provides a visual representation of how the model fits the data. If a segment or an intersection category has a p-value percentage metric that is less than 0.1 and a reasonable CURE plot, we consider the SPF to be trustworthy. If neither of these criteria are met, the SPF is suspect, and caution is recommended when using the SPF. If only one criterion is met, the SPF could be useful.

4.5 Summary

The research team used a Bayesian approach to develop SPFs for large datasets, while also being able to analyze smaller data categories hierarchically. This chapter outlines the statistical model to accomplish this task, while explaining how roadway categories with fewer than 30 or 40 data points were also analyzed using a hierarchical model. Although the hierarchical model, which borrows information from other categories with similar characteristics to create SPFs, provided the opportunity to increase the number of categories in which SPFs could be developed, it was still not possible to create SPFs for all roadway categories. To determine whether the developed SPFs were statistically fit, the overdispersion parameter, CURE plots, and the p-value percentage metric from the model were used to identify when caution is recommended for their use. The final SPFs and their corresponding CURE plots and existing vs. predicted plots (segments only) are provided in Appendix A and Appendix B for segments and intersections, respectively.

5.0 CONCLUSIONS

5.1 Summary

The HSM provides guidance as to the development of predictive models used to estimate the predicted average crash frequency for a particular site using regression models developed from data for similar sites across a network. These regression models are called SPFs and are introduced in the HSM for base conditions and base geometry (AASHTO, 2010). UDOT has contracted with Numetric (AASHTOWare Safety) to provide a data-driven platform for the analysis of crash data in the state. The AASHTOWare Safety tool provides a suite of apps that can be used to evaluate crash data and trends, as well as to estimate traffic crashes using supplied SPFs. The SPFs in the AASHTOWare Safety tool are generic SPFs for base conditions and base geometry. To provide a more accurate representation of crashes across the state of Utah, the purpose of this project was to utilize state-specific data to develop SPFs for predetermined segment and intersection groupings in the AASHTOWare Safety tool for Utah. These SPFs have been developed such that they are compatible with the AASHTOWare Safety tool and will be input into AASHTOWare Safety for use across the state.

This chapter presents a review of the methodology, findings, and limitations of the research. First, an overview of the methodology will be described. Second, the major findings from the research will be presented. Last, a description of limitations encountered in the research will be discussed.

5.2 Methodology

To obtain SPF results, two primary research methods were followed. First, the data were cleaned and second, base SPF equations were developed. To begin the research, UDOT Traffic and Safety provided the research team with segment and intersection segmentation files as well as the 2016 to 2021 crash data. The research team then combined the datasets and prepared the data for modeling. The first phase involved combining the crash dataset with the segment and intersection datasets provided by UDOT. To do this, the research team first determined if each crash was a segment- or intersection-related crash. This was done using both the "intersection related” attribute and the area of influence for each intersection type. If a crash was categorized as “intersection related” and fell within the area of influence for the intersection type, it was considered an intersection-related crash. If it did not meet both criteria, it was considered a segment-related crash. The second phase involved combining roadway characteristics and forming categories that mimic the segmentation and intersection categories found in the AASHTOWare Safety tool. The overall data preparations varied slightly between segment and intersection crashes; however, most of the procedure was the same for both. A seven-step procedure and a six-step procedure for segments and intersections, respectively, were executed.

The data were modeled using a negative binomial distribution with parameters for the expected number of crashes and the overdispersion parameter. Coefficients for the segment model included terms for the intercept, the alignment AADT, and the overdispersion parameter. Coefficients for the intersection model included terms for the intercept, the major street AADT, the minor street AADT, and the overdispersion parameter. The research team then developed models for both segments and intersections based on these base model forms. The team also utilized the SPF-R model developed by Green et al. (2022) at the University of Kentucky to generate CURE plots and to compare the model results.

5.3 Findings

The research team used a Bayesian approach to develop the SPFs so that categories with fewer data points could also have SPFs developed using hierarchical groupings. The Bayesian approach for segments and intersections (not included in hierarchical groupings) yielded similar results to those developed using the SPF-R tool (Green et al., 2022). Slight differences arose by using a prior distribution (required for a Bayesian framework) and possible Monte Carlo error introduced in the posterior sampling.

SPFs were developed for most of the segment and intersection categories in the AASHTOWare Safety tool. Some categories did not have a sufficient sample size to develop an SPF. For many of these categories, a hierarchical model was developed to generate SPFs. Not all the categories with small sample sizes could be analyzed hierarchically due to a lack of compatibility with other categories. In this case, the categories were reported with no SPF.

The results of the segment-related SPFs are summarized in Appendix A, while the results of the intersection-related SPFs are summarized in Appendix B. These results include tables outlining those categories where SPFs could not be developed.

5.4 Limitations and Challenges

The primary limitations of the research findings relate to the categorization of the data. Although many categories had sufficient data to develop SPFs, several categories failed to meet the data requirements to develop a robust statistical model. These categories should be evaluated further to determine if some categories should be aggregated to develop a more robust dataset. The other limitation noted was that in several instances the CURE plots showed variability in the residuals as a function of AADT. In these instances, the categories should be evaluated to determine if the data should be disaggregated by AADT. This would require future research to evaluate the data and to refine the SPFs developed.

It is important to note that several of the SPFs developed should be used with caution based on the statistical diagnostic tools used to evaluate the model fit. This is noted using symbols explained in the footnote in the tables.

6.0 RECOMMENDATIONS AND IMPLEMENTATION

6.1 Recommendations

It is recommended that the SPFs be incorporated into the AASHTOWare Safety tool for use by UDOT and their Consultants. It is important to note which of the SPFs should be used with caution, and future research should be conducted to improve model fit and develop SPFs for categories that do not have an SPF from this research.

6.2 Implementation Plan

The results of this research will be implemented by incorporating the developed SPFs in the AASHTOWare Safety tool.

Future research should be conducted to further develop the SPFs and identify ways to improve the model fit. Research should also be conducted to test the current base conditions of the HSM for their sensitivity with the Utah-specific SPFs. Future research could also be conducted to quantify the impacts of the assumed base conditions through a sensitivity analysis comparison of the SPFs developed as a way to narrow down the number of SPFs used in the state.

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APPENDIX A: SEGMENT RESULTS

Segment SPFs are provided in this appendix. First, Table A.1 provides a summary of the field headings and their corresponding definitions. Table A.2 summarizes the SPF results. Figures A.1 through A.70 illustrate the CURE plot and observed vs. predicted plots for each category. Finally, Table A.3 summarizes the categories where an SPF was not developed due to a small sample size (number of segments in the category).

Table A.1 Field Headings and Definitions

Field Heading	Definition
Category	Numetric (AASHTOWare Safety) segmentation category
Figure	Figure number for CURE plot and observed vs. predicted plot
#Seg	Number of segments in the category
Crashes	Total number of crashes in the category
beta_0	Slope coefficient estimate for the category (β_0)
beta_1	Alignment AADT coefficient estimate for the category (β_1)
phi	Overdispersion estimate for the category (ϕ)
%pval	Percentage of p-values < 0.05 (goodness of fit)
SPF	Complete SPF equation with estimated parameters
HG	Hierarchical grouping number (if applicable)

Table A.2 Segment Safety Performance Function Model Results

Category (Figure) #Seg	Crashes	beta_0	beta_1	phi	%pval	SPF	HG
Divided Protected Rural 1 Lanes Interstate* (Figure A.1)							
1	1	-4.06	0.38	3.76	0.00	seg_length * exp(-4.06) * AADT^0.38	17
Divided Protected Rural 2 Lanes Interstate*† (Figure A.2)							
282	5414	-6.62	0.82	3.75	0.15	seg_length * exp(-6.62) * AADT^0.82	17
Divided Protected Rural 3 Lanes Interstate† (Figure A.3)							
39	1296	-11.08	1.32	5.89	0.04	seg_length * exp(-11.08) * AADT^1.32	16
Divided Protected Urban 1 Lanes Interstate* (Figure A.4)							
1	8	-4.41	0.61	4.84	0.00	seg_length * exp(-4.41) * AADT^0.61	21
Divided Protected Urban 2 Lanes + 1 Passing Interstate (Figure A.5)							
4	108	-16.32	1.84	5.75	0.00	seg_length * exp(-16.32) * AADT^1.84	22
Divided Protected Urban 2 Lanes Interstate*† (Figure A.6)							
116	3281	-9.68	1.16	4.83	0.02	seg_length * exp(-9.68) * AADT^1.16	21
Divided Protected Urban 2 Lanes Non-Interstate*† (Figure A.7)							
70	970	-6.33	0.84	1.36	0.59	seg_length * exp(-6.33) * AADT^0.84	11

*Segment categories with SPFs that should be used with caution (SPFs with a %pval > 0.1 and/or a suspect CURE plot)
† Segment categories that were a primary roadway category in a hierarchical model grouping but were not influenced by other categories in that grouping

Table A.2 Continued

Category (Figure) #Seg	Crashes	beta_0	beta_1	phi	%pval	SPF	HG
Divided Protected Urban 3 Lanes Interstate*† (Figure A.8)							
106	7397	-14.03	1.56	6.08	0.10	seg_length * exp(-14.03) * AADT^1.56	22
Divided Protected Urban 3 Lanes Non-Interstate (Figure A.9)							
31	1010	-5.09	0.75	6.09	0.02	seg_length * exp(-5.09) * AADT^0.75	N/A
Divided Protected Urban 4 Lanes Interstate + HOV*† (Figure A.10)							
32	4081	-6.5	0.9	3.95	0.05	seg_length * exp(-6.5) * AADT^0.9	15
Divided Protected Urban 4 Lanes Interstate† (Figure A.11)							
74	4405	-8.18	1.03	4.45	0.09	seg_length * exp(-8.18) * AADT^1.03	23
Divided Protected Urban 4 Lanes Non-Interstate† (Figure A.12)							
38	1202	-4.11	0.64	2.41	0.02	seg_length * exp(-4.11) * AADT^0.64	2
Divided Protected Urban 5 Lanes Interstate + HOV*† (Figure A.13)							
69	8621	-15.13	1.63	4.57	0.67	seg_length * exp(-15.13) * AADT^1.63	14
Divided Protected Urban 5 Lanes Interstate*† (Figure A.14)							
32	1738	-15.85	1.74	5.01	0.20	seg_length * exp(-15.85) * AADT^1.74	24
Divided Protected Urban 5 Lanes Non-Interstate* (Figure A.15)							
16	535	-8.28	1.07	2.76	0.02	seg_length * exp(-8.28) * AADT^1.07	2
Divided Protected Urban 6 Lanes Interstate + HOV† (Figure A.16)							
76	15187	-13.25	1.47	5.26	0.03	seg_length * exp(-13.25) * AADT^1.47	13
Divided Protected Urban 6 Lanes Non-Interstate*† (Figure A.17)							
28	1563	-1.82	0.43	5.08	0.04	seg_length * exp(-1.82) * AADT^0.43	25
Divided Protected Urban 7 Lanes Interstate + HOV* (Figure A.18)							
23	2669	-16.12	1.72	5.58	0.01	seg_length * exp(-16.12) * AADT^1.72	13
Divided Unprotected Rural 2 Lanes Interstate*† (Figure A.19)							
305	5115	-6.14	0.73	4.32	0.58	seg_length * exp(-6.14) * AADT^0.73	4
Divided Unprotected Rural 3 Lanes Interstate* (Figure A.20)							
30	535	-6.28	0.78	7.31	0.14	seg_length * exp(-6.28) * AADT^0.78	N/A
Divided Unprotected Urban 1 Lanes Interstate* (Figure A.21)							
4	12	-33.27	3.77	595.63	0.06	seg_length * exp(-33.27) * AADT^3.77	8
Divided Unprotected Urban 1 Lanes Non-Interstate* (Figure A.22)							
4	28	-2.65	0.56	1.59	0.03	seg_length * exp(-2.65) * AADT^0.56	6
Divided Unprotected Urban 2 Lanes + 1 Passing Interstate* (Figure A.23)							
2	143	-8.25	0.99	595.63	0.00	seg_length * exp(-8.25) * AADT^0.99	8
Divided Unprotected Urban 2 Lanes Interstate*† (Figure A.24)							
68	929	-12.24	1.42	2.66	0.07	seg_length * exp(-12.24) * AADT^1.42	8
Divided Unprotected Urban 2 Lanes Non-Interstate*† (Figure A.25)							
70	1022	-11.6	1.4	1.78	0.38	seg_length * exp(-11.6) * AADT^1.4	6
Divided Unprotected Urban 3 Lanes Interstate* (Figure A.26)							
13	246	-16.36	1.79	595.63	0.16	seg_length * exp(-16.36) * AADT^1.79	8
Divided Unprotected Urban 3 Lanes Non-Interstate* (Figure A.27)							
6	20	-3.26	0.49	1.59	0.00	seg_length * exp(-3.26) * AADT^0.49	6
Divided Unprotected Urban 4 Lanes Interstate* (Figure A.28)							
3	108	-23.36	2.56	595.63	0.00	seg_length * exp(-23.36) * AADT^2.56	8

*Segment categories with SPFs that should be used with caution (SPFs with a %pval > 0.1 and/or a suspect CURE plot)
† Segment categories that were a primary roadway category in a hierarchical model grouping but were not influenced by other categories in that grouping

Table A.2 Continued

Category (Figure) #Seg	Crashes	beta_0	beta_1	phi	%pval	SPF	HG
Divided Unprotected Urban 4 Lanes Non-Interstate* (Figure A.29)							
9	78	-11.87	1.36	1.59	0.01	seg_length * exp(-11.87) * AADT^1.36	6
Divided Unprotected Urban 5 Lanes + HOV Interstate* (Figure A.30)							
3	58	-18.65	1.96	4.76	0.00	seg_length * exp(-18.65) * AADT^1.96	14
No Median/Undivided Rural 1 Lanes + 1 Passing Non-Interstate* (Figure A.31)							
1	2	-4.38	0.32	2.15	0.00	seg_length * exp(-4.38) * AADT^0.32	20
No Median/Undivided Rural 1 Lanes Non-Interstate* (Figure A.32)							
11	67	-7.4	0.99	2.15	0.01	seg_length * exp(-7.4) * AADT^0.99	20
No Median/Undivided Rural 2 Lanes + 1 Passing Non-Interstate (Figure A.33)							
176	1916	-3.28	0.46	1.84	0.01	seg_length * exp(-3.28) * AADT^0.46	N/A
No Median/Undivided Rural 2 Lanes + 2 Passing Non-Interstate* (Figure A.34)							
23	187	2.41	-0.19	1.87	0.00	seg_length * exp(2.41) * AADT^-0.19	19
No Median/Undivided Rural 2 Lanes Non-Interstate*† (Figure A.35)							
964	15107	-5.73	0.74	2.16	0.19	seg_length * exp(-5.73) * AADT^0.74	20
No Median/Undivided Rural 3 Lanes + 1 Passing Non-Interstate† (Figure A.36)							
30	181	0.73	-0.03	1.98	0.03	seg_length * exp(0.73) * AADT^-0.03	19
No Median/Undivided Rural 3 Lanes Non-Interstate (Figure A.37)							
122	976	-5.92	0.79	2.41	0.03	seg_length * exp(-5.92) * AADT^0.79	N/A
No Median/Undivided Rural 4 Lanes Non-Interstate† (Figure A.38)							
100	847	-7.81	1	2.09	0.02	seg_length * exp(-7.81) * AADT^1	19
No Median/Undivided Rural 5 Lanes Non-Interstate* (Figure A.39)							
1	1	-1.98	0.2	1.87	0.00	seg_length * exp(-1.98) * AADT^0.2	19
No Median/Undivided Urban 1 Lanes Non-Interstate* (Figure A.40)							
5	61	-1.73	0.44	2.45	0.02	seg_length * exp(-1.73) * AADT^0.44	29
No Median/Undivided Urban 2 Lanes Non-Interstate*† (Figure A.41)							
316	3494	-6.24	0.83	2.45	0.01	seg_length * exp(-6.24) * AADT^0.83	29
No Median/Undivided Urban 3 Lanes Non-Interstate*† (Figure A.42)							
82	503	-6.59	0.9	1.03	0.48	seg_length * exp(-6.59) * AADT^0.9	12
No Median/Undivided Urban 4 Lanes Non-Interstate* (Figure A.43)							
524	8068	-6.22	0.87	1.77	0.62	seg_length * exp(-6.22) * AADT^0.87	N/A
No Median/Undivided Urban 5 Lanes Non-Interstate (Figure A.44)							
82	1235	-6.41	0.89	2.63	0.02	seg_length * exp(-6.41) * AADT^0.89	N/A
No Median/Undivided Urban 6 Lanes Non-Interstate*† (Figure A.45)							
95	2398	-7.59	1.02	2.1	0.07	seg_length * exp(-7.59) * AADT^1.02	7
No Median/Undivided Urban 7 Lanes Non-Interstate (Figure A.46)							
9	374	-9.85	1.23	2.18	0.01	seg_length * exp(-9.85) * AADT^1.23	7
No Median/Undivided Urban 9 Lanes Non-Interstate* (Figure A.47)							
2	24	-3.21	0.6	2.18	0.00	seg_length * exp(-3.21) * AADT^0.6	7
Raised Median Urban 1 Lanes Non-Interstate* (Figure A.48)							
3	7	-4.15	0.56	1.17	0.00	seg_length * exp(-4.15) * AADT^0.56	18
Raised Median Urban 2 Lanes Non-Interstate† (Figure A.49)							
28	167	-7.56	1	1.14	0.02	seg_length * exp(-7.56) * AADT^1	18

*Segment categories with SPFs that should be used with caution (SPFs with a %pval > 0.1 and/or a suspect CURE plot)
† Segment categories that were a primary roadway category in a hierarchical model grouping but were not influenced by other categories in that grouping

Table A.2 Continued

Category (Figure) #Seg	Crashes	beta_0	beta_1	phi	%pval	SPF	HG
Raised Median Urban 3 Lanes Non-Interstate* (Figure A.50)							
14	171	-8.16	1.07	1.95	0.02	seg_length * exp(-8.16) * AADT^1.07	1
Raised Median Urban 4 Lanes Non-Interstate*† (Figure A.51)							
171	3772	-5.01	0.77	1.94	0.77	seg_length * exp(-5.01) * AADT^0.77	1
Raised Median Urban 5 Lanes Non-Interstate (Figure A.52)							
60	1227	-5.16	0.8	2.76	0.02	seg_length * exp(-5.16) * AADT^0.8	N/A
Raised Median Urban 6 Lanes Non-Interstate*† (Figure A.53)							
159	4951	-5.97	0.86	2.27	0.03	seg_length * exp(-5.97) * AADT^0.86	10
Raised Median Urban 7 Lanes Non-Interstate* (Figure A.54)							
20	479	-14.17	1.64	2.36	0.01	seg_length * exp(-14.17) * AADT^1.64	10
Raised Median Urban 8 Lanes Non-Interstate* (Figure A.55)							
6	138	-12.71	1.45	2.36	0.03	seg_length * exp(-12.71) * AADT^1.45	10
Two-Way Left-Turn Lane Rural 2 Lanes + 1 Passing Non-Interstate* (Figure A.56)							
10	94	-14.92	1.84	1.85	0.05	seg_length * exp(-14.92) * AADT^1.84	28
Two-Way Left-Turn Lane Rural 2 Lanes + 2 Passing Non-Interstate (Figure A.57)							
6	208	-18.57	2.12	4.77	0.06	seg_length * exp(-18.57) * AADT^2.12	3
Two-Way Left-Turn Lane Rural 2 Lanes Non-Interstate (Figure A.58)							
96	314	-5.56	0.69	4.59	0.04	seg_length * exp(-5.56) * AADT^0.69	N/A
Two-Way Left-Turn Lane Rural 3 Lanes + 2 Passing Non-Interstate* (Figure A.59)							
1	3	-4.52	0.69	4.77	0.00	seg_length * exp(-4.52) * AADT^0.69	3
Two-Way Left-Turn Lane Rural 3 Lanes Non-Interstate* (Figure A.60)							
19	73	-4.72	0.66	1.85	0.02	seg_length * exp(-4.72) * AADT^0.66	28
Two-Way Left-Turn Lane Rural 4 Lanes Non-Interstate† (Figure A.61)							
55	628	-5.84	0.77	4.13	0.01	seg_length * exp(-5.84) * AADT^0.77	3
Two-Way Left-Turn Lane Urban 2 Lanes + 1 Passing Non-Interstate* (Figure A.62)							
3	34	-2.04	0.39	2.18	0.00	seg_length * exp(-2.04) * AADT^0.39	26
Two-Way Left-Turn Lane Urban 2 Lanes Non-Interstate (Figure A.63)							
174	2176	-5.78	0.8	1.88	0.04	seg_length * exp(-5.78) * AADT^0.8	N/A
Two-Way Left-Turn Lane Urban 3 Lanes + 1 Passing Non-Interstate* (Figure A.64)							
1	4	-4.89	0.66	1.89	0.00	seg_length * exp(-4.89) * AADT^0.66	27
Two-Way Left-Turn Lane Urban 3 Lanes Non-Interstate*† (Figure A.65)							
57	483	-6.97	0.93	2.06	0.15	seg_length * exp(-6.97) * AADT^0.93	26
Two-Way Left-Turn Lane Urban 4 Lanes Non-Interstate*† (Figure A.66)							
467	9762	-8.81	1.11	1.89	0.01	seg_length * exp(-8.81) * AADT^1.11	27
Two-Way Left-Turn Lane Urban 5 Lanes Non-Interstate (Figure A.67)							
31	685	-11.96	1.46	1.33	0.05	seg_length * exp(-11.96) * AADT^1.46	N/A
Two-Way Left-Turn Lane Urban 6 Lanes Non-Interstate*† (Figure A.68)							
75	3262	-9.96	1.25	2.41	0.12	seg_length * exp(-9.96) * AADT^1.25	5
Two-Way Left-Turn Lane Urban 7 Lanes Non-Interstate* (Figure A.69)							
3	36	-10.87	1.27	2.49	0.00	seg_length * exp(-10.87) * AADT^1.27	5
Two-Way Left-Turn Lane Urban 8 Lanes Non-Interstate* (Figure A.70)							
2	29	-3.37	0.55	2.49	0.00	seg_length * exp(-3.37) * AADT^0.55	5

*Segment categories with SPFs that should be used with caution (SPFs with a %pval > 0.1 and/or a suspect CURE plot)
† Segment categories that were a primary roadway category in a hierarchical model grouping but were not influenced by other categories in that grouping

Insufficient Data

No CURE Plot Available

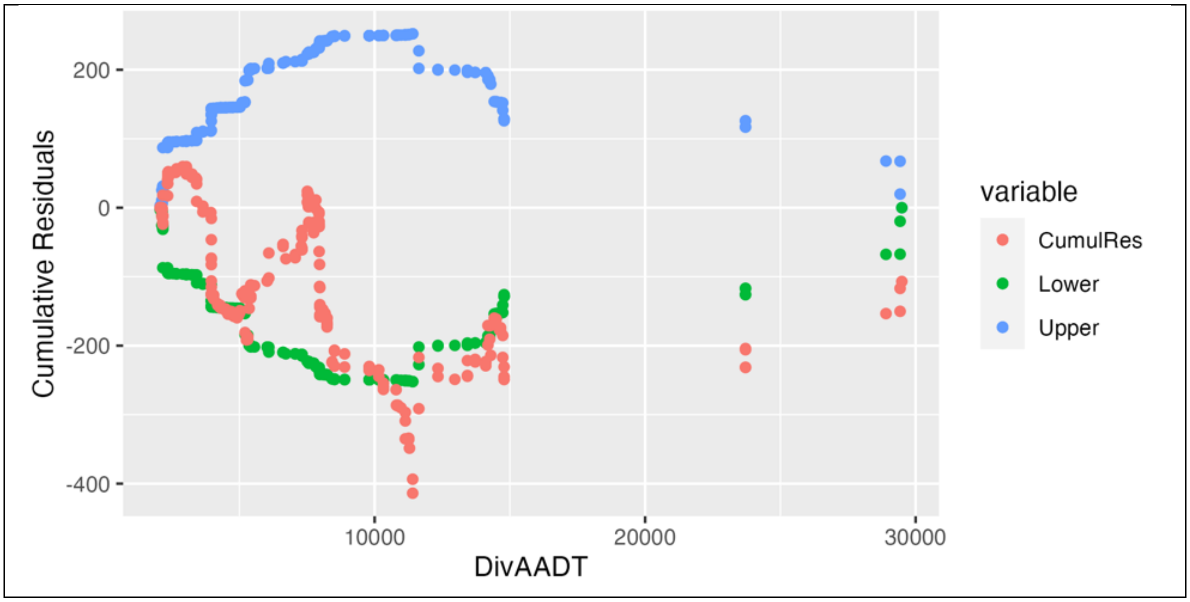
(a)

Insufficient Data

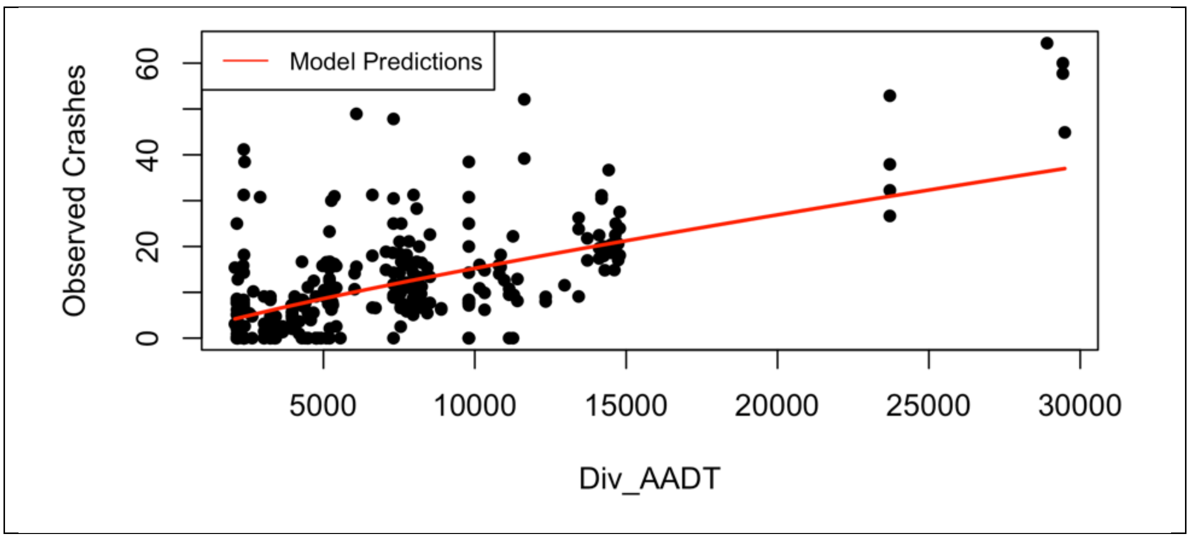
No Observed vs. Predicted Plot Available

(b)

Figure A.1 Divided Protected Rural 1 Lanes Interstate* (a) CURE plot and (b) observed vs. predicted plot.

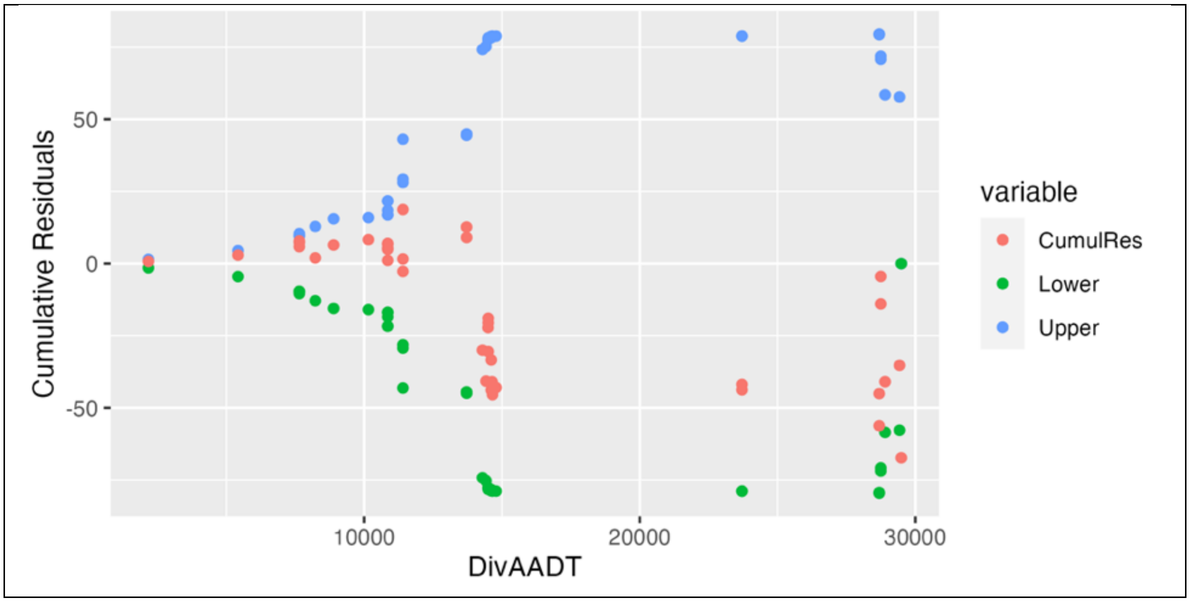


(a)

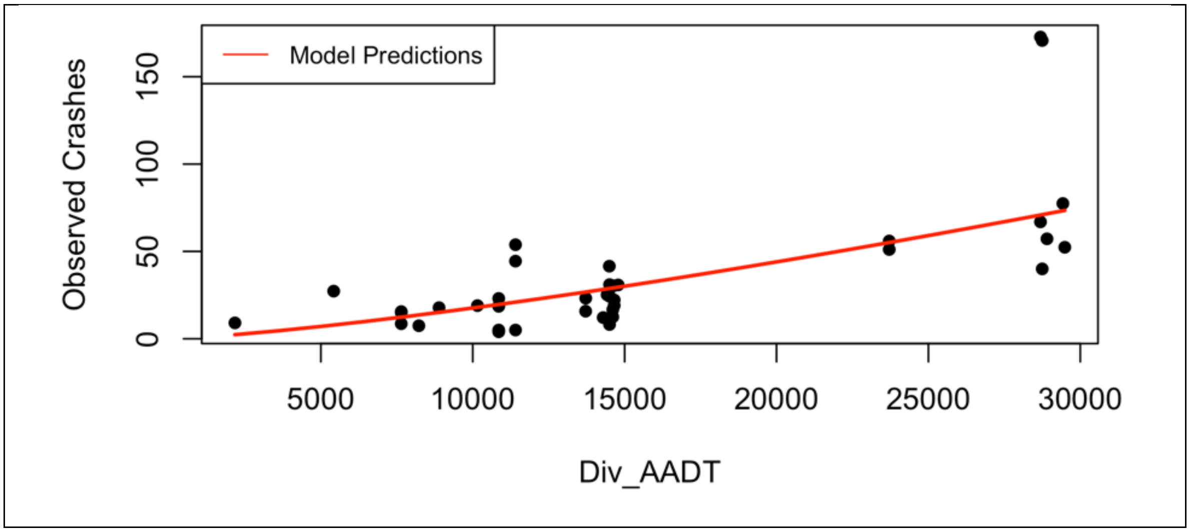


(b)

Figure A.2 Divided Protected Rural 2 Lanes Interstate*† (a) CURE plot and (b) observed vs. predicted plot.



(a)



(b)

Figure A.3 Divided Protected Rural 3 Lanes Interstate† (a) CURE plot and (b) observed vs. predicted plot.

Insufficient Data

No CURE Plot Available

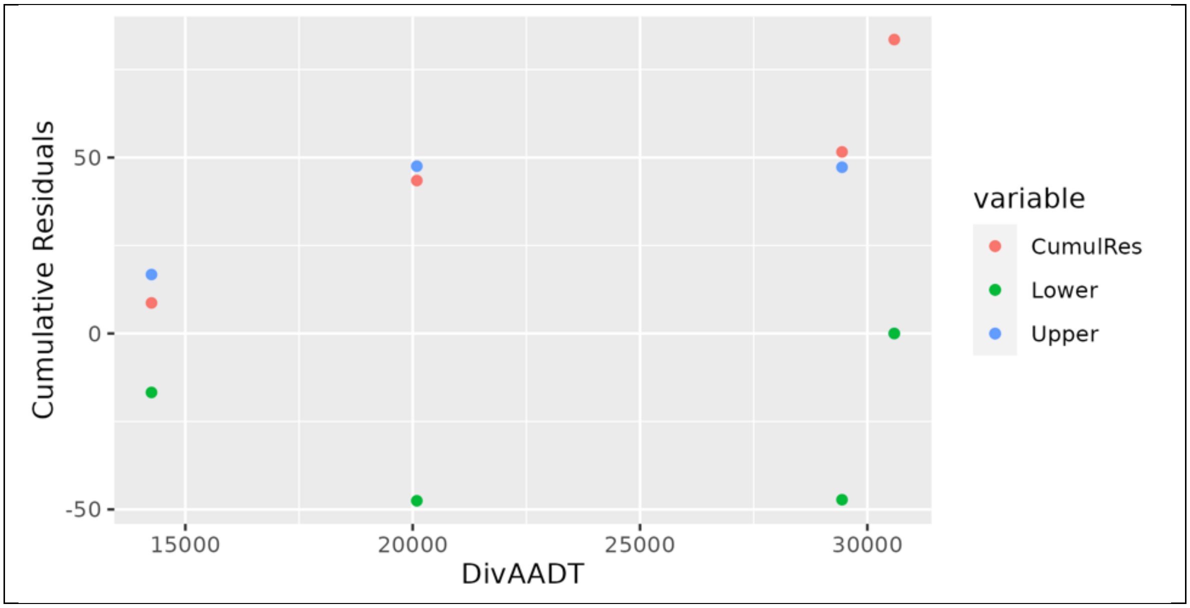
(a)

Insufficient Data

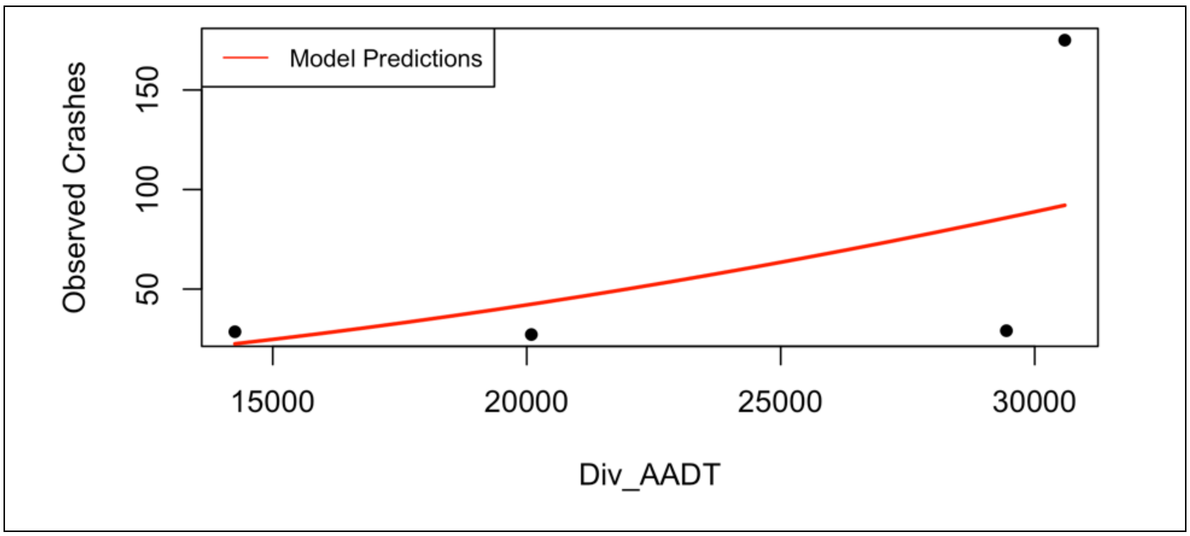
No Observed vs. Predicted Plot Available

(b)

Figure A.4 Divided Protected Urban 1 Lanes Interstate* (a) CURE plot and (b) observed vs. predicted plot.

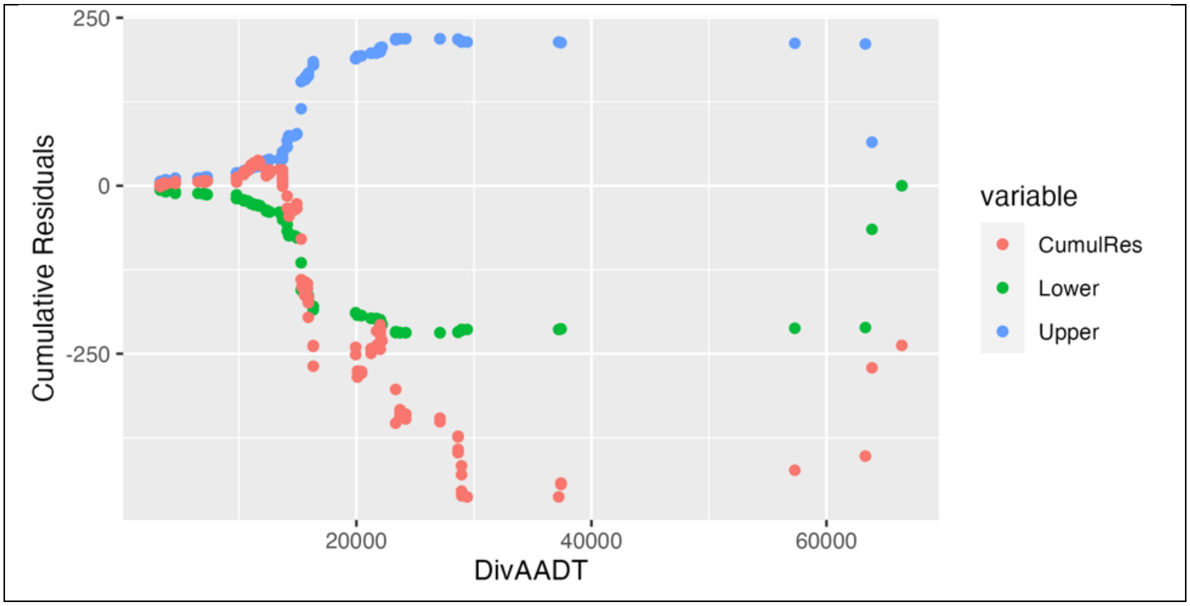


(a)

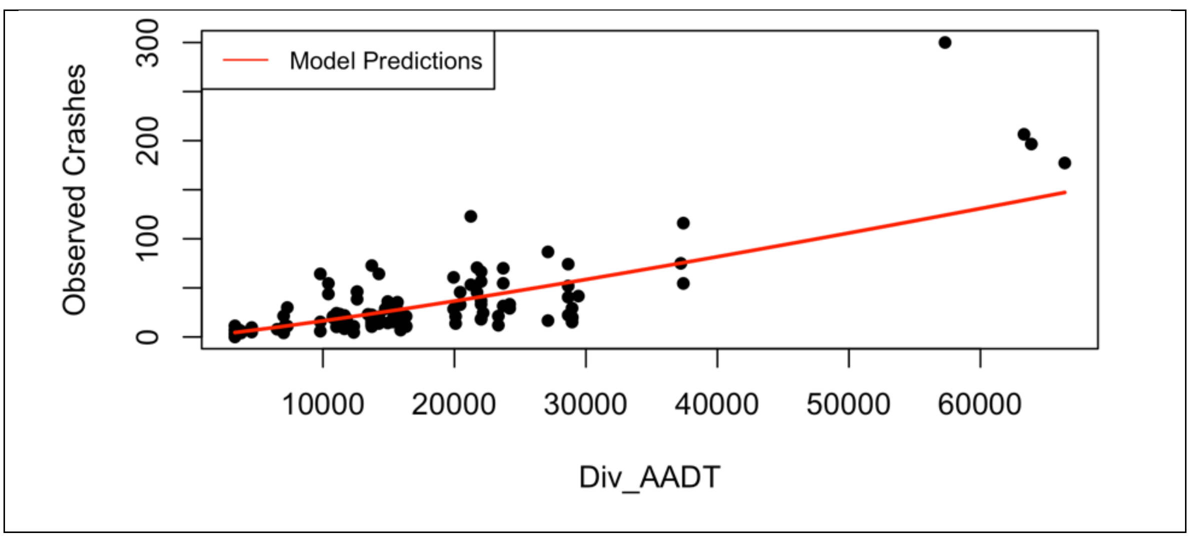


(b)

Figure A.5 Divided Protected Urban 2 Lanes + 1 Passing Interstate (a) CURE plot and (b) observed vs. predicted plot.

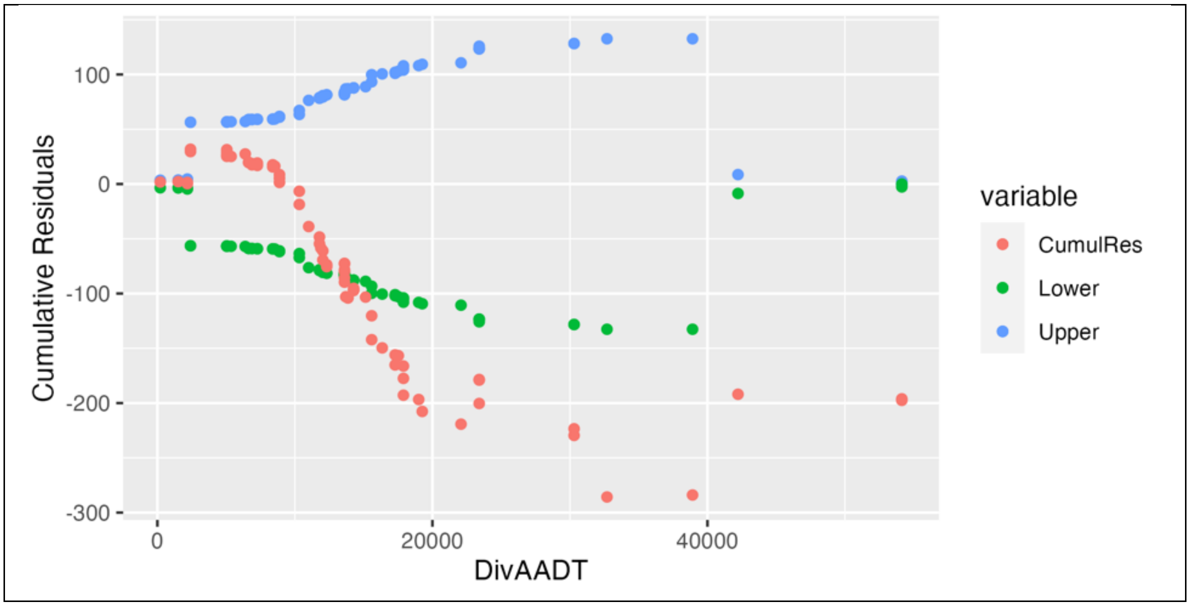


(a)



(b)

Figure A.6 Divided Protected Urban 2 Lanes Interstate*† (a) CURE plot and (b) observed vs. predicted plot.



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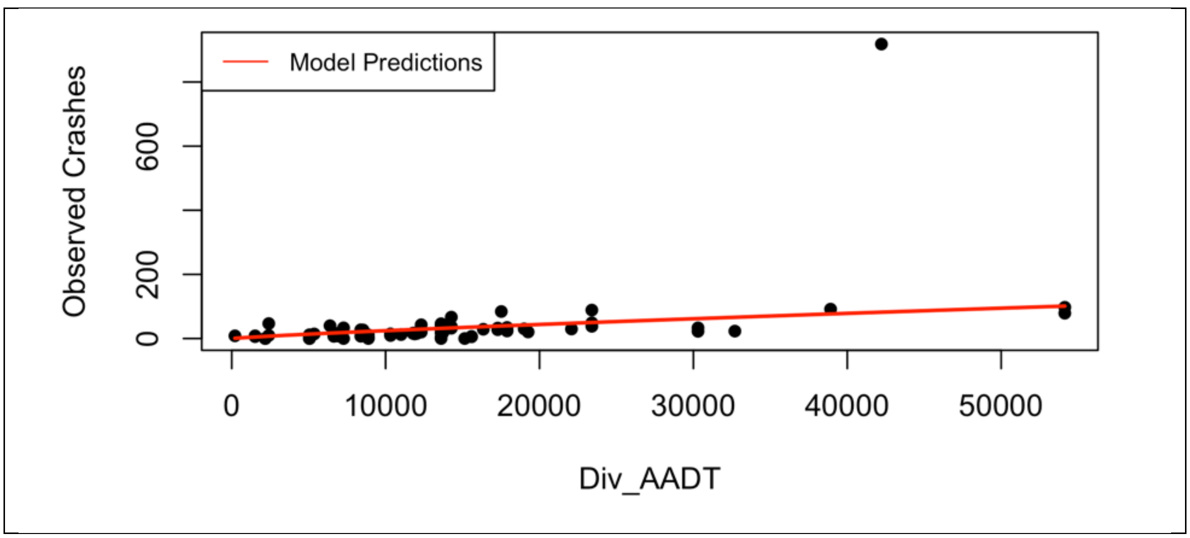
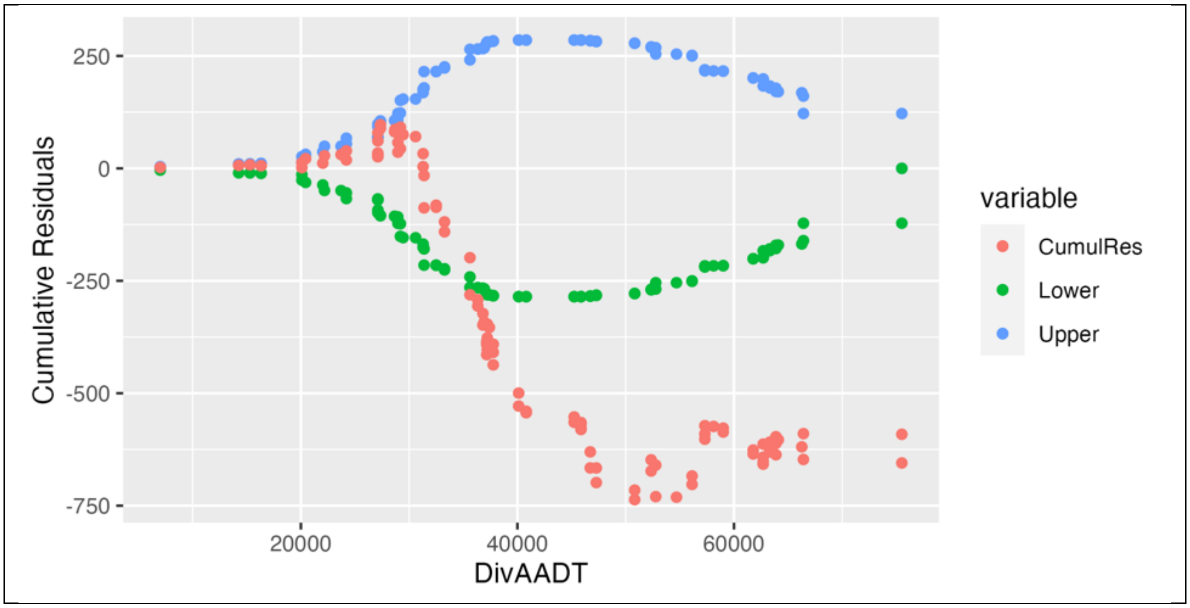


(b)

Figure A.7 Divided Protected Urban 2 Lanes Non-Interstate*† (a) CURE plot and (b) observed vs. predicted plot.



