Final Report

on

Predicting Crashes and Crash Causes on Ohio Roadways

(District 2)

Prepared for

The Ohio State Highway Patrol

By

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Executive Summary

A primary goal of the Ohio State Highway Patrol (OSHP) is to develop and implement strategies for reducing the number of injury and fatal vehicle crashes on Ohio highways. In order to help OSHP effectively allocate its resources to reduce crash rates, the Statistical Consulting Service (SCS) constructed a probability model to forecast crash rates on several metro roadways in Ohio (Holloman, 2006). This probability model was then extended from the metro roadways on which it was developed to the interstates and US/State routes throughout the state. This report details the extension of the model to these additional roadways.

In order to construct the probability model, several databases were collected and merged together to create a master database. The master database contained information on close to two million crashes on Ohio roadways between January 1, 2001, and December 31, 2005. Of these, 172,665 crashes were analyzed because they were injury or fatal crashes that occurred on interstates, US routes, and State routes within Ohio.

Most of the exploratory statistical work required for creating the model was conducted for a previous project. However, some exploratory analysis was conducted to determine whether the model could be extended to all interstates, US routes, and State routes in Ohio. This analysis found that all interstate routes could be modeled, but that US/State routes in nine counties would have to be excluded due to large amounts of missing geolocation data.

Fitting the statistical model required substantial computing power, so resources from the Ohio Supercomputer Center were used. The model was fit over a two-week period. Model diagnostics suggest that the model fit the data well.

Fitting the model produced a large amount of output that can be summarized in numerous ways, and the majority of this report is dedicated to presenting the output in ways that will be useful to individuals making resource allocation decisions. Section 4.4.1 presents information for comparing crash rates across different districts and on different days. Section 4.4.2 presents time series plots of crash rates that can be used to determine optimal timing for officer patrols and the most likely causes of crashes at different times. Section 4.4.3 presents crash rates geographically for District 2. This section shows the most dangerous roadways on different days and the most dangerous roadways for different types of crashes. Section 4.4.3.1 presents tables of the most dangerous sections of roadway for different types of crashes. Finally, Section 4.4.5 presents parameter estimates that provide some insight into the impact of inclement weather and month of the year on crash rates.

1. Project Background

A primary goal of the Ohio State Highway Patrol (OSHP) is to develop and implement strategies for reducing the number of injury and fatal vehicle crashes on Ohio highways. The Ohio Department of Public Safety (ODPS) maintains data obtained from completed reports on crashes investigated by law enforcement agencies in the state of Ohio. Historically OSHP has used experience, judgment, and the crash report data in both qualitative and quantitative ways to dispatch patrol officers to specific locations at specific times where it is likely that injury or fatal crashes may occur. It is believed that the presence and monitoring activities of officers in these locations significantly reduces the likelihood that injury or fatal crashes will occur.

Between March, 2006, and July, 2006, the Statistical Consulting Service (SCS) worked with representatives from the OSHP to develop a probabilistic model to forecast the likelihood of future crashes (Holloman, 2006). This model was developed using only information from a few interstates in major cities in Ohio. The model produced forecasts for the following roads:

- Cleveland Area: I-271, I-480, I-71, I-77, I-90, and I-490
- Cincinnati Area: I-275, I-75, I-71, and I-74
- Columbus Area: I-270
- Dayton Area: I-675
- Toledo Area: I-280 and I-475

Based on the model's performance, the OSHP determined that the model should be expanded to produce forecasts on all interstates, US routes, and State routes throughout Ohio. Expanding the model to more roadways will allow post commanders in all districts to have useful information to guide resource allocation decisions.

2. Study Design

This study is a retrospective study of crashes investigated by law enforcement officers in Ohio. For each traffic crash, the investigating officer records many pieces of information including:

- Details about the road and weather conditions related to the crash,
- Information about the driver(s) including the presence of drugs and alcohol,
- The sequence of events that occurred during the crash, and
- Information on other factors that may have been causal in the crash (e.g., vehicle speed).

All of these data are stored by ODPS in relational databases that can then be queried to find information on individual crashes.

For the current project, researchers at the Statistical Consulting Service (SCS) examined crash records for the complete years 2001 through 2005. The records were delivered to SCS on CD-ROM in files called TRACTAPE files. These files summarize the important aspects of each crash, but they do not report every piece of information that was recorded about each crash.

Information in the TRACTAPE files covers all interstates, US routes, and State routes in Ohio. These three types of roads constituted the areas of focus for this project.

3. Database Development and Data Editing

The information used to develop the predictive models in this project was obtained from several sources. First, as mentioned in the previous section, crash information was obtained from the ODPS TRACTAPE files for 2001 through 2005. These files contain a single record for each crash investigated by a law enforcement employee in Ohio. Each of these records contains close to 200 variables describing different aspects of the crash and individuals involved.

The second major source of data for the project was the Ohio Department of Transportation (ODOT) geolocation files. These files contain information on the geographic locations where crashes occurred. For each crash in the ODPS database, ODOT uses information in the crash report to assign the crash to a segment of roadway and to determine the latitude and longitude of the crash. For many crashes, the crash report does not contain enough information to geolocate the crash, so no information is reported.

The first step in building an analysis database was to select the crashes of interest from the ODPS TRACTAPE files and merge in the geolocation information. The original TRACTAPE data files contained information on 1,905,602 crashes that occurred over the five years of 2001 through 2005. The crashes of interest are those in which an injury or fatality was recorded, so only crashes with a *crash_severity_flag* value of 1 (fatal injury) or 2 (injury) were used in the analysis. Subsetting the data this way eliminates all crashes that involved property damage only or had unknown crash severity levels. After subsetting, the database contained 474,005 crash records. Next, the geolocation information from the ODOT files was merged by the crash document number. This merged database constituted the main database of crashes for the project.