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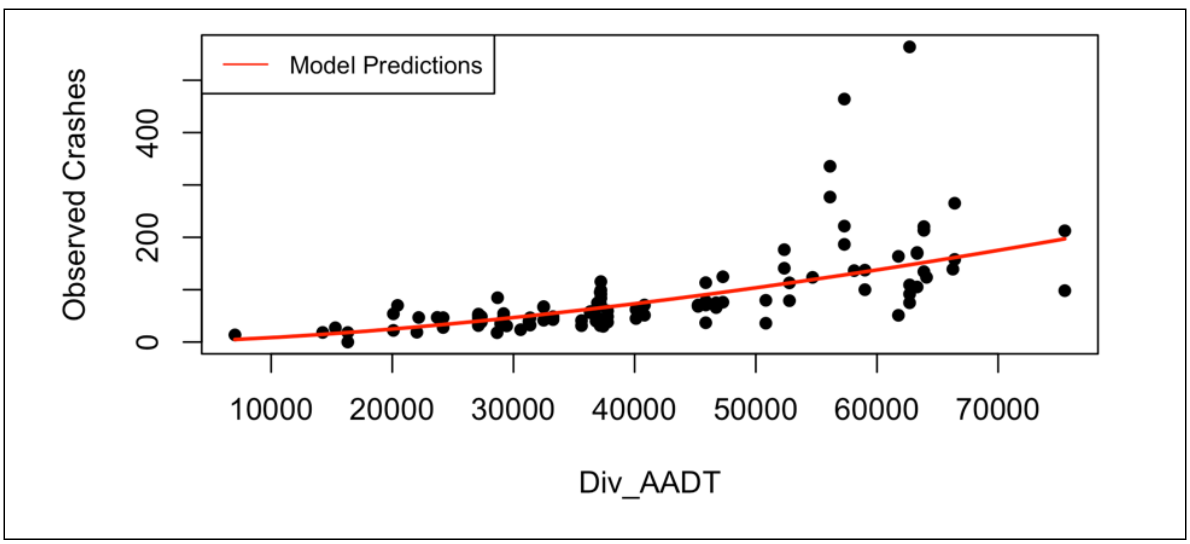
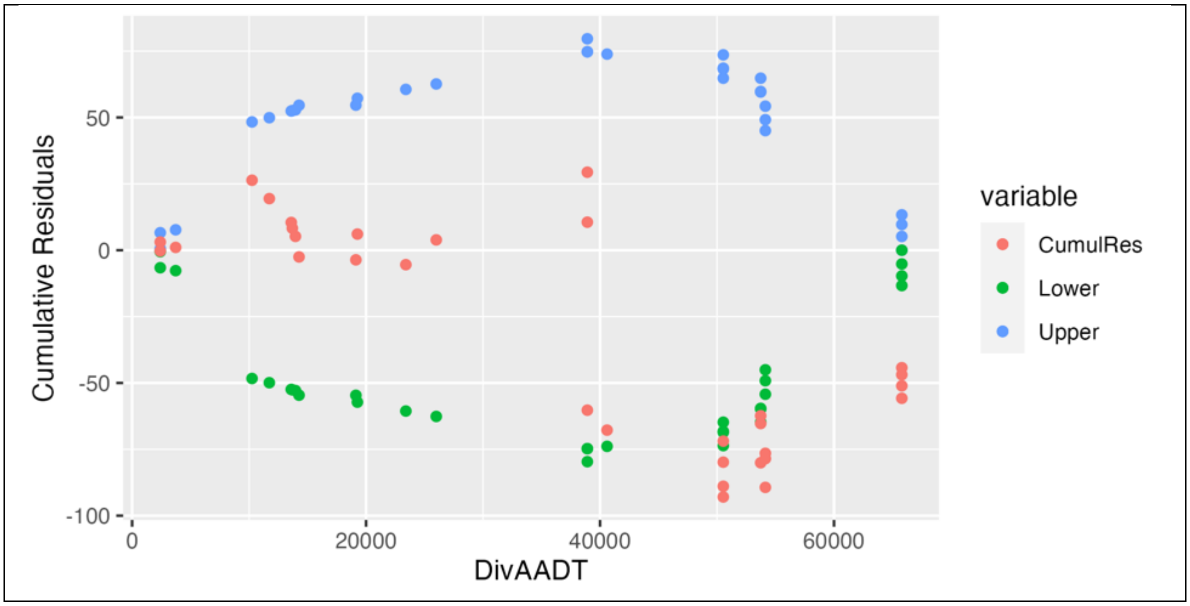
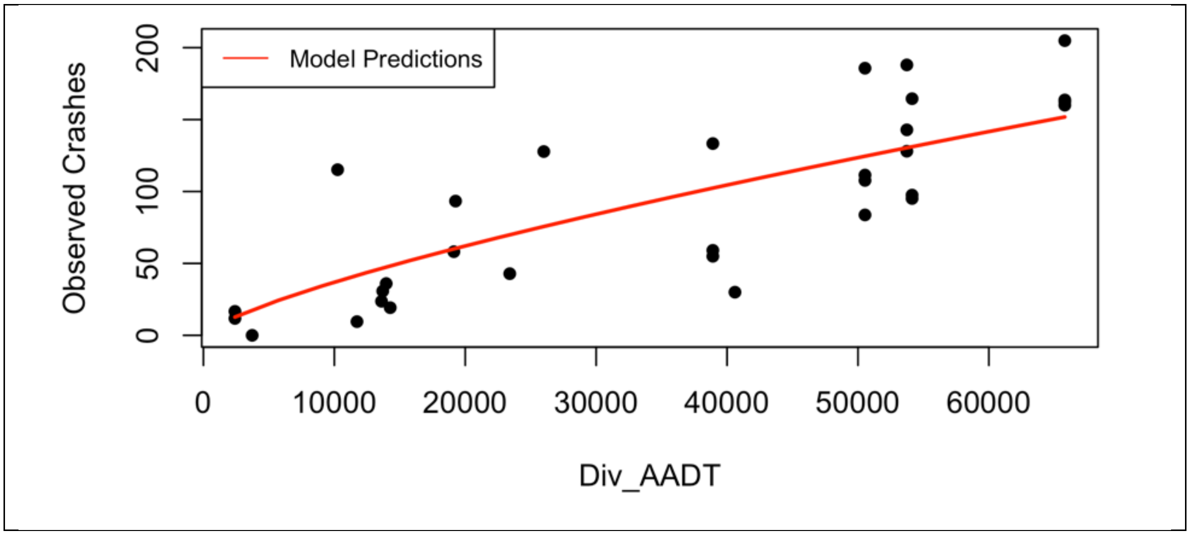


(b)

Figure A.8 Divided Protected Urban 3 Lanes Interstate*† (a) CURE plot and (b) observed vs. predicted plot.

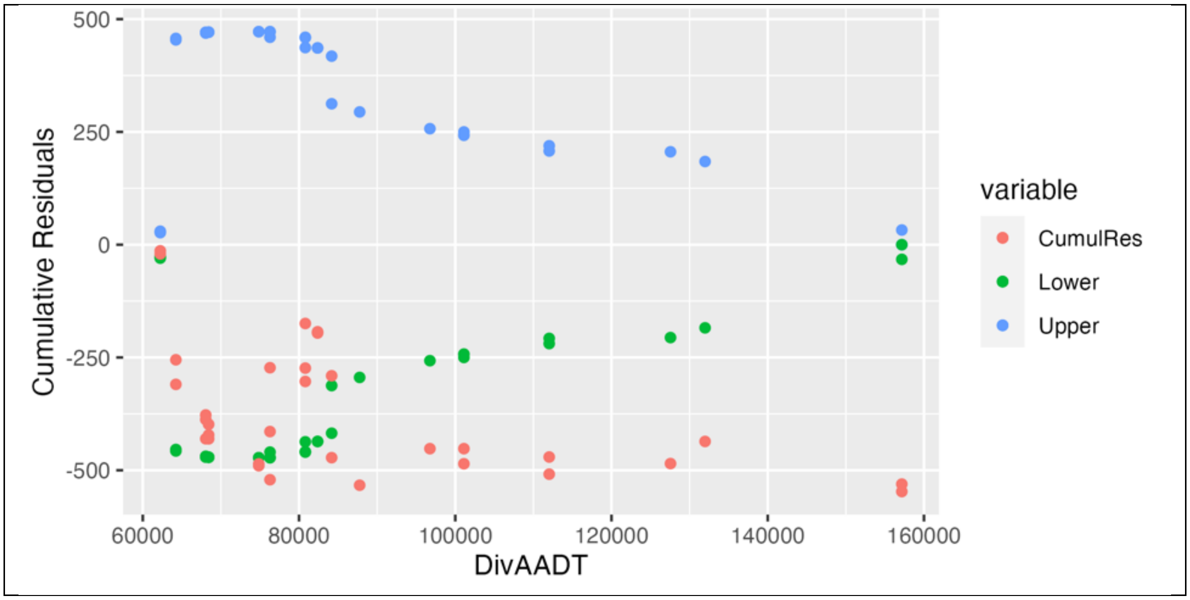


(a)

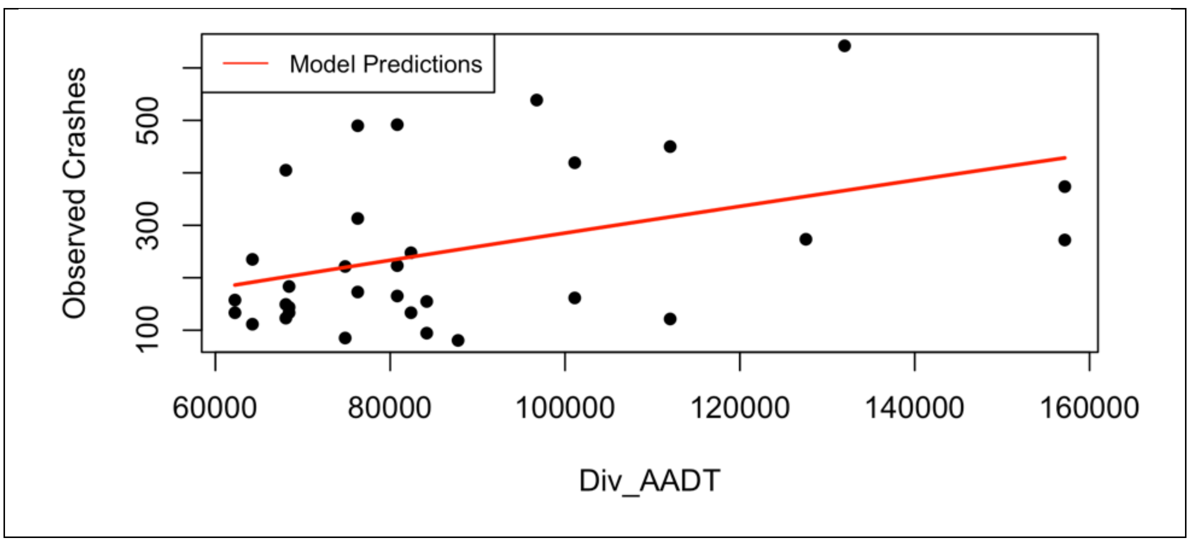


(b)

Figure A.9 Divided Protected Urban 3 Lanes Non-Interstate (a) CURE plot and (b) observed vs. predicted plot.

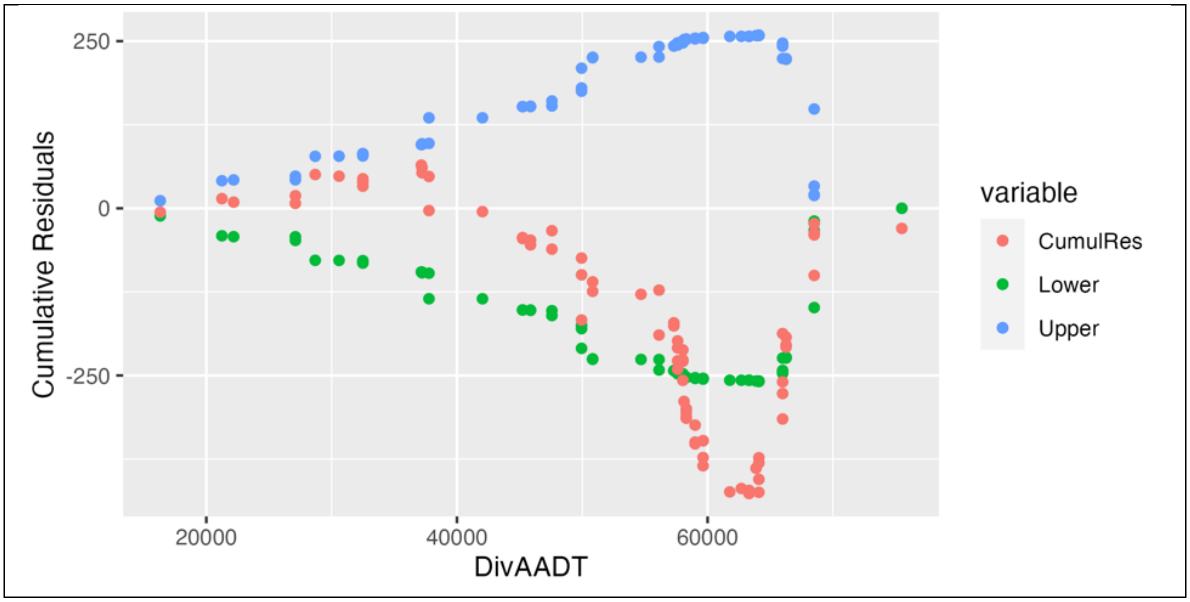


(a)

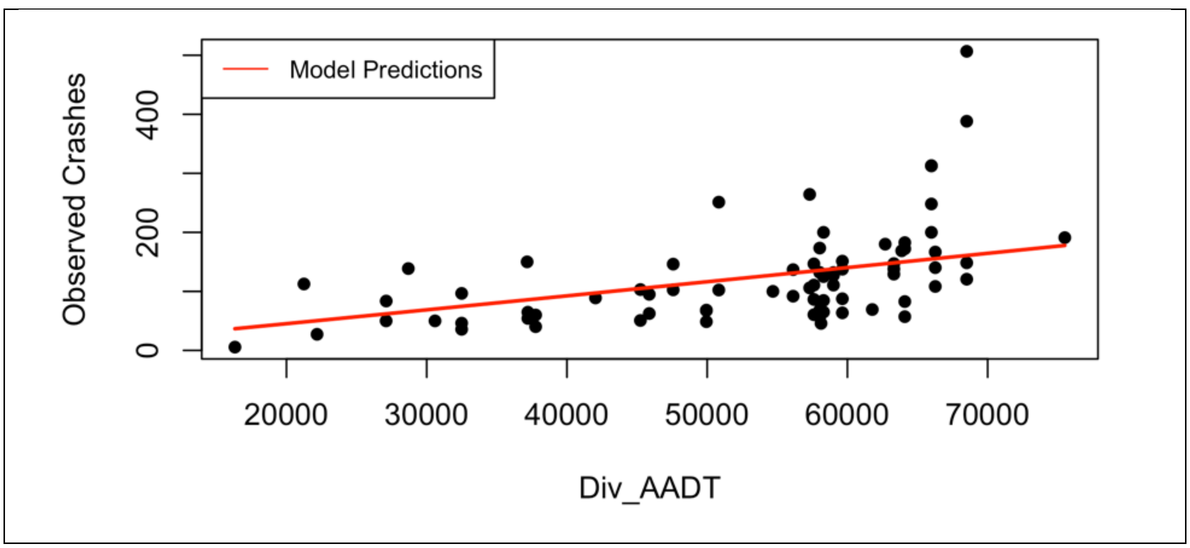


(b)

Figure A.10 Divided Protected Urban 4 Lanes Interstate + HOV*† (a) CURE plot and (b) observed vs. predicted plot.

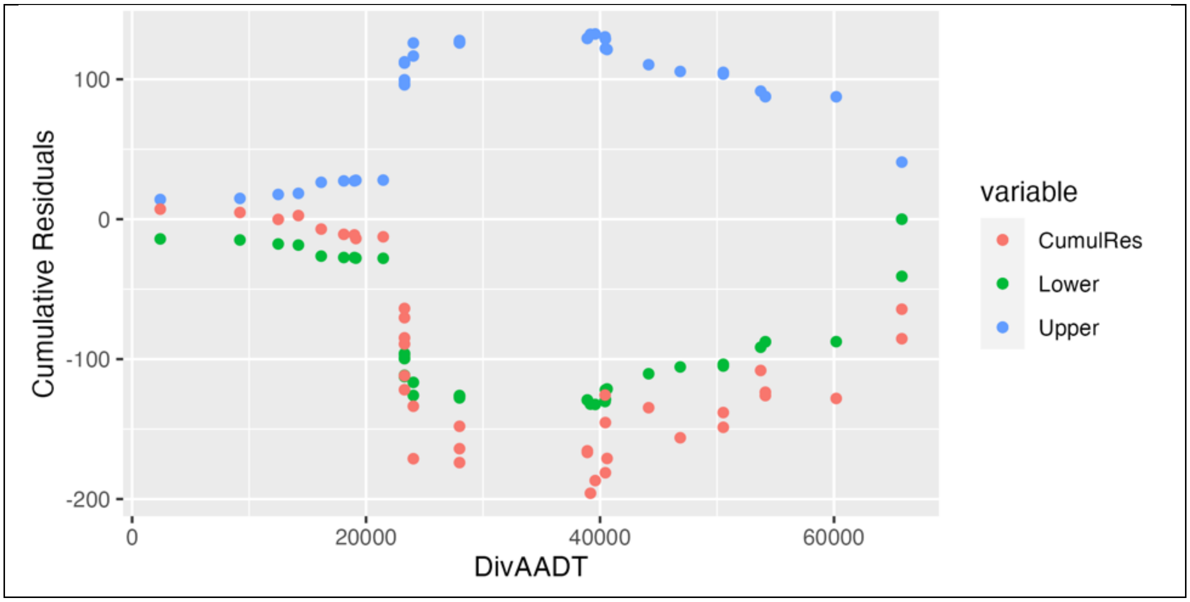


(a)

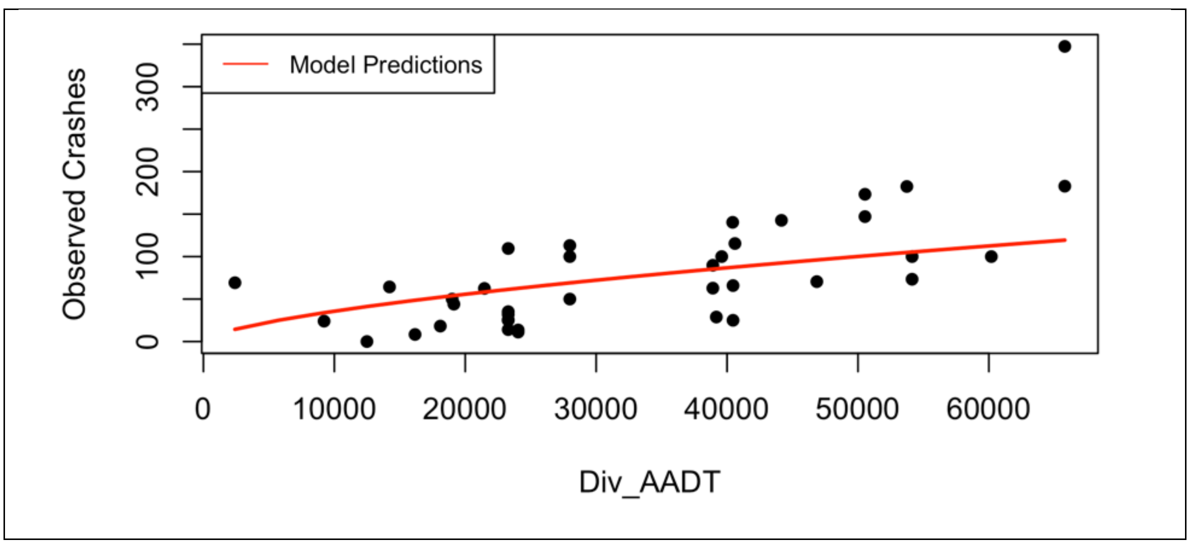


(b)

Figure A.11 Divided Protected Urban 4 Lanes Interstate† (a) CURE plot and (b) observed vs. predicted plot.

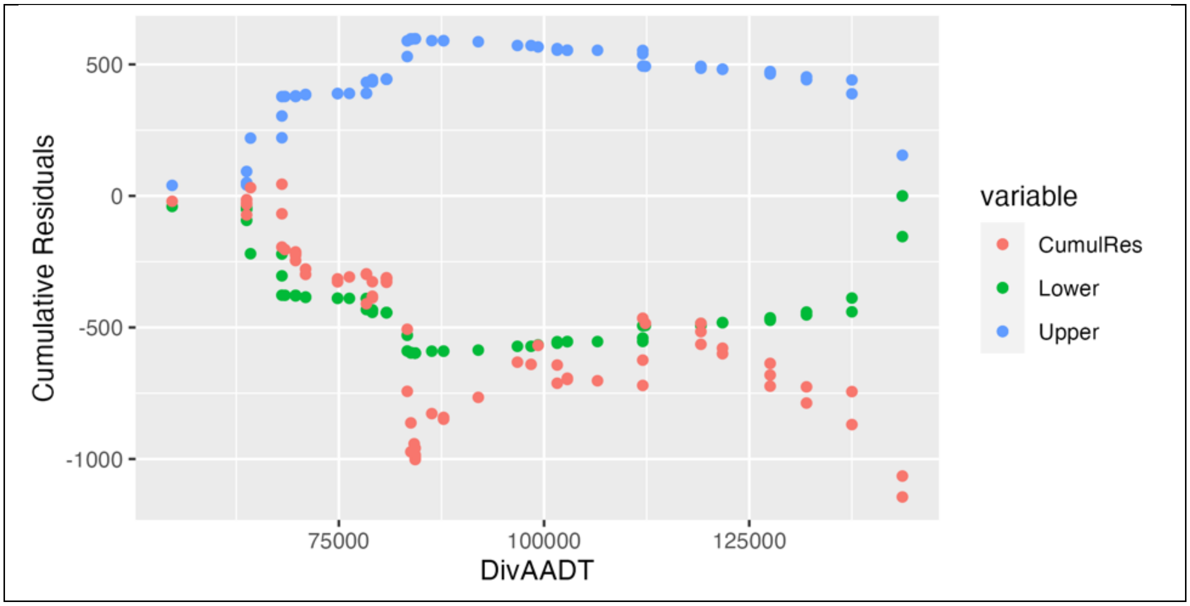


(a)

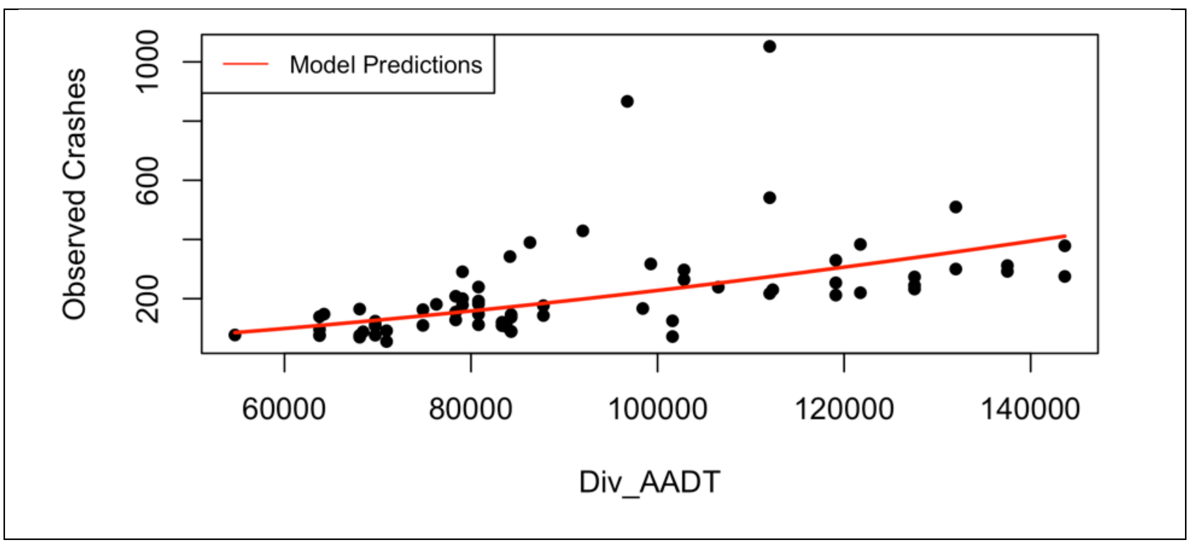


(b)

Figure A.12 Divided Protected Urban 4 Lanes Non-Interstate† (a) CURE plot and (b) observed vs. predicted plot.

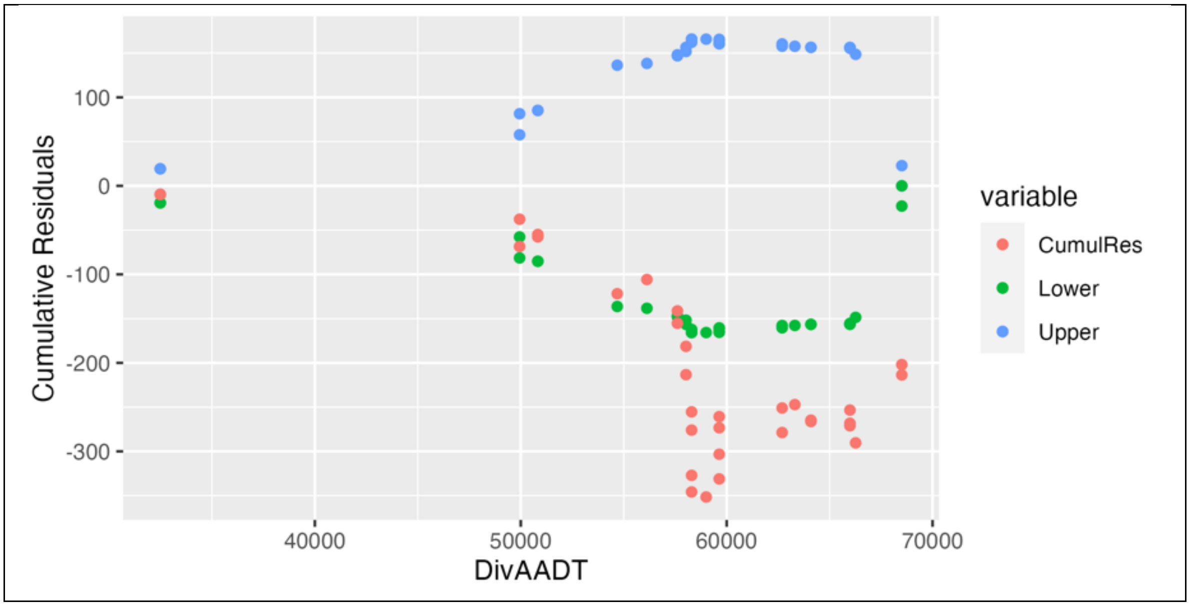


(a)

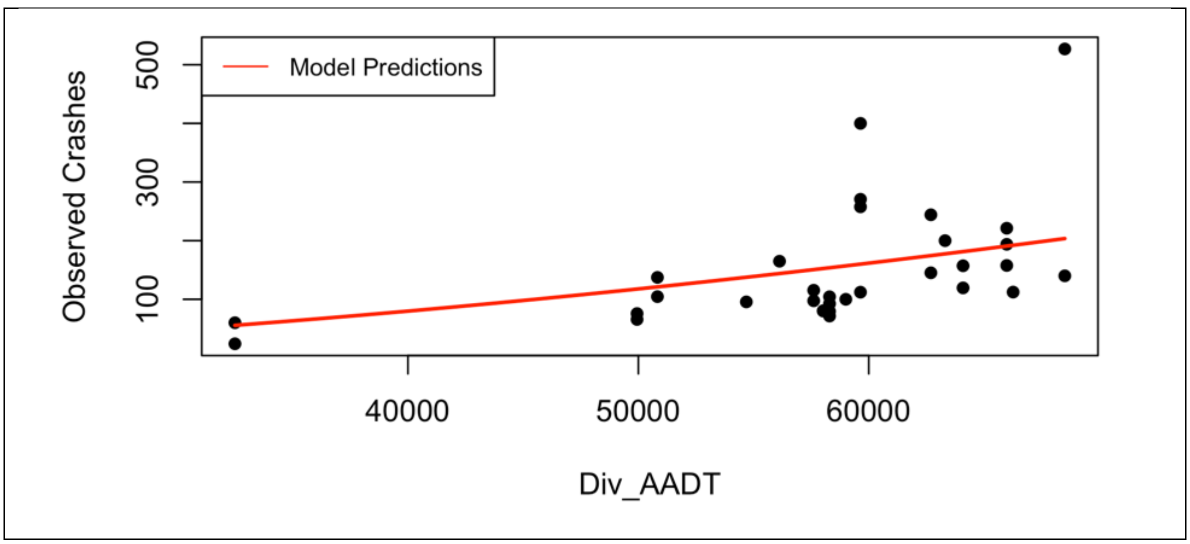


(b)

Figure A.13 Divided Protected Urban 5 Lanes Interstate + HOV*† (a) CURE plot and (b) observed vs. predicted plot.

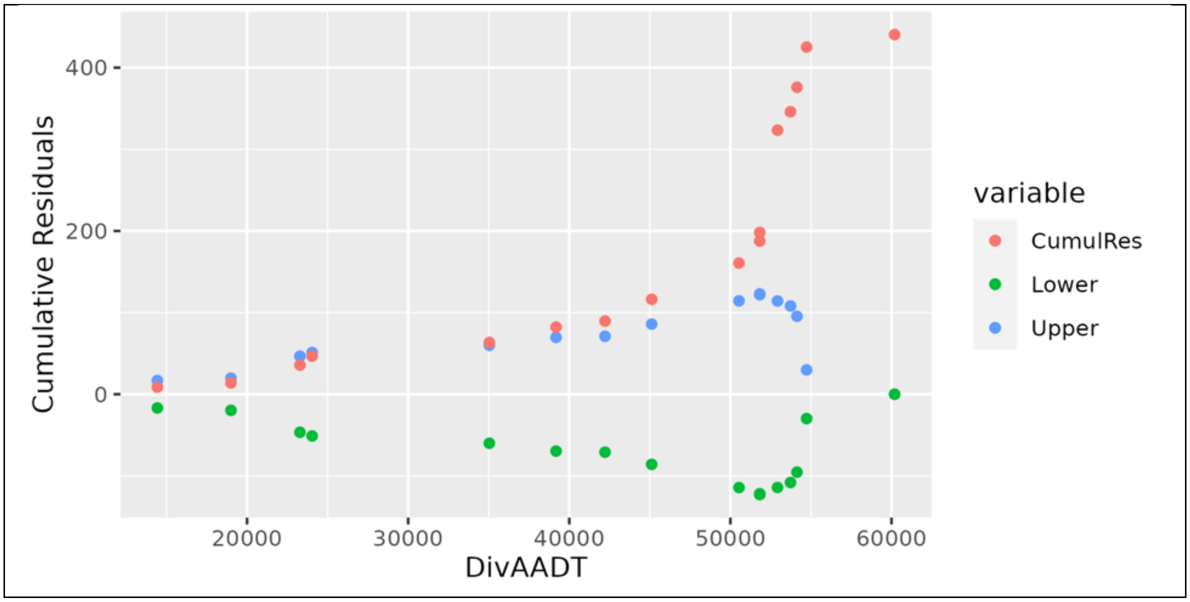


(a)

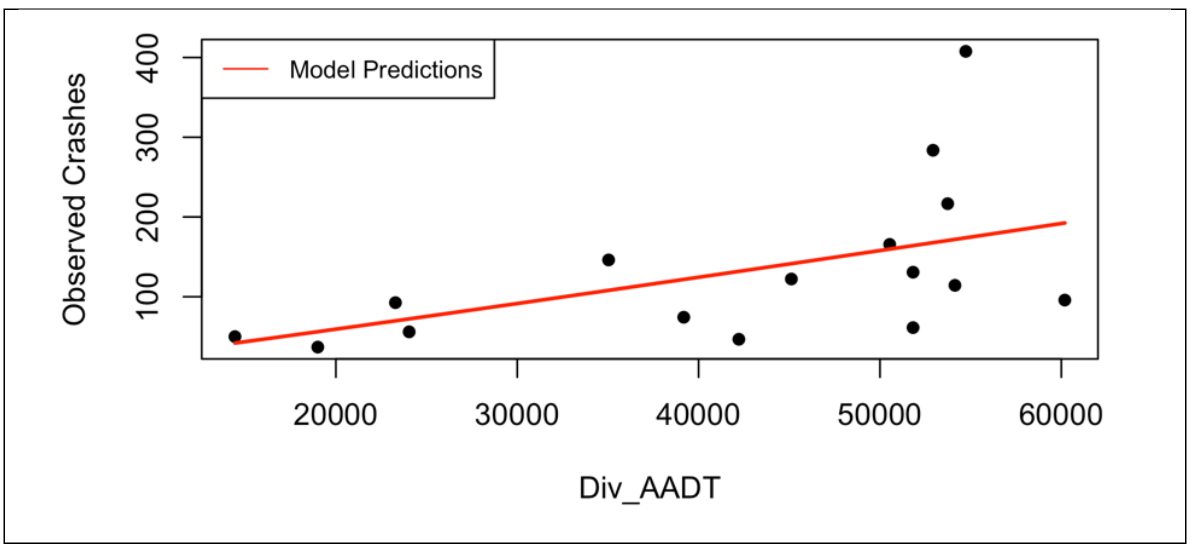


(b)

Figure A.14 Divided Protected Urban 5 Lanes Interstate*† (a) CURE plot and (b) observed vs. predicted plot.

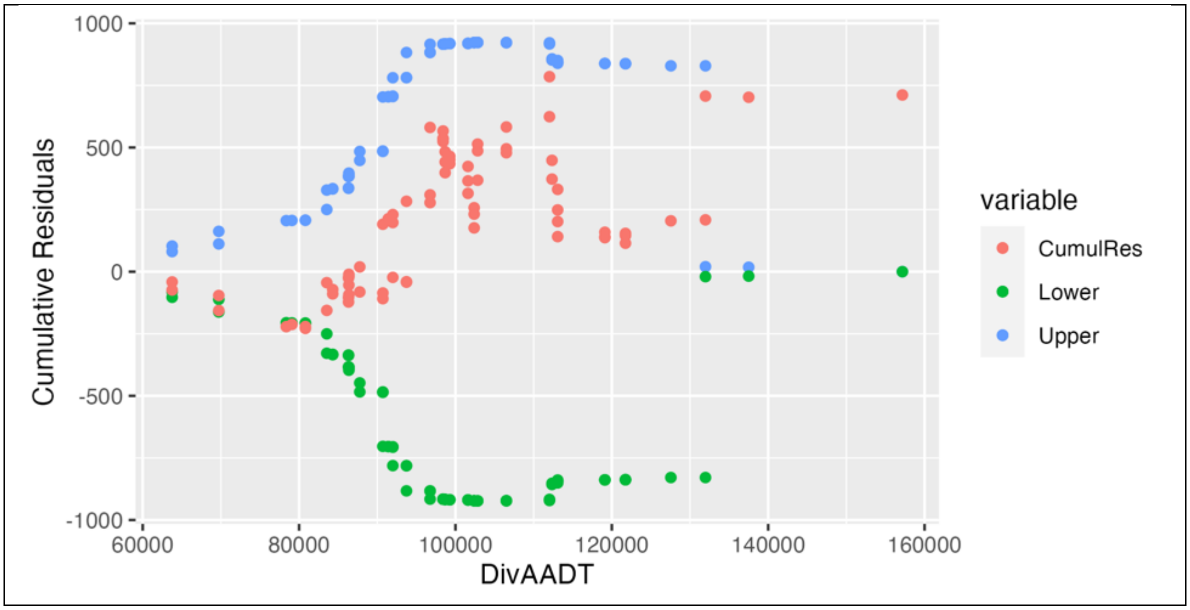


(a)

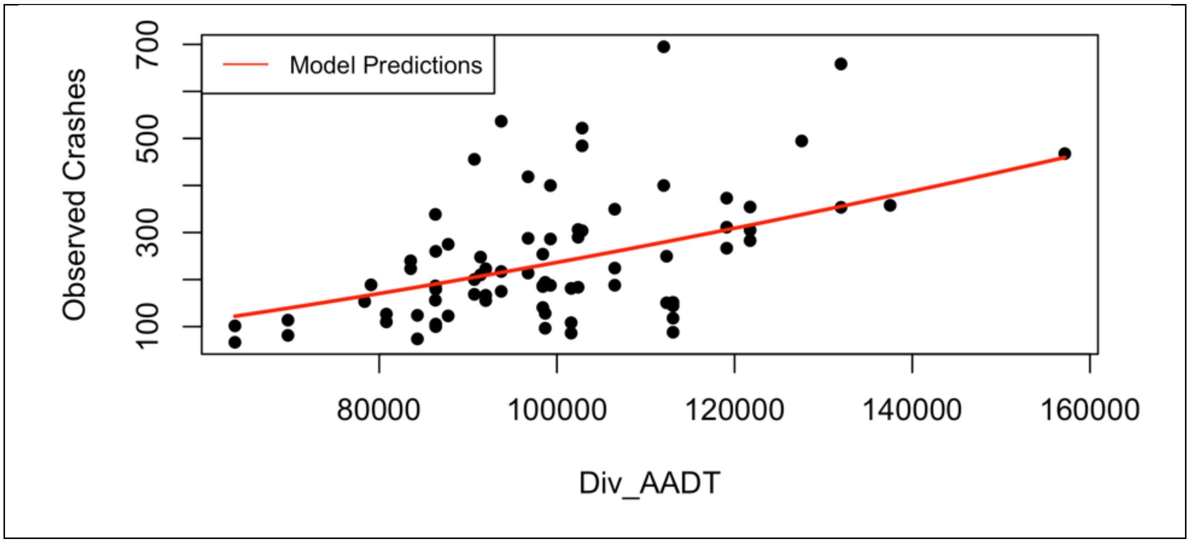


(b)

Figure A.15 Divided Protected Urban 5 Lanes Non-Interstate* (a) CURE plot and (b) observed vs. predicted plot.

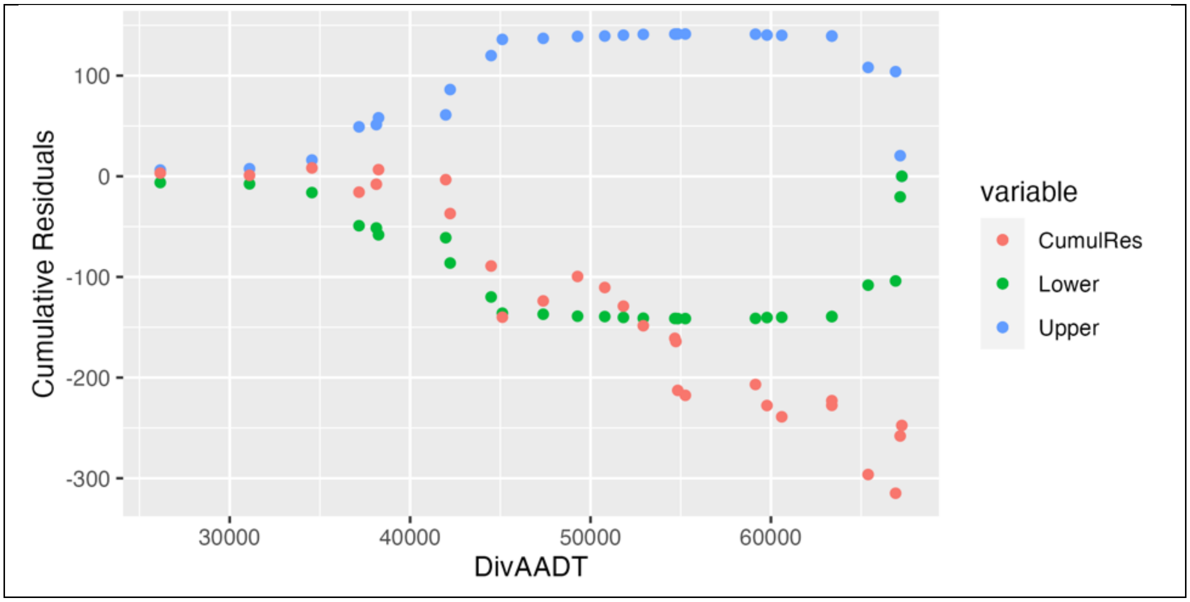


(a)

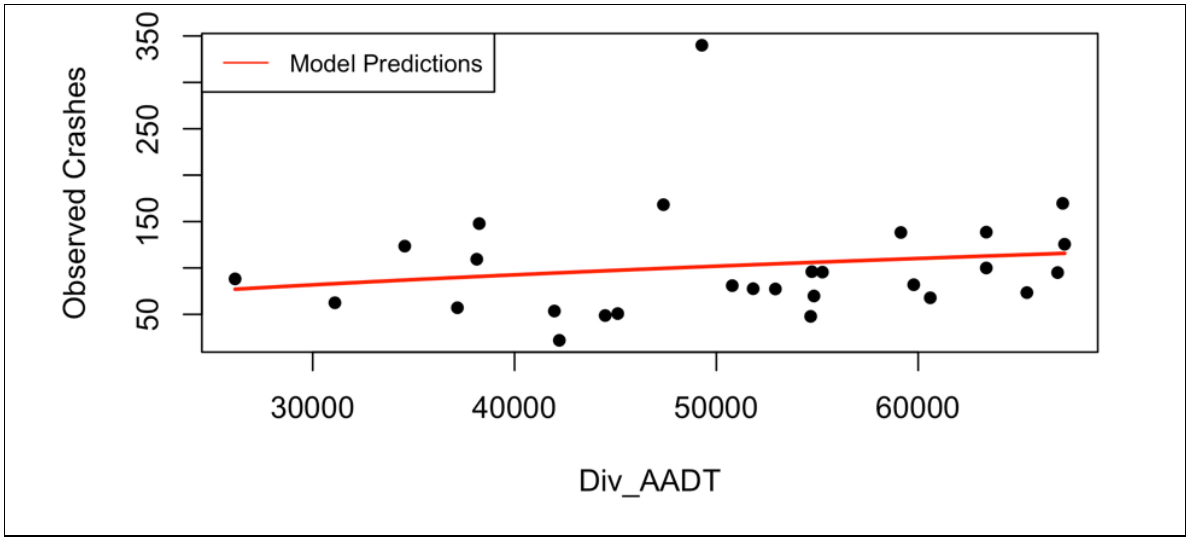


(b)

Figure A.16 Divided Protected Urban 6 Lanes Interstate + HOV† (a) CURE plot and (b) observed vs. predicted plot.

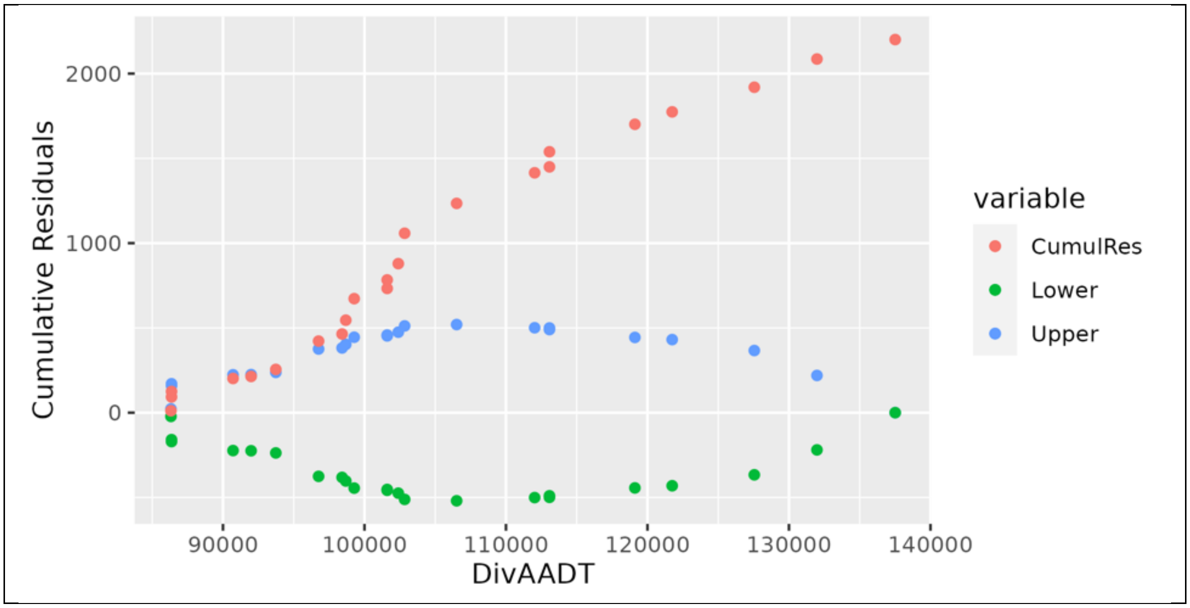


(a)

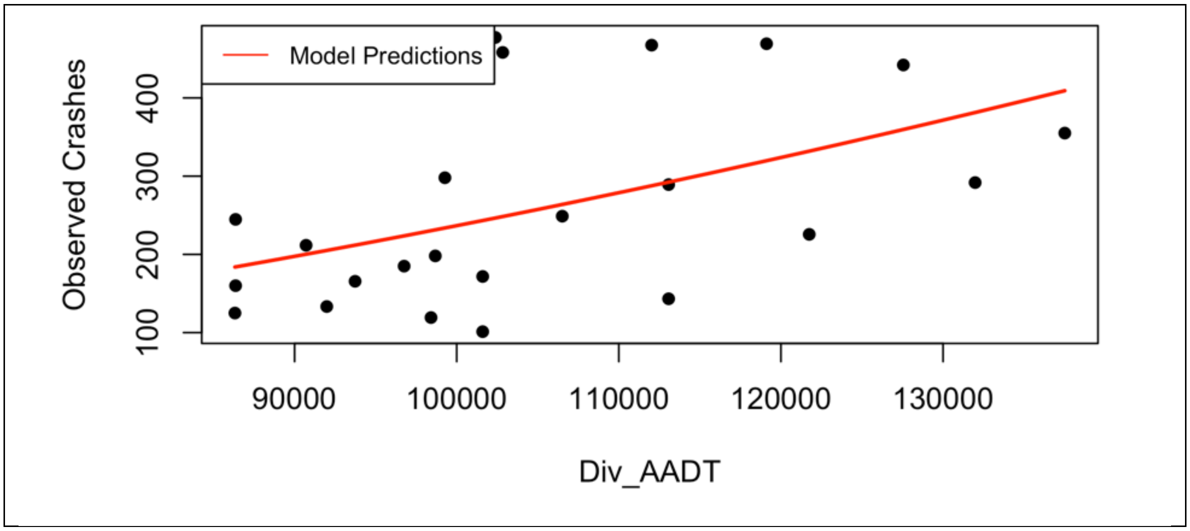


(b)

Figure A.17 Divided Protected Urban 6 Lanes Non-Interstate*† (a) CURE plot and (b) observed vs. predicted plot.

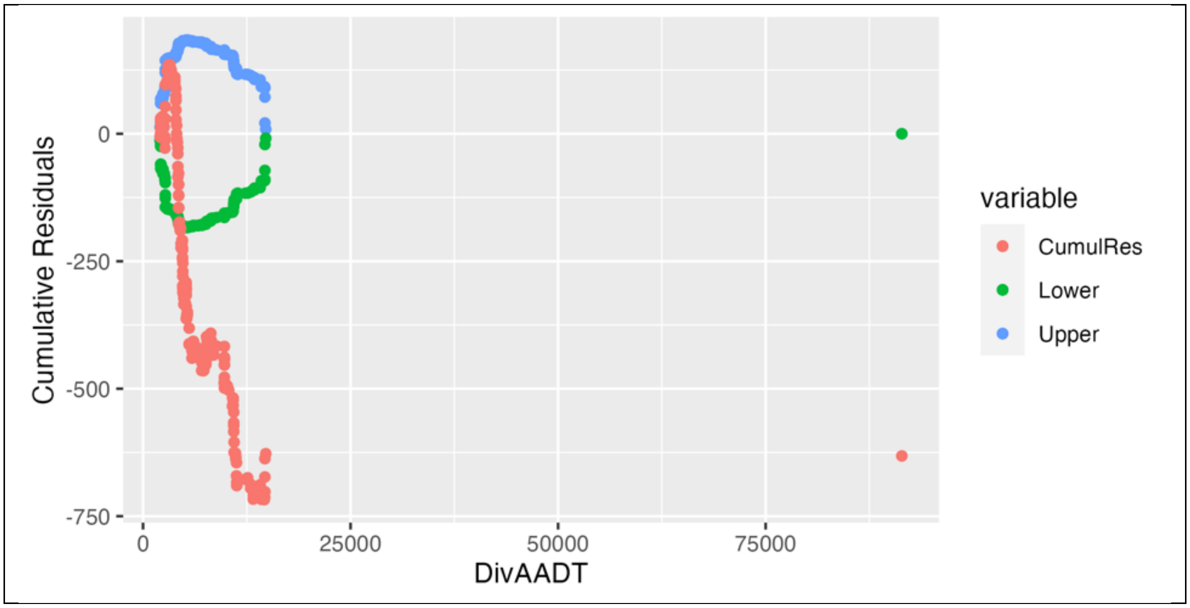


(a)

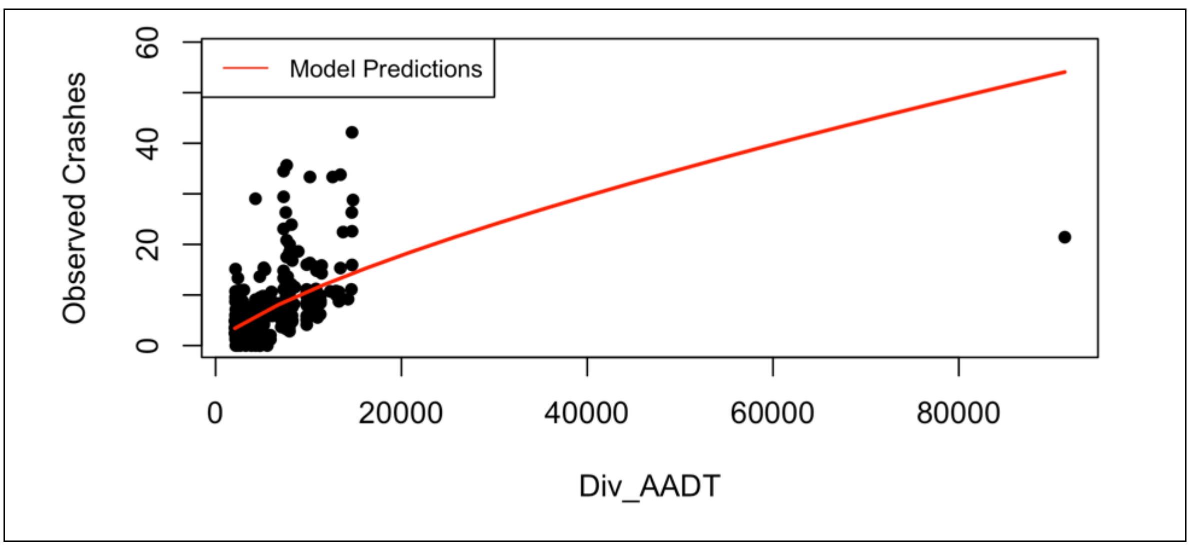


(b)

Figure A.18 Divided Protected Urban 7 Lanes Interstate + HOV* (a) CURE plot and (b) observed vs. predicted plot.

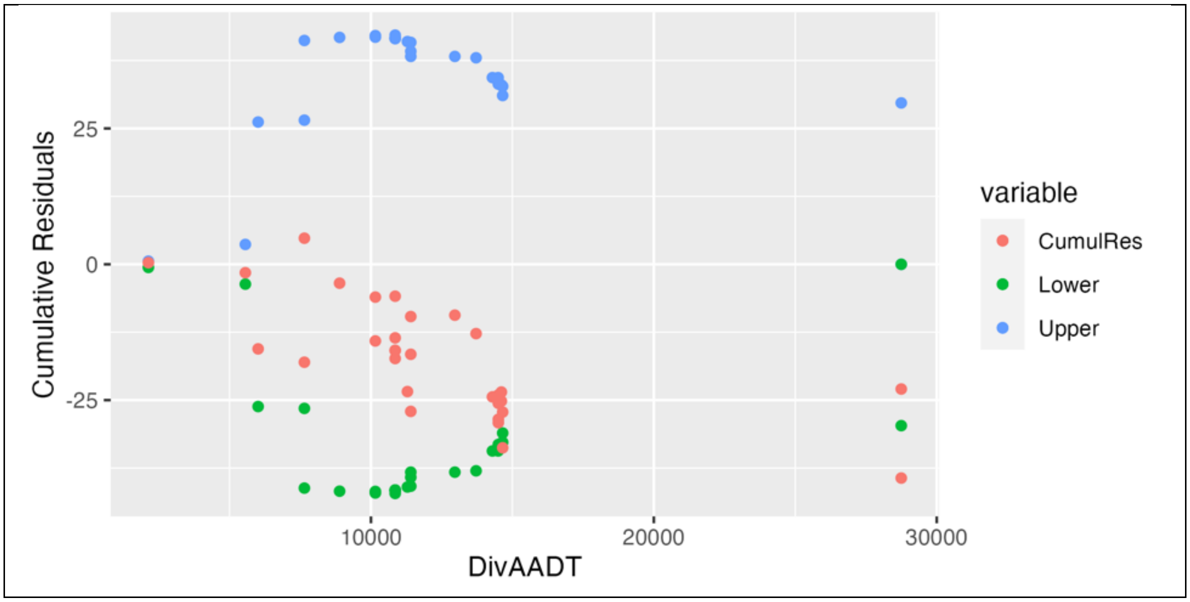


(a)

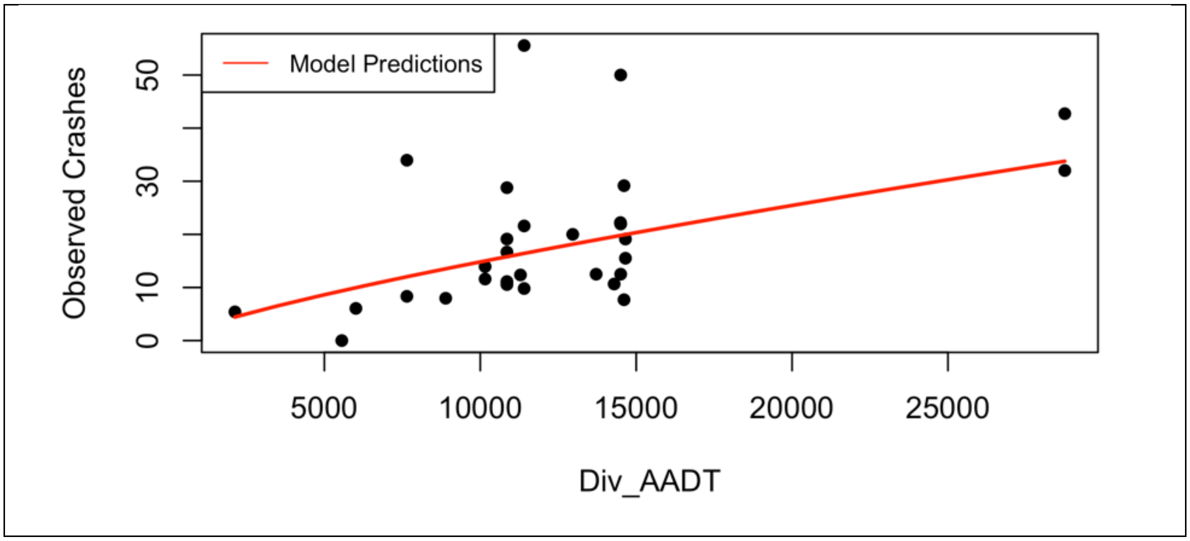


(b)

Figure A.19 Divided Unprotected Rural 2 Lanes Interstate*† (a) CURE plot and (b) observed vs. predicted plot.

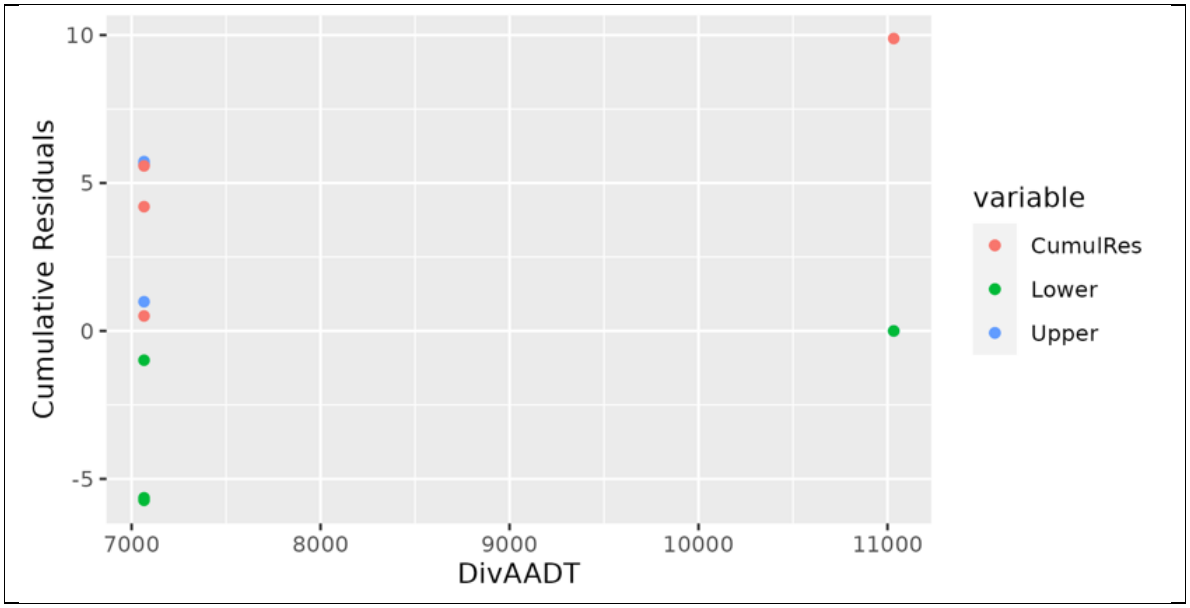


(a)



(b)

Figure A.20 Divided Unprotected Rural 3 Lanes Interstate* (a) CURE plot and (b) observed vs. predicted plot.



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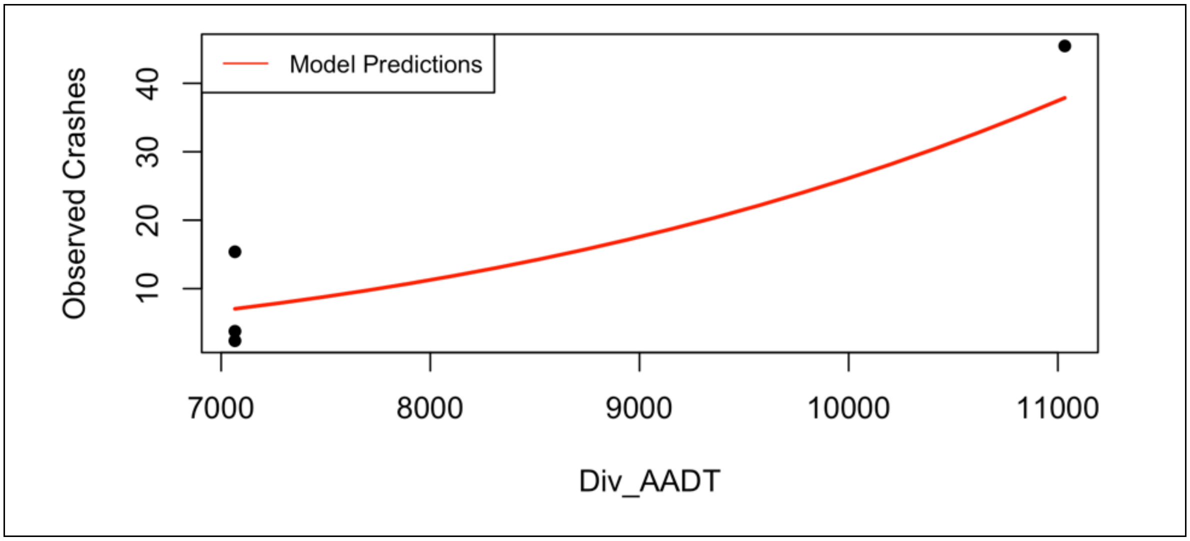
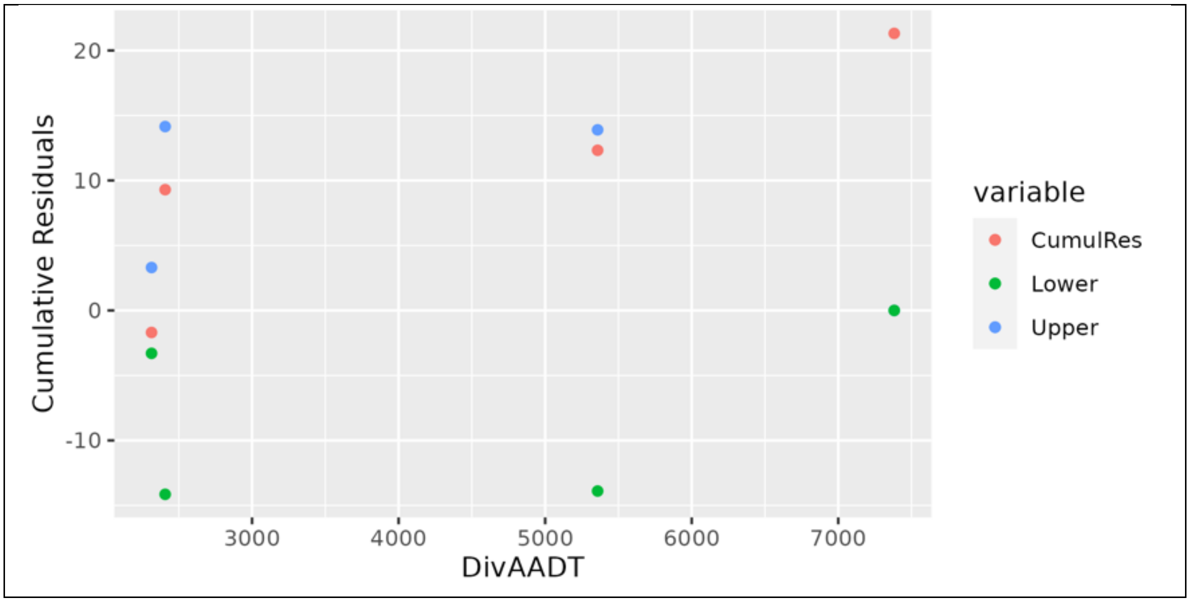


(b)

Figure A.21 Divided Unprotected Urban 1 Lanes Interstate* (a) CURE plot and (b) observed vs. predicted plot.



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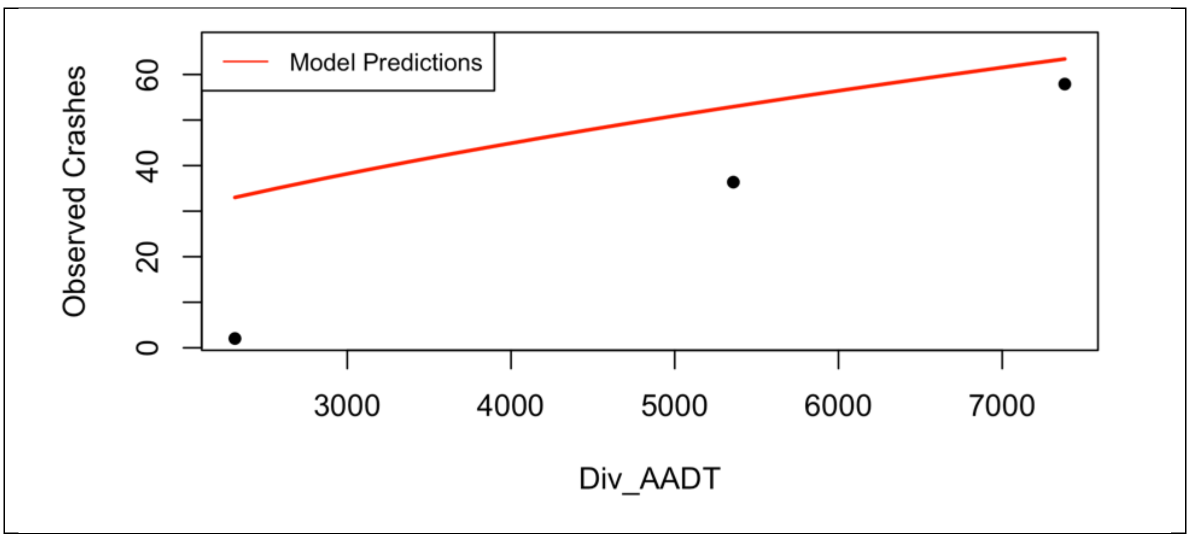
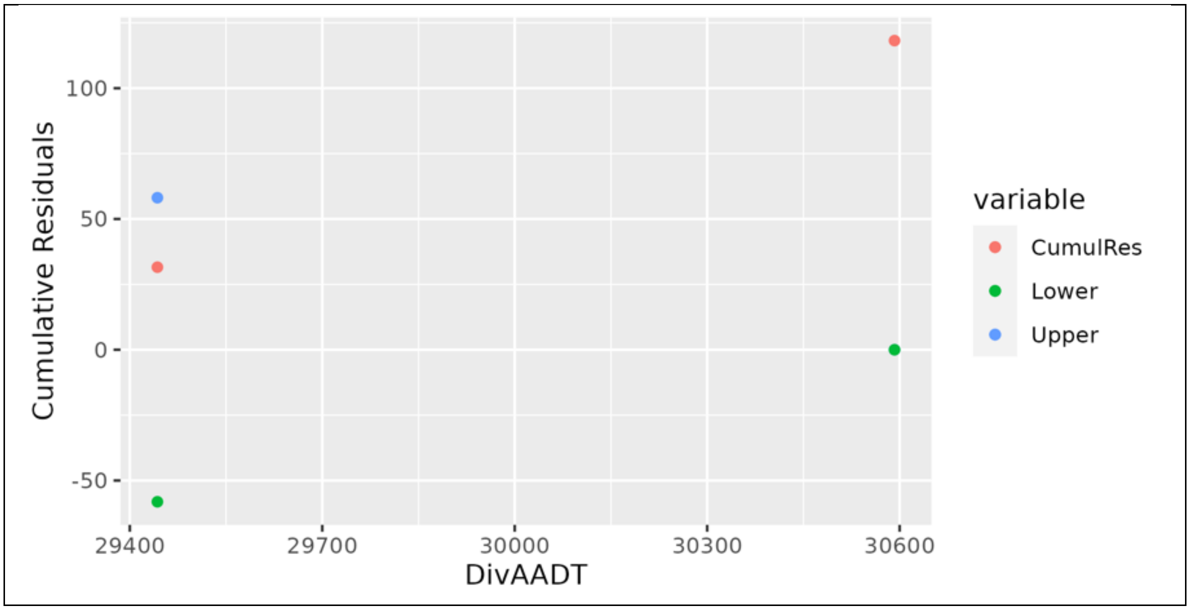
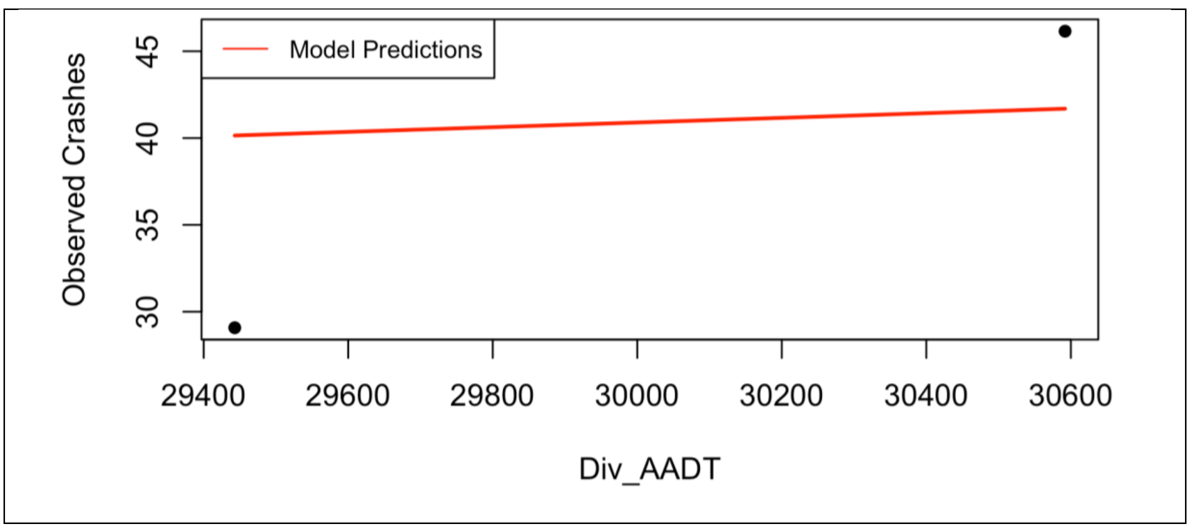


(b)

Figure A.22 Divided Unprotected Urban 1 Lanes Non-Interstate* (a) CURE plot and (b) observed vs. predicted plot.

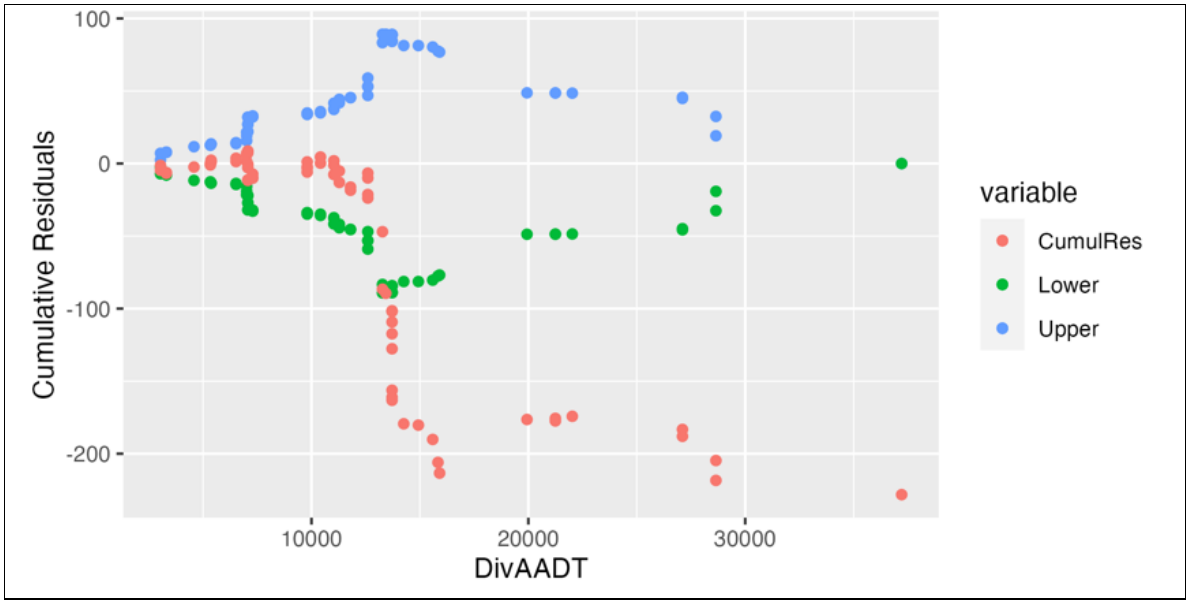


(a)

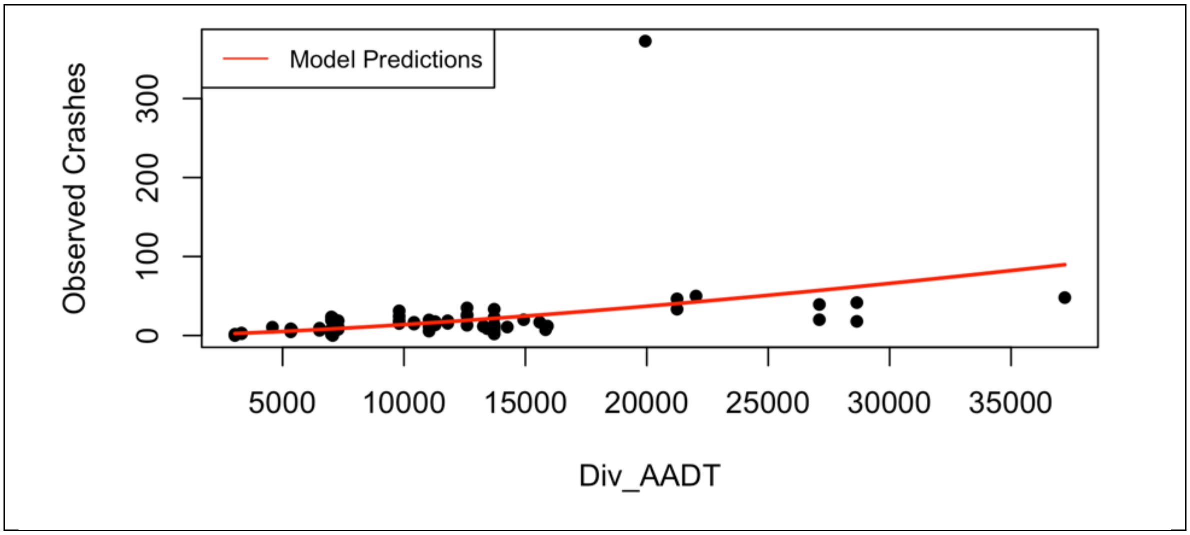


(b)

Figure A.23 Divided Unprotected Urban 2 Lanes + 1 Passing Interstate* (a) CURE plot and (b) observed vs. predicted plot.

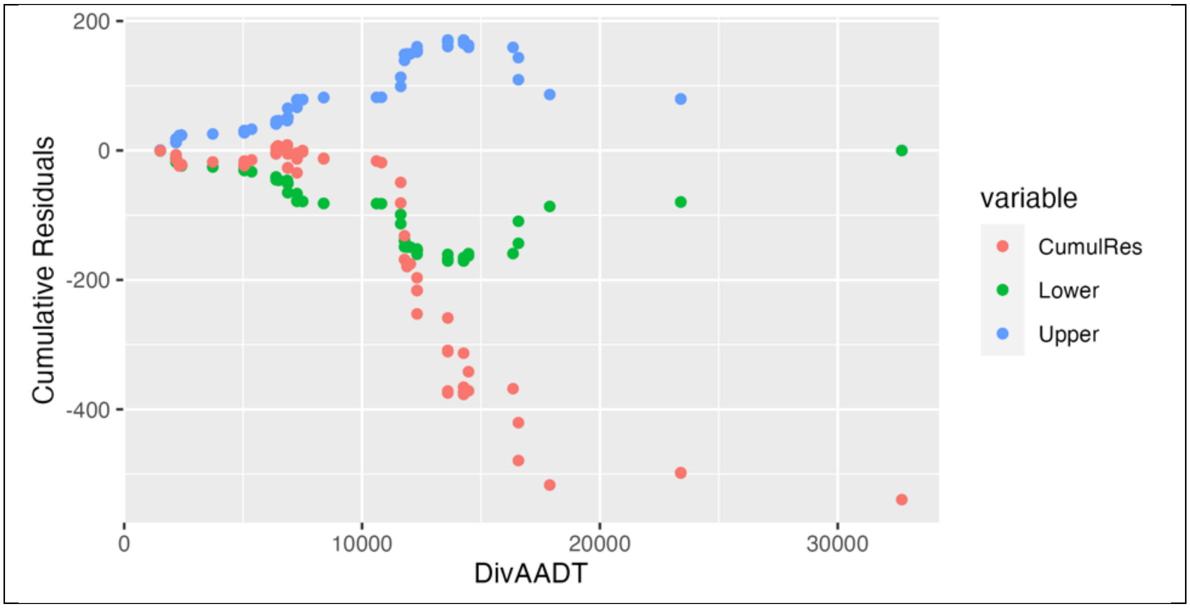


(a)

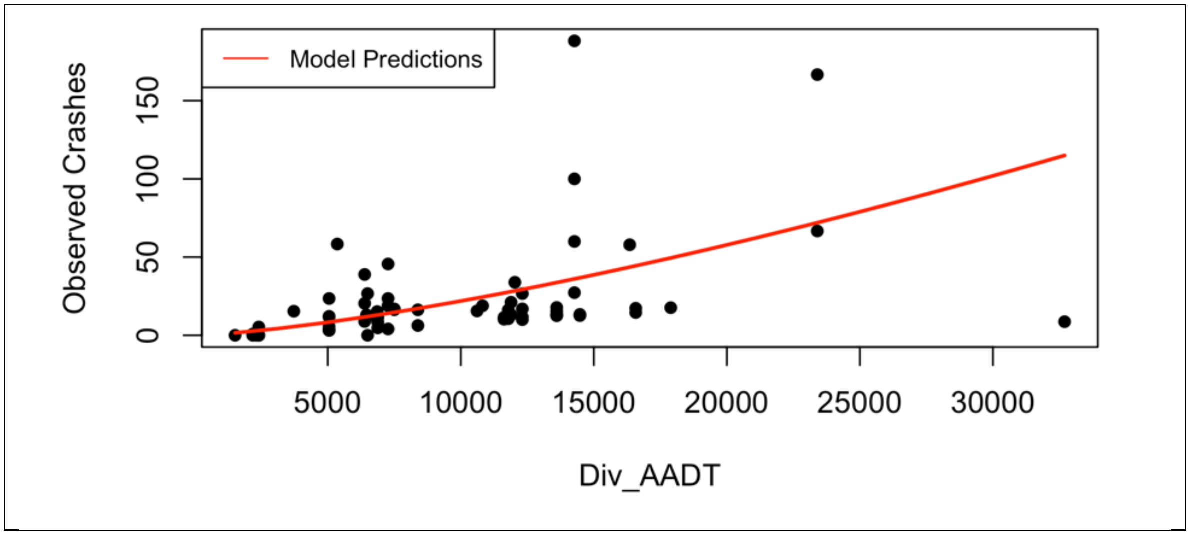


(b)

Figure A.24 Divided Unprotected Urban 2 Lanes Interstate*† (a) CURE plot and (b) observed vs. predicted plot.

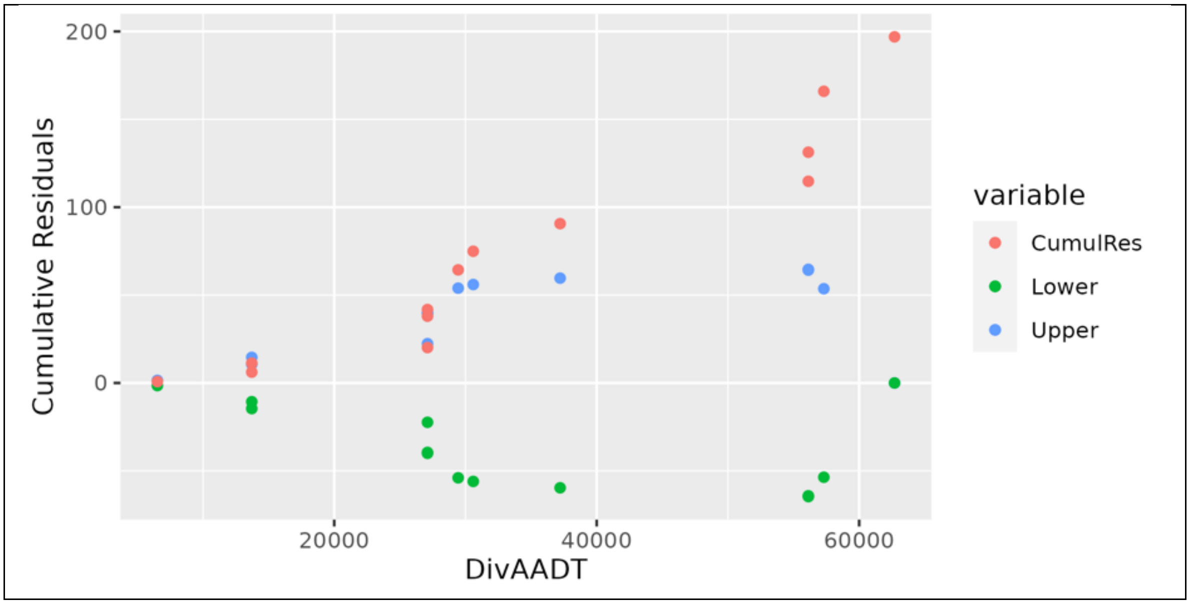


(a)

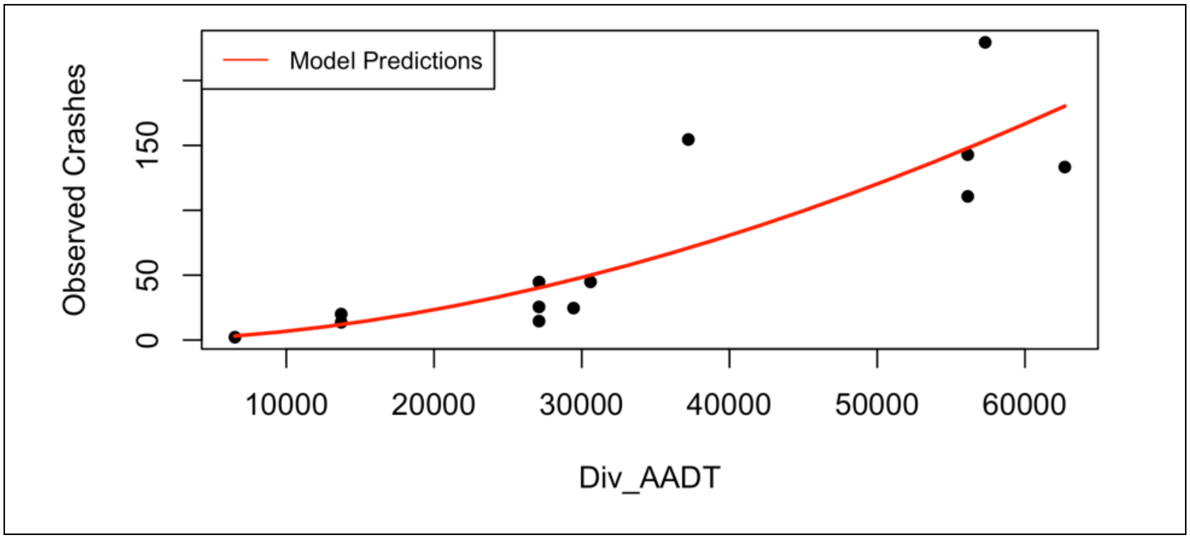


(b)

Figure A.25 Divided Unprotected Urban 2 Lanes Non-Interstate*† (a) CURE plot and (b) observed vs. predicted plot.

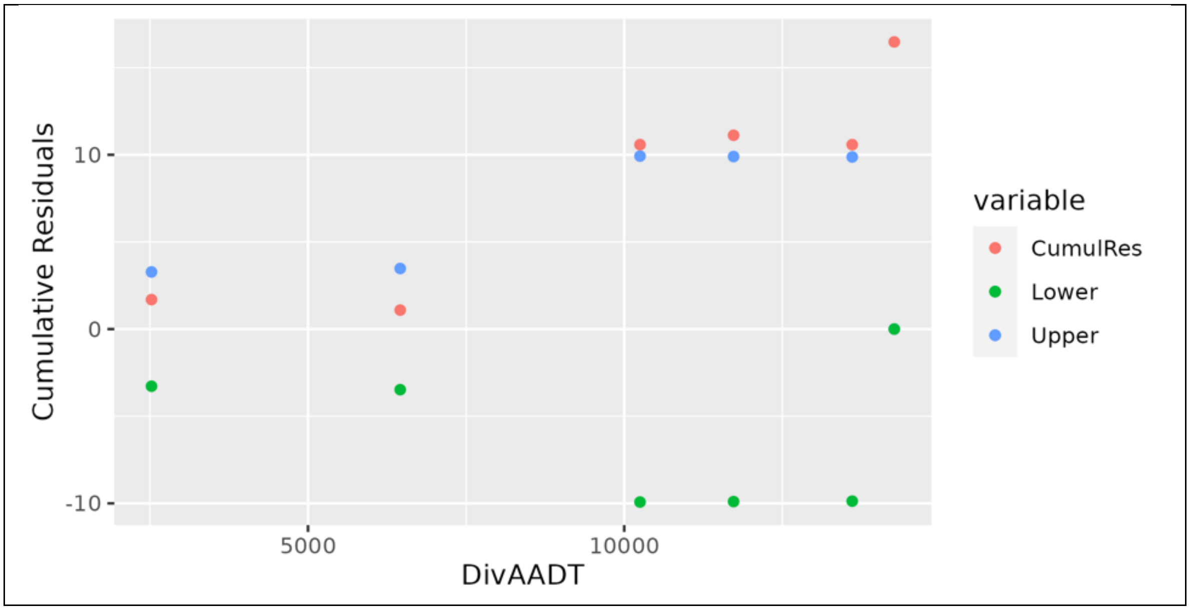


(a)

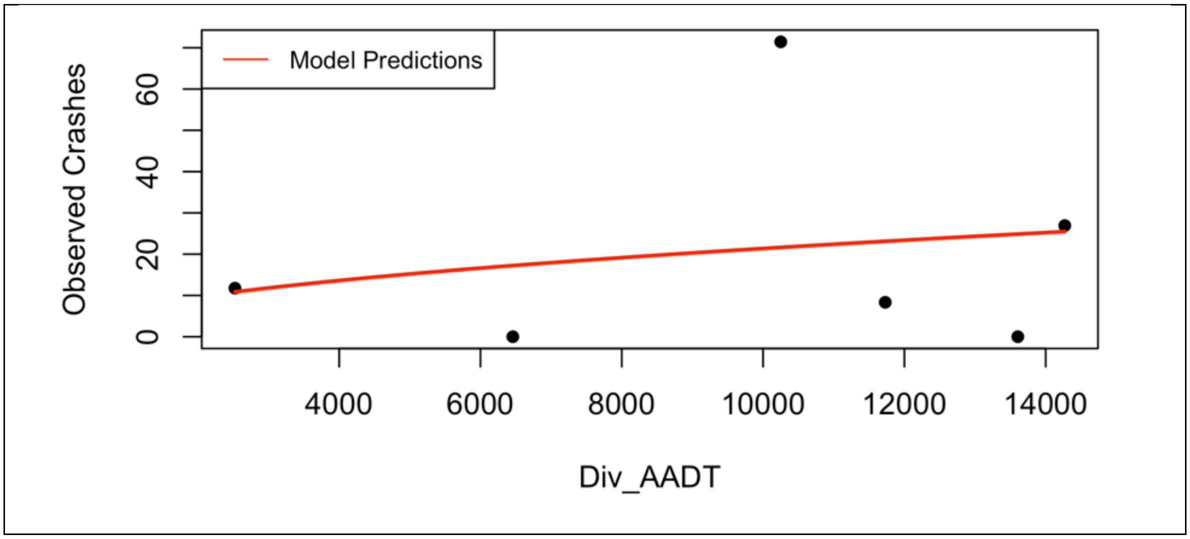


(b)

Figure A.26 Divided Unprotected Urban 3 Lanes Interstate* (a) CURE plot and (b) observed vs. predicted plot.

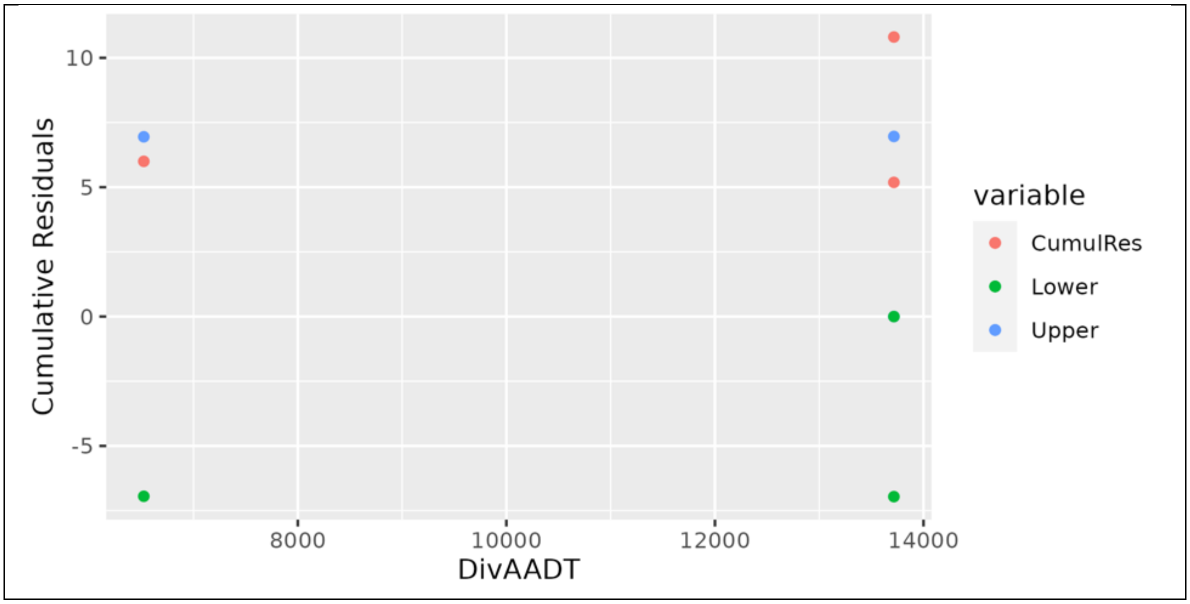


(a)



(b)

Figure A.27 Divided Unprotected Urban 3 Lanes Non-Interstate* (a) CURE plot and (b) observed vs. predicted plot.



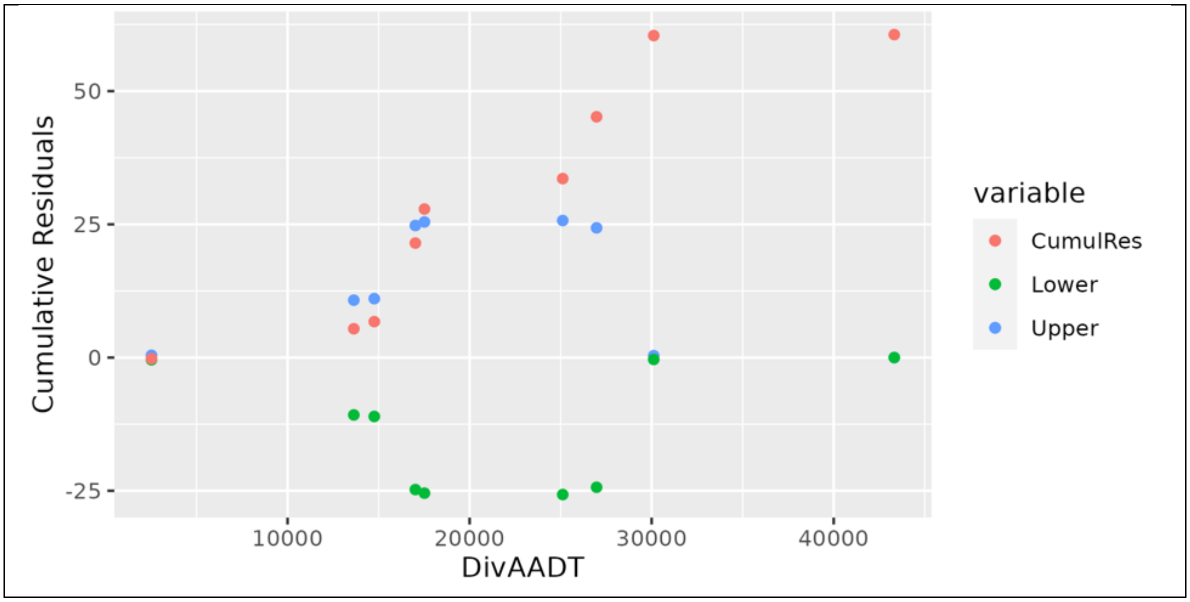
(a)

Insufficient Data

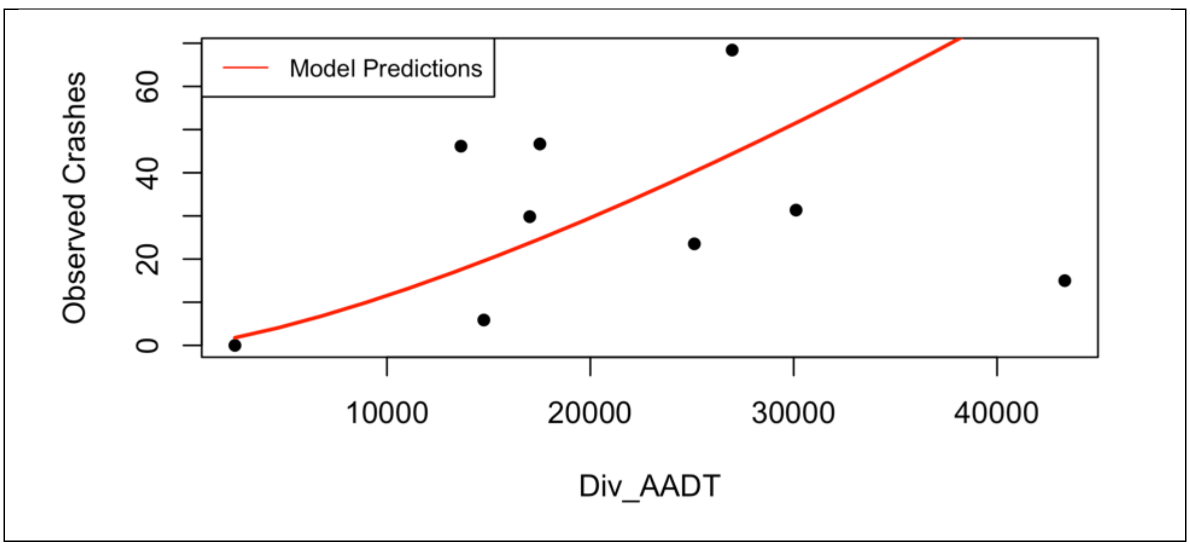
No Observed vs. Predicted Plot Available

(b)

Figure A.28 Divided Unprotected Urban 4 Lanes Interstate* (a) CURE plot and (b) observed vs. predicted plot.