The second step in building the analysis database was to connect the selected crashes to individual road segments of interest and subset the data to only those crashes that occurred on the roads of interest. To accomplish this step, OSHP supplied SCS with a GIS dataset of Ohio roadways broken into one-mile segments. This dataset was converted from NAD 83 coordinates to ordinary decimal degrees using ArcGIS software. Next, SAS statistical software was used to select only crashes that occurred on interstates, US routes, and State routes, and these crashes were each matched to the closest 1-mile segment of roadway. Only crashes that were geolocated to one of the roads of interest were used in the matching. A QC check was performed to ensure that all crashes identified as being located on a roadway of interest were, in fact, geolocated close to a roadway. Crashes that failed this QC test were removed from the database. The database obtained by performing this matching constituted the final analysis database for the project since it contained all of the crashes of interest matched up with all of the road segments of interest. After removing crashes that did not occur on interstates, US routes, or State routes, 172,665 crash records remained in the database. After eliminating records for which no geolocation data was available or which failed the QC test, 144,783 crash records remained.

4. Statistical Models and Analysis

Before expanding the statistical model to all interstates, US routes, and State routes in Ohio, some exploratory analyses were conducted. The main objective of these exploratory analyses was to assess the extent to which missing geolocation information might affect the statistical model. Before conducting any analyses, it was known that some counties have worse problems with geolocation than others and that US and State routes have more geolocation problems than interstates.

Based on the exploratory analysis, it was determined that the model could be fit in most of the 88 Ohio counties. Section 4.1gives information on the areas in which the model fitting was performed, and briefly describes the important issues. A detailed description of the model was provided to the OSHP in a previous report, so it is not presented again here. Section 4.2 presents some information on the model and model fitting process. Diagnostics of the model fit are presented in Section 4.3. Results of the model fitting are presented in Section 4.4.

4.1. Exploratory Analysis of Geolocation Data

Geolocation data, defined as the latitude and longitude coordinates of a crash, are not available for every crash contained in the ODOT database. These data may not be available for a number of reasons, but the most common reasons are that the address or reference point listed on the crash report could not be automatically coded into latitude and longitude coordinates or that the description of the crash location was ambiguous. On interstates, US routes, and State routes, 83.9% of crashes do have useable geolocation information.

Before conducting any modeling, it is important to understand the geographic dispersion of the crashes that do not have geolocation information. If any individual type of road or any individual county has a disproportionate amount of missing data, it is meaningless to conduct a statistical analysis on that road type or within that county. For example, suppose that 50% of the crashes that occurred within a single county had no geolocation data available. It is likely that many crashes occurred on a single segment of road but that segment of road is poorly marked and none of those crashes were geolocated. As a result, the statistical model would indicate that the poorly marked segment of road is safe when, in fact, there have been many crashes there.

To explore the spatial distribution of missing geolocation data, the data were first divided into two categories: interstate crashes and US/State route crashes. Within each of these categories, the percentage of crashes missing geolocation data within each county was calculated. These percentages were then plotted on a map to show locations where missing geolocation data present a problem. Also, histograms of the percentage of crashes missing geolocation data within each county were made for interstate routes and for US/State routes.

Figure 1 shows the geographic distribution of missing data for crashes marked as occurring on interstates. Within each county, the number of crashes missing geolocation data and the total number of crashes are shown as a fraction of the form

$$\text{crashes missing geolocation data} / \text{total number of crashes}.$$

The colors of the counties represent different fractions missing. It appears from the map that, in general, urban counties have more missing data than rural counties.

Figure 2 shows a histogram of the data presented in Figure 1. From this histogram, it appears that there are no counties with more than 20% missing geolocation information on the interstates.

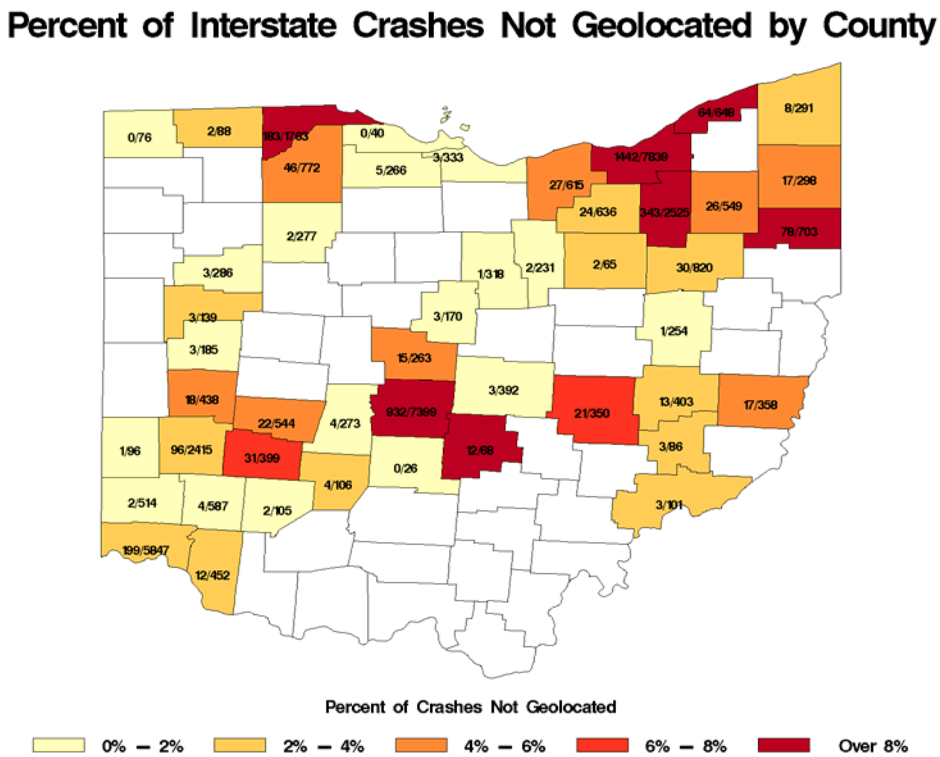

Figure 1. Geographic plot of missing geolocation data for crashes marked as occurring on interstates.

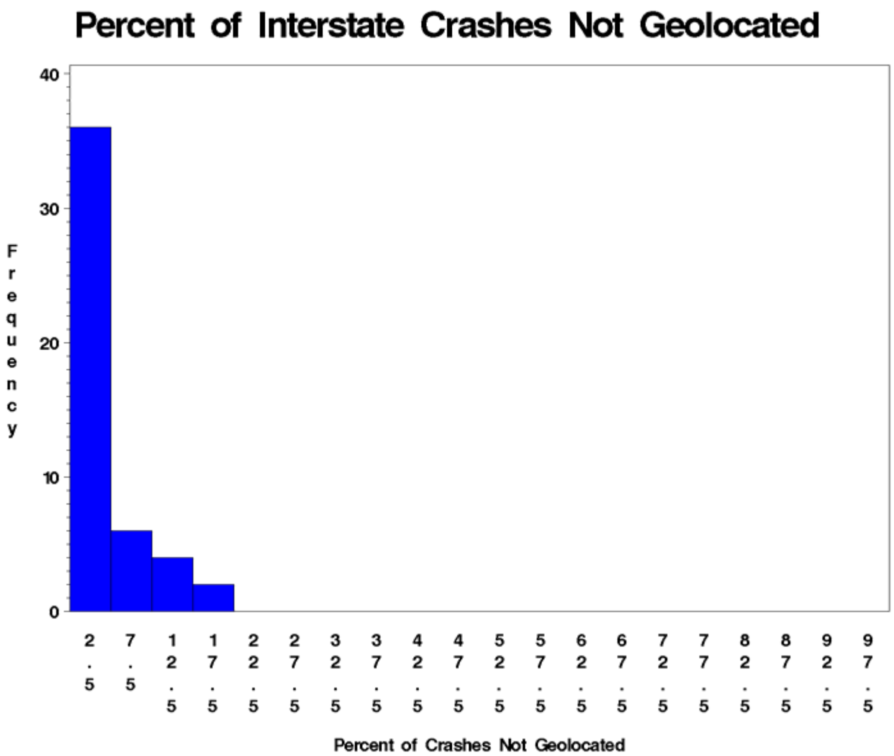

Figure 2. Histogram of the percentage of interstate crashes missing geolocation data (by county).

Figures similar to the previous two were also created for US/State routes. Figure 3 shows the geographic distribution of missing geolocation information by county, and Figure 4 shows a histogram of the same data. For the US and State routes, there do appear to counties where a large fraction of the crash records are missing geolocation data. Based on these plots, it was decided that US and State routes could not be modeled in counties with more than 30% missing. The counties eliminated from the analysis for US and State routes were Champaign, Coshocton, Fayette, Fulton, Hamilton, Henry, Miami, Putnam, Shelby, and Vinton.

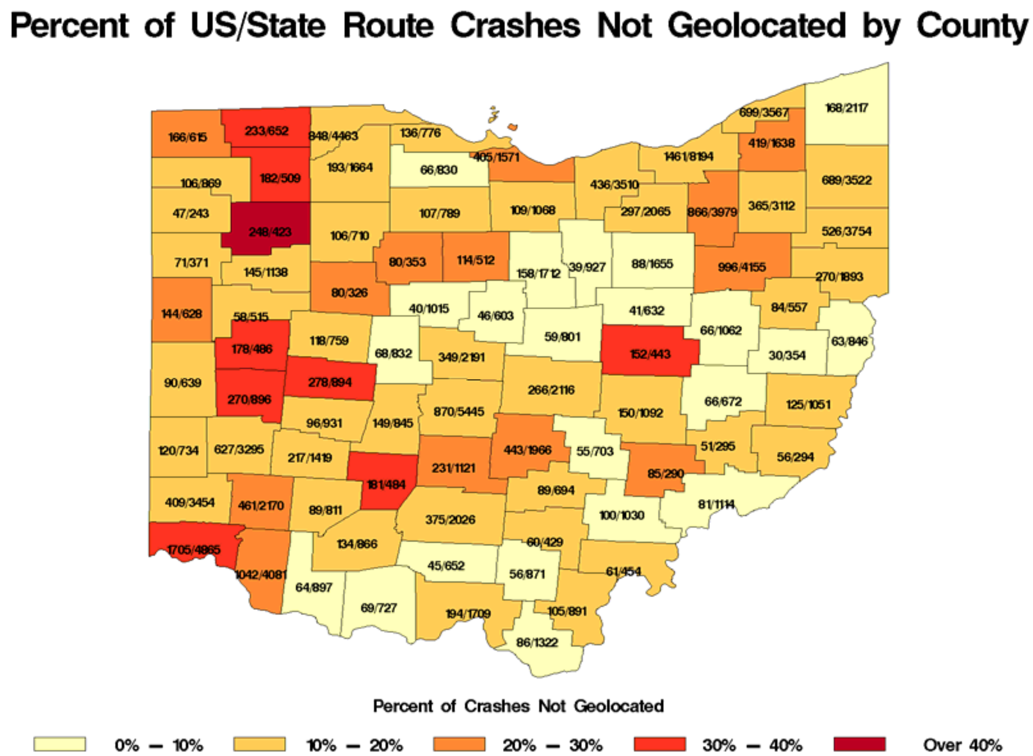

Figure 3. Geographic plot of missing geolocation data for crashes marked as occurring on US/State routes.