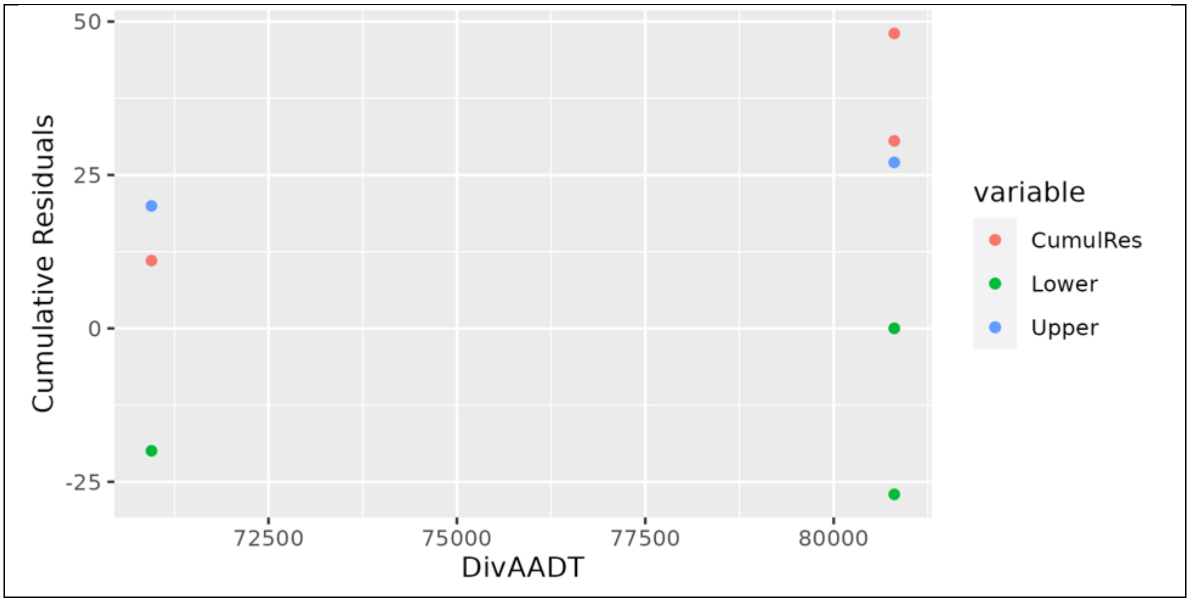


(a)

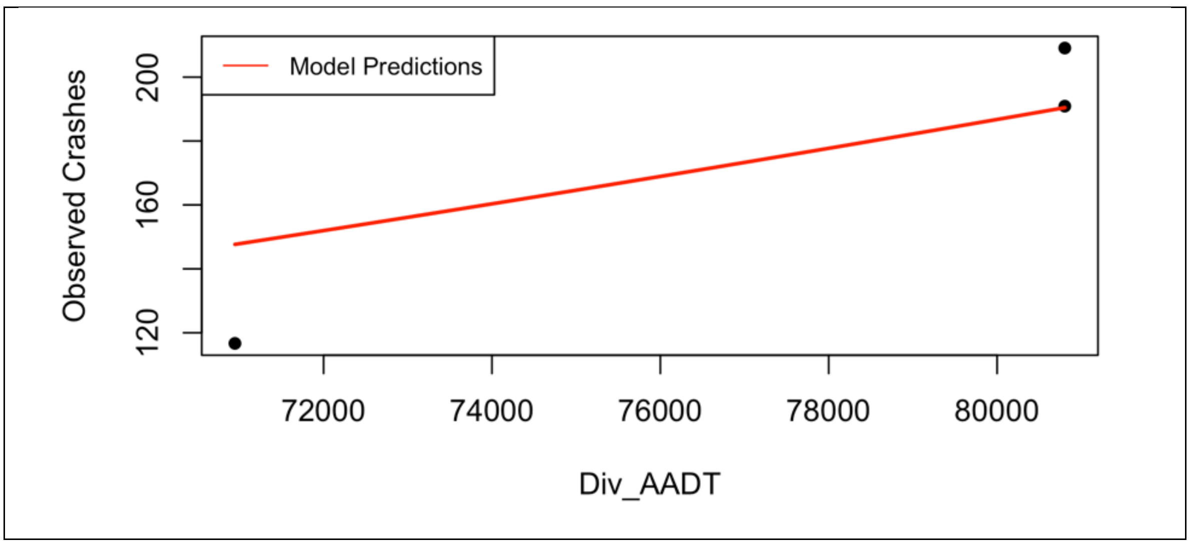


(b)

Figure A.29 Divided Unprotected Urban 4 Lanes Non-Interstate* (a) CURE plot and (b) observed vs. predicted plot.



(a)



(b)

Figure A.30 Divided Unprotected Urban 5 Lanes + HOV Interstate *(a) CURE plot and (b) observed vs. predicted plot.

Insufficient Data

No CURE Plot Available

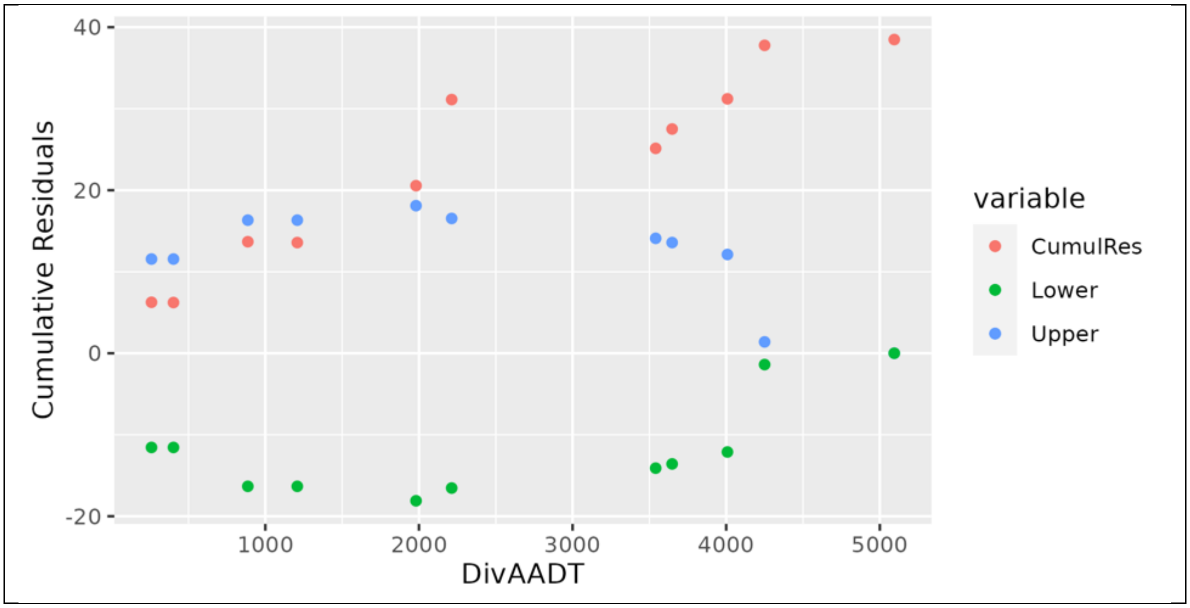
(a)

Insufficient Data

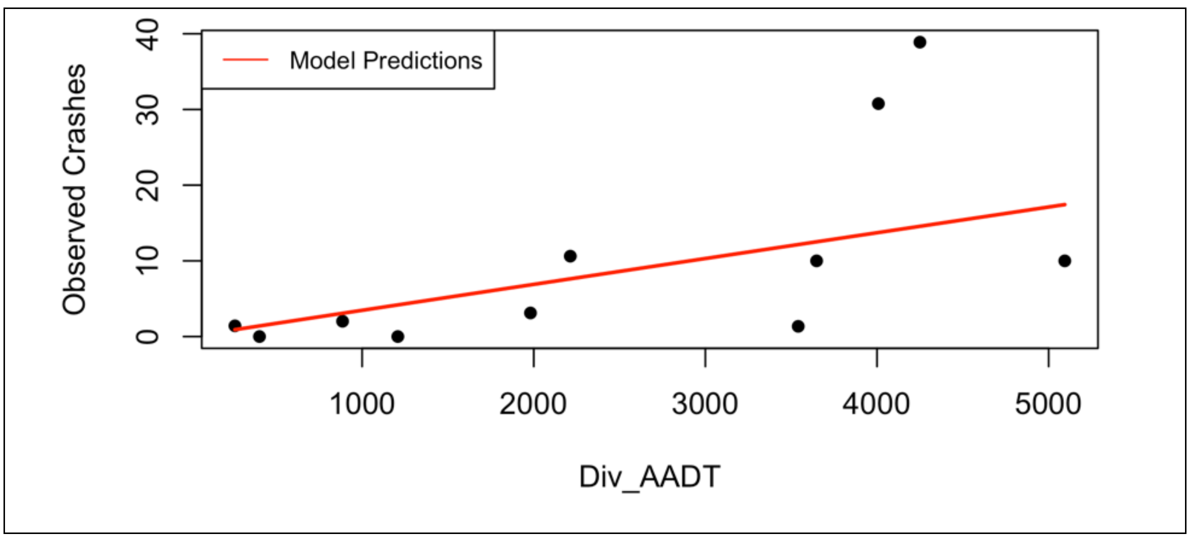
No Observed vs. Predicted Plot Available

(b)

Figure A.31 No Median/Undivided Rural 1 Lanes + 1 Passing Non-Interstate* (a) CURE plot and (b) observed vs. predicted plot.

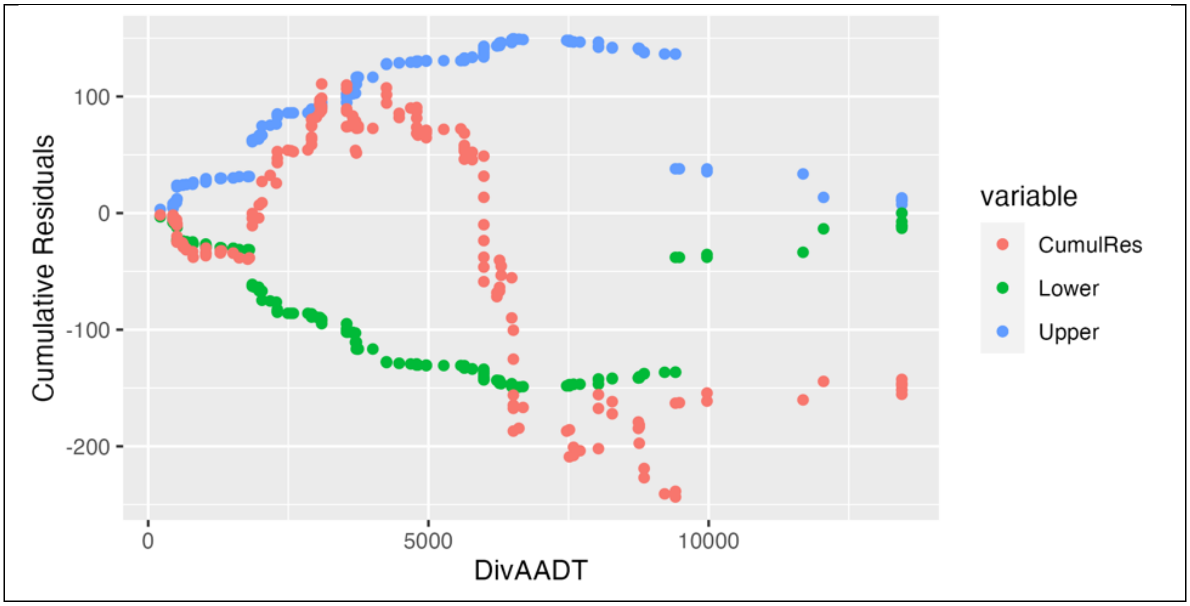


(a)

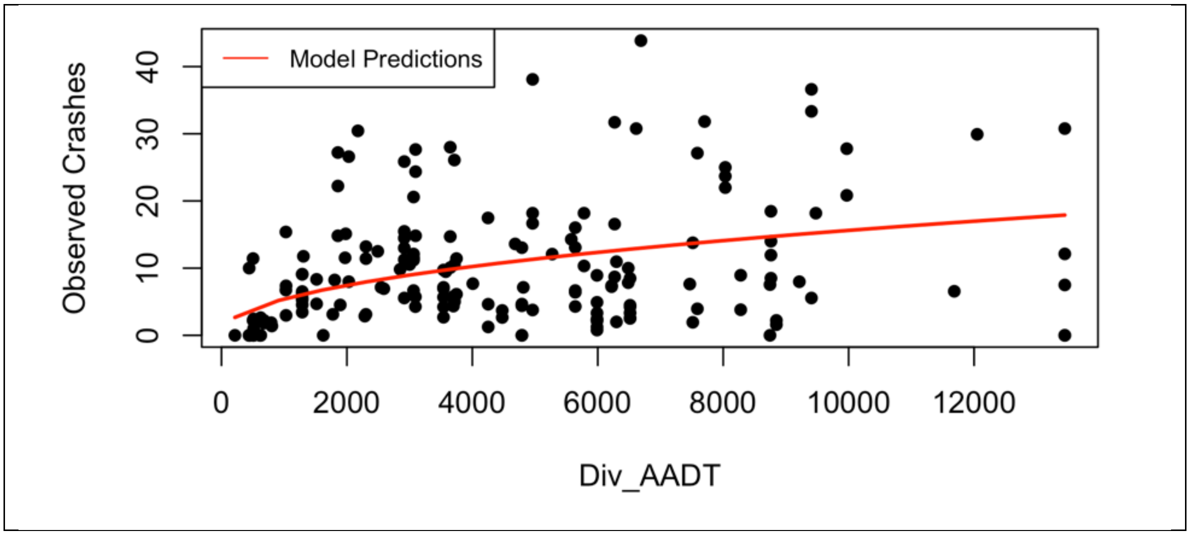


(b)

Figure A.32 No Median/Undivided Rural 1 Lanes Non-Interstate* (a) CURE plot and (b) observed vs. predicted plot.

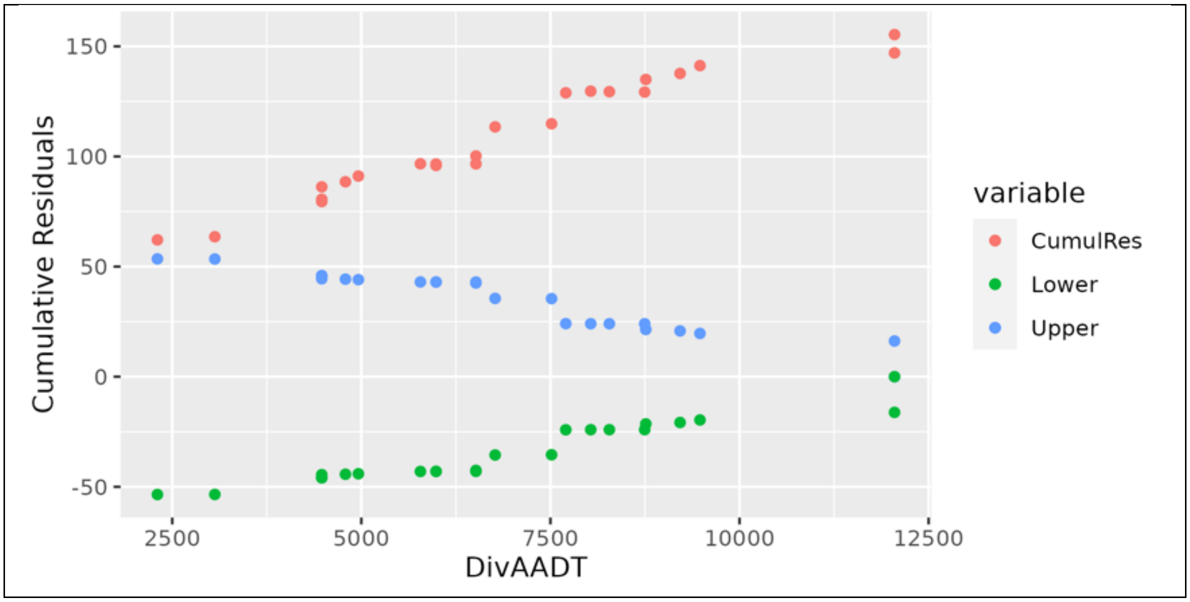


(a)

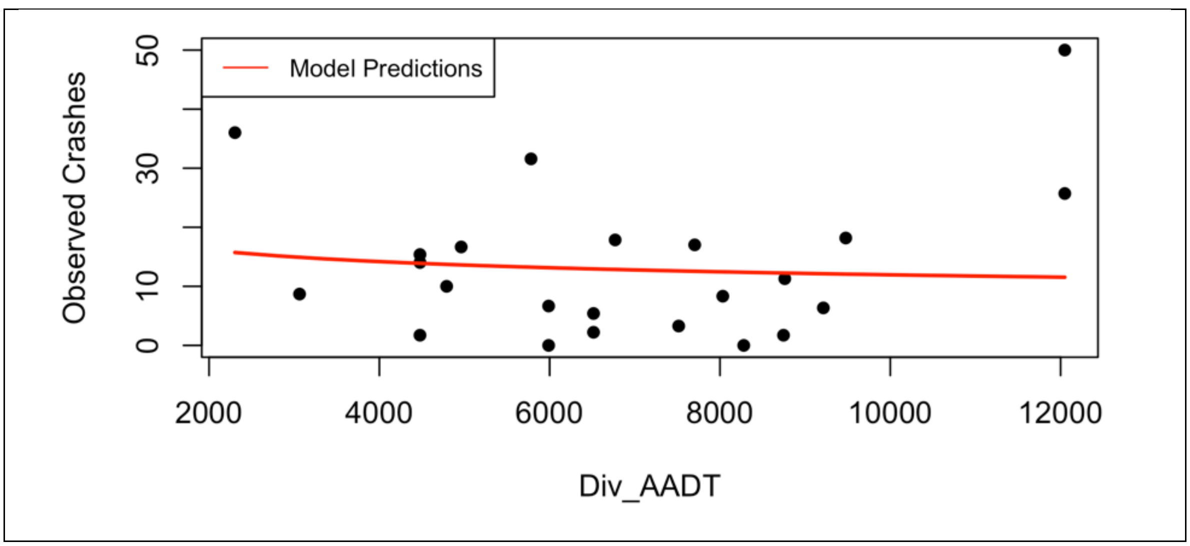


(b)

Figure A.33 No Median/Undivided Rural 2 Lanes + 1 Passing Non-Interstate (a) CURE plot and (b) observed vs. predicted plot.

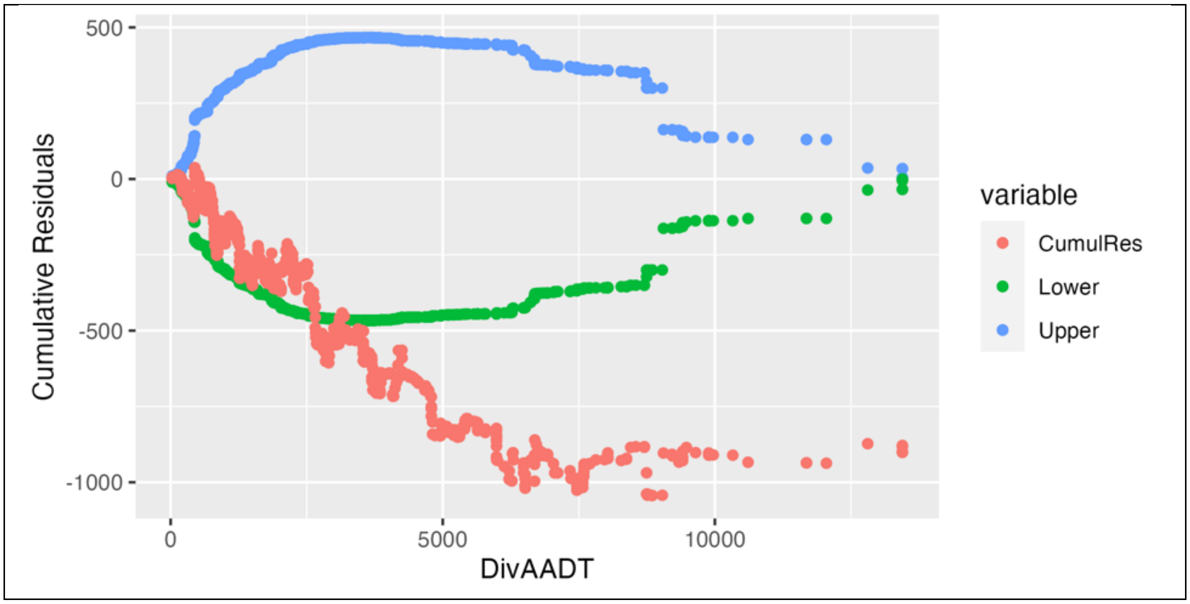


(a)

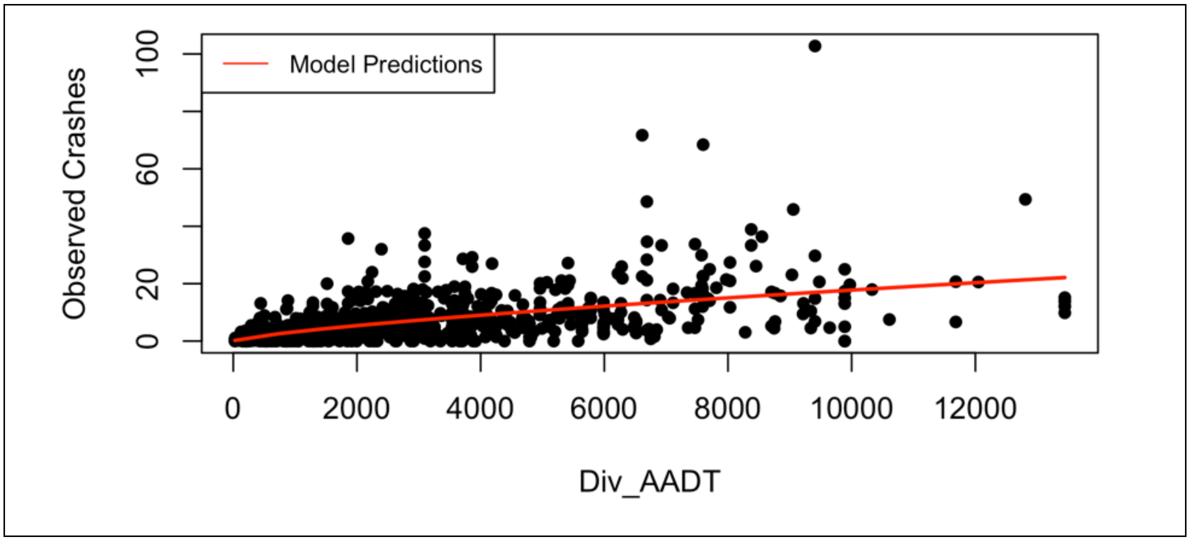


(b)

Figure A.34 No Median/Undivided Rural 2 Lanes + 2 Passing Non-Interstate* (a) CURE plot and (b) observed vs. predicted plot.

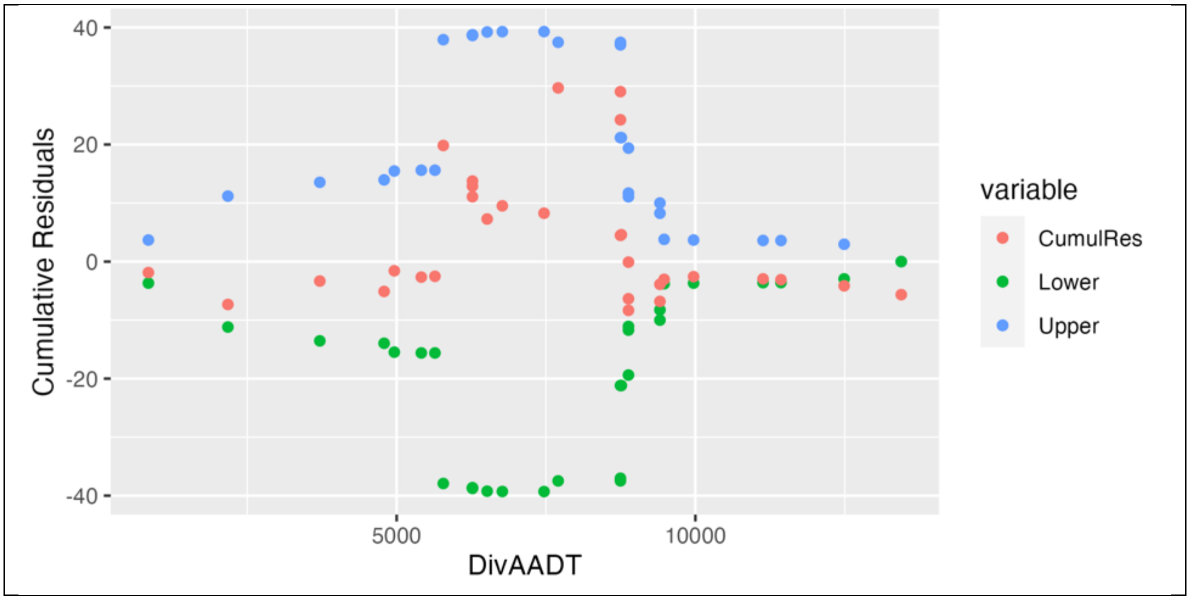


(a)

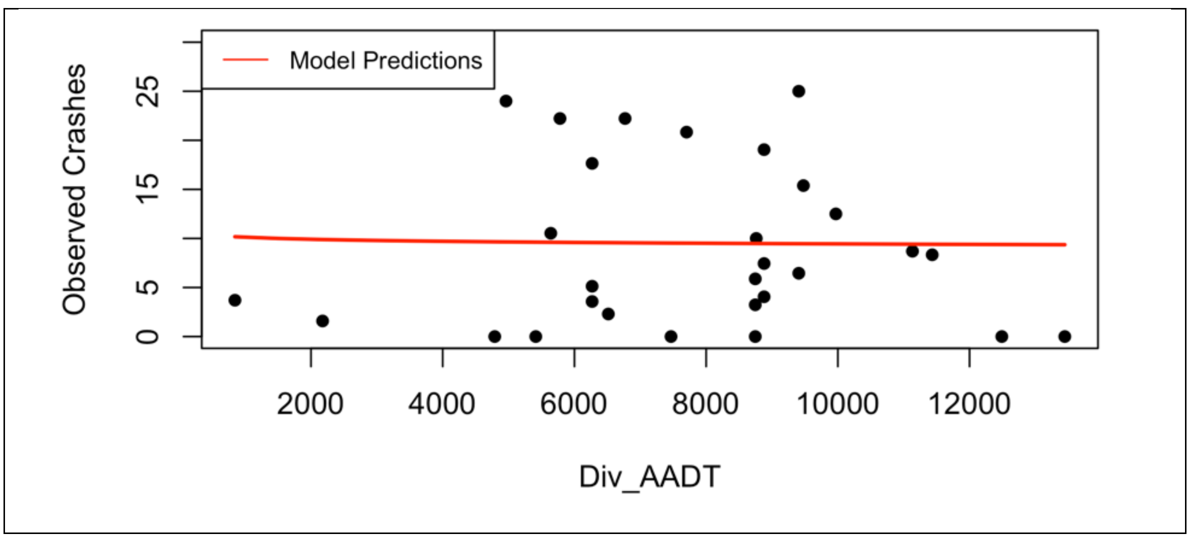


(b)

Figure A.35 No Median/Undivided Rural 2 Lanes Non-Interstate*† (a) CURE plot and (b) observed vs. predicted plot.

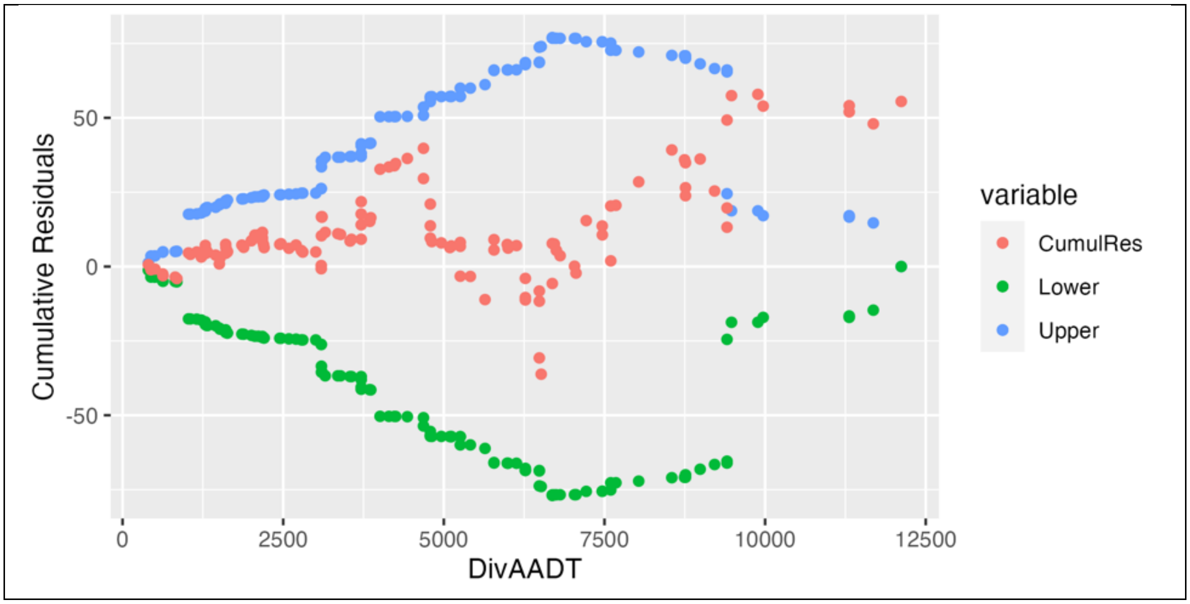


(a)

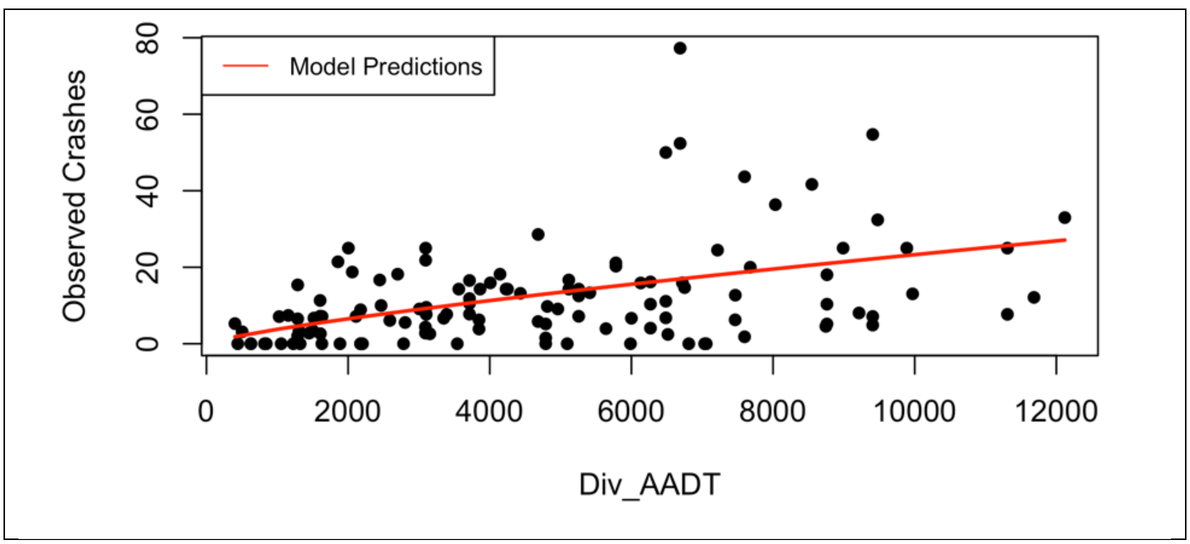


(b)

Figure A.36 No Median/Undivided Rural 3 Lanes + 1 Passing Non-Interstate† (a) CURE plot and (b) observed vs. predicted plot.

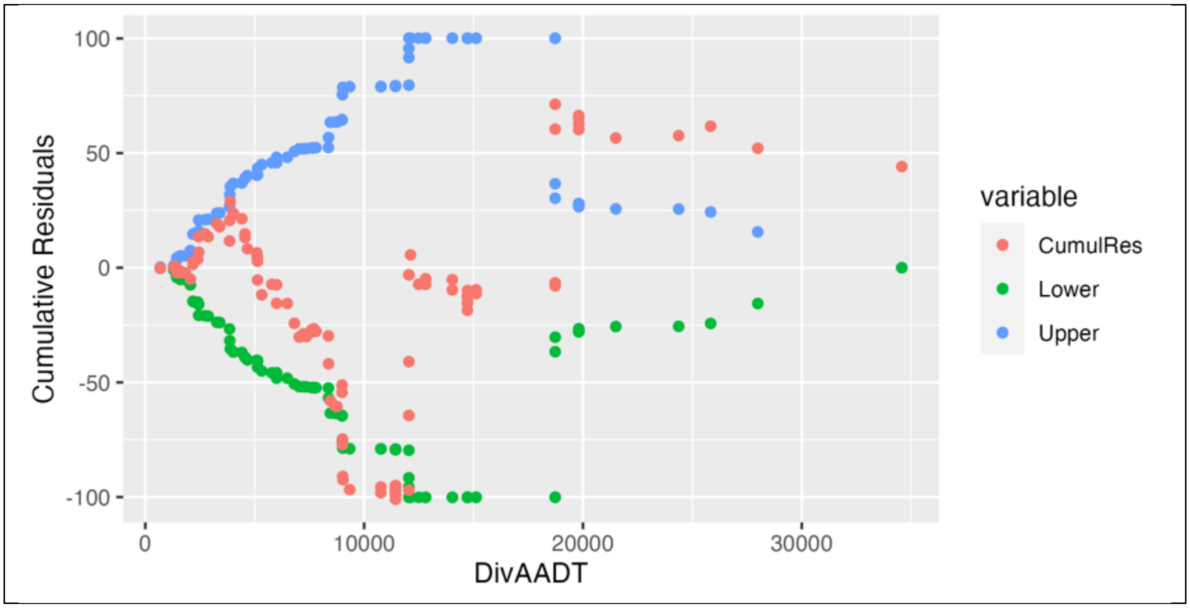


(a)

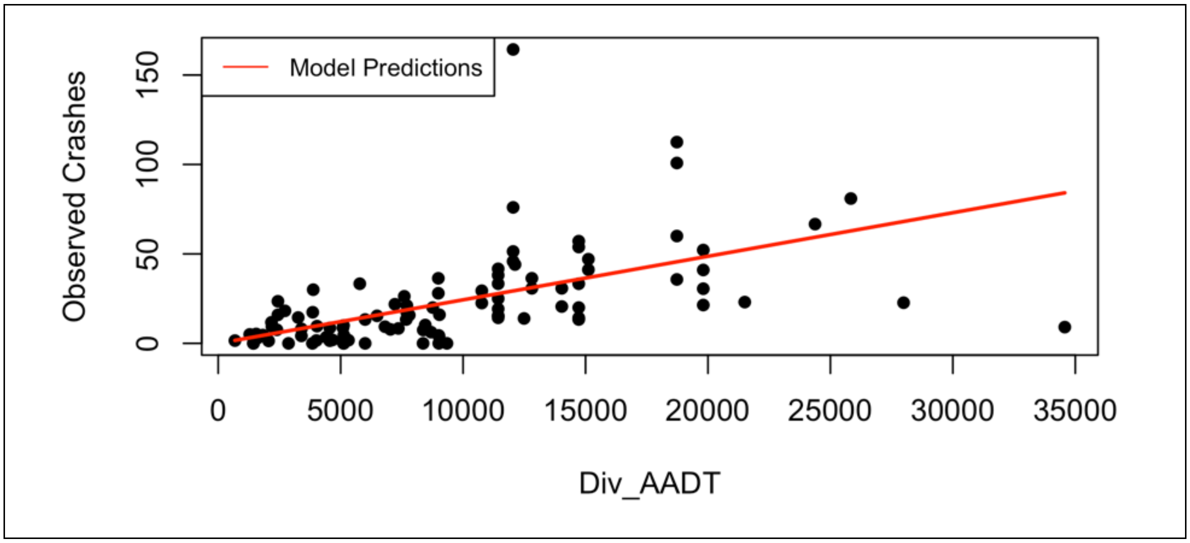


(b)

Figure A.37 No Median/Undivided Rural 3 Lanes Non-Interstate (a) CURE plot and (b) observed vs. predicted plot.



(a)



(b)

Figure A.38 No Median/Undivided Rural 4 Lanes Non-Interstate† (a) CURE plot and (b) observed vs. predicted plot.

Insufficient Data

No CURE Plot Available

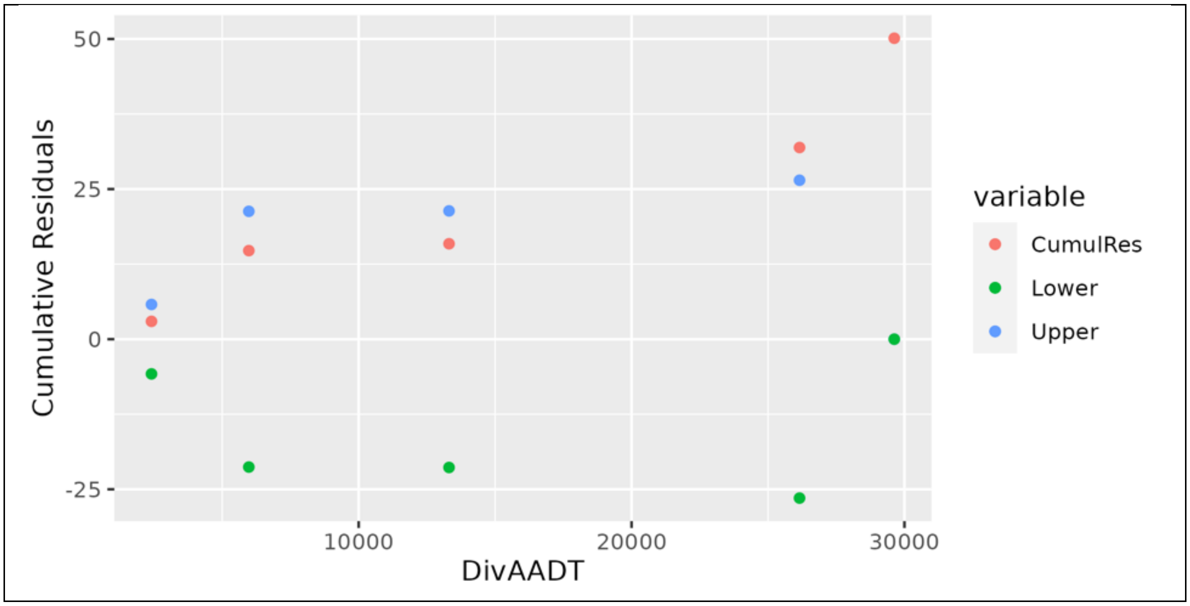
(a)

Insufficient Data

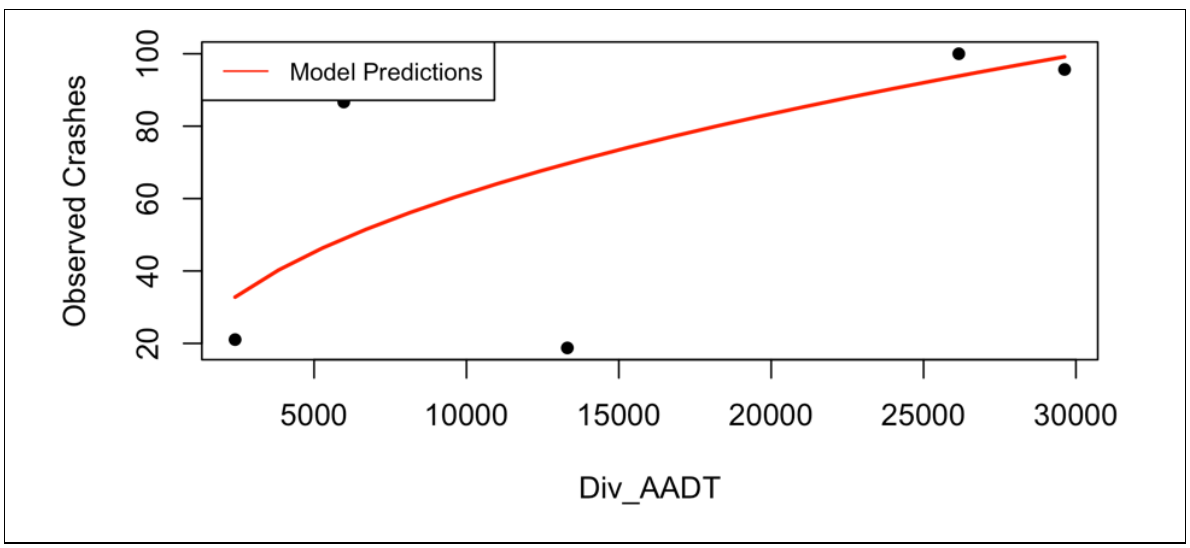
No Observed vs. Predicted Plot Available

(b)

Figure A.39 No Median/Undivided Rural 5 Lanes Non-Interstate* (a) CURE plot and (b) observed vs. predicted plot.

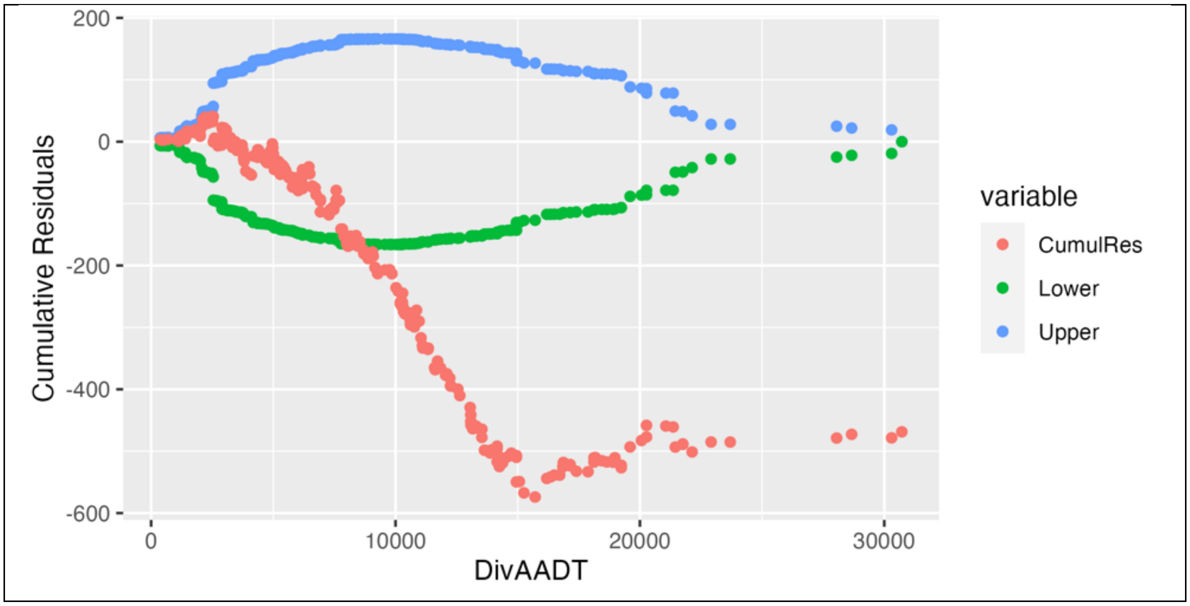


(a)

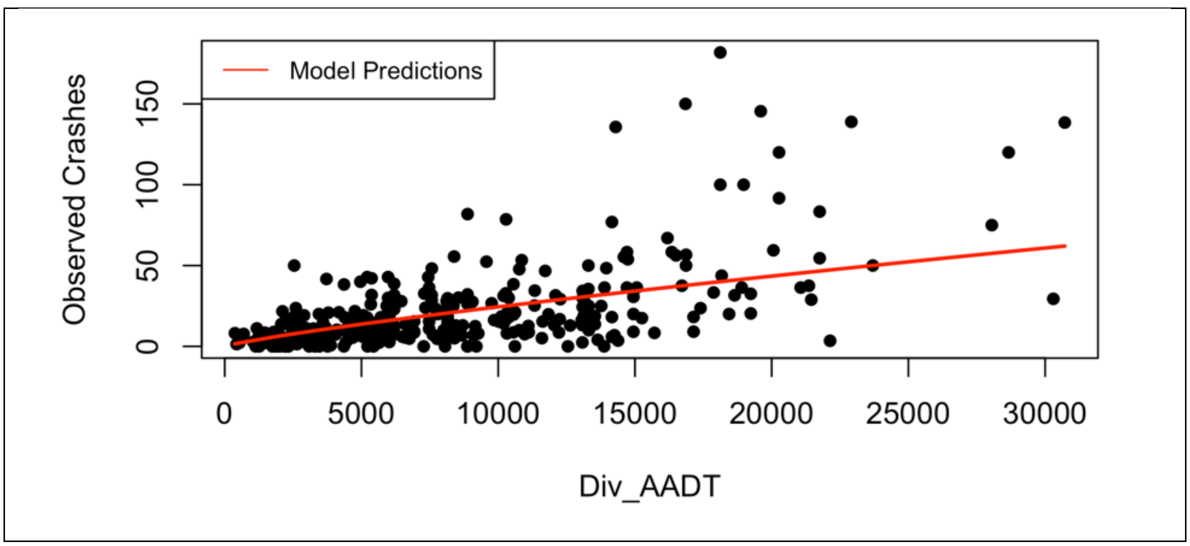


(b)

Figure A.40 No Median/Undivided Urban 1 Lanes Non-Interstate* (a) CURE plot and (b) observed vs. predicted plot.