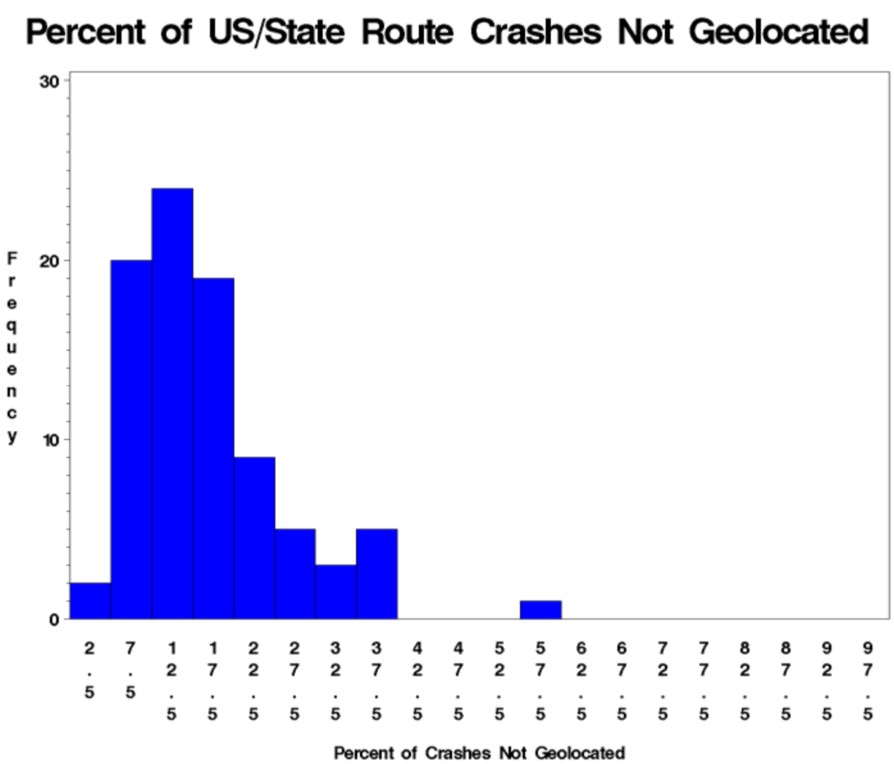

Figure 4. Histogram of the percentage of US/State route crashes missing geolocation data (by county).

4.2. Statistical Model and Model Fitting

The statistical model used to fit the crash data was described in detail in a previous report to OSHP (Holloman, 2006). However, some modifications to the model were necessary to allow expansion to the large number of roadways in this analysis.

The first modification was to fit the model in pieces rather than fitting the model on all roadways of interest at once. The model had to be fit in pieces due to computational limitations. The pieces were defined by first dividing the state into districts according to the OSHP district map (see Figure 5). Within each district, the roads were then divided into two groups: interstates and US/State routes. The model was fit separately within each district and on each of the two groups of roadways. Thus, the model was fit 20 separate times, once for each possible combination of district and interstate vs. US/State routes. Although District 10 technically includes the Ohio turnpike as well as Cuyahoga County, turnpike crashes were subsumed into the county in which they occurred.

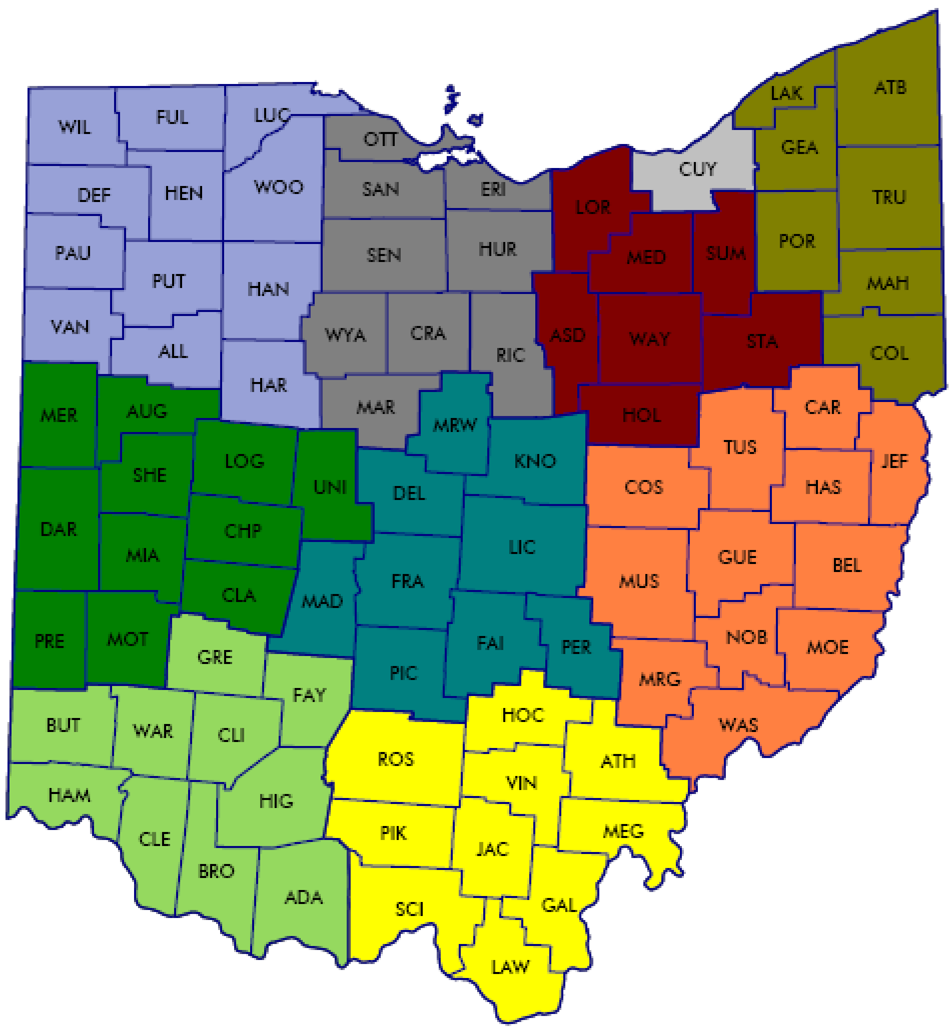

Figure 5. Ohio counties and OSHP districts.

Fitting the model separately in each district raised concerns about continuity of estimates at the borders of the districts. As a result, when the model was fit in a district, the counties sharing a border with any county in that district were included in the dataset used to estimate crash risks. These additional counties influenced the estimates of the crash risks in the district being modeled, but no predictions were calculated for the adjacent counties. As an example, consider District 1 (the purple counties in the northwest corner of the map in Figure 5). This district includes Williams, Fulton, Lucas, Defiance, Henry, Wood, Paulding, Putnam, Hancock, Van Wert, Allen, and Hardin. When the model was fit for this district, predictions were produced for all of these counties. The adjacent counties that were also included in the modeling dataset for this district included Mercer, Auglaize, Logan, Union, Marion, Wyandot, Seneca, Sandusky, and Ottawa. No predictions were created for these counties when the model was being fit for District 1.

Within each district, the model was fit separately for interstates and for US/State routes. For the interstates, each one-mile segment of roadway was used as the unit of analysis – risk was assessed separately under a broad range of conditions for each of these one-mile segments. For the US/State routes, roadways were aggregated into five-mile segments before model fitting. This aggregation was necessary because exploratory analysis found that computational limitations would prevent the model from being fit separately on all one-mile segments of roadway for US/State routes.

All of the models were fit using computers at the Ohio Supercomputer Center (OSC). The models were fit using SAS software running on the OSC Itanium 2 cluster.

4.3. Model Validation and Diagnostics

The model was fit using the crash information from January 1, 2001 through June 30, 2005. Data from the final six months (approximately 10% of the total dataset) were withheld for validation purposes.

After fitting the model, predicted crash rates were calculated for each segment of roadway during each hour of each day of the last six months of 2005. The model cannot be validated by comparing each of these predicted crash rates against the number of crashes that actually occurred – for most 1-mile segments of roadway during a 1-hour segment of time the predicted crash rate is very small and the number of crashes that occurred was zero. However, it is possible to validate the model by summing up the total number of crashes that occurred on a given day or on a given segment of roadway and summing up the predicted crash rates over the same temporal period or geographic segment. By comparing the predicted crash rate (or number of crashes) to the total number of actual crashes, it is possible to calculate residual values.

Figure 6 shows a scatterplot of the predicted and actual number of crashes when aggregating by road segment. The black dots represent US/State routes, aggregated into 5-mile segments, and the red dots represent Interstates, aggregated into 1-mile stretches. The points appear to follow the 45˚ line suggesting accurate prediction when aggregating to roadways.

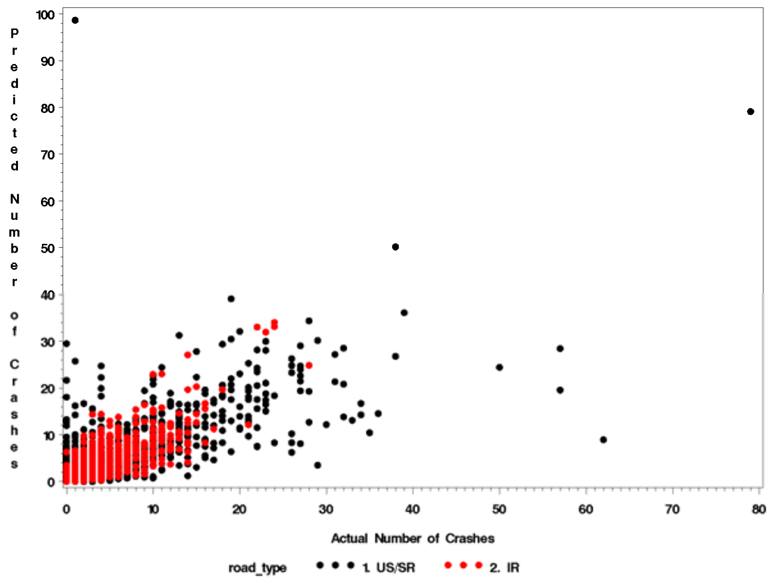

Figure 6. Predicted and actual number of crashes by road segment.

Figure 7 shows a scatterplot of the predicted and actual number of crashes when aggregating by date. In this plot, Interstates and US/State routes were split into two groups to search for any differences in model fit across dates in these two categories. Again, the pattern of residuals seems to suggest that the model is fitting the data well.