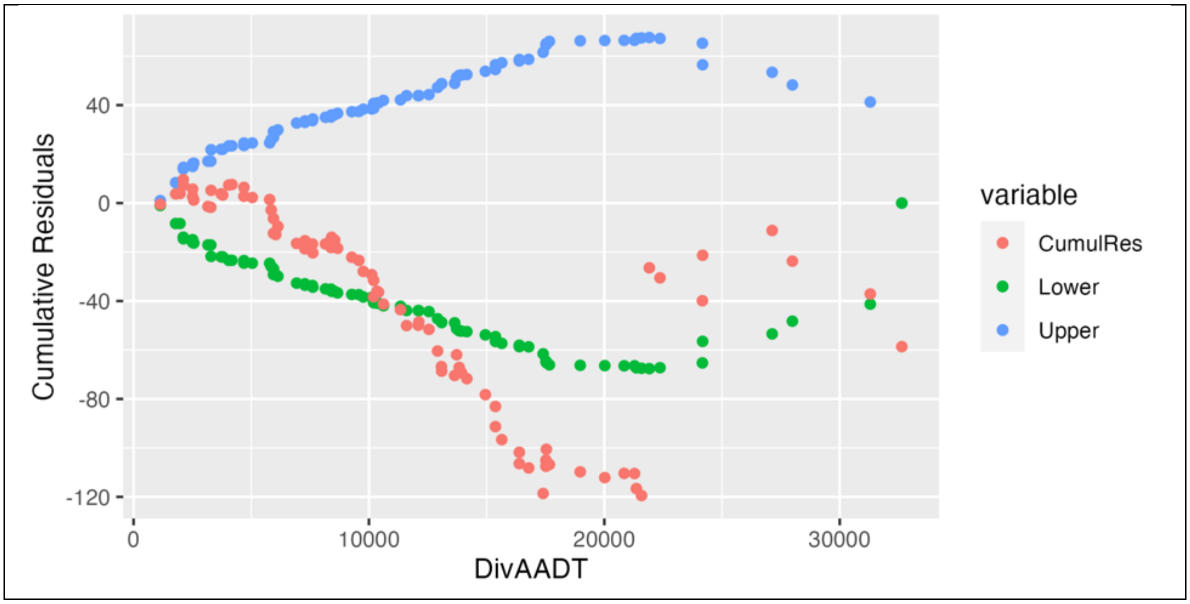


(a)

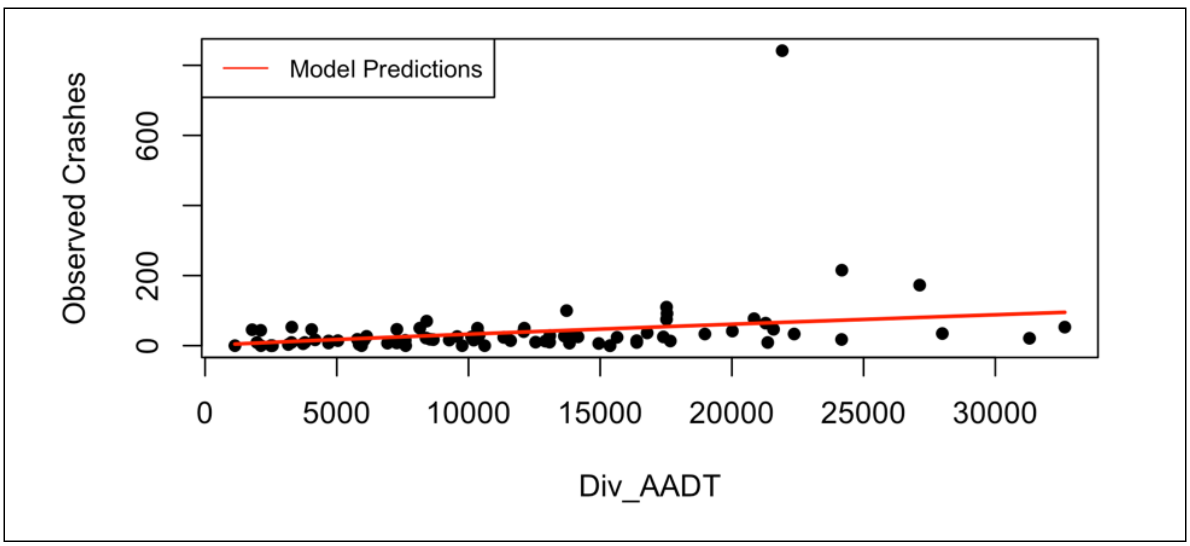


(b)

Figure A.41 No Median/Undivided Urban 2 Lanes Non-Interstate*† (a) CURE plot and (b) observed vs. predicted plot.

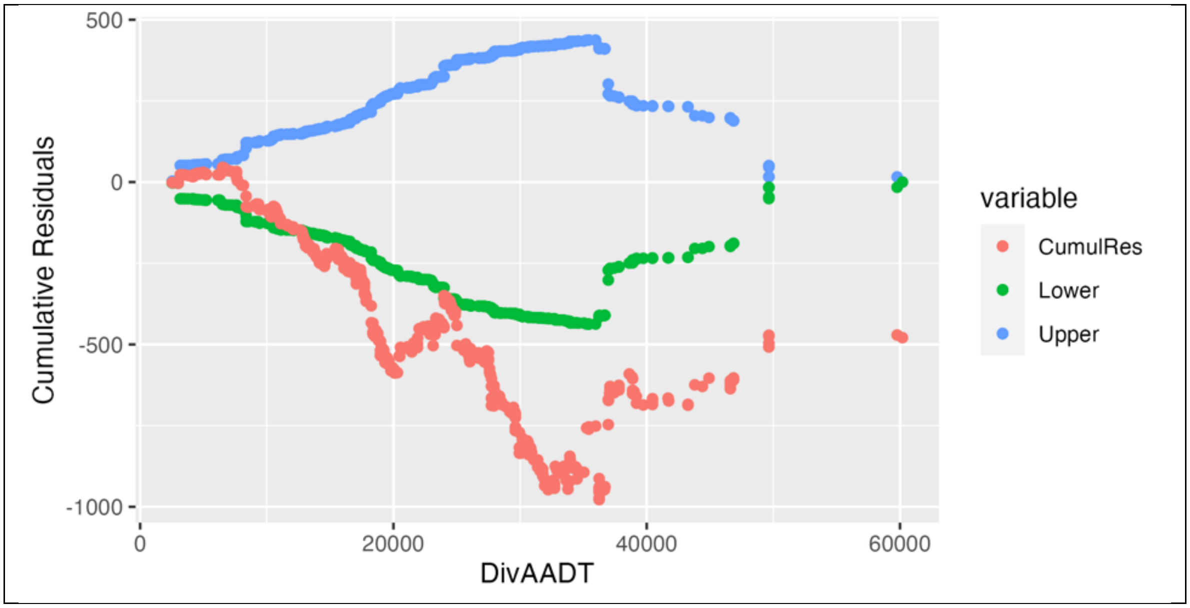


(a)

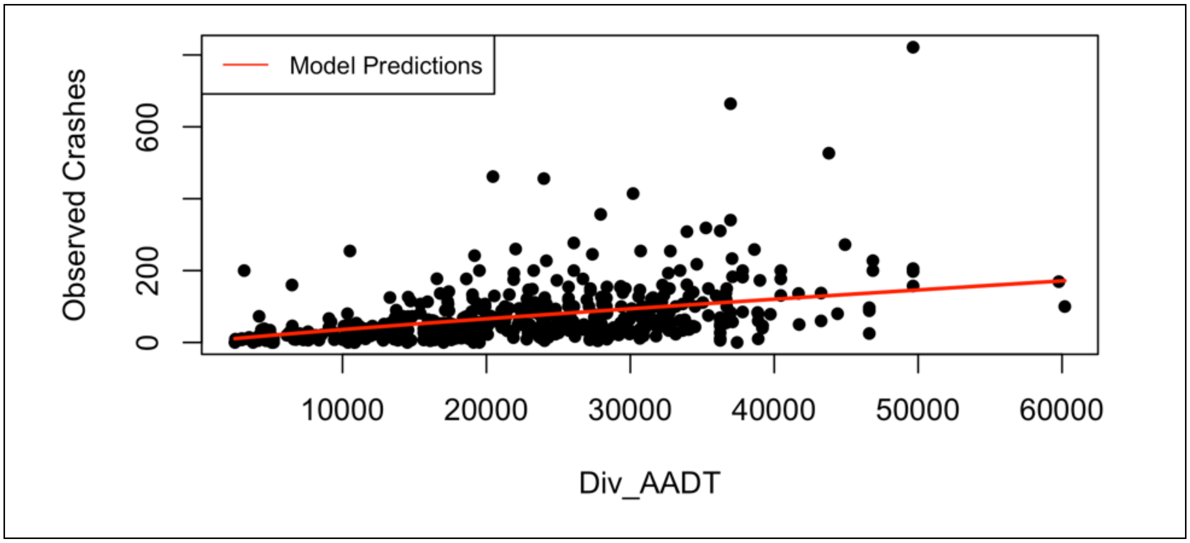


(b)

Figure A.42 No Median/Undivided Urban 3 Lanes Non-Interstate*† (a) CURE plot and (b) observed vs. predicted plot.

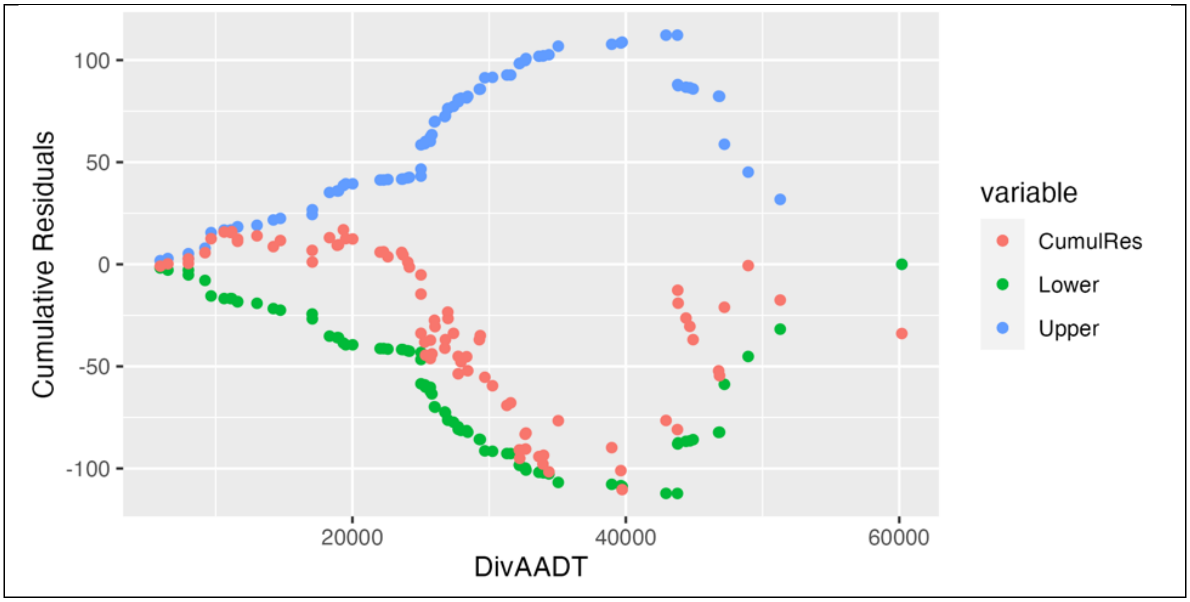


(a)

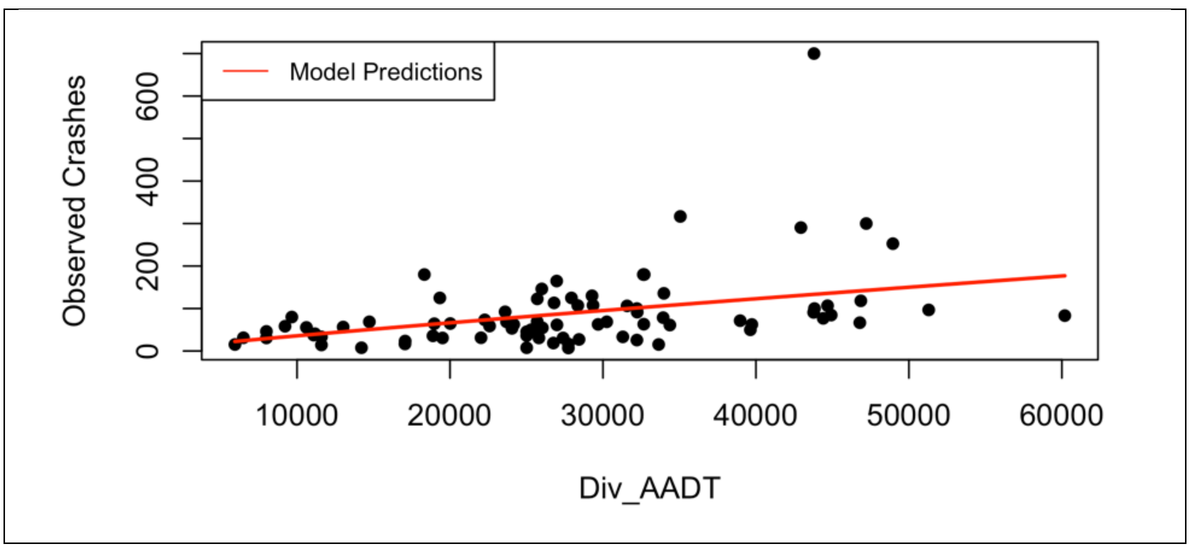


(b)

Figure A.43 No Median/Undivided Urban 4 Lanes Non-Interstate* (a) CURE plot and (b) observed vs. predicted plot.

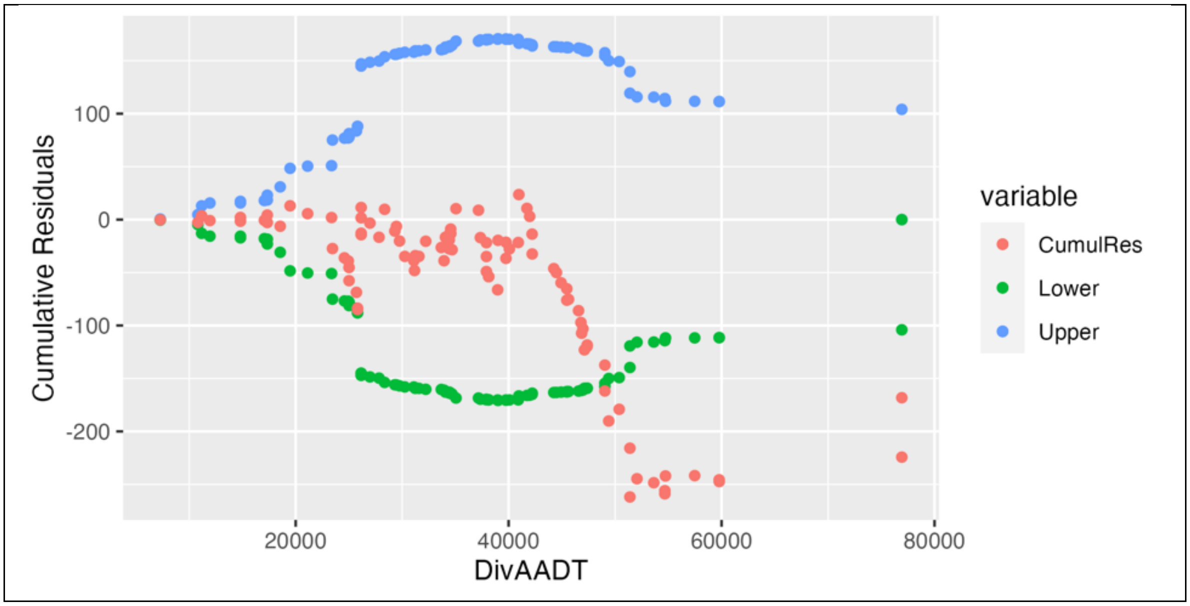


(a)

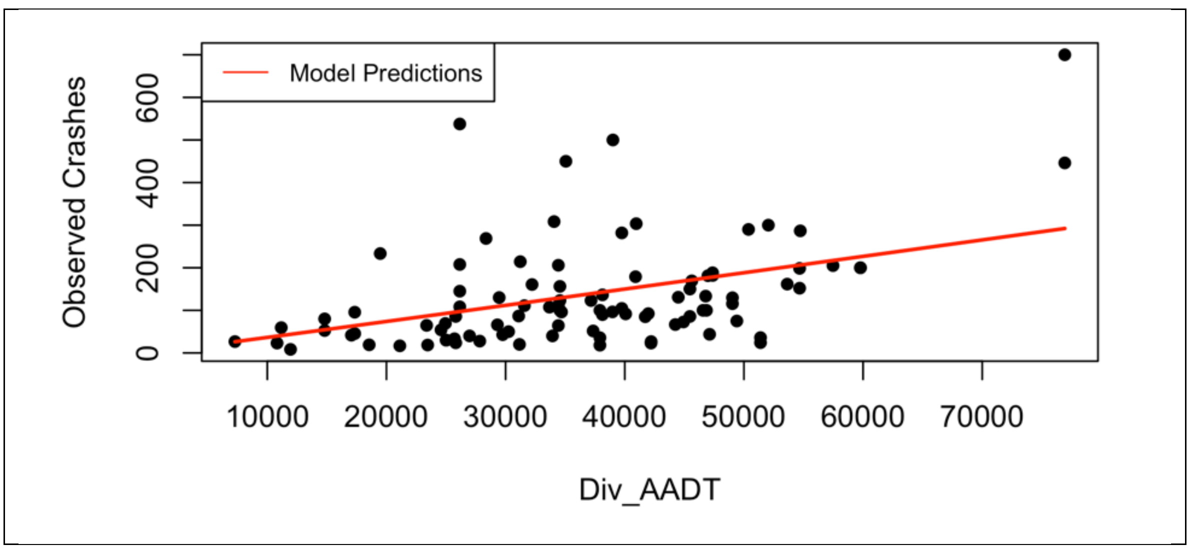


(b)

Figure A.44 No Median/Undivided Urban 5 Lanes Non-Interstate (a) CURE plot and (b) observed vs. predicted plot.

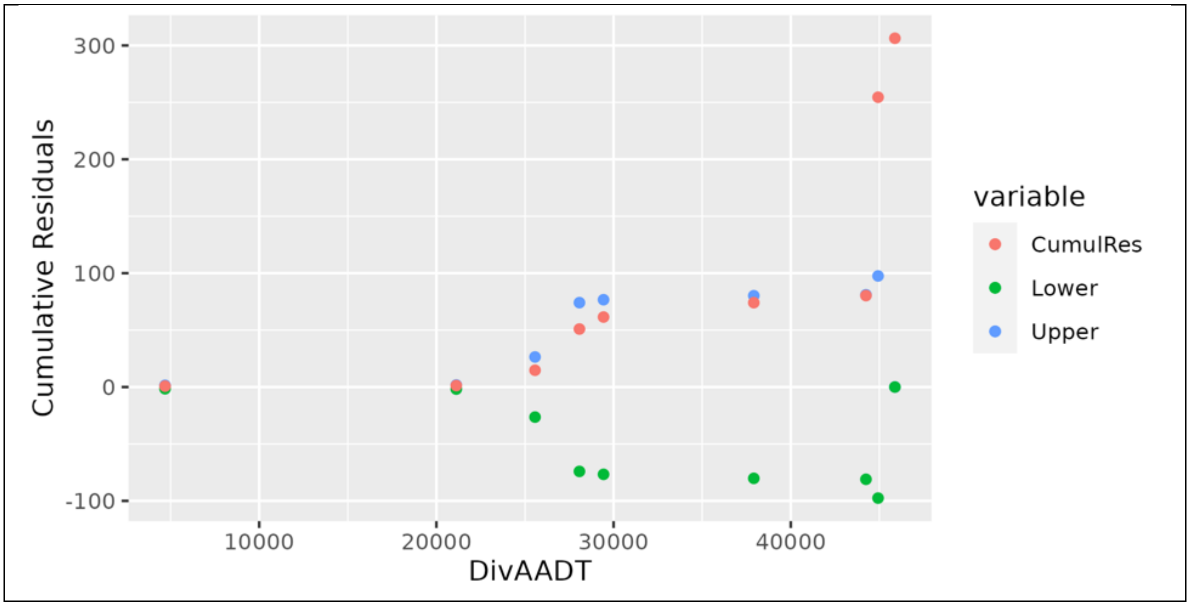


(a)

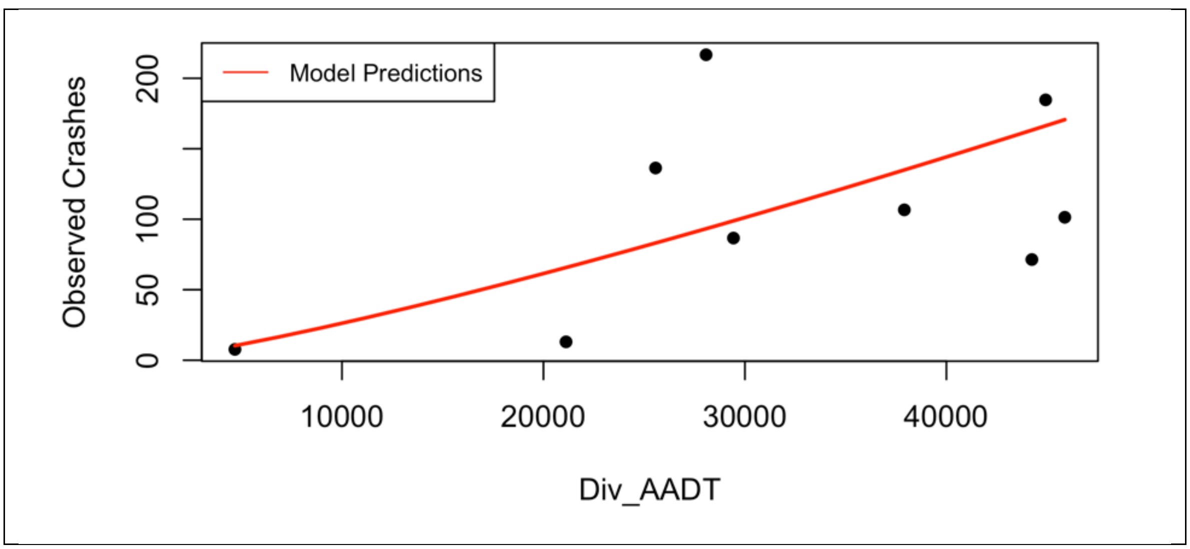


(b)

Figure A.45 No Median/Undivided Urban 6 Lanes Non-Interstate*† (a) CURE plot and (b) observed vs. predicted plot.

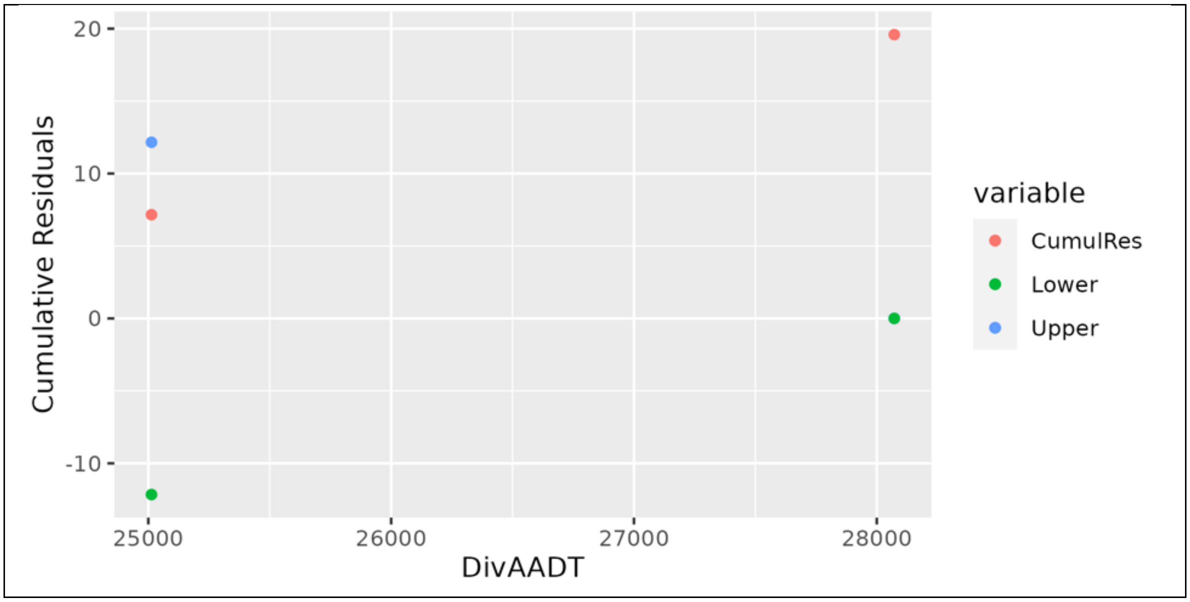


(a)

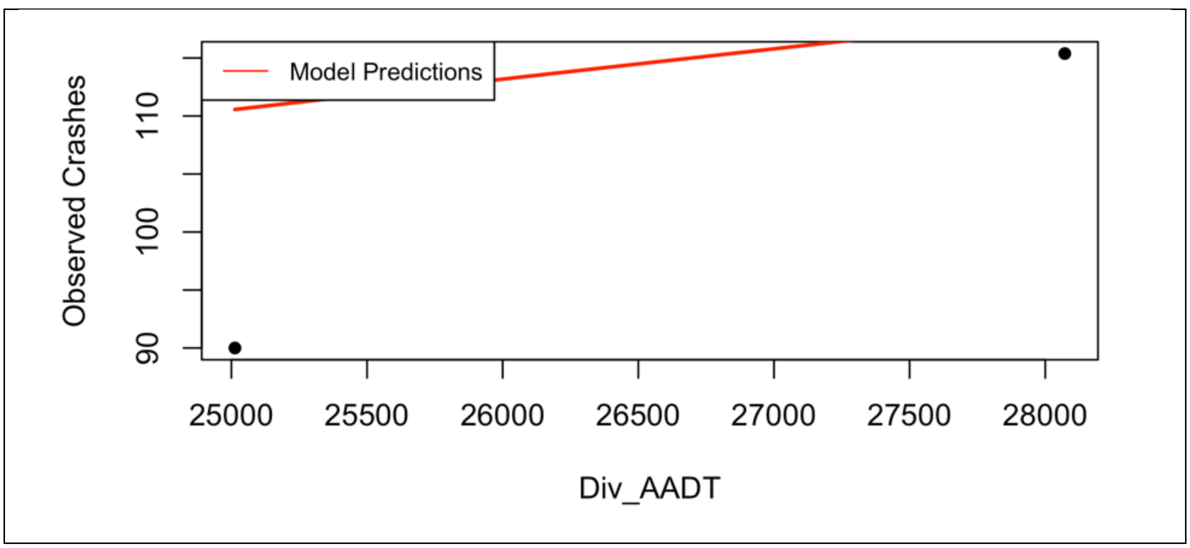


(b)

Figure A.46 No Median/Undivided Urban 7 Lanes Non-Interstate (a) CURE plot and (b) observed vs. predicted plot.

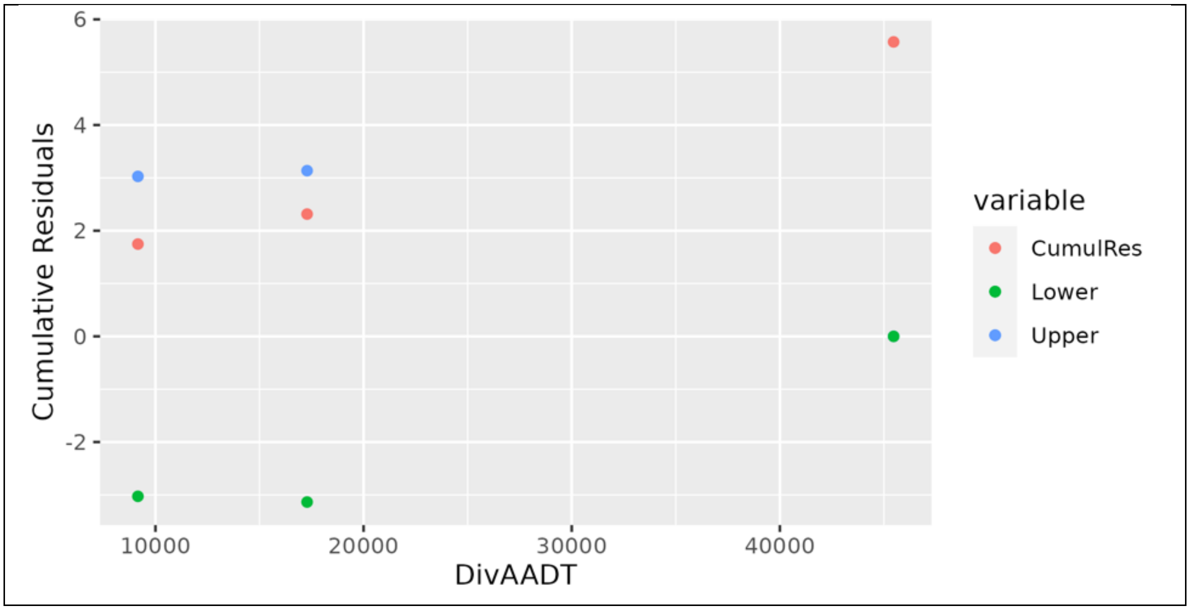


(a)

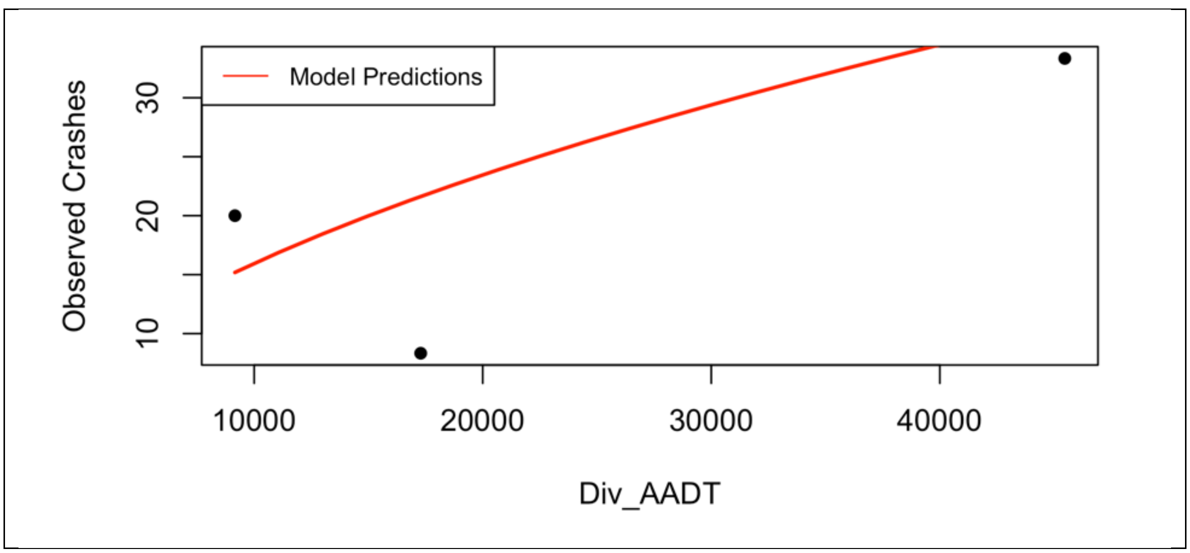


(b)

Figure A.47 No Median/Undivided Urban 9 Lanes Non-Interstate* (a) CURE plot and (b) observed vs. predicted plot.

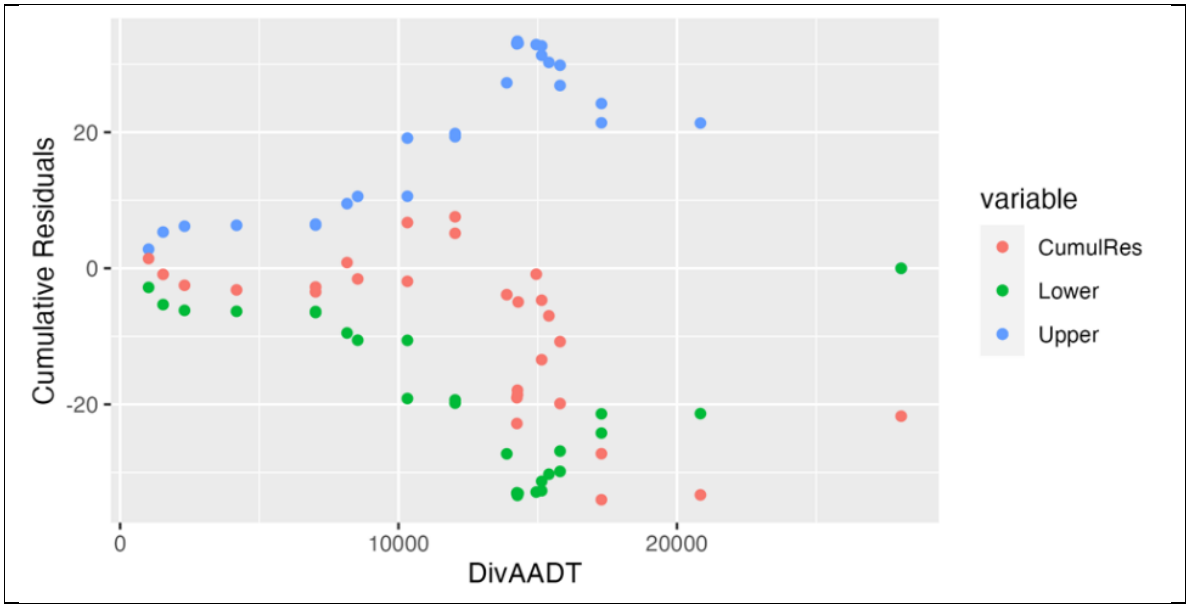


(a)

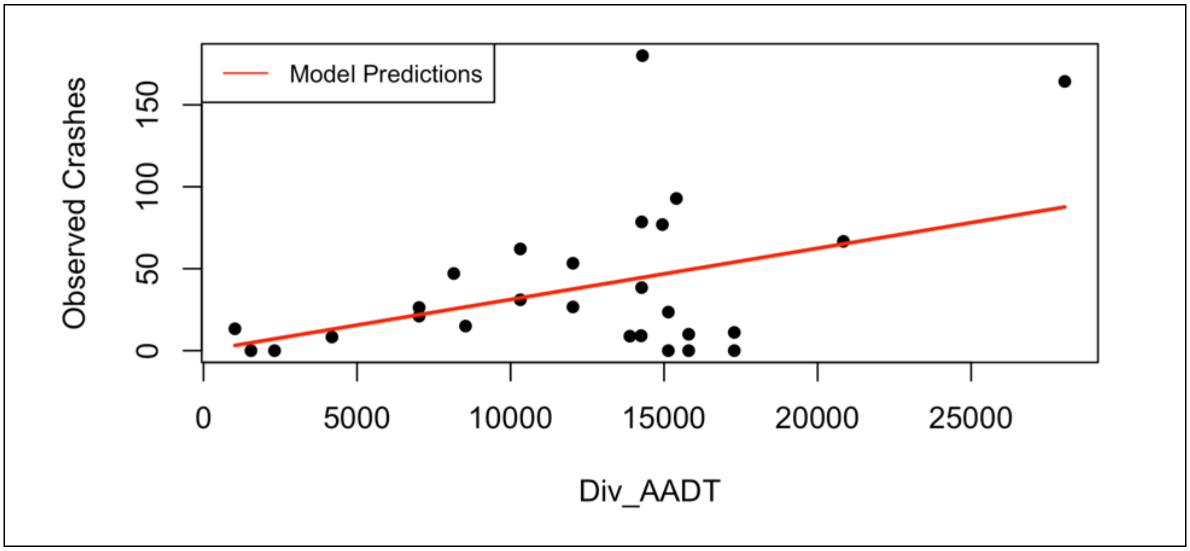


(b)

Figure A.48 Raised Median Urban 1 Lanes Non-Interstate* (a) CURE plot and (b) observed vs. predicted plot.

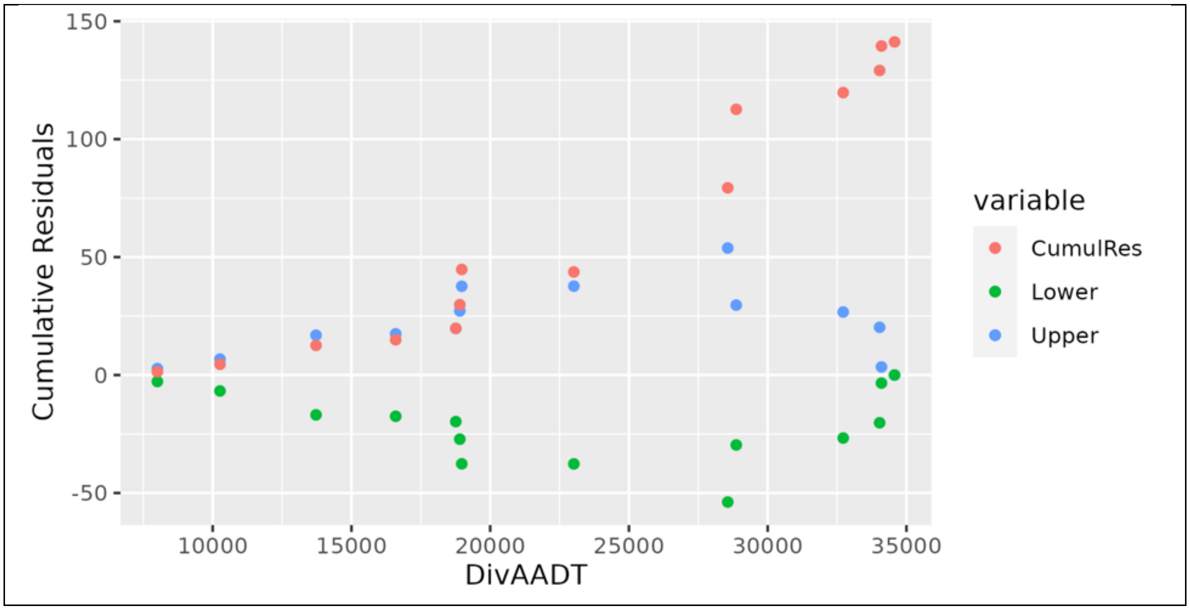


(a)

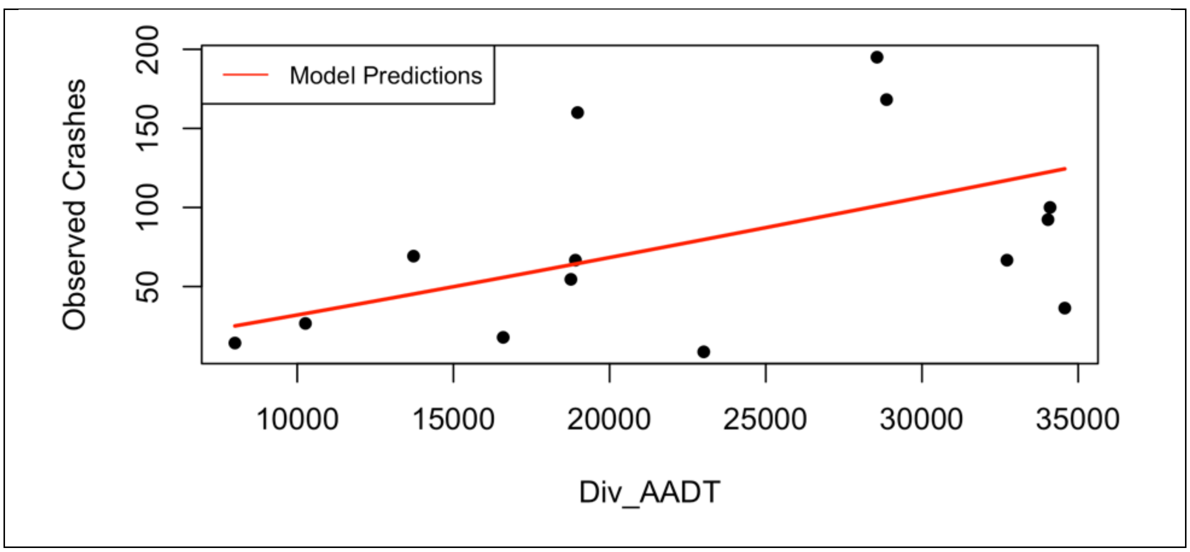


(b)

Figure A.49 Raised Median Urban 2 Lanes Non-Interstate† (a) CURE plot and (b) observed vs. predicted plot.



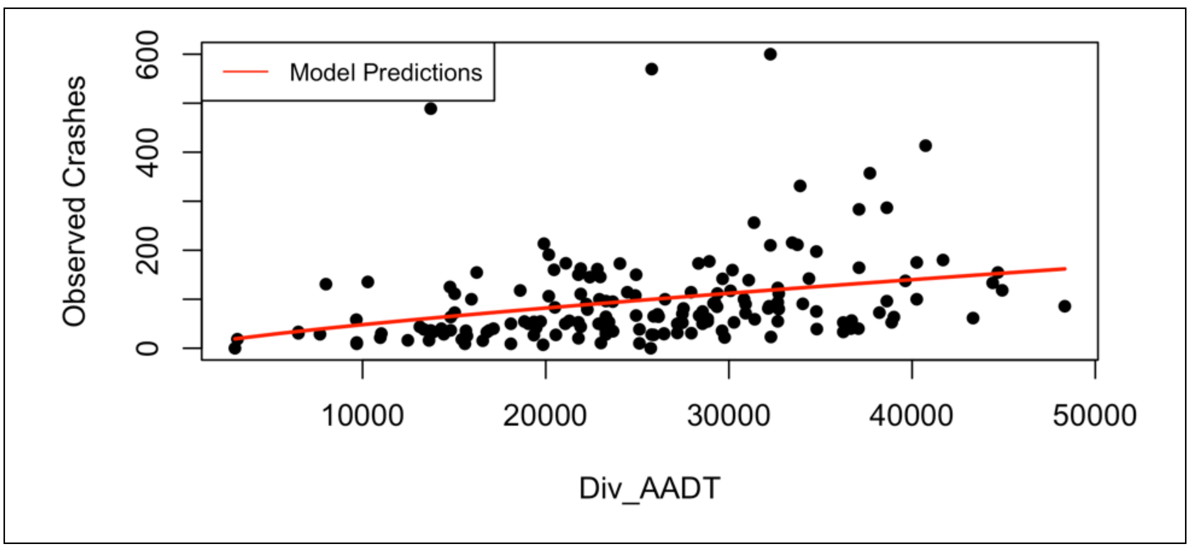
(a)



(b)

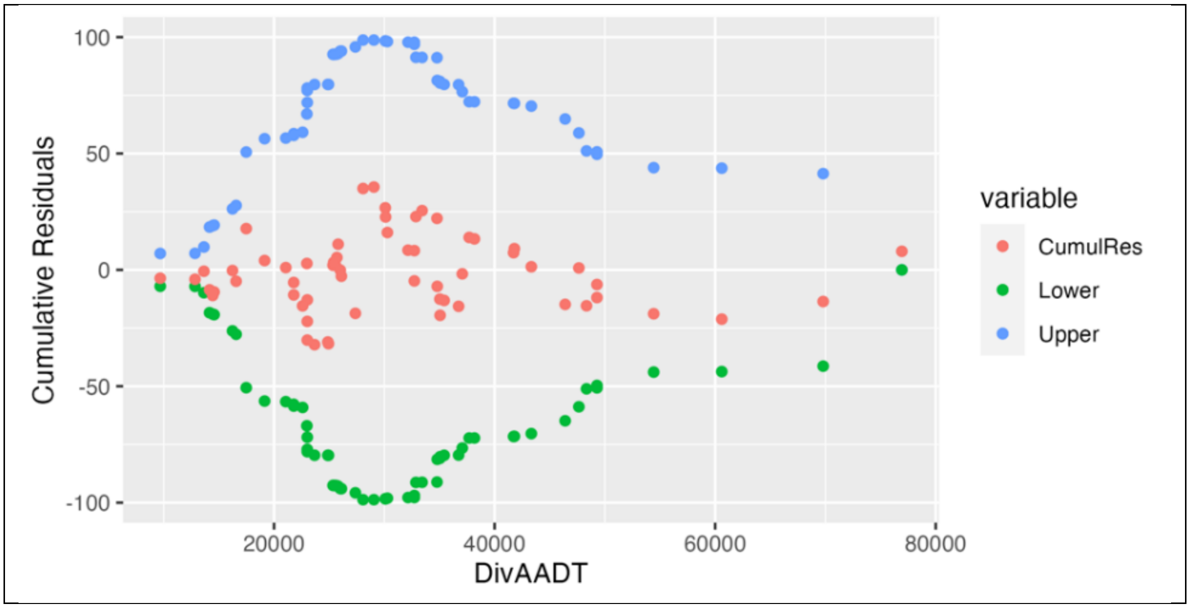
Figure A.50 Raised Median Urban 3 Lanes Non-Interstate* (a) CURE plot and (b) observed vs. predicted plot.

(a)

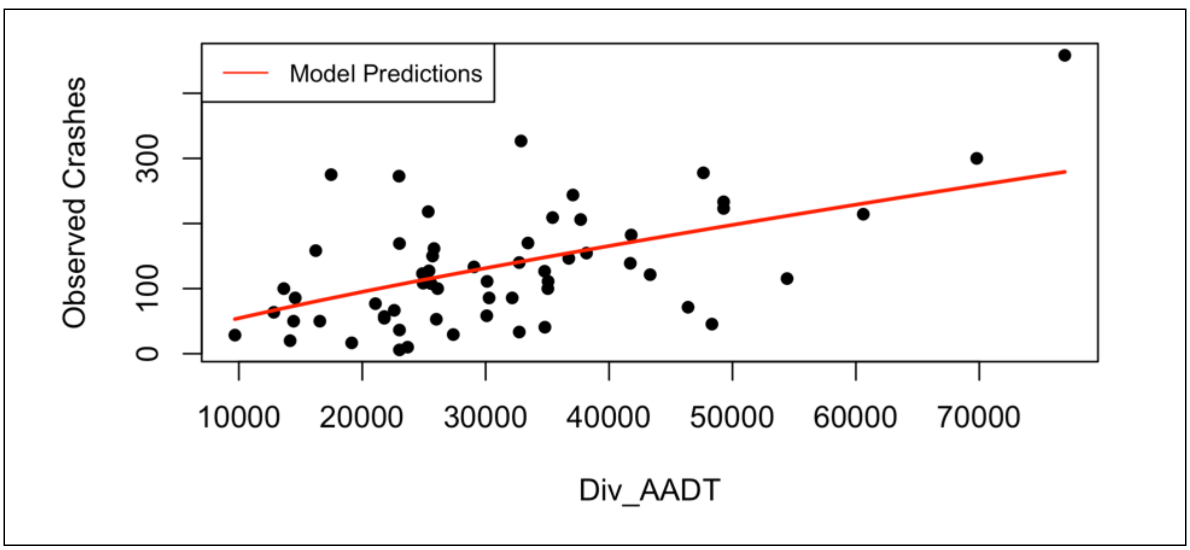


(b)

Figure A.51 Raised Median Urban 4 Lanes Non-Interstate*† (a) CURE plot and (b) observed vs. predicted plot.