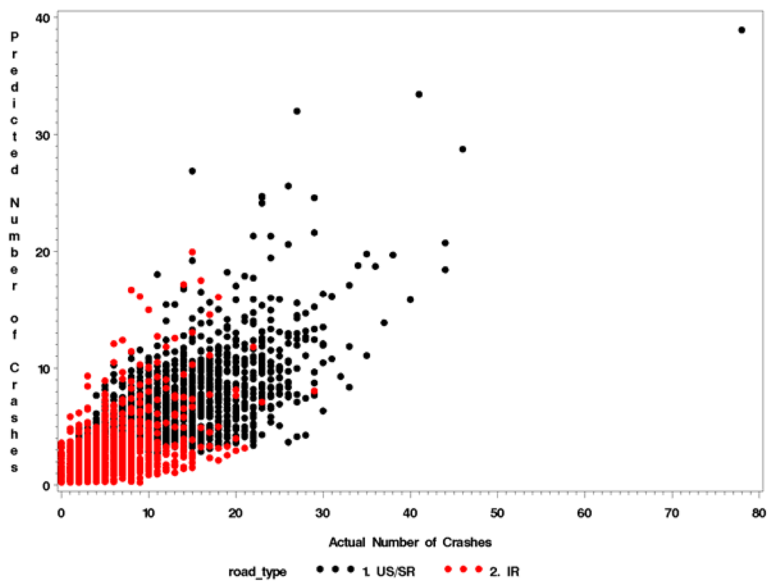

Figure 7. Predicted and actual number of crashes by date.

4.4. Results of Model Fitting

Fitting the statistical model across the entire state produces predictions of crash rates for each modeled segment of roadway under a variety of conditions. There is no way to present every aspect of this voluminous output, but some useful summary information can be presented. Summaries of the model output that are considered the most valuable for guiding resource allocation decisions are presented in Sections 4.4.1 through 4.4.3.1. First, Section 4.4.1 presents information that is useful for comparing crash rates across different districts. Next, Section 4.4.2 gives information on the temporal patterns observed in crash rates across all districts and roadways. Sections 4.4.3 and 4.4.3.1 present information broken down by district. For each district, information is presented on the geographic differences in roadway risk levels on different days and for different types of crashes. Finally, Section 4.4.5 presents some information on parameter estimates related to inclement weather and month of the year.

The information in the following sections can be used by individual post commanders to make data-driven decisions about where to position officers and what types of driving dangers they should be looking for. Starting with Section 4.4.2, it is possible to determine what categories of drivers present the most danger at a specific time. Once decisions have been made regarding the allocation of officers to different shifts and regarding the types of behaviors to monitor (e.g., speeding, erratic driving), the district-specific geographic information in Sections 4.4.3 through 4.4.3.1 can be used to determine where those officers should be stationed.

4.4.1. Comparison across Districts and Time Groups

First, we examine some average crash rates across the ten OSHP districts during the five different time groups. As described in a previous report to OSHP (Holloman, 2006), each day included in the modeling is classified into one of five groups:

- Group 0 – Monday, Tuesday, Wednesday, and Thursday when the date is not a holiday or the last work-day before a three- or four-day weekend.
- Group 1 – Saturday and Sunday when the date is not a holiday.
- Group 2 – Friday when the date is not a holiday or the last work-day before a three- or four-day weekend.
- Group 3 – The final work-day before a three-day (or four-day) weekend.
- Group 4 – Holidays.

To compare these groups across different cities, some predicted values were calculated from the crash model. In each district and for each time group, the average crash rate on a one-mile segment of road during a one-hour period was calculated. For all of these crash rates, no inclement weather is assumed, and January is used as the month (choosing another month will simply increase all the values in each graph by an equal proportion – comparisons between values will retain the same meanings).

Figure 8 shows the average crash rate on interstates for each of the districts in the analysis. Note that the last panel only holds information from Cuyahoga County since the District 10 turnpike roads are subsumed into counties from other districts. Also, note that the panel for District 9 is blank because there are no interstates in District 9. Figure 9 shows the average crash rate on US/State routes for each of the districts in the analysis. From Figure 8, it appears that average crash rates on interstates (per 1-mile of roadway) are highest in District 6, District 8, and Cuyahoga County. This figure also shows a somewhat regular pattern in the crash rates. In Districts 3, 4, 5, 6, 7, 8, and Cuyahoga County, the overall crash rate is higher during time groups 0 (Monday through Thursday), 2 (Friday), and 3 (final workday before a long weekend), all corresponding to weekdays. The pattern is flatter in Districts 1 and 2, where only the day before a long weekend (time group 3) appears to have a significantly higher overall crash rate on interstates.

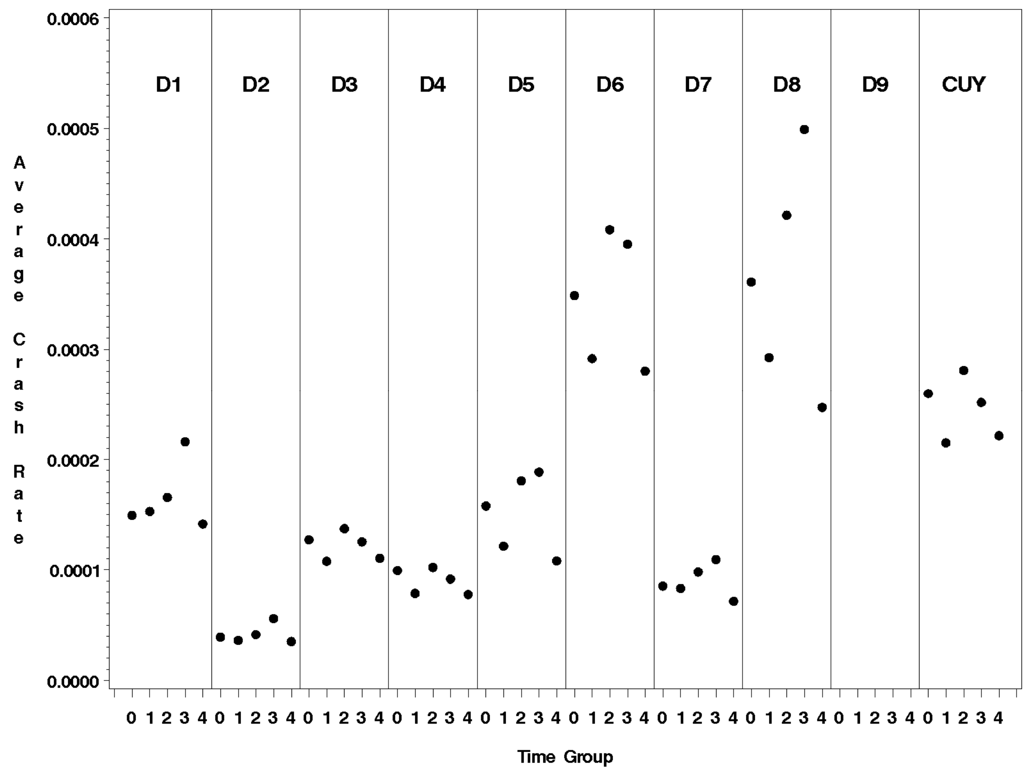

Figure 8. Average fatal and injury crash rate on interstates during different time groups in different districts.

Examining Figure 9, there appears to be a different pattern of crash rates on US/State routes than was observed on interstates. For US/State routes, District 4 seems to have the greatest average crash rate per 1-mile segment of roadway. Across all districts, a similar temporal pattern emerges – crash rates are the lowest on weekends (time group 1) and holidays (time group 4). Crash rates on ordinary weekdays (time group 0) are slightly higher, and the highest crash rates are found on ordinary Fridays (time group 2) and the day before a long weekend (time group 3).

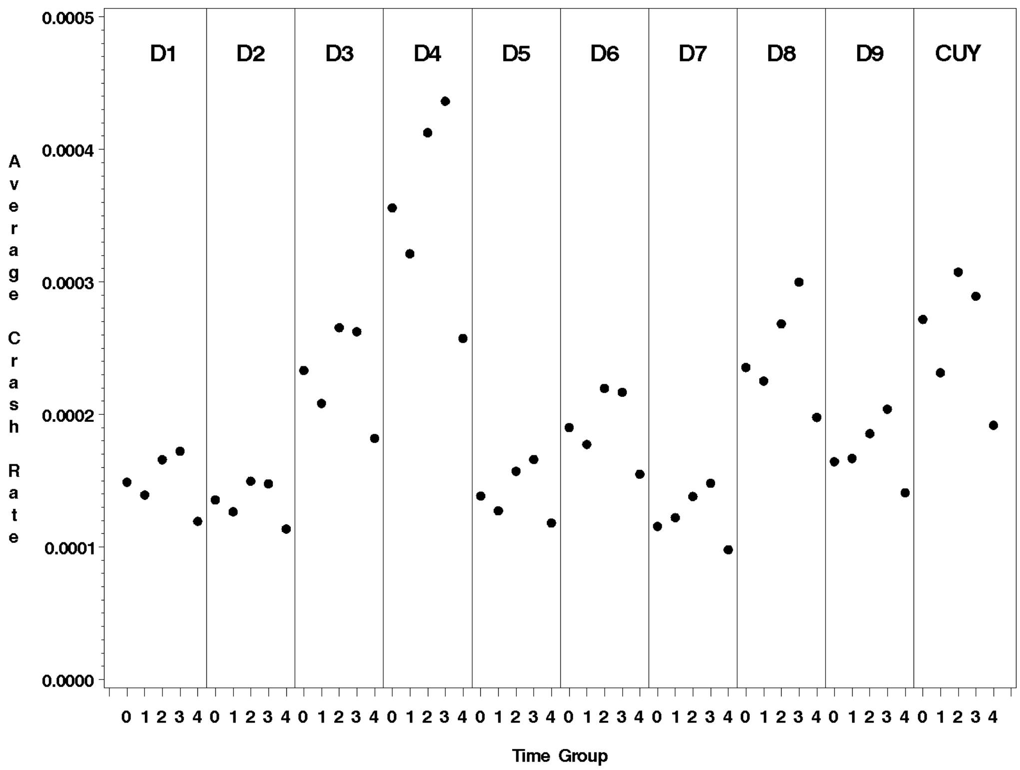

Figure 9. Average fatal and injury crash rate on US/State routes during different time groups in different districts.

Next, we present the same types of plots broken down by different types of crashes. Figure 10 and Figure 11 show the crash rates during the different time groups for alcohol-related crashes on interstates and US/State routes, respectively. Some changes from the pattern of overall crash rates are worth noting. First, it should be noted that these figures present the crash rates on a different scale, so interpretation of the rates must be made carefully. The left axis is approximately one tenth the height of the axes in Figure 8 and Figure 9. In most districts, time group 1 shows a higher crash rate than time group 0 – the average alcohol-related crash rate is higher on weekend days than on ordinary weekdays. Another interesting pattern is the high values for District 4 on US/State routes. These crash rates are clearly higher than in other districts.