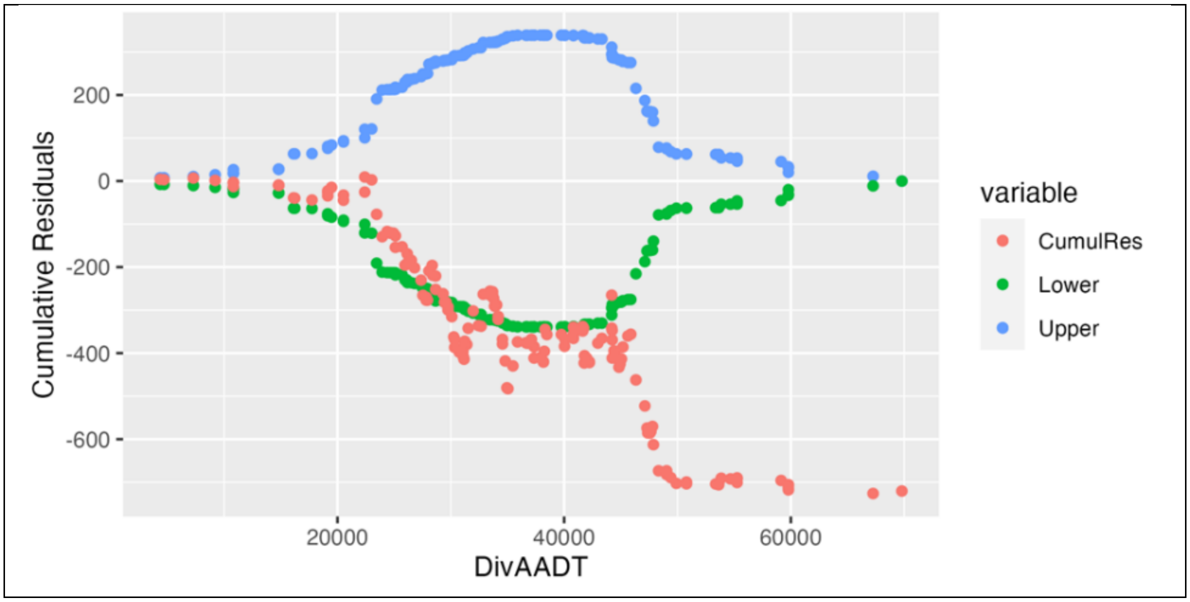


(a)

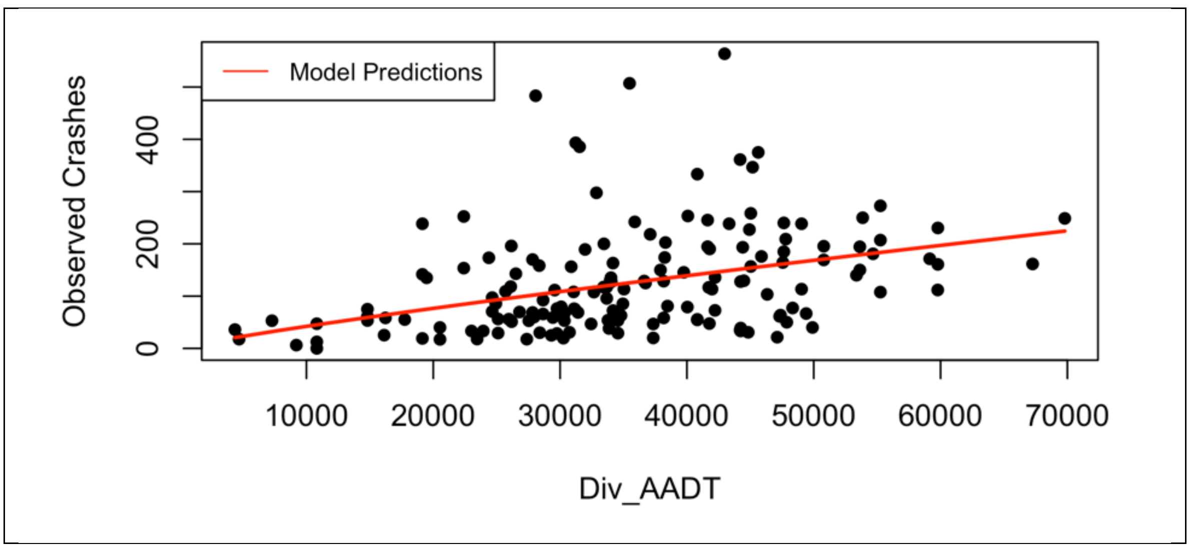


(b)

Figure A.52 Raised Median Urban 5 Lanes Non-Interstate (a) CURE plot and (b) observed vs. predicted plot.

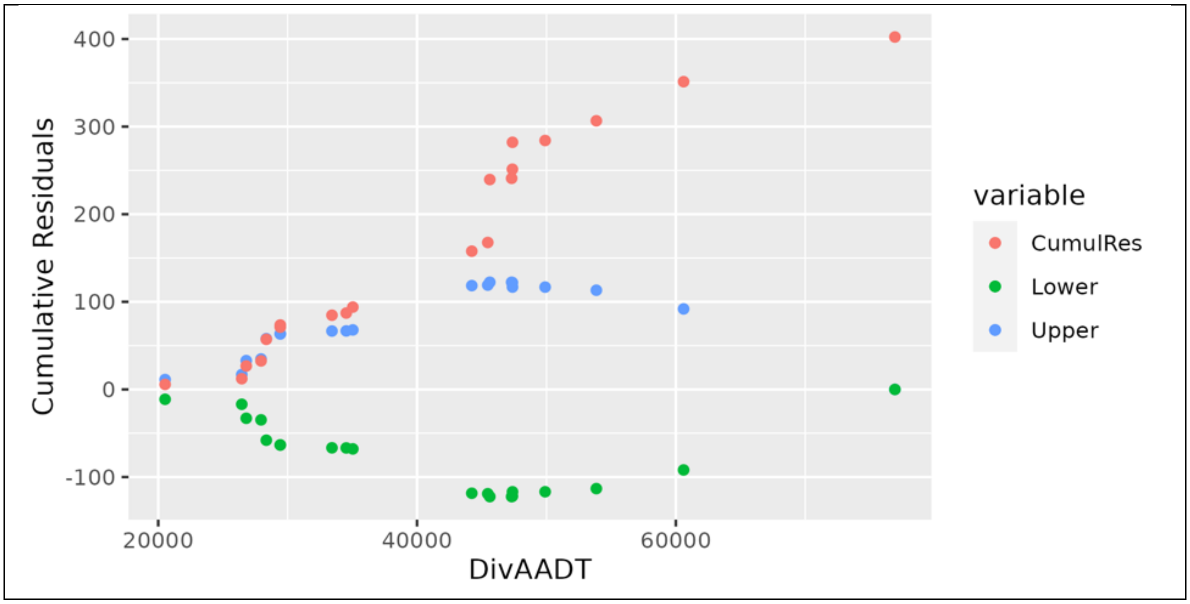


(a)

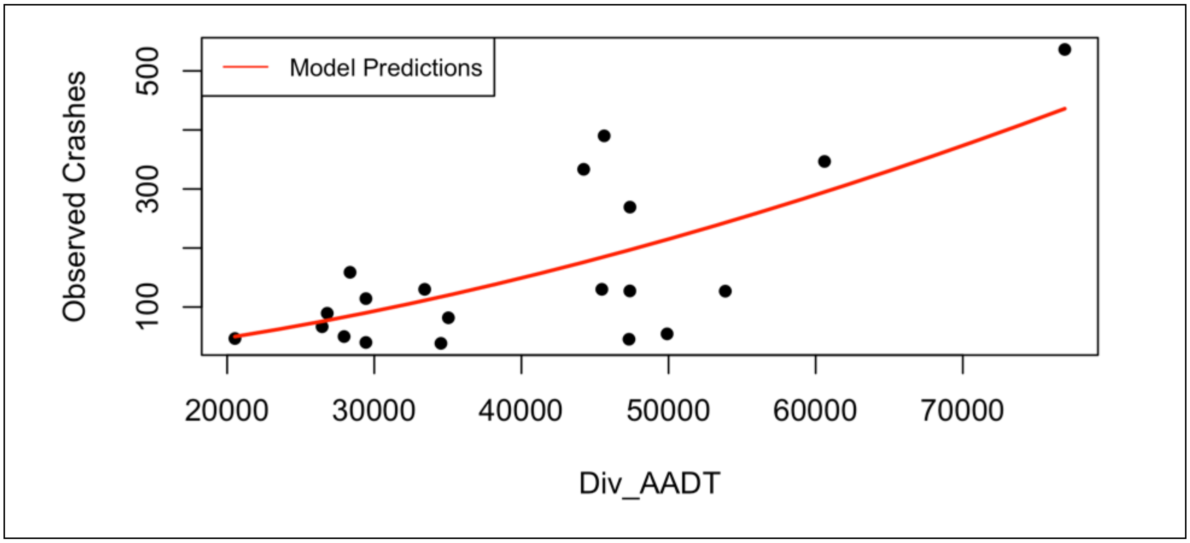


(b)

Figure A.53 Raised Median Urban 6 Lanes Non-Interstate*† (a) CURE plot and (b) observed vs. predicted plot.

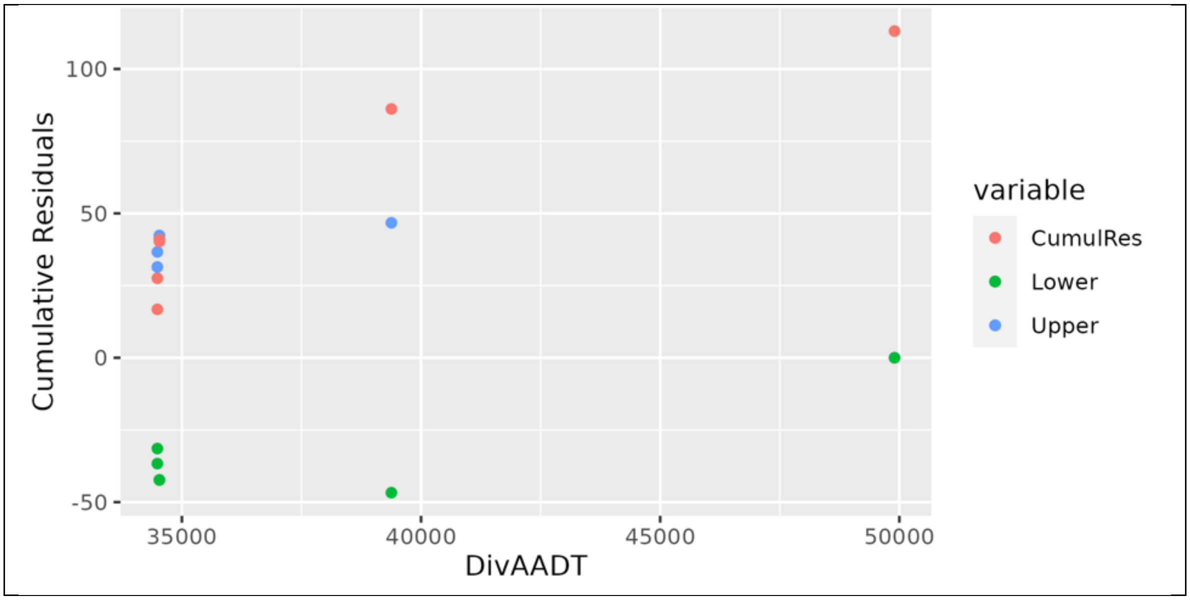


(a)

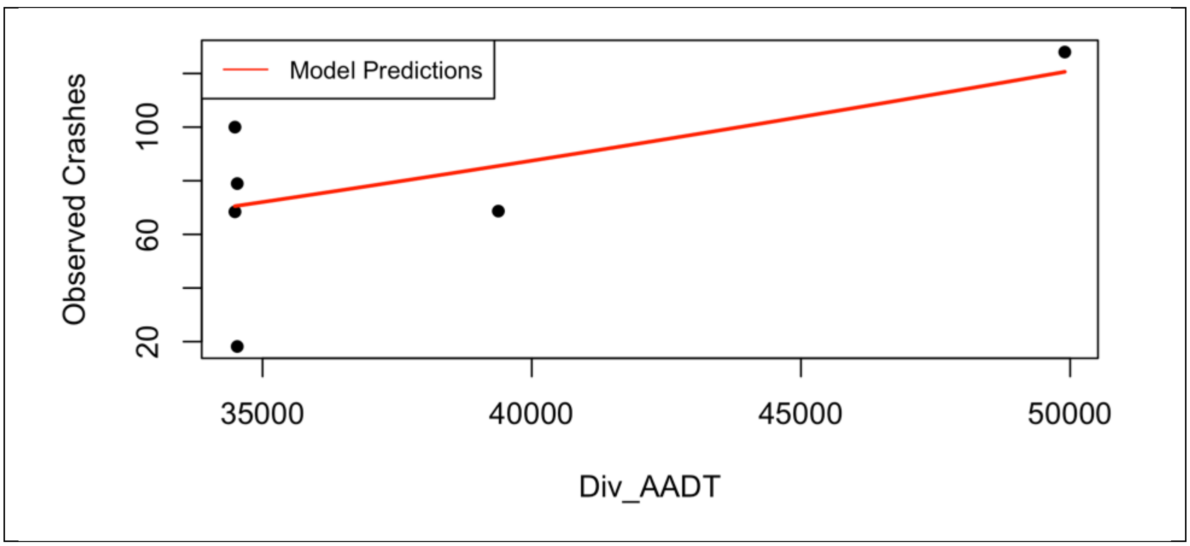


(b)

Figure A.54 Raised Median Urban 7 Lanes Non-Interstate* (a) CURE plot and (b) observed vs. predicted plot.

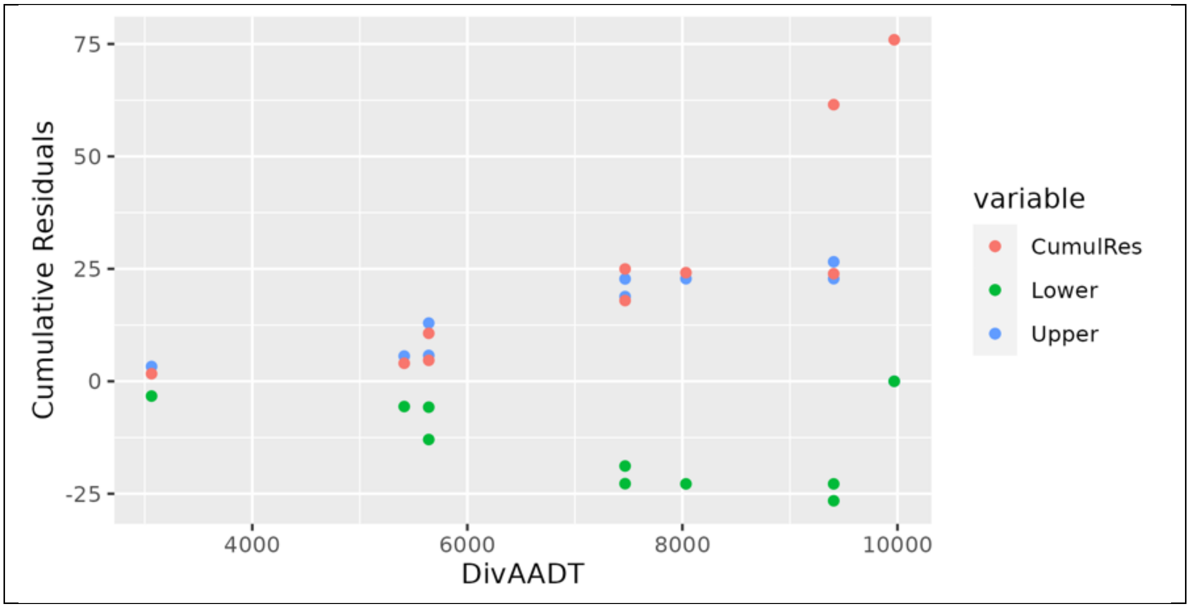


(a)

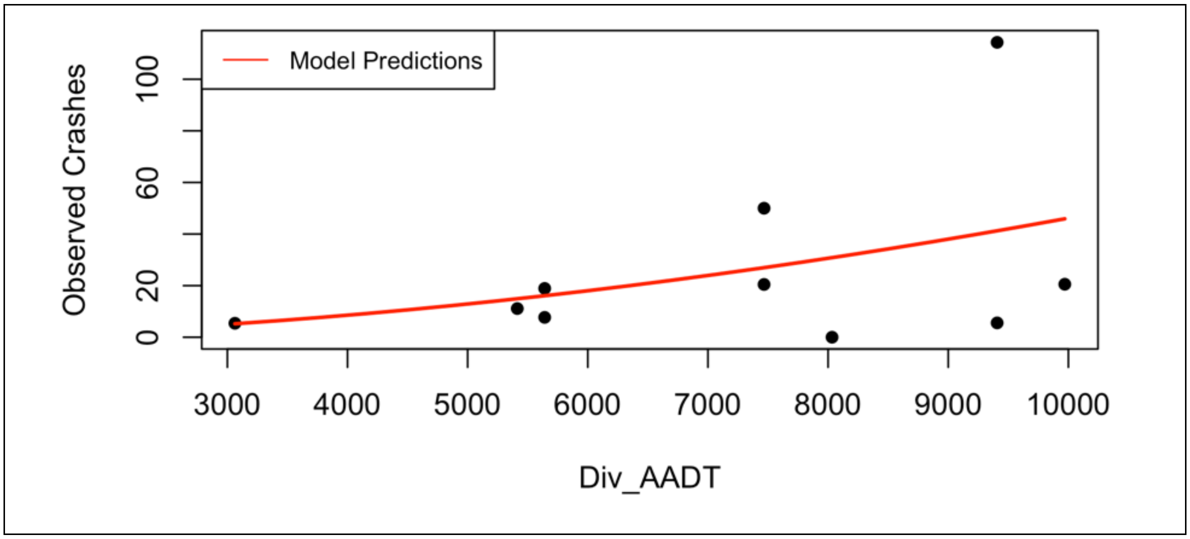


(b)

Figure A.55 Raised Median Urban 8 Lanes Non-Interstate* (a) CURE plot and (b) observed vs. predicted plot.

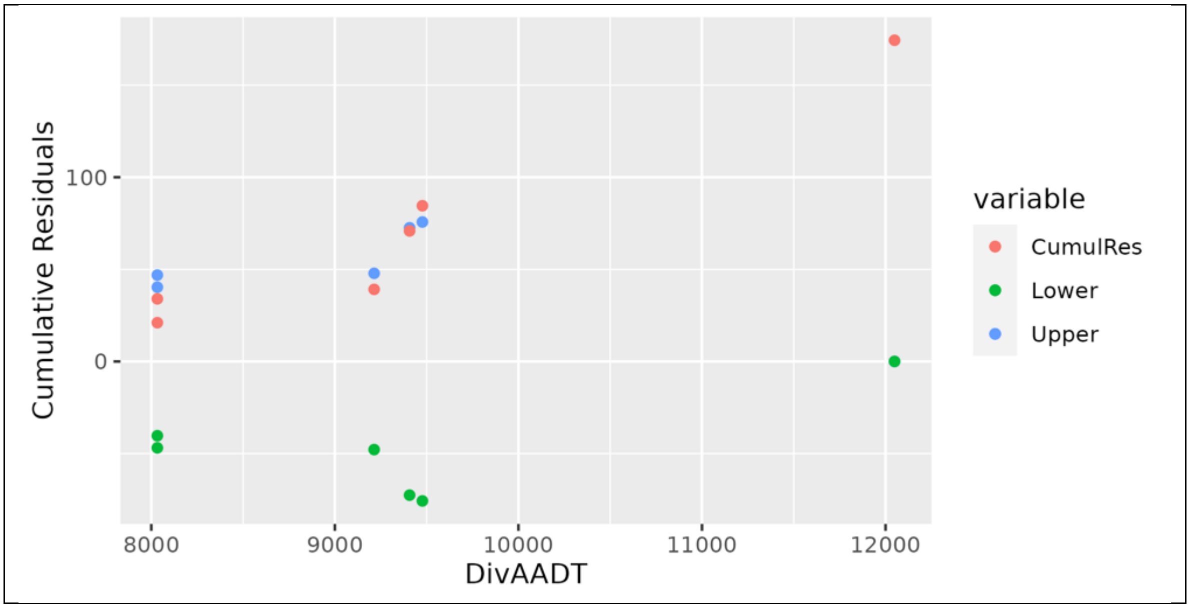


(a)

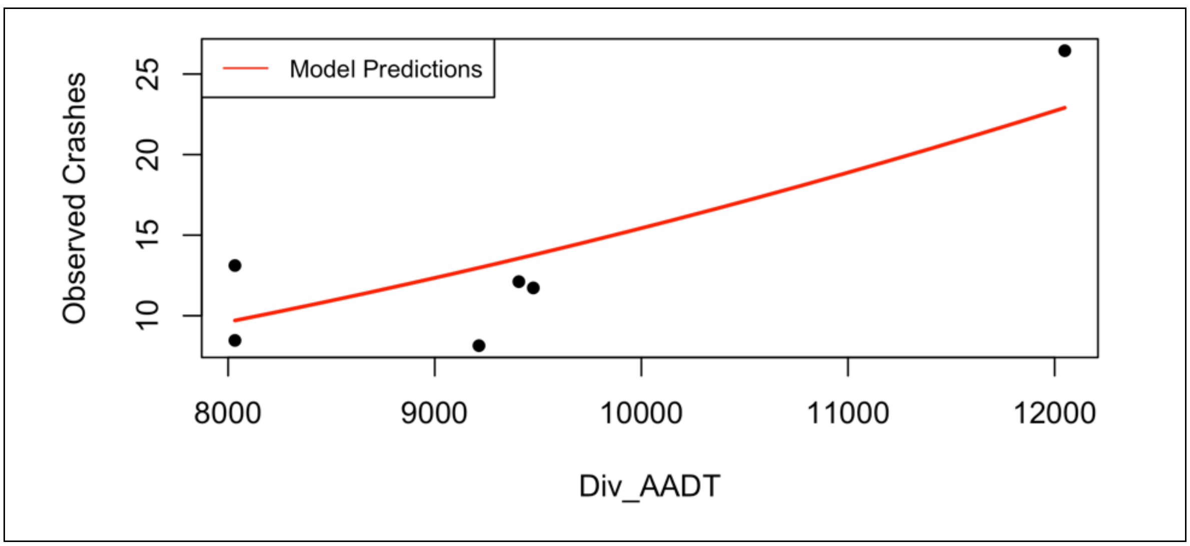


(b)

Figure A.56 Two-Way Left-Turn Lane Rural 2 Lanes + 1 Passing Non-Interstate*
(a) CURE plot and (b) observed vs. predicted plot.

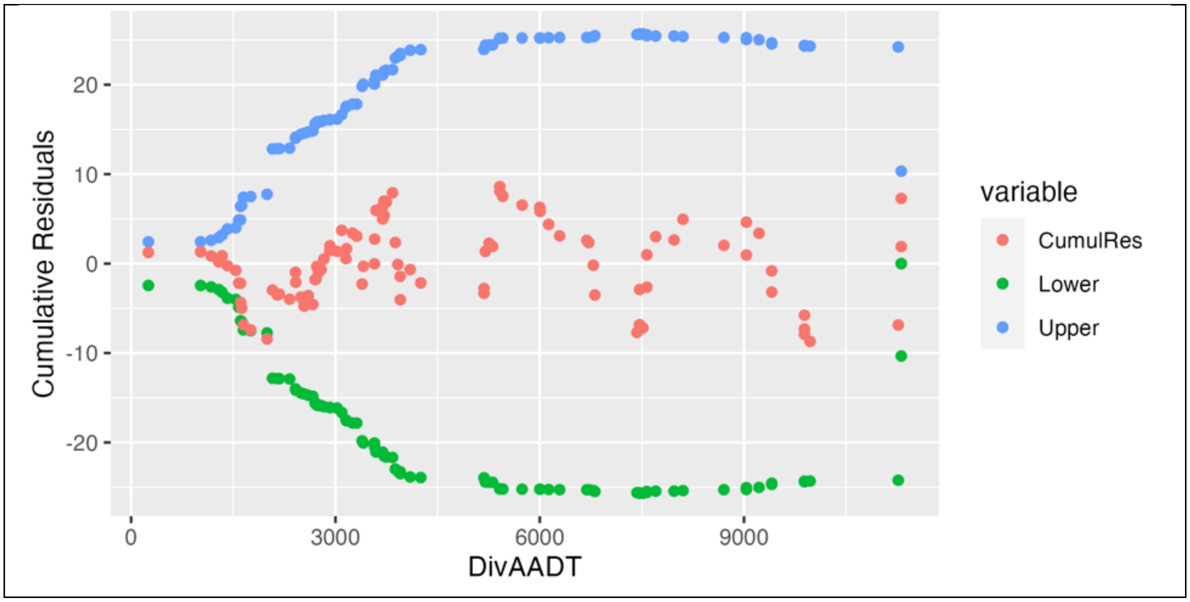


(a)

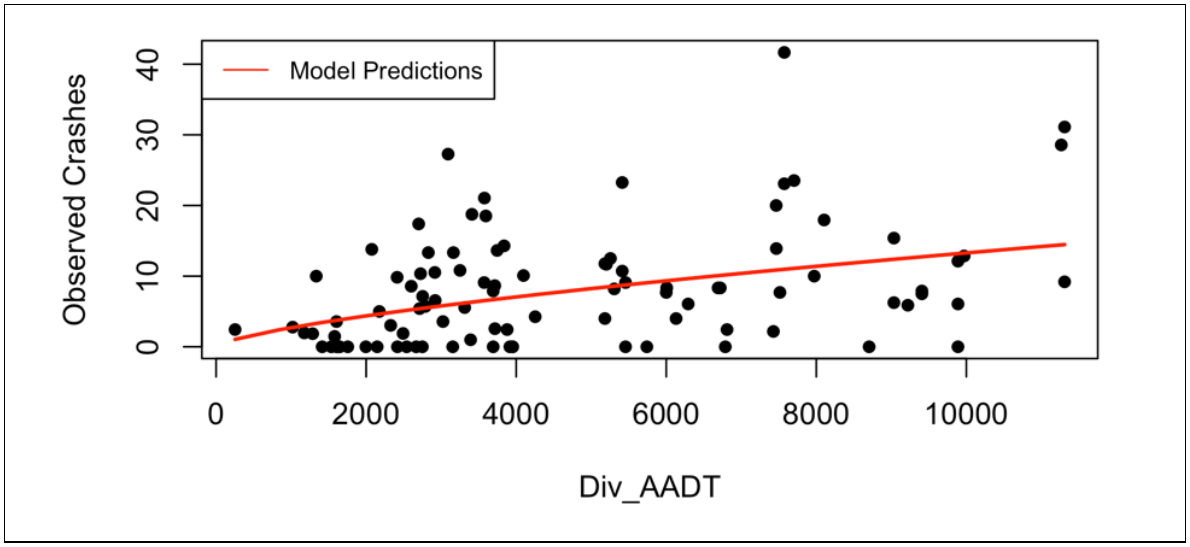


(b)

Figure A.57 Two-Way Left-Turn Lane Rural 2 Lanes + 2 Passing Non-Interstate (a) CURE plot and (b) observed vs. predicted plot.

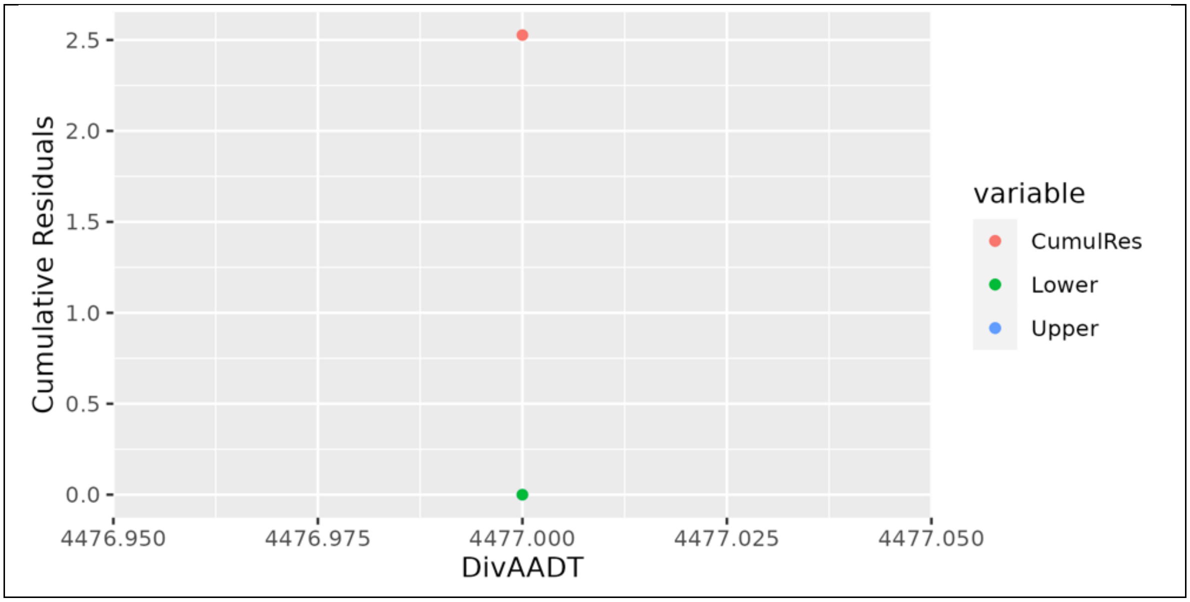


(a)

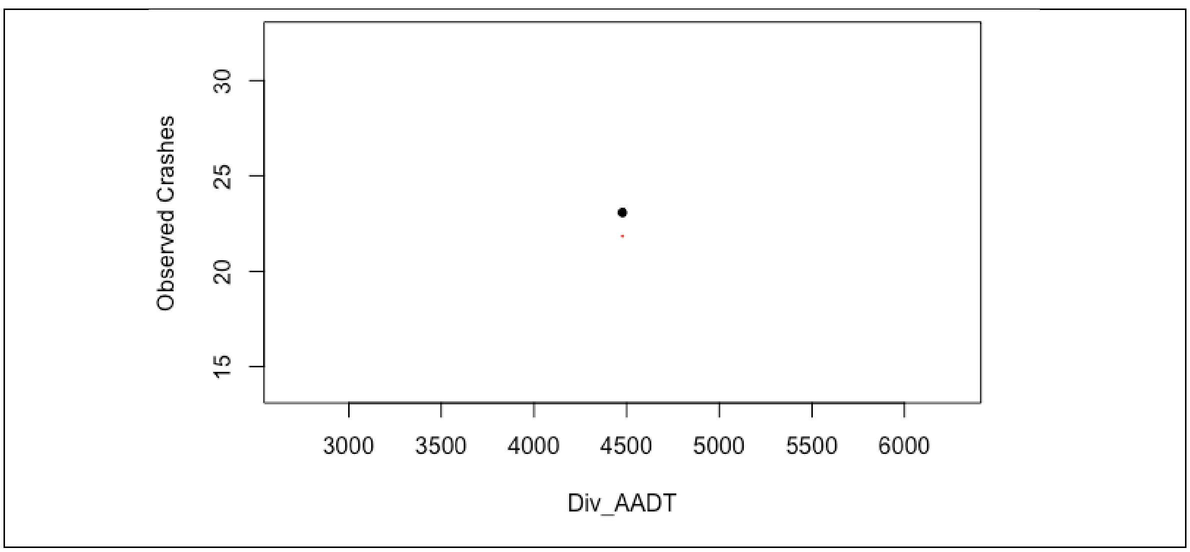


(b)

Figure A.58 Two-Way Left-Turn Lane Rural 2 Lanes Non-Interstate (a) CURE plot and (b) observed vs. predicted plot.

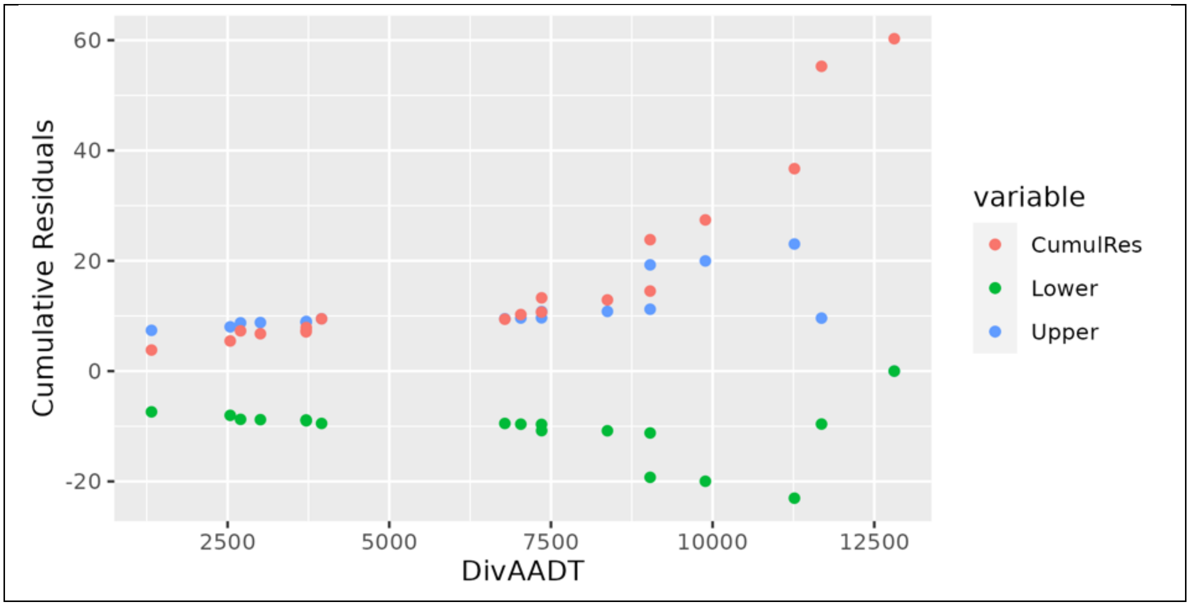


(a)

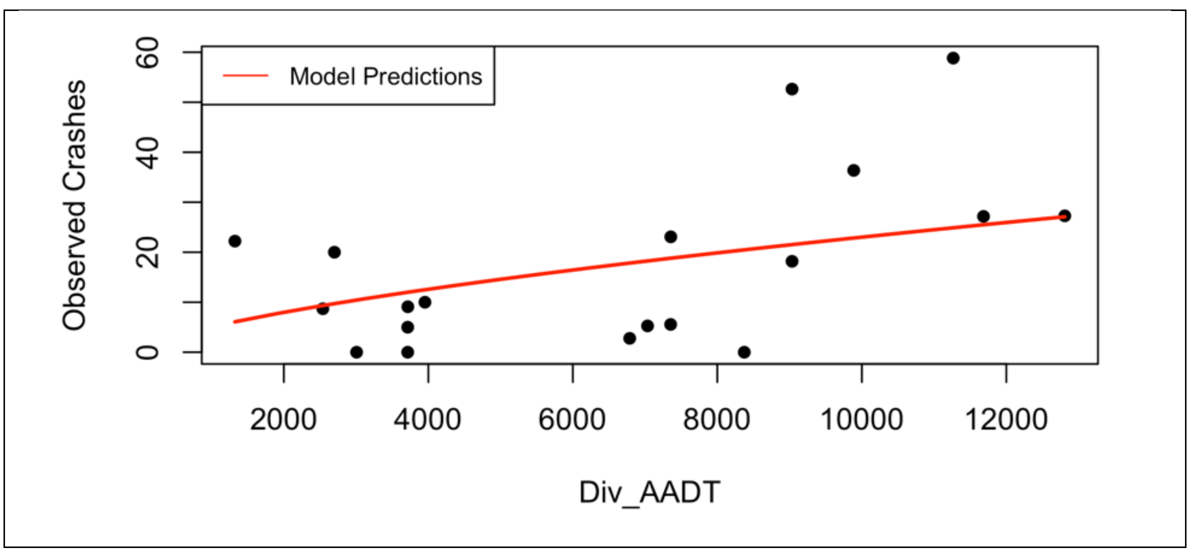


(b)

Figure A.59 Two-Way Left-Turn Lane Rural 3 Lanes + 2 Passing Non-Interstate*
(a) CURE plot and (b) observed vs. predicted plot.

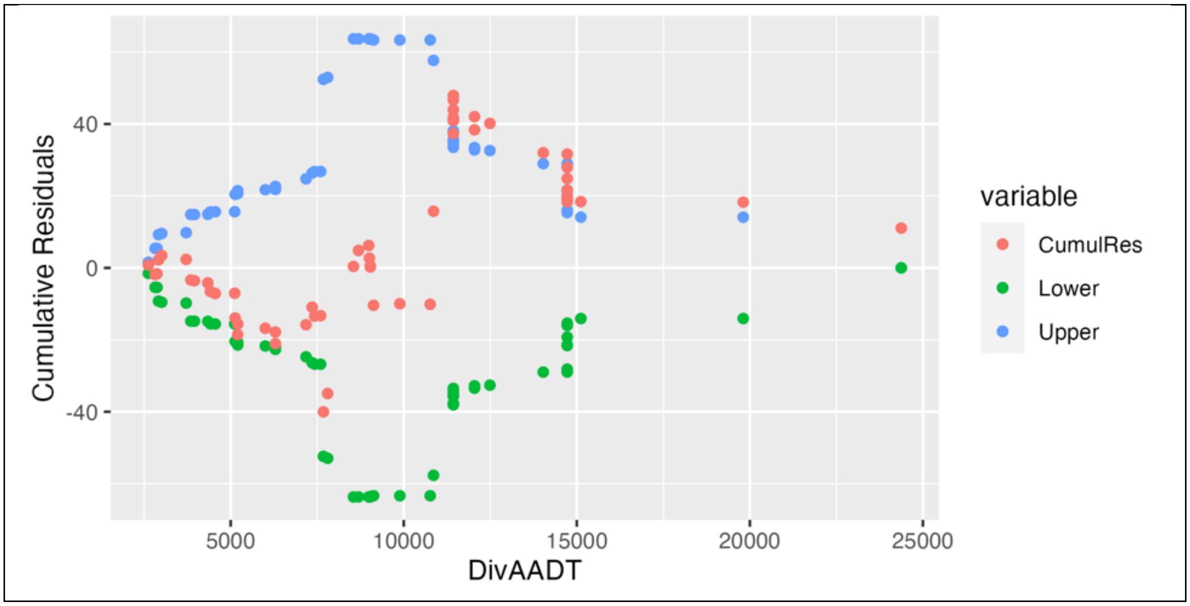


(a)

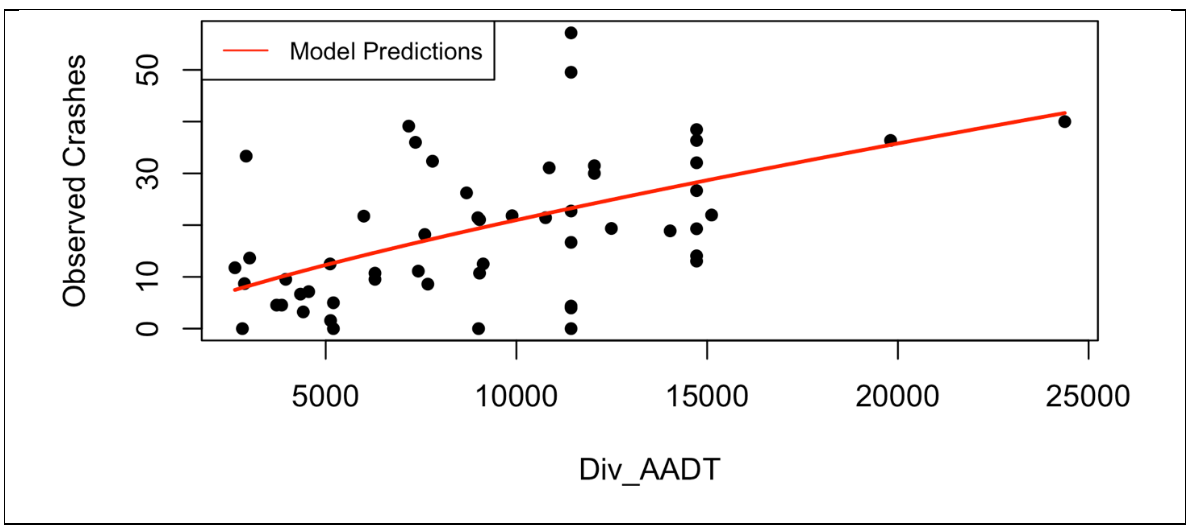


(b)

Figure A.60 Two-Way Left-Turn Lane Rural 3 Lanes Non-Interstate* (a) CURE plot and (b) observed vs. predicted plot.

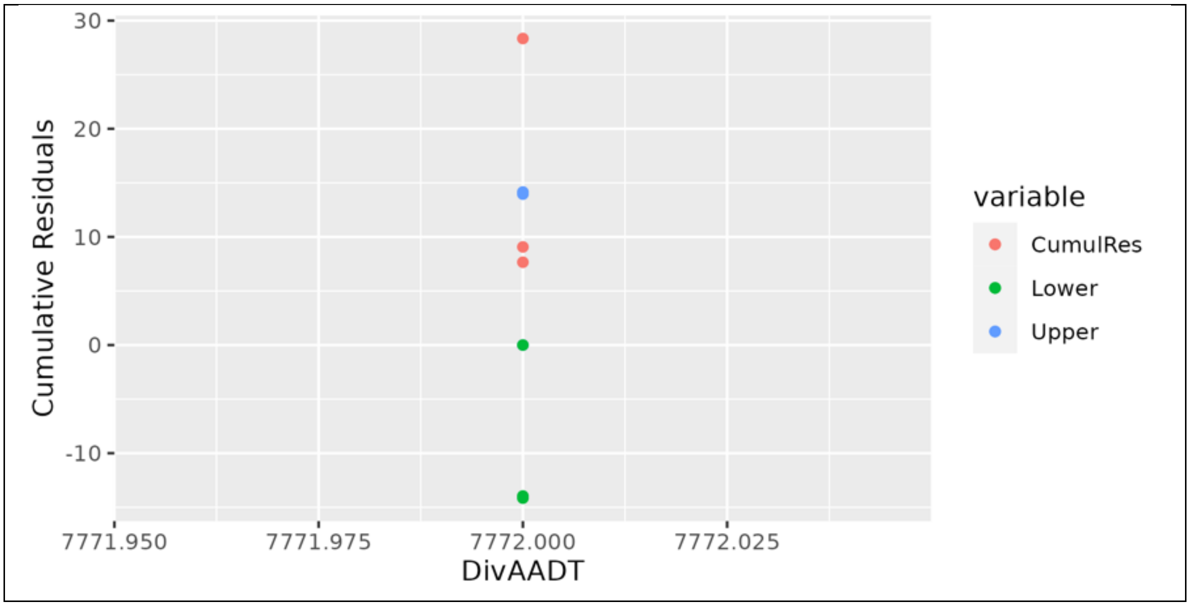


(a)

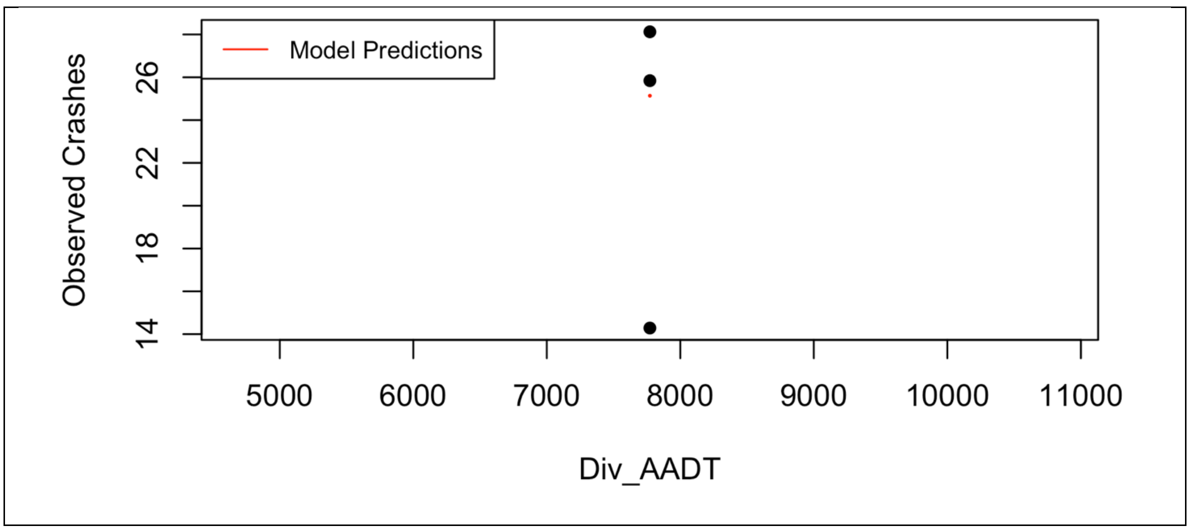


(b)

Figure A.61 Two-Way Left-Turn Lane Rural 4 Lanes Non-Interstate† (a) CURE plot and (b) observed vs. predicted plot.

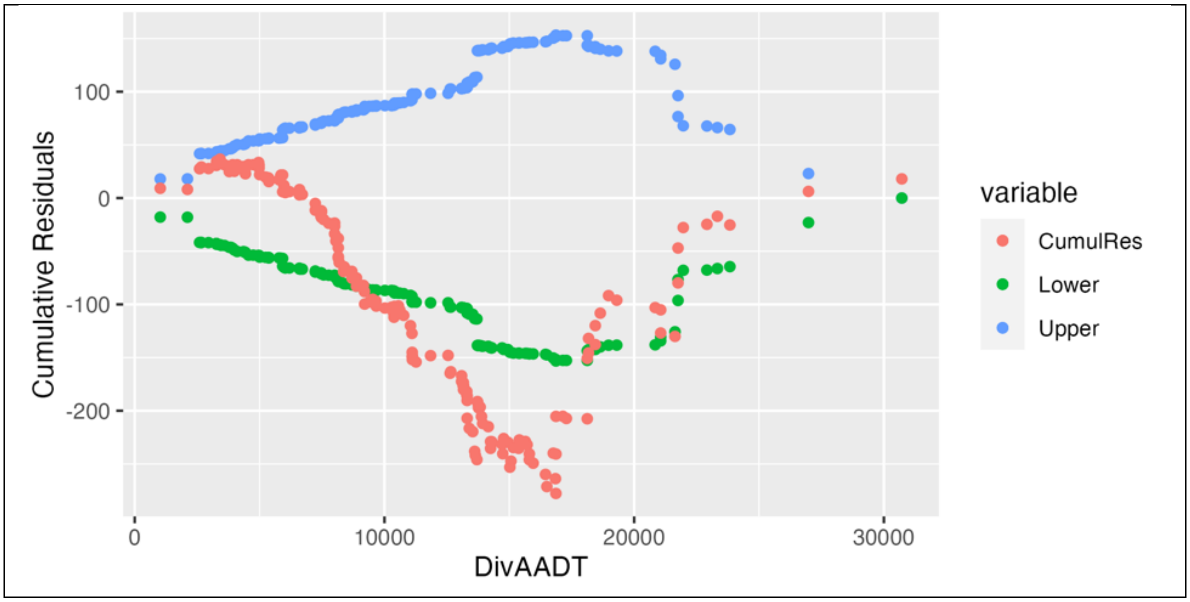


(a)

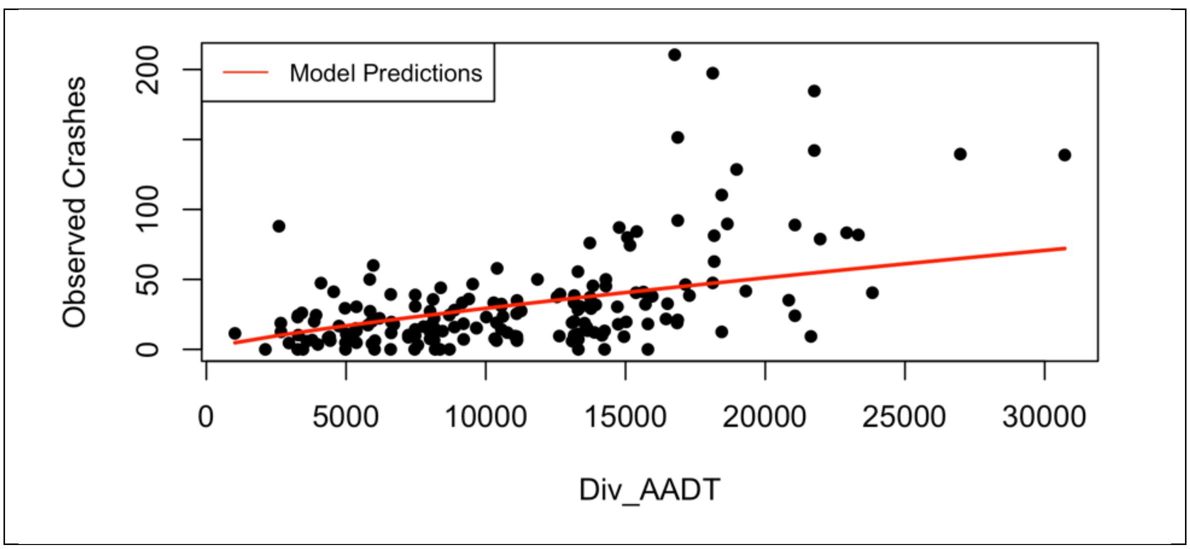


(b)

Figure A.62 Two-Way Left-Turn Lane Urban 2 Lanes + 1 Passing Non-Interstate*
(a) CURE plot and (b) observed vs. predicted plot.



(a)



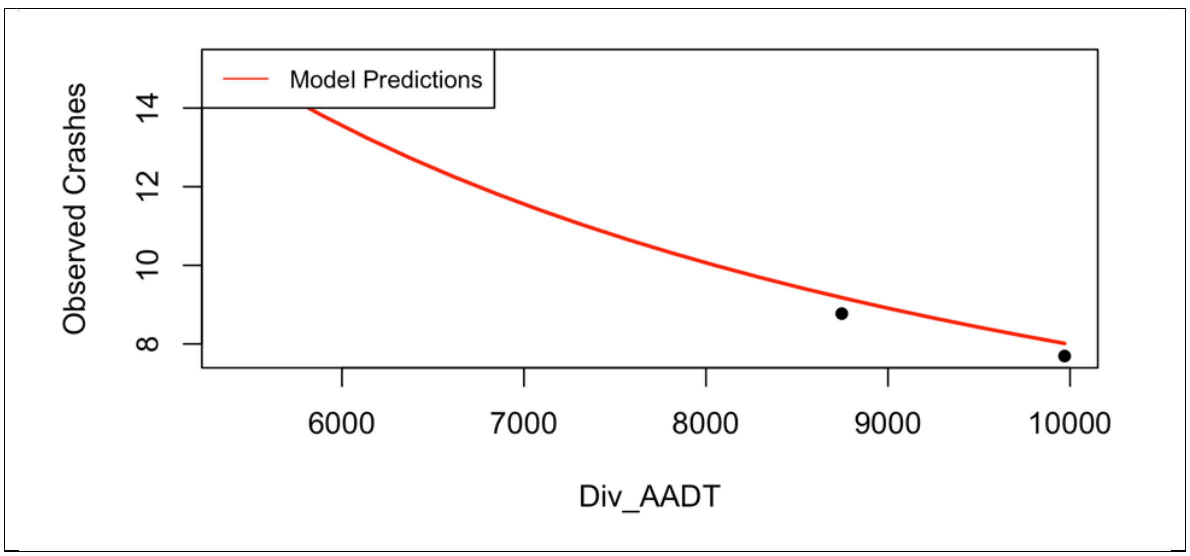
(b)

Figure A.63 Two-Way Left-Turn Lane Urban 2 Lanes Non-Interstate (a) CURE plot and (b) observed vs. predicted plot.

Insufficient Data

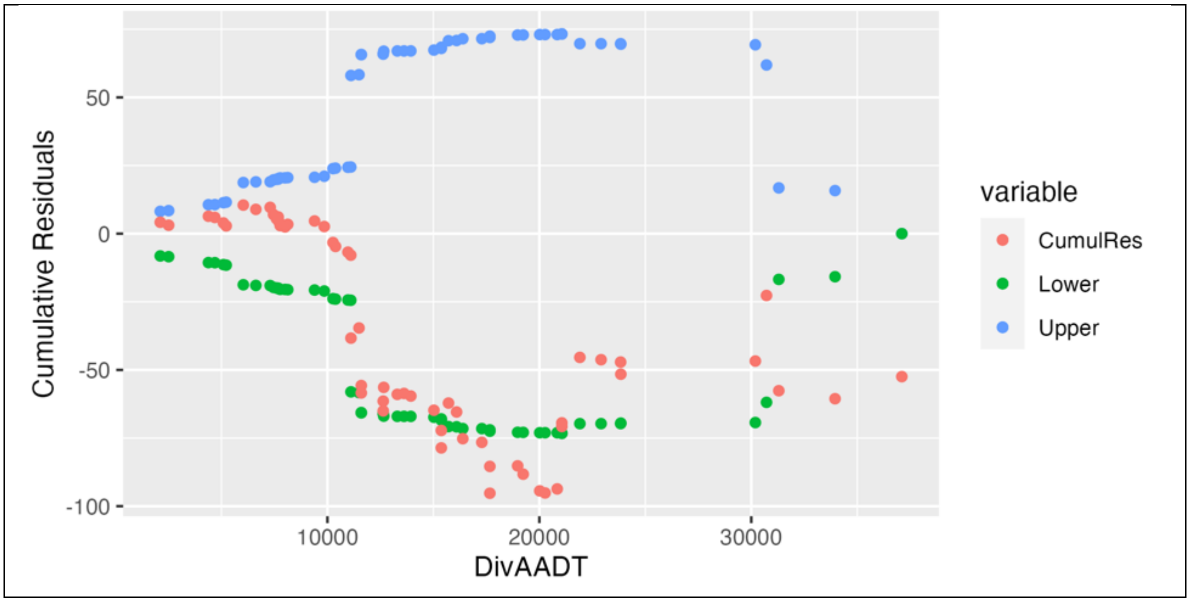
No CURE Plot Available

(a)

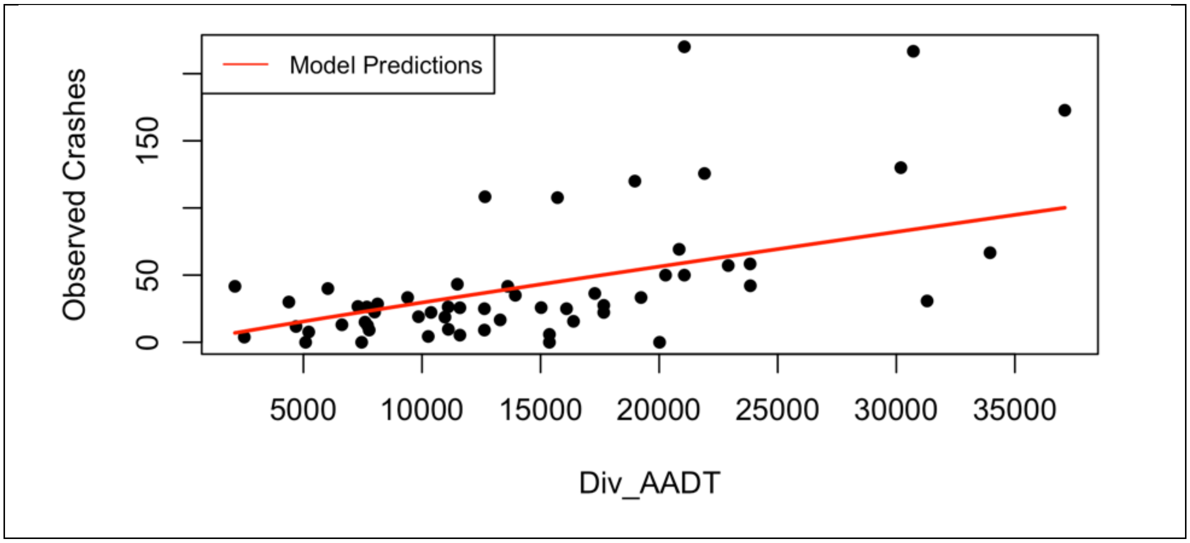


(b)

Figure A.64 Two-Way Left-Turn Lane Urban 3 Lanes + 1 Passing Non-Interstate*
(a) CURE plot and (b) observed vs. predicted plot.

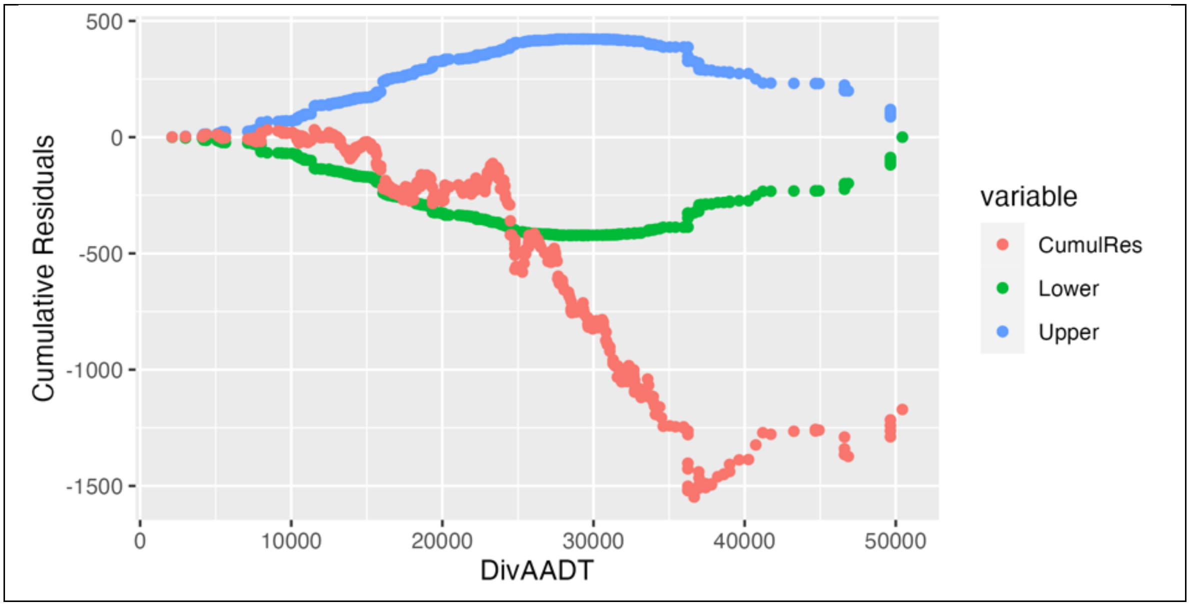


(a)

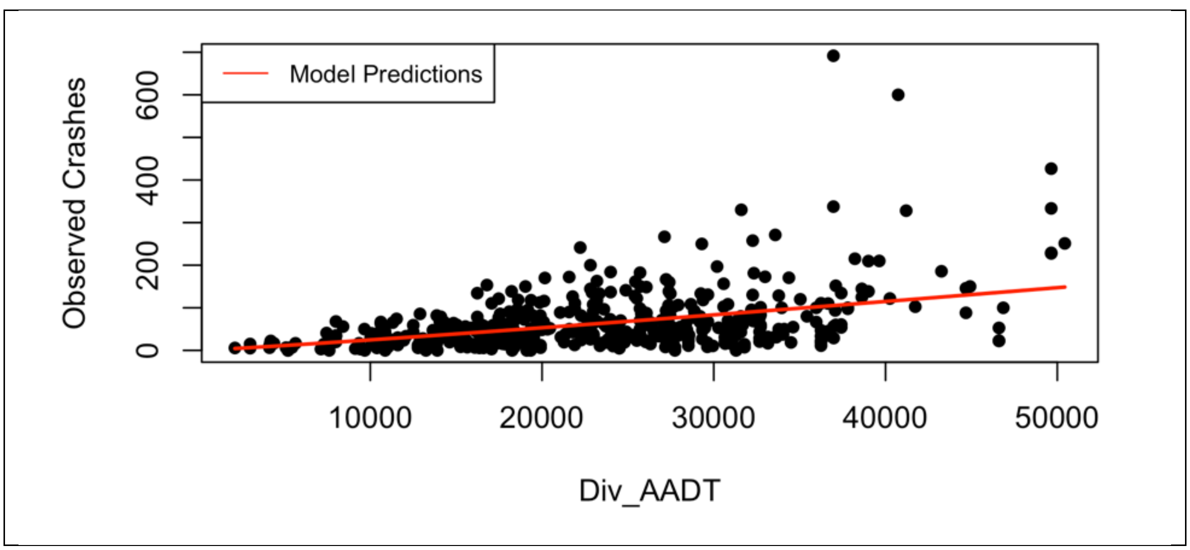


(b)

Figure A.65 Two-Way Left-Turn Lane Urban 3 Lanes Non-Interstate*† (a) CURE plot and (b) observed vs. predicted plot.

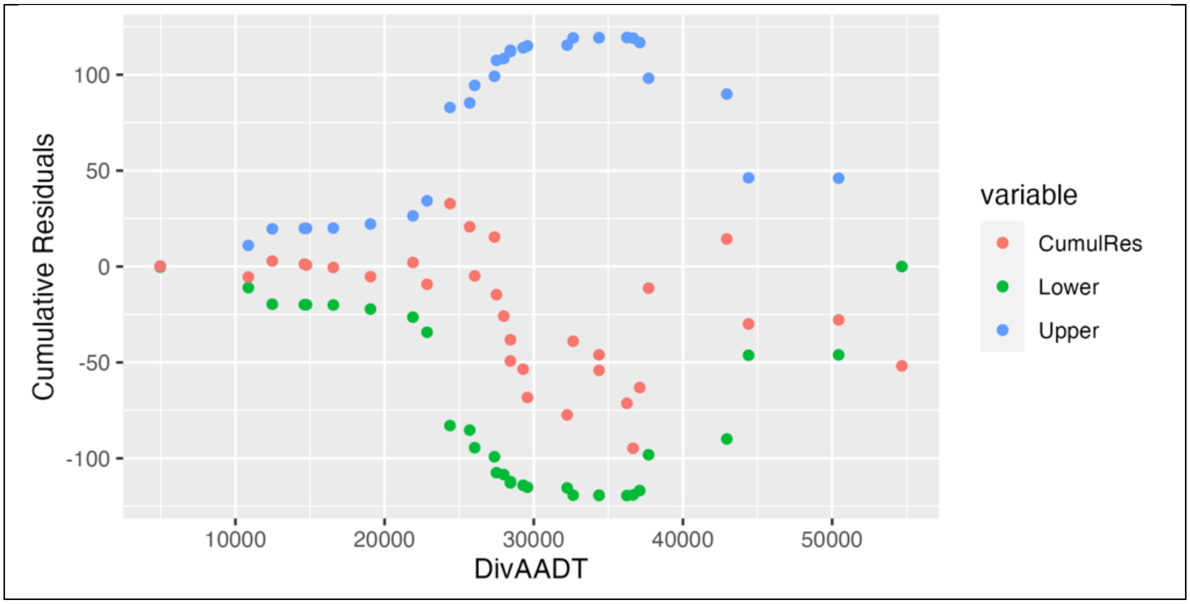


(a)

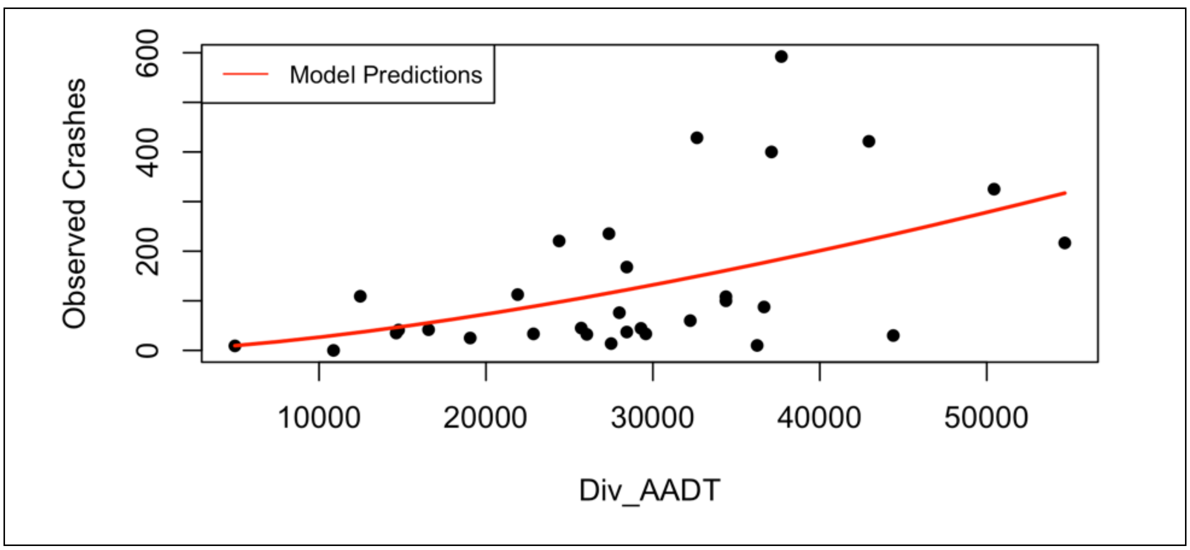


(b)

Figure A.66 Two-Way Left-Turn Lane Urban 4 Lanes Non-Interstate*† (a) CURE plot and (b) observed vs. predicted plot.

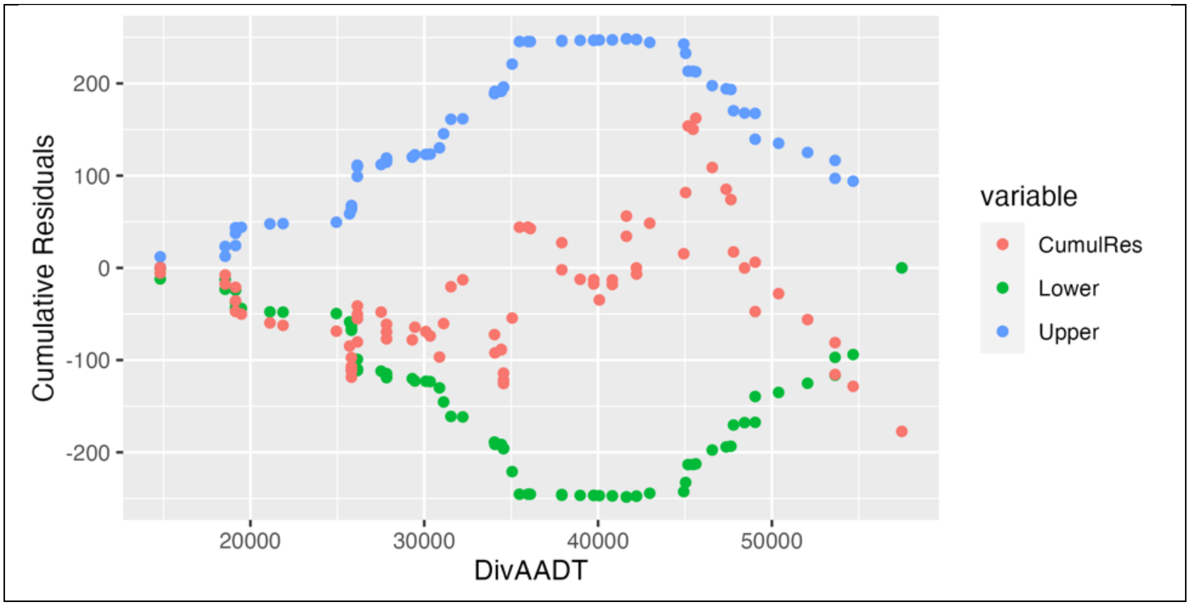


(a)

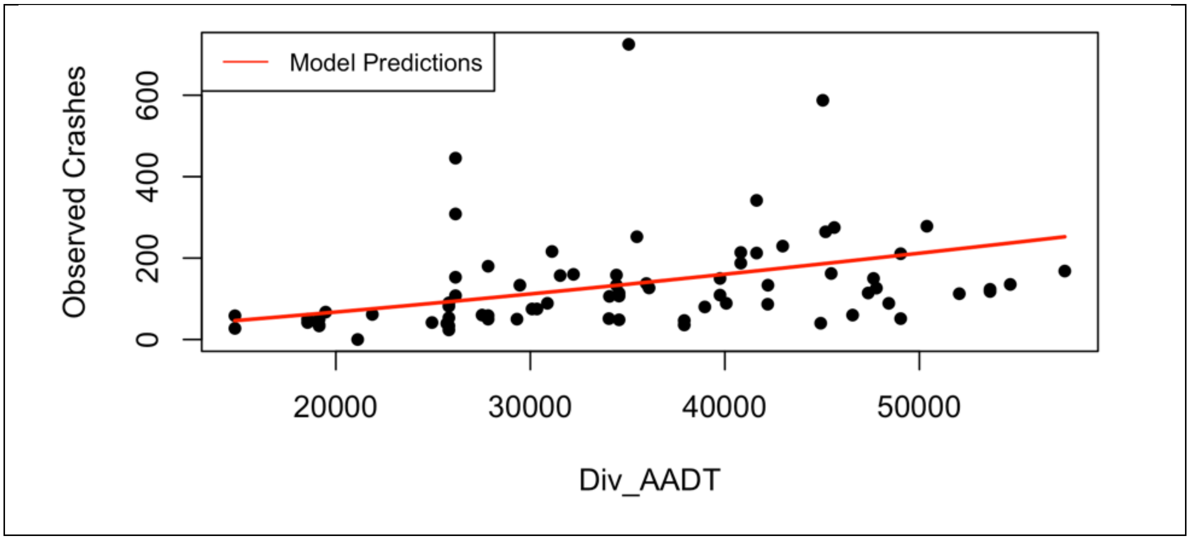


(b)

Figure A.67 Two-Way Left-Turn Lane Urban 5 Lanes Non-Interstate (a) CURE plot and (b) observed vs. predicted plot.

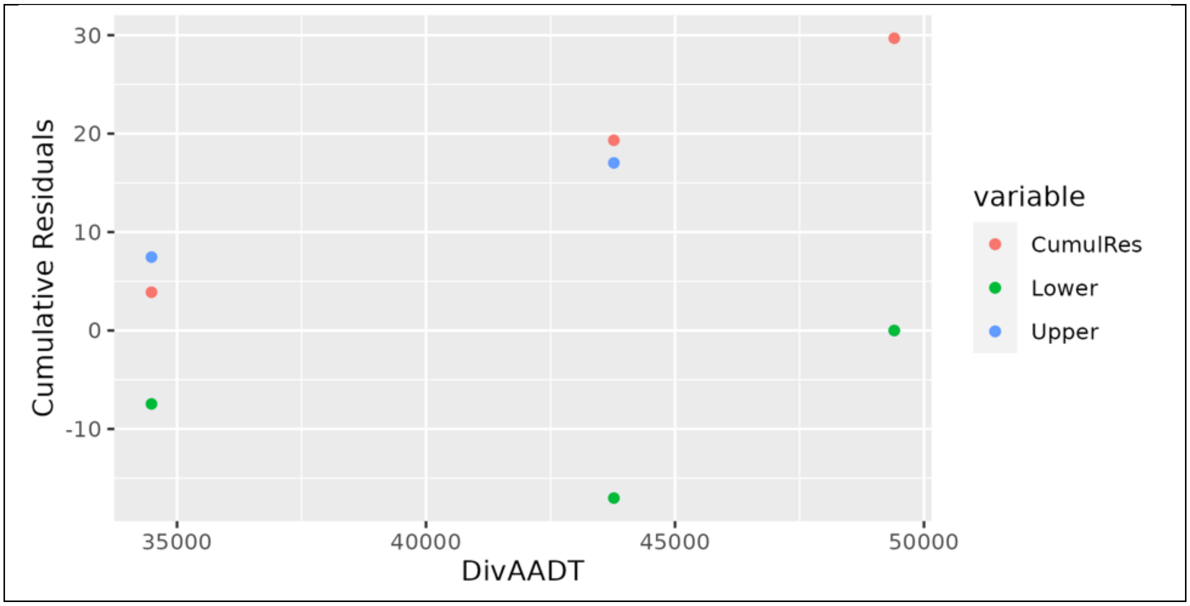


(a)

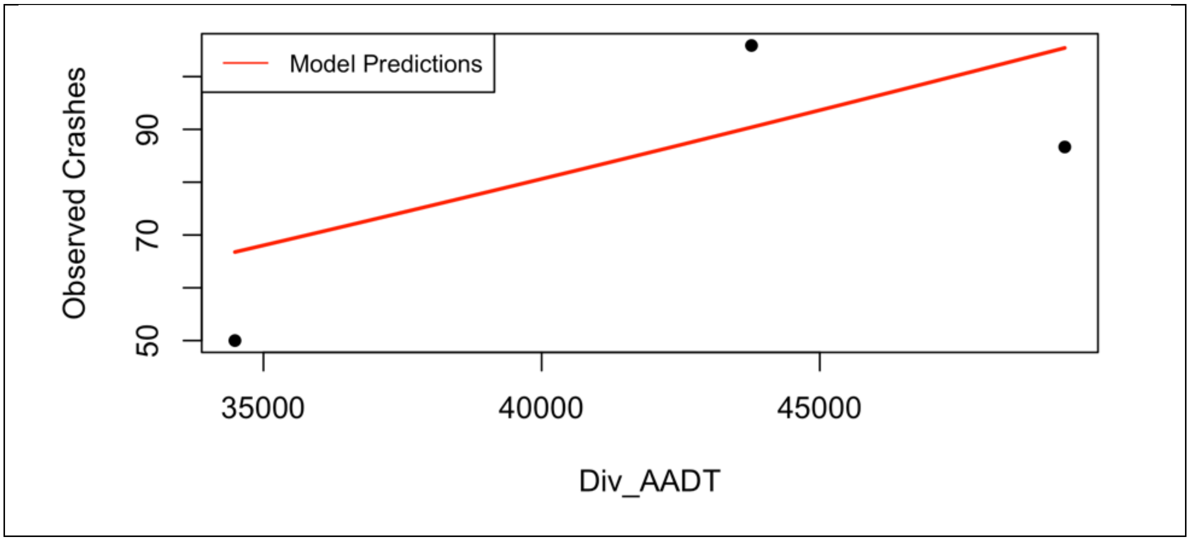


(b)

Figure A.68 Two-Way Left-Turn Lane Urban 6 Lanes Non-Interstate*† (a) CURE plot and (b) observed vs. predicted plot.

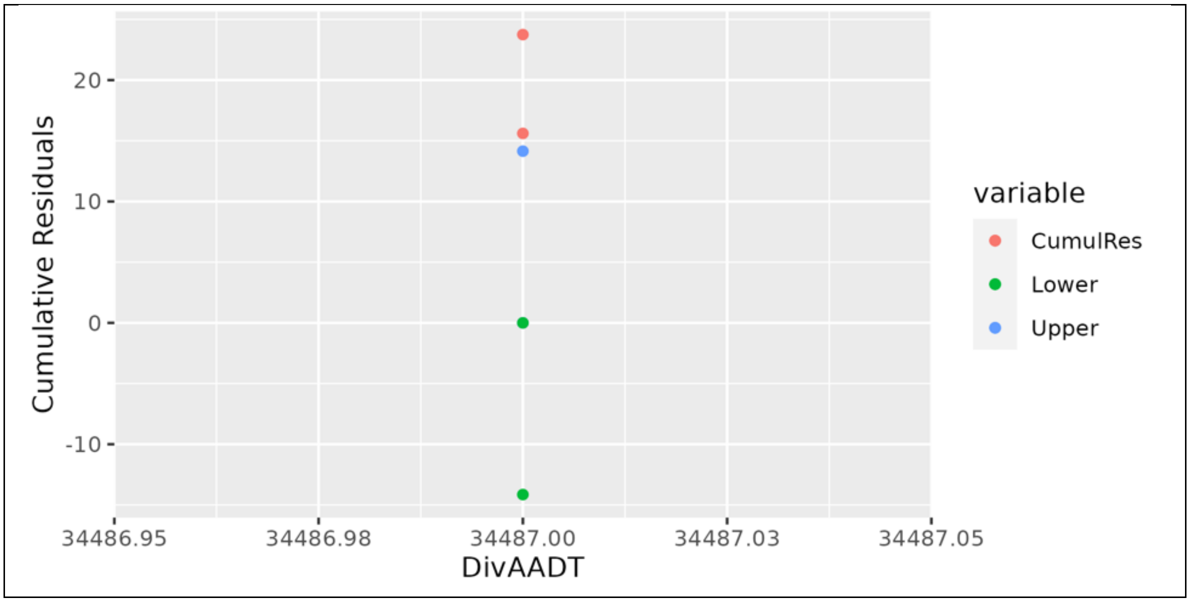


(a)

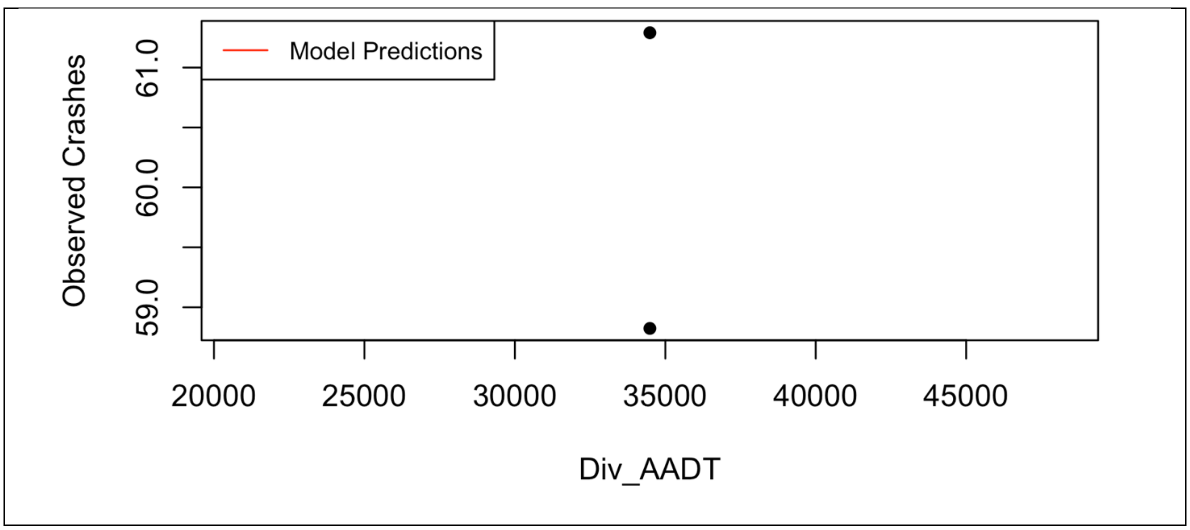


(b)

Figure A.69 Two-Way Left-Turn Lane Urban 7 Lanes Non-Interstate* (a) CURE plot and (b) observed vs. predicted plot.



(a)



(b)

Figure A.70 Two-Way Left-Turn Lane Urban 8 Lanes Non-Interstate* (a) CURE plot and (b) observed vs. predicted plot.

Table A.3 Segments with Small Sample Sizes with No SPF Developed

Category	#Seg	Crashes
Divided Protected Rural 1 Lanes Non-Interstate	1	27
Divided Protected Rural 2 Lanes + 1 Passing Interstate	2	28
Divided Protected Rural 2 Lanes + 2 Passing Non-Interstate	2	27
Divided Protected Rural 2 Lanes Non-Interstate	13	657
Divided Protected Rural 3 Lanes + 1 Passing Interstate	1	118
Divided Protected Rural 3 Lanes Non-Interstate	1	3
Divided Protected Rural 4 Lanes Interstate	1	53
Divided Protected Rural 4 Lanes Non-Interstate	13	767
Divided Protected Urban 1 Lanes Non-Interstate	5	21
Divided Protected Urban 3 Lanes + 1 Passing Interstate	2	51
Divided Protected Urban 3 Lanes Interstate + HOV	1	26
Divided Protected Urban 5 Lanes + 1 Passing Interstate	1	4
Divided Protected Urban 6 Lanes Interstate	2	43
Divided Protected Urban 7 Lanes Non-Interstate	2	49
Divided Protected Urban 8 Lanes Non-Interstate	2	27
Divided Protected Urban Unknown Non-Interstate	1	9
Divided Unprotected Rural 1 Lanes Interstate	2	4
Divided Unprotected Rural 2 Lanes + 1 Passing Interstate	4	29
Divided Unprotected Rural 2 Lanes Non-Interstate	4	25
Divided Unprotected Rural 3 Lanes + 1 Passing Non-Interstate	1	6
Divided Unprotected Urban 0 Lanes Non-Interstate	1	0
Divided Unprotected Urban 5 Lanes Non-Interstate	1	24
Divided Unprotected Urban 6 Lanes Non-Interstate	1	50
Divided Unprotected Urban 7 Lanes Non-Interstate	1	14
Divided Unprotected Urban Unknown Non-Interstate	1	7
No Median/Undivided Rural 2 Lanes + 1 Passing Interstate	1	4
No Median/Undivided Rural 2 Lanes Interstate	4	100
No Median/Undivided Urban 2 Lanes + 1 Passing Non-Interstate	3	19
No Median/Undivided Urban 2 Lanes Interstate	2	6
No Median/Undivided Urban 3 Lanes + 1 Passing Non-Interstate	3	23
No Median/Undivided Urban 3 Lanes Interstate	1	8
No Median/Undivided Urban 4 Lanes Interstate	1	27
No Median/Undivided Urban 5 Lanes Interstate	1	5
No Median/Undivided Urban 8 Lanes Non-Interstate	4	77
No Median/Undivided Urban Unknown Non-Interstate	1	7
Raised Median Rural 1 Lanes Non-Interstate	1	0
Raised Median Rural 2 Lanes Interstate	1	60
Raised Median Rural 2 Lanes Non-Interstate	5	14
Raised Median Rural 3 Lanes Non-Interstate	1	1
Two-Way Left-Turn Lane Rural 3 Lanes + 1 Passing Non-Interstate	3	18

APPENDIX B: INTERSECTION RESULTS

Intersection SPFs are provided in this appendix. First, Table B.1 provides a summary of the field headings and their corresponding definitions. Table B.2 summarizes the SPF results. Figures B.1 through B.23 illustrate the CURE plots for each category using major AADT only. Note that observed vs. predicted plots are not available for the intersection results due to the number of variables in the SPFs. Finally, Table B.3 summarizes the categories where an SPF was not developed due to a small sample size (number of intersections in the category).

Table B.1 Field Headings and Definitions

Field Heading	Definition
Category	Numetric (AASHTOWare Safety) segmentation category
Figure	Figure number for CURE plot
#Int	Number of intersections in the category
Crashes	Total number of crashes in the category
beta_0	Slope coefficient estimate for the category (β_0)
beta_1	Major AADT coefficient estimate for the category (β_1)
beta_2	Minor AADT coefficient estimate for the category (β_2)
phi	Overdispersion estimate for the category (ϕ)
%pval	Percentage of p-values < 0.05 (goodness of fit)
SPF	Complete SPF equation with estimated parameters

Table B.2 Intersection Safety Performance Function Model Results

Category (Figure) #Int	 Crashes	 beta_0	 beta_1	 beta_2	 phi	 %pval	 SPF
3-Leg Minor Stop, Rural (Figure B.1)							exp(-9.38) * {AADT_maj}^0.74 *
1633	380	-9.38	0.74	0.27	0.52	0.05	{AADT_min}^0.27
3-Leg Minor Stop, Urban* (Figure B.2)							exp(-6.25) * {AADT_maj}^0.8 *
1389	1530	-6.25	0.8	-0.15	0.92	0.41	{AADT_min}^-0.15
3-Leg Signal, Urban* (Figure B.3)							exp(-6.54) * {AADT_maj}^0.87 *
442	2577	-6.54	0.87	-0.06	2.02	0.18	{AADT_min}^-0.06
4+ Leg Minor Stop, Rural (Figure B.4)							exp(-2.61) * {AADT_maj}^-0.18 *
1320	440	-2.61	-0.18	0.43	0.56	0.04	{AADT_min}^0.43
4+ Leg Minor Stop, Urban* (Figure B.5)							exp(-6.97) * {AADT_maj}^0.67 *
1256	2926	-6.97	0.67	0.17	0.76	0.05	{AADT_min}^0.17
4+ Leg Signal, Rural (Figure B.6)							exp(-7.22) * {AADT_maj}^0.95 *
72	164	-7.22	0.95	-0.06	11.86	0.03	{AADT_min}^-0.06
4+ Leg Signal, Urban* (Figure B.7)							exp(-5.71) * {AADT_maj}^0.68 *
4529	46050	-5.71	0.68	0.12	2.52	0.07	{AADT_min}^0.12

*Intersection categories with SPFs that should be used with caution (SPFs with a %pval > 0.1 and/or a suspect CURE plot)
† Intersection categories that did not have a Minor AADT in the data – these categories were analyzed using Major AADT only

Table B.2 Continued

Category (Figure) #Int	Crashes	beta_0	beta_1	beta_2	phi	%pval	SPF
Active Transportation, Rural*† (Figure B.8)							
48	1	-29.41	2.91	N/A	10.01	0.05	exp(-29.41) * {AADT_maj}^2.91
Active Transportation, Urban† (Figure B.9)							
210	89	-12.07	1.16	N/A	7.82	0.05	exp(-12.07) * {AADT_maj}^1.16
All-Way Stop, Rural (Figure B.10)							
36	15	3.33	1.24	-1.87	11.32	0.04	exp(3.33) * {AADT_maj}^1.24 * {AADT_min}^-1.87
All-Way Stop, Urban (Figure B.11)							
42	46	-8.37	0.98	-0.04	10.11	0.08	exp(-8.37) * {AADT_maj}^0.98 * {AADT_min}^-0.04
CFI Central, Urban* (Figure B.12)							
48	1754	-5.62	0.79	0.06	16.08	0.08	exp(-5.62) * {AADT_maj}^0.79 * {AADT_min}^0.06
CFI Offset Left, Urban (Figure B.13)							
84	62	-4.82	0.38	0.04	1.82	0.04	exp(-4.82) * {AADT_maj}^0.38 * {AADT_min}^0.04
DDI, Urban (Figure B.14)							
84	453	-6.77	-0.08	0.91	3.65	0.01	exp(-6.77) * {AADT_maj}^-0.08 * {AADT_min}^0.91
Other, Rural* (Figure B.15)							
42	1	50.04	-28.68	20.58	9.9	0.05	exp(50.04) * {AADT_maj}^-28.68 * {AADT_min}^20.58
Railroad, Rural*† (Figure B.16)							
186	1	-2.87	-0.47	N/A	10.49	0.05	exp(-2.87) * {AADT_maj}^-0.47
Railroad, Urban† (Figure B.17)							
240	30	-7.76	0.58	N/A	0.18	0.06	exp(-7.76) * {AADT_maj}^0.58
Roundabout, Urban (Figure B.18)							
35	117	-4.85	1.15	-0.55	15.93	0.02	exp(-4.85) * {AADT_maj}^1.15 * {AADT_min}^-0.55
SPUI, Urban (Figure B.19)							
149	1954	-10.94	0.67	0.66	4.39	0.06	exp(-10.94) * {AADT_maj}^0.67 * {AADT_min}^0.66
Uncontrolled, Rural* (Figure B.20)							
378	3	-21.42	0.92	1.13	9.91	0.05	exp(-21.42) * {AADT_maj}^0.92 * {AADT_min}^1.13
Uncontrolled, Urban (Figure B.21)							
82	55	-16.88	1.93	-0.37	1.32	0.06	exp(-16.88) * {AADT_maj}^1.93 * {AADT_min}^-0.37
Yield, Rural (Figure B.22)							
24	8	-9.49	3.14	-2.2	11.65	0.06	exp(-9.49) * {AADT_maj}^3.14 * {AADT_min}^-2.2
Yield, Urban (Figure B.23)							
24	6	-3.56	1.75	-1.73	9.45	0.04	exp(-3.56) * {AADT_maj}^1.75 * {AADT_min}^-1.73

*Intersection categories with SPFs that should be used with caution (SPFs with a %pval > 0.1 and/or a suspect CURE plot)
† Intersection categories that did not have a Minor AADT in the data – these categories were analyzed using Major AADT only

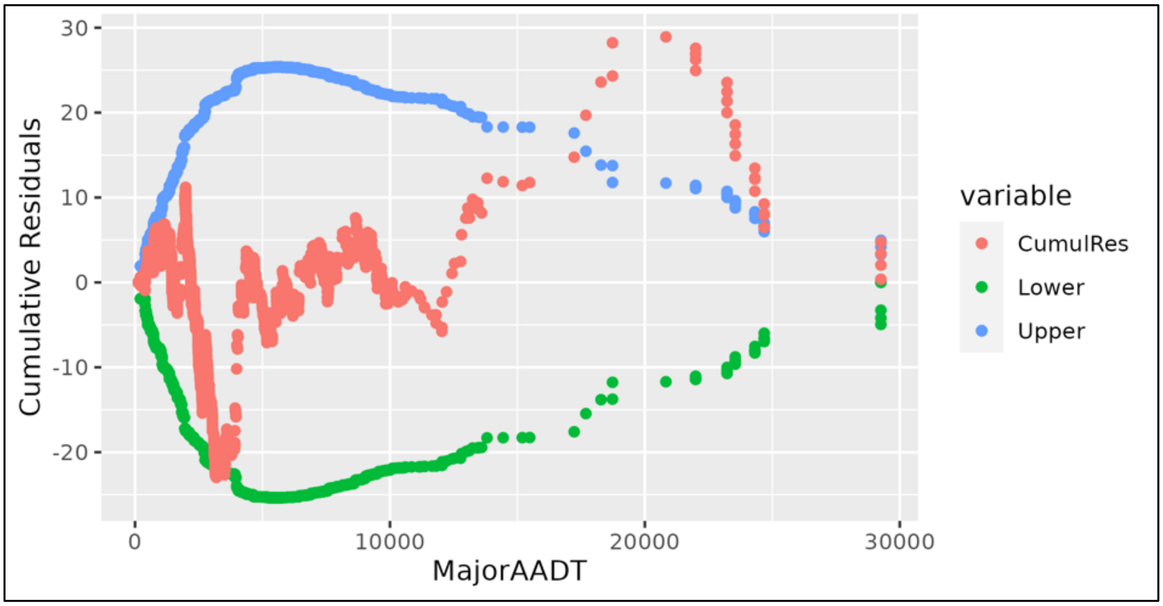


Figure B.1 3-Leg Minor Stop, Rural CURE plot.

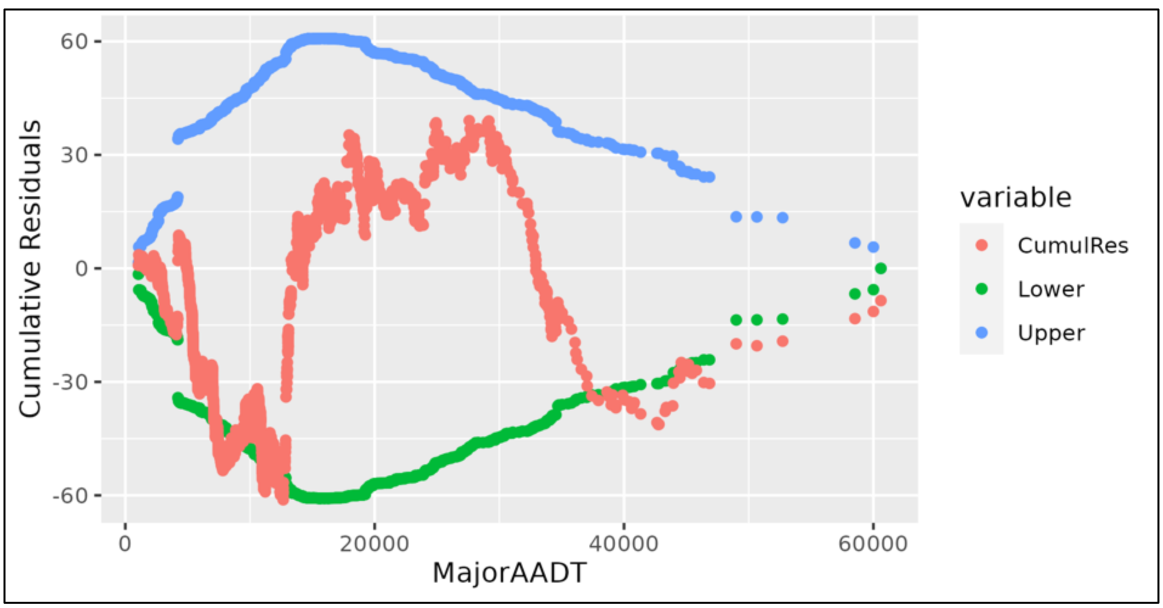


Figure B.2 3-Leg Minor Stop, Urban* CURE plot.

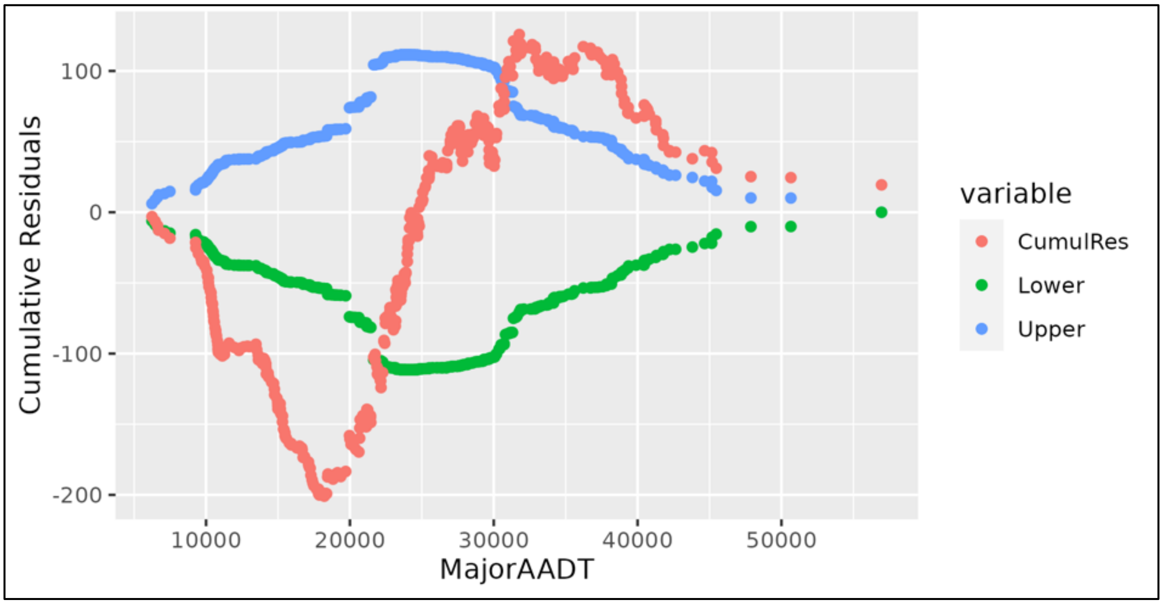


Figure B.3 3-Leg Signal, Urban* CURE plot.

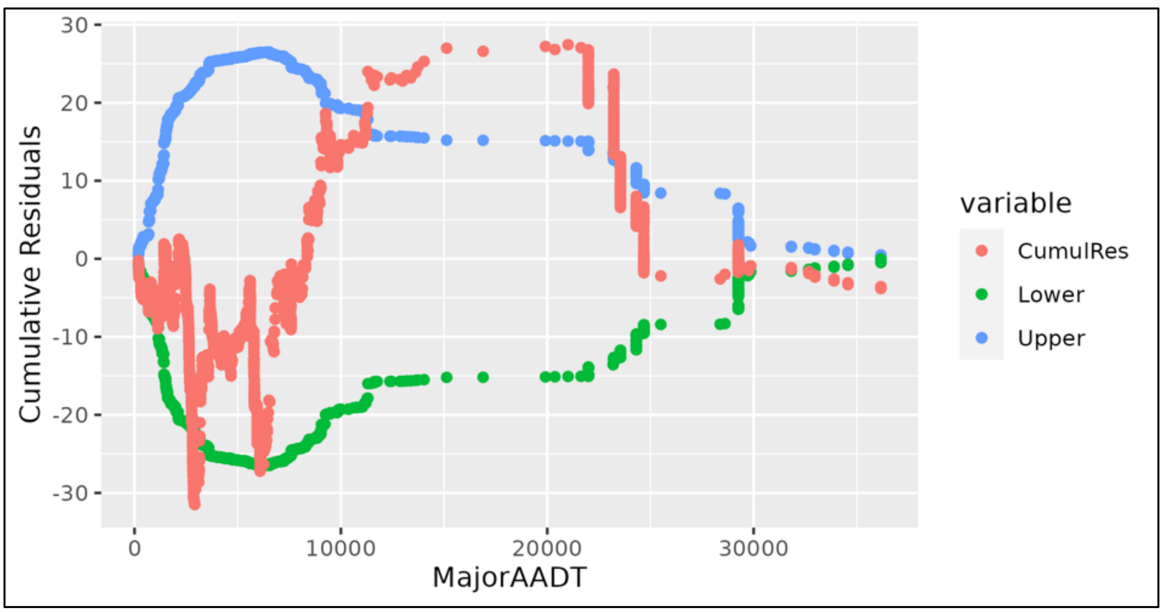


Figure B.4 4+ Leg Minor Stop, Rural CURE plot.

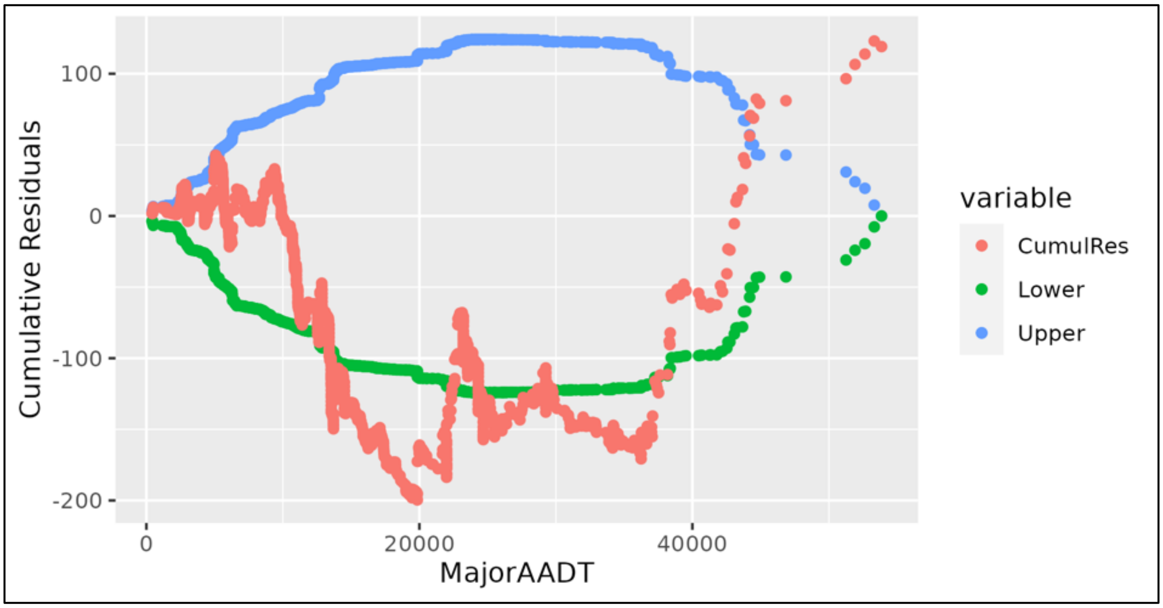


Figure B.5 4+ Leg Minor Stop, Urban* CURE plot.

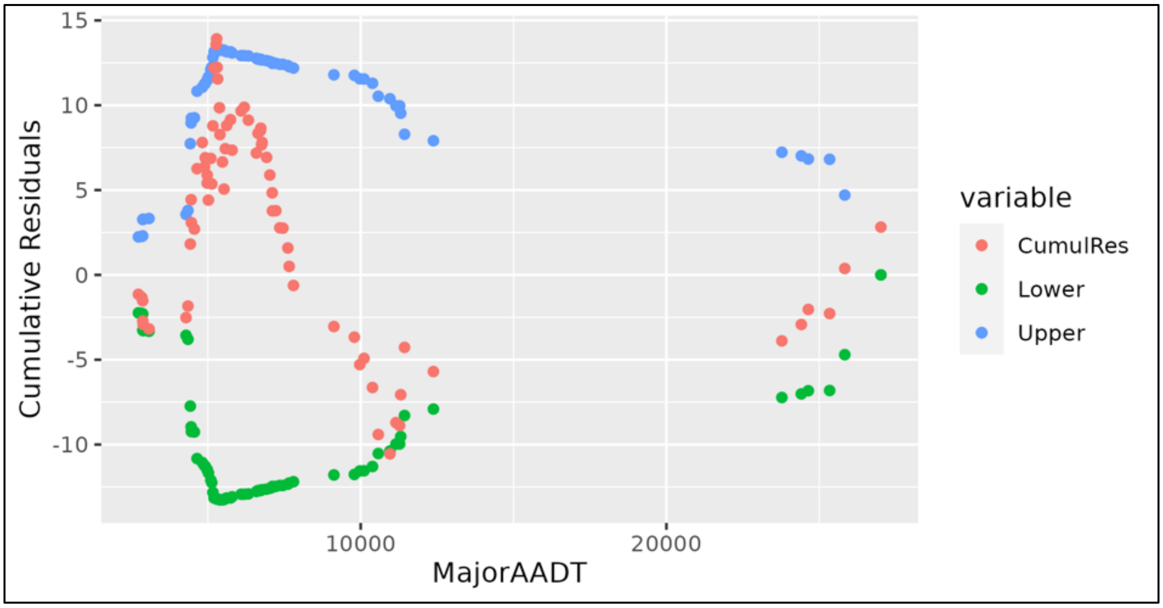


Figure B.6 4+ Leg Signal, Rural CURE plot.

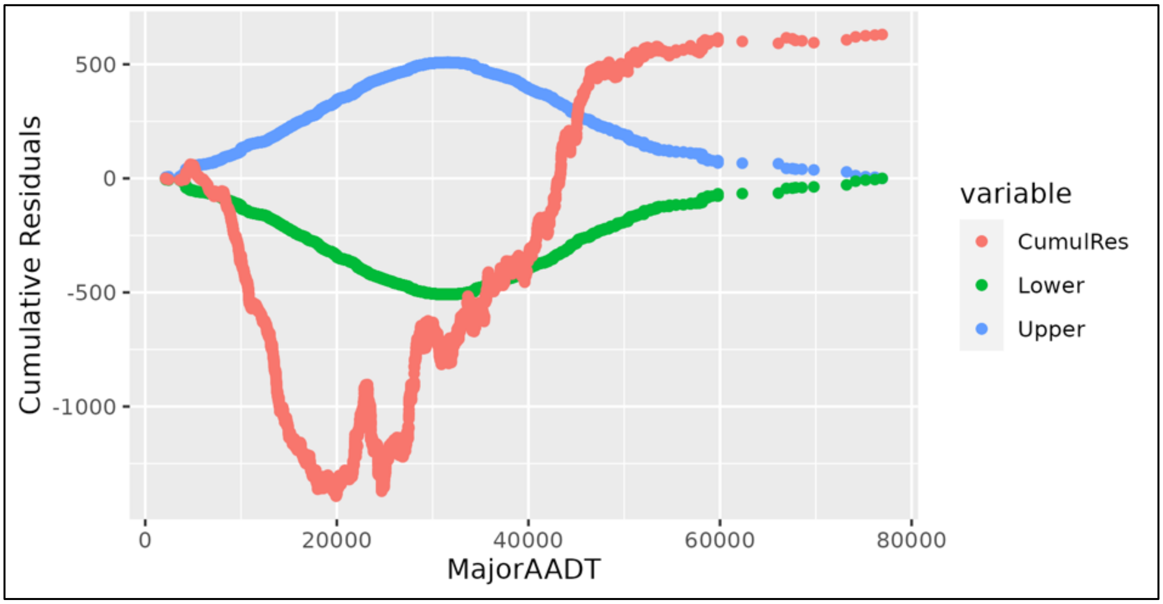


Figure B.7 4+ Leg Signal, Urban* CURE plot.

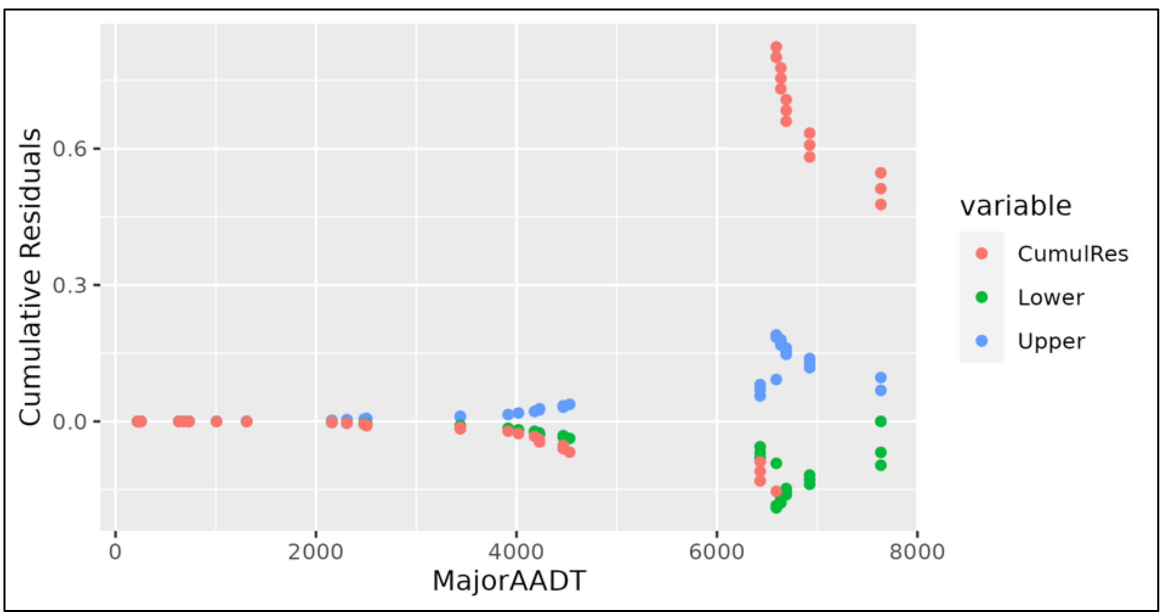


Figure B.8 Active Transportation, Rural*† CURE plot.

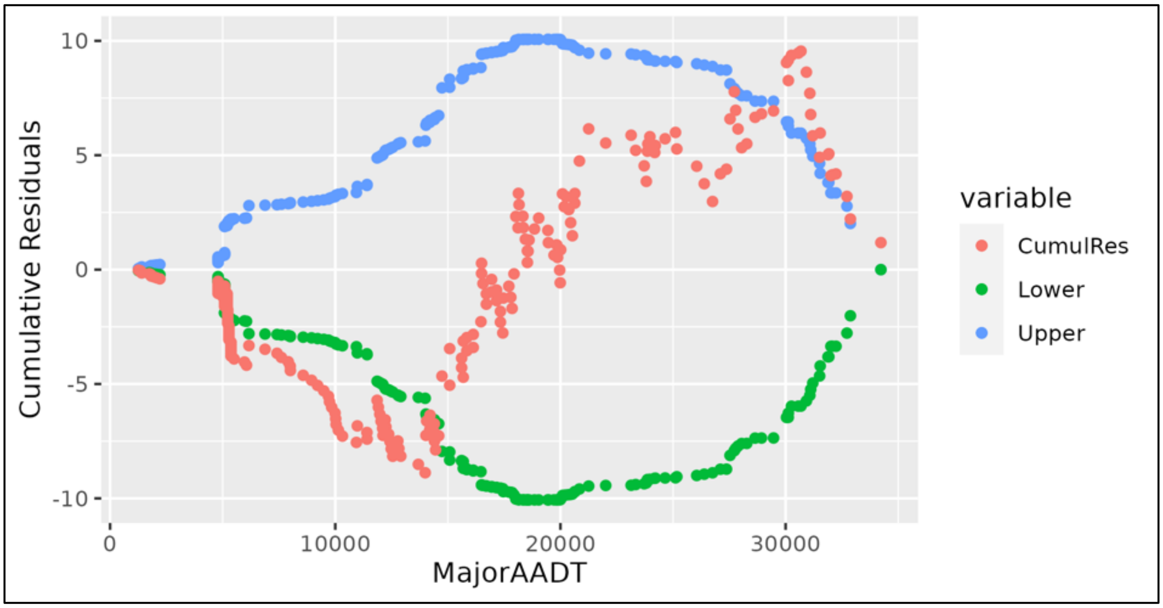


Figure B.9 Active Transportation, Urban† CURE plot.

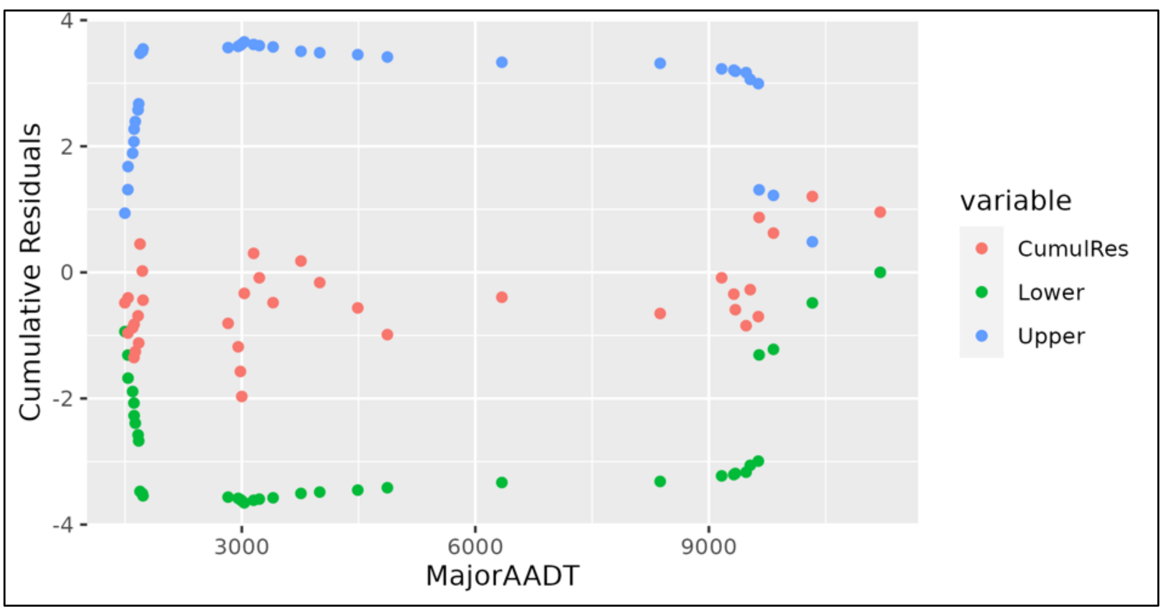


Figure B.10 All-Way Stop, Rural CURE plot.

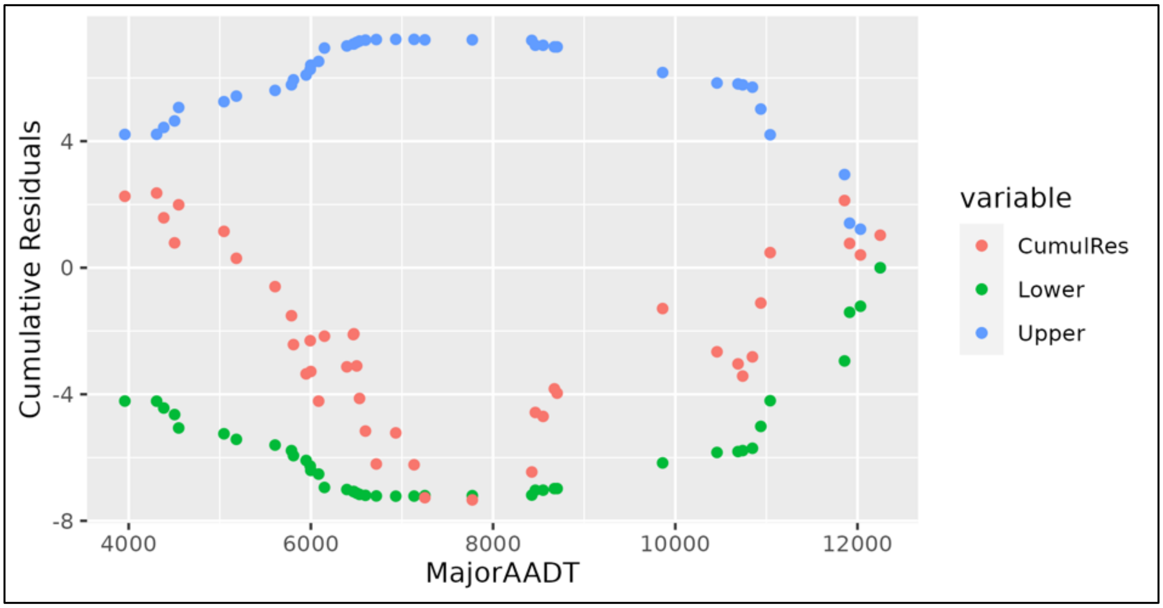


Figure B.11 All-Way Stop, Urban CURE plot.

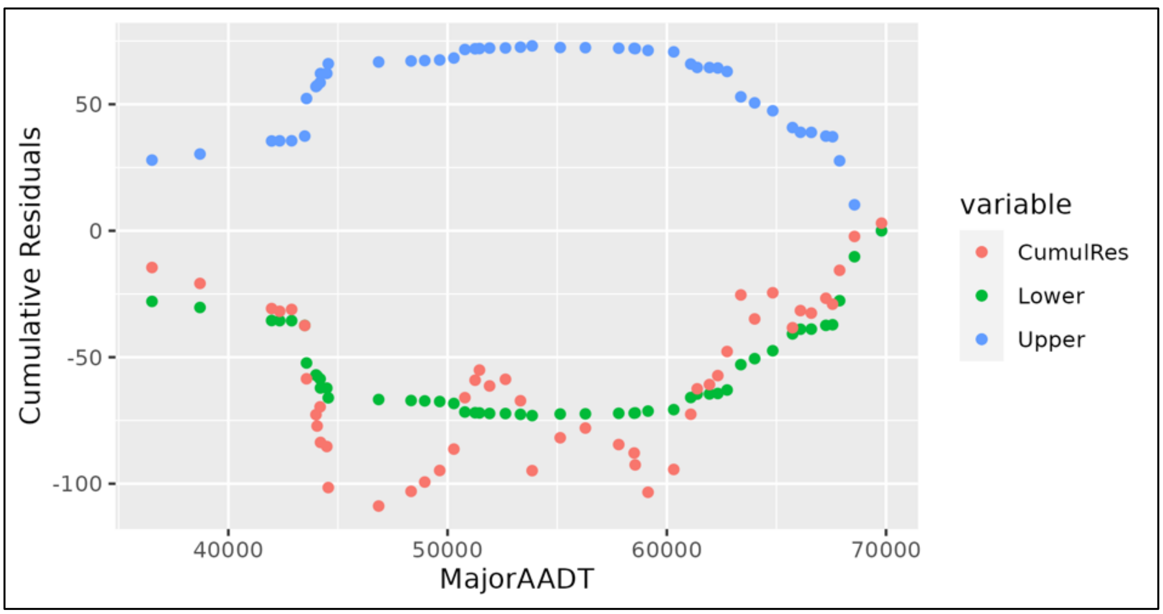


Figure B.12 CFI Central, Urban* CURE plot.

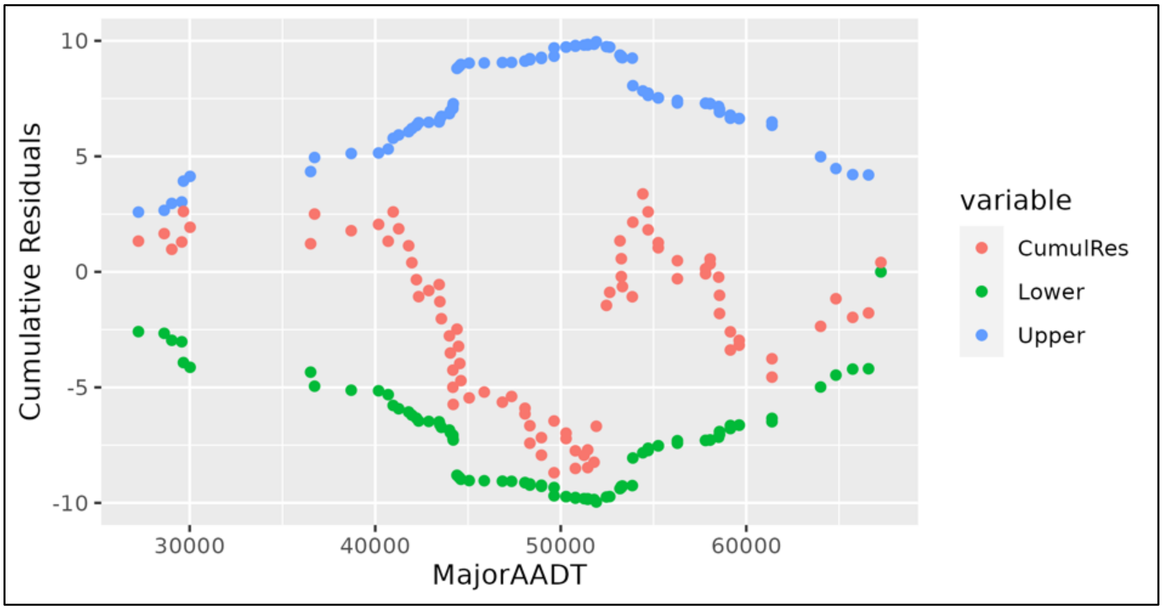


Figure B.13 CFI Offset Left, Urban CURE plot.

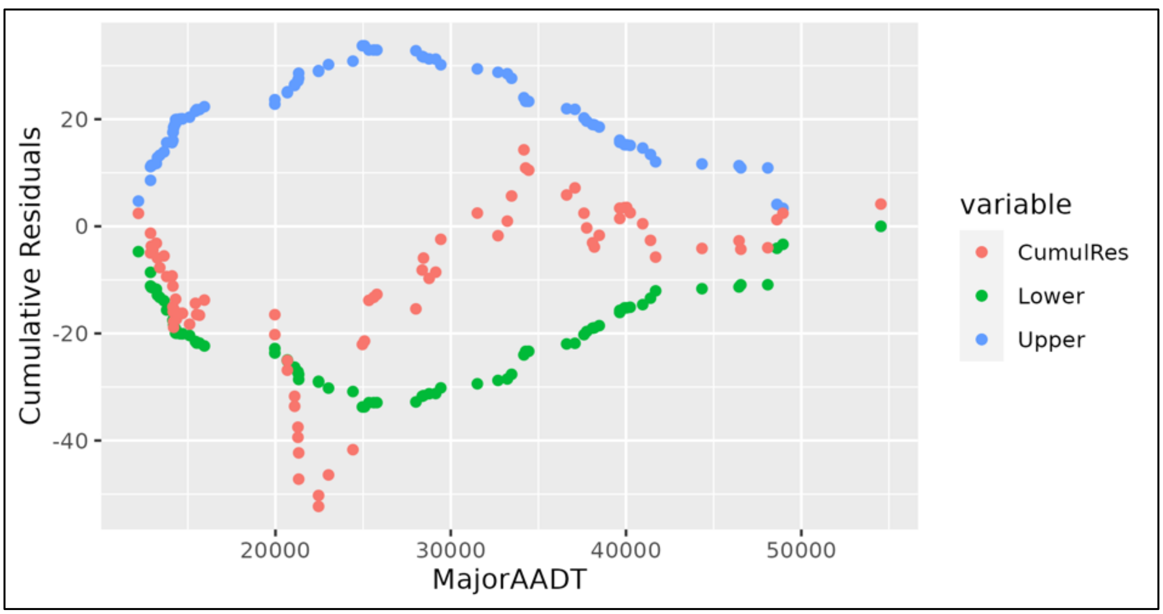


Figure B.14 DDI, Urban CURE plot.

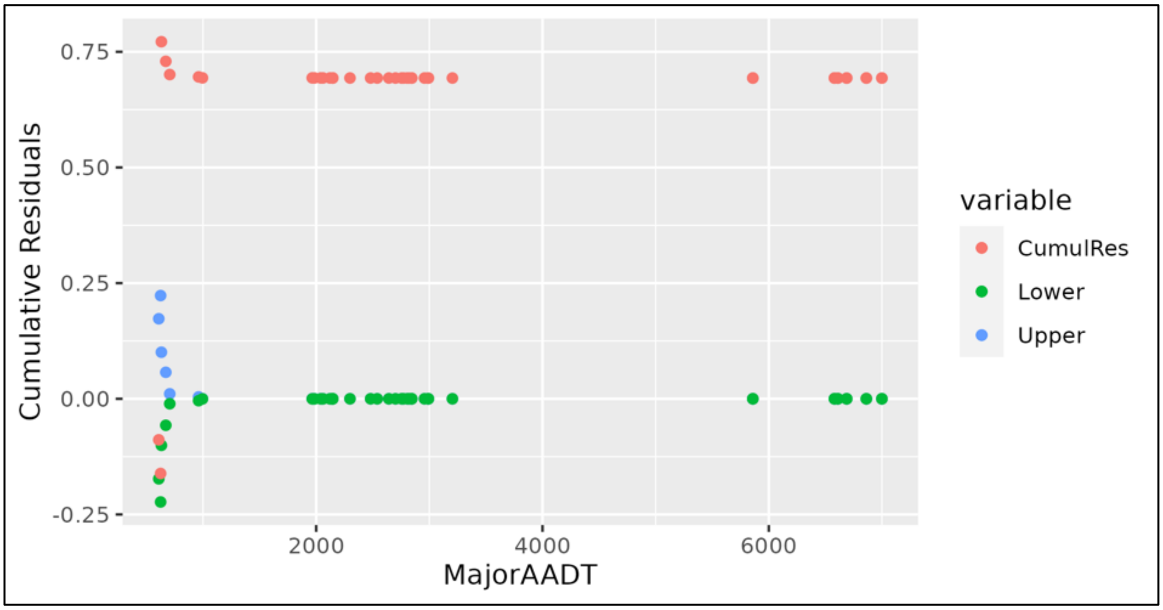


Figure B.15 Other, Rural* CURE plot.

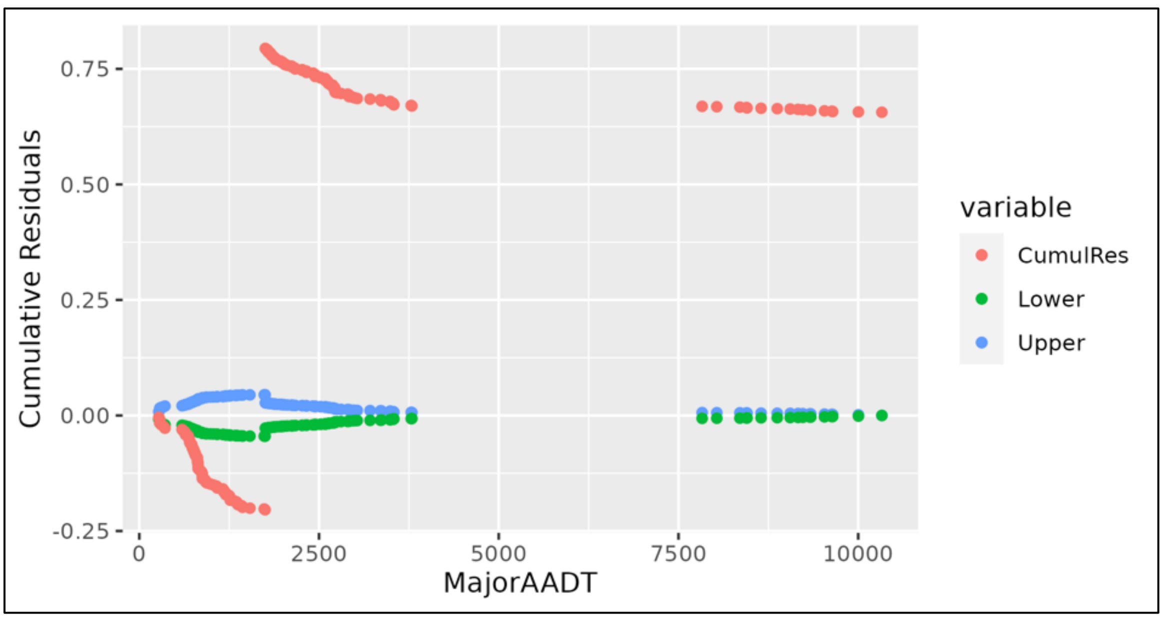


Figure B.16 Railroad, Rural*† CURE plot.

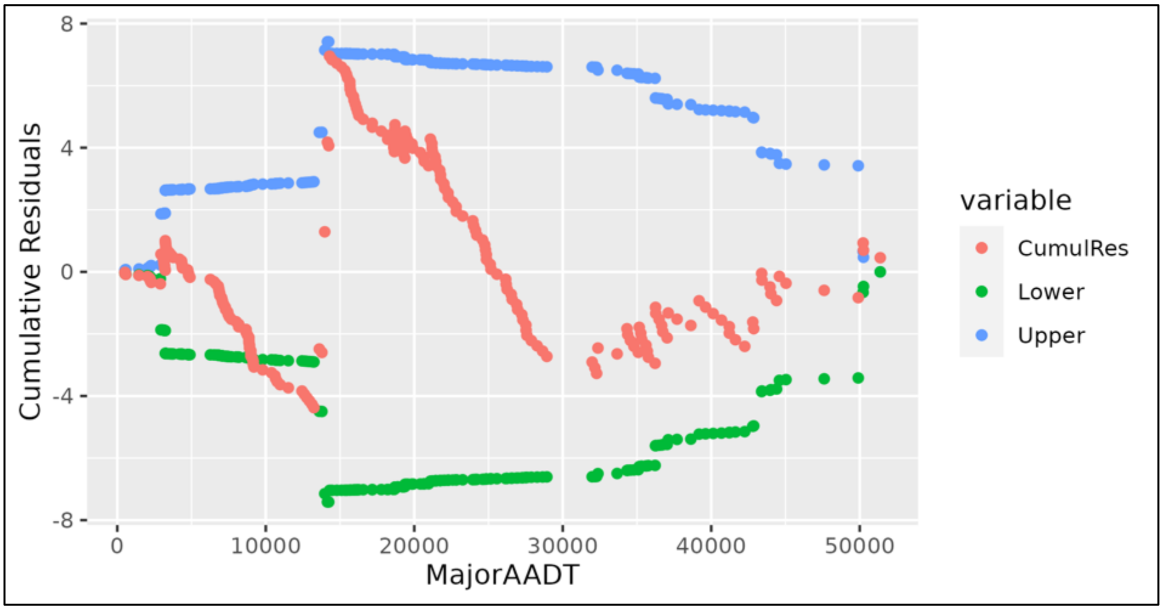


Figure B.17 Railroad, Urban† CURE plot.

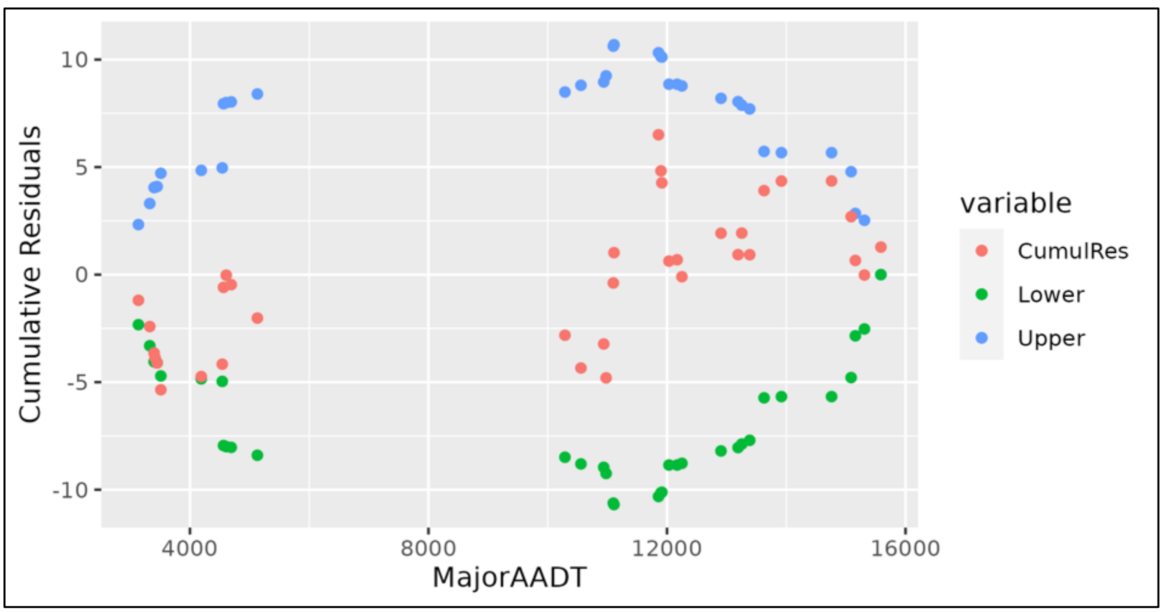


Figure B.18 Roundabout, Urban CURE plot.

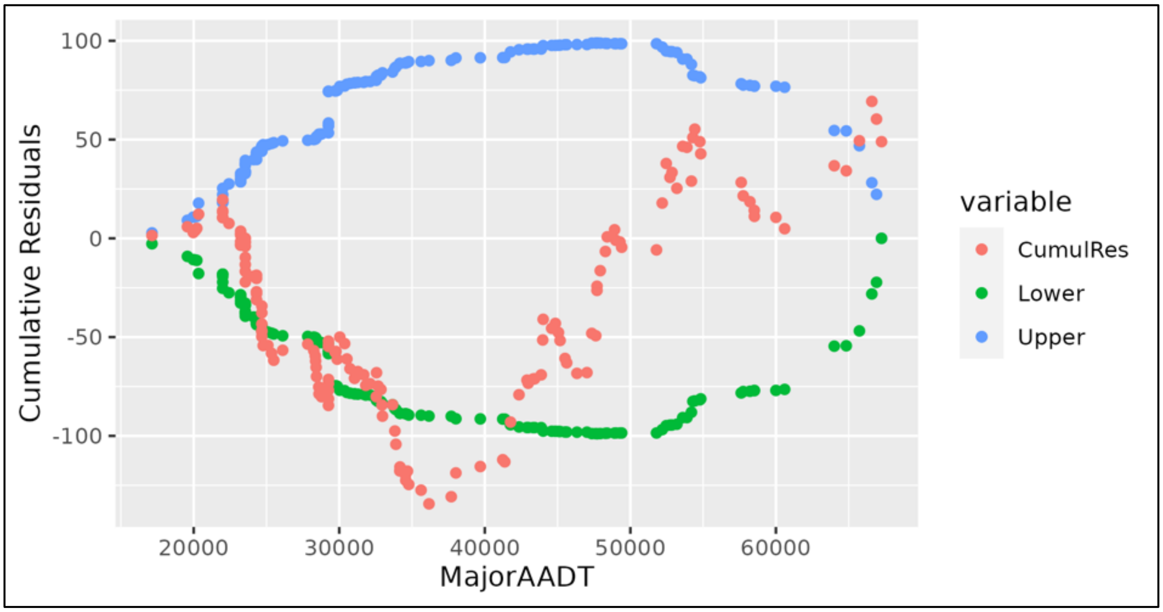


Figure B.19 SPUI, Urban CURE plot.

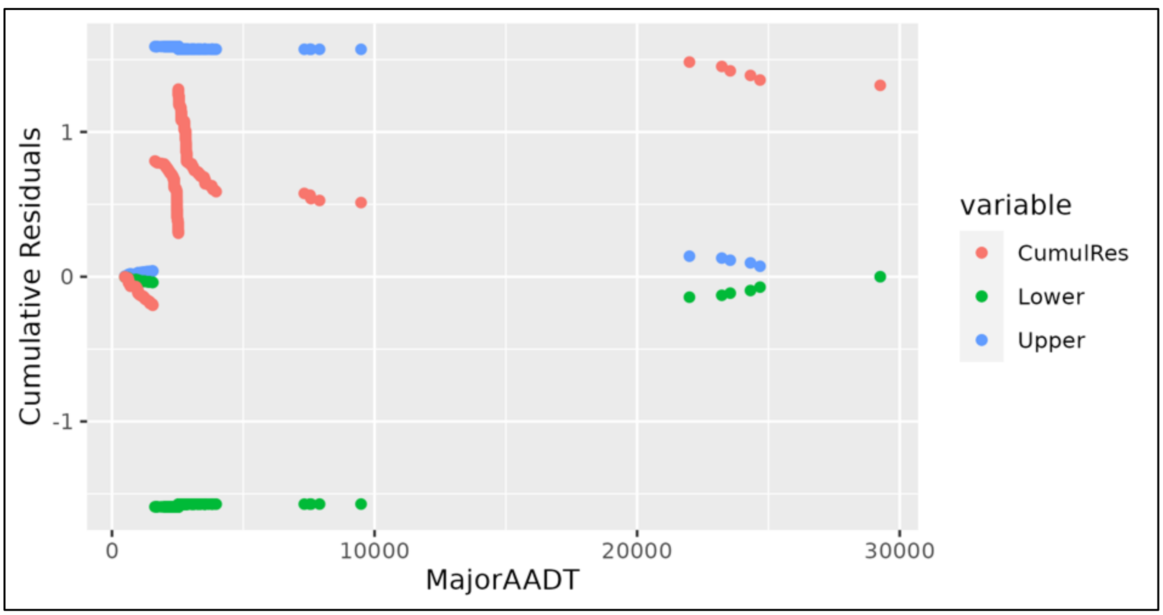


Figure B.20 Uncontrolled, Rural* CURE plot.

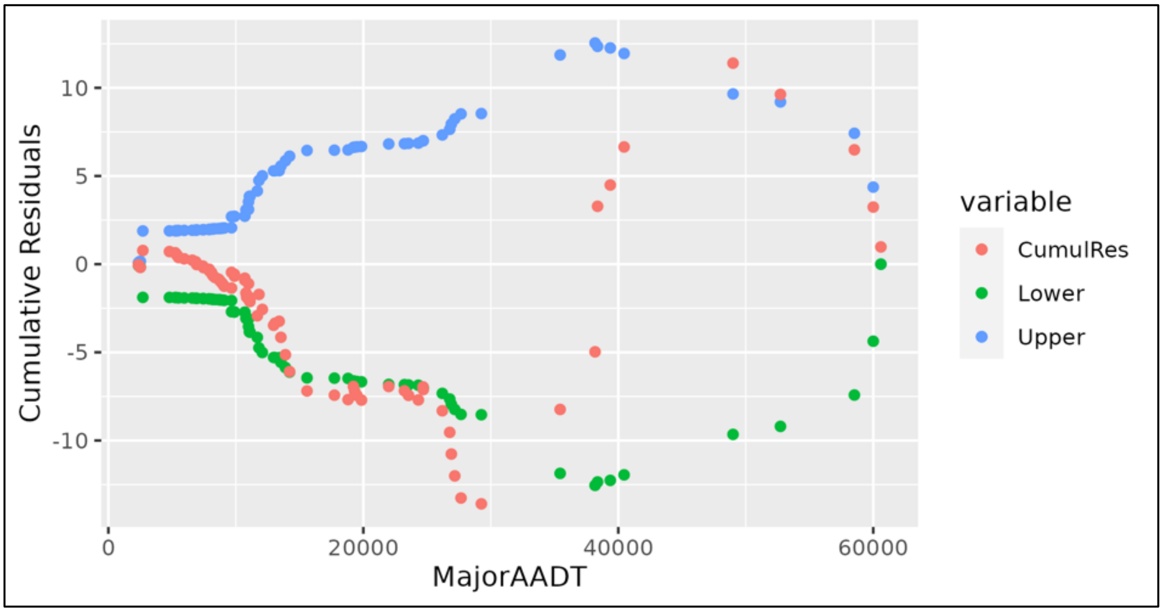


Figure B.21 Uncontrolled, Urban CURE plot.

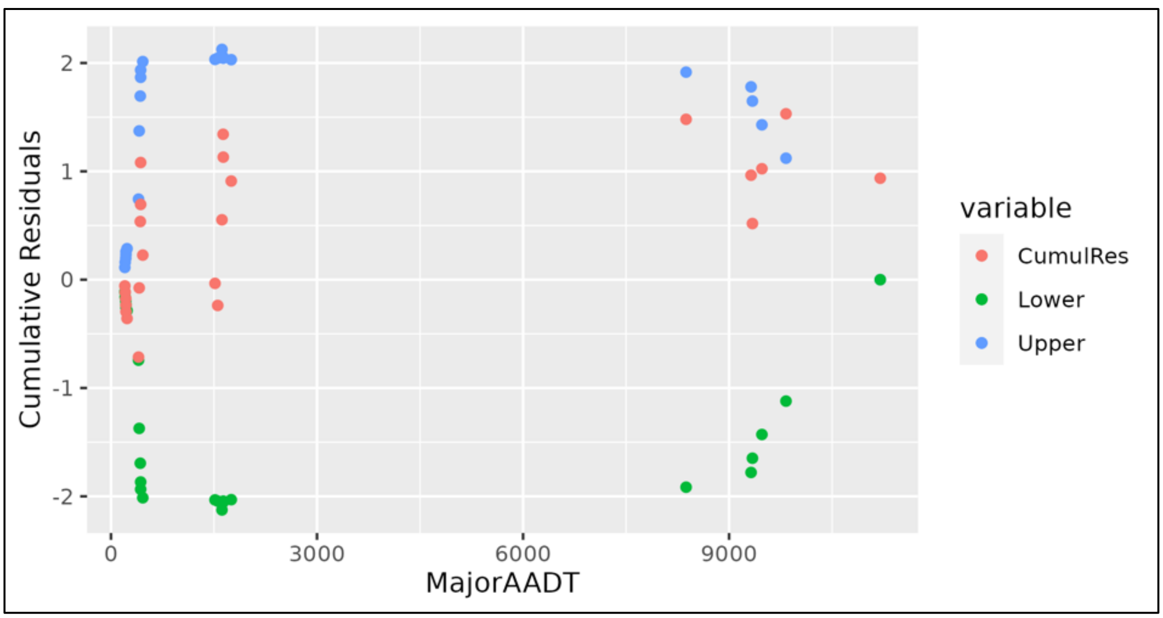


Figure B.22 Yield, Rural CURE plot.

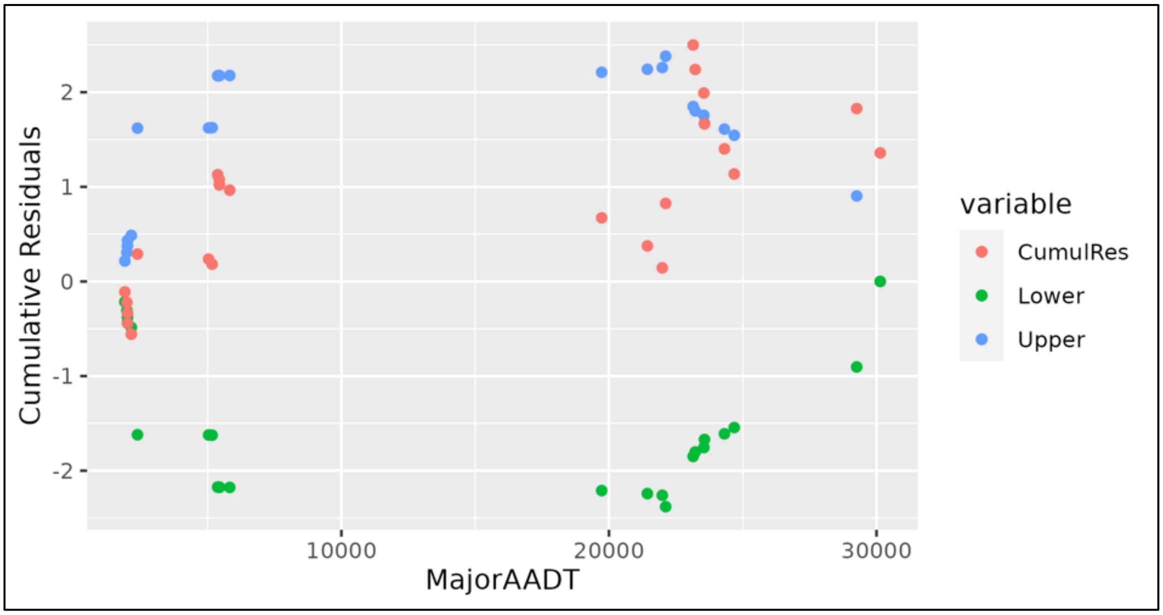


Figure B.23 Yield, Urban CURE plot.

Table B.3 Intersections with Small Sample Sizes with No SPF Developed

Category	#Int	Crashes
Other, Urban	23	11
Thru-Turn-U, Urban	30	52
Thru-Turn, Urban	18	289
Roundabout, Rural	10	4
3-Leg Signal, Rural	12	26