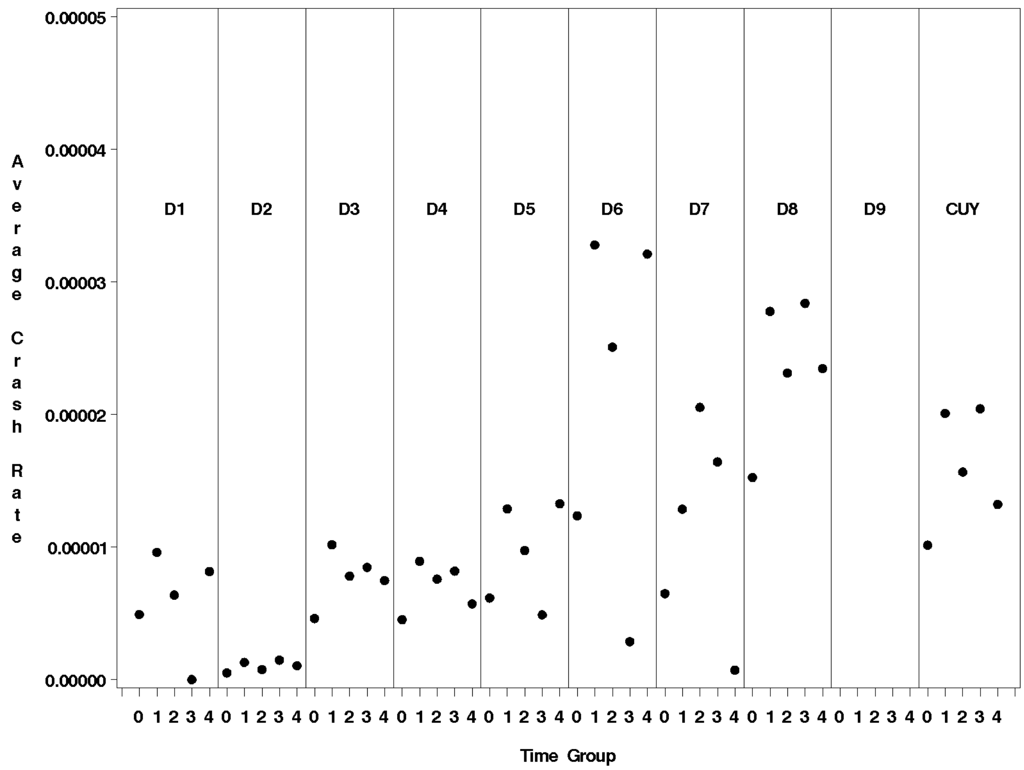

Figure 10. Average fatal and injury crash rate for alcohol-related crashes on interstates during different time groups in different districts.

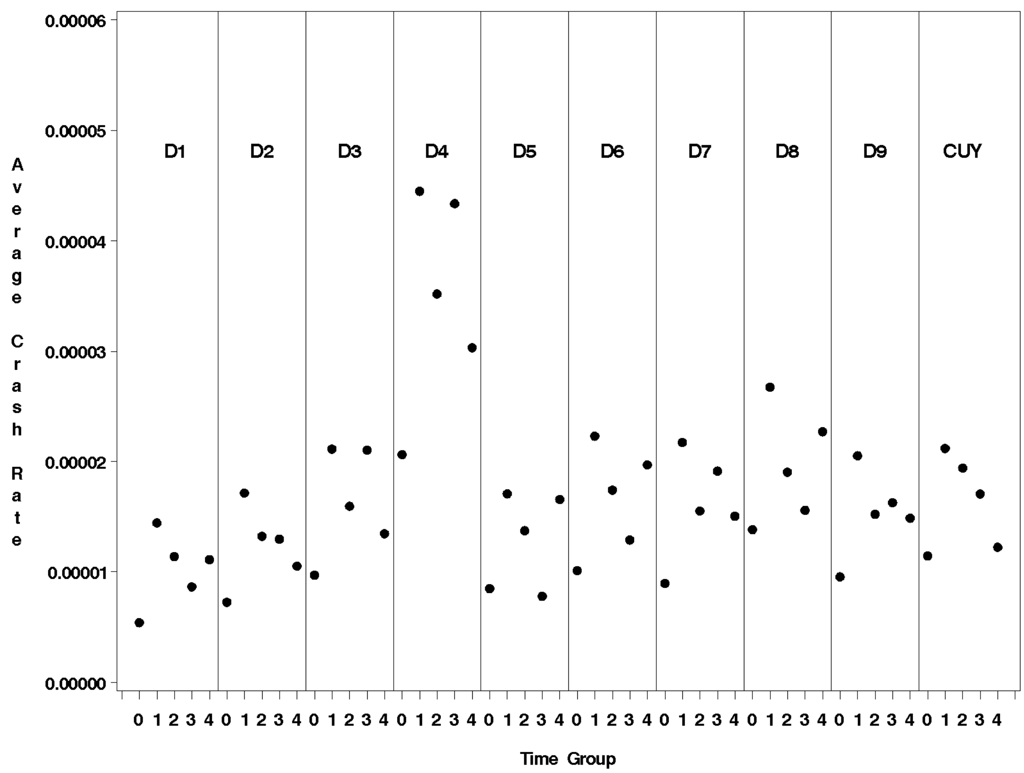

Figure 11. Average fatal and injury crash rate for alcohol-related crashes on US/State routes during different time groups in different districts.

Figure 12 shows the average crash rates for the different time groups and districts for speed-related crashes on interstates, and Figure 13 shows the same information for US/State routes. On interstates, Districts 5, 6, 7, and 8 have the highest crash rates per 1-mile segment of roadway. On US/State routes, Districts 7, 8, and 9 have the highest rates. In both plots, it is worth noting that Cuyahoga County has a very low speed-related crash rate when compared to other districts.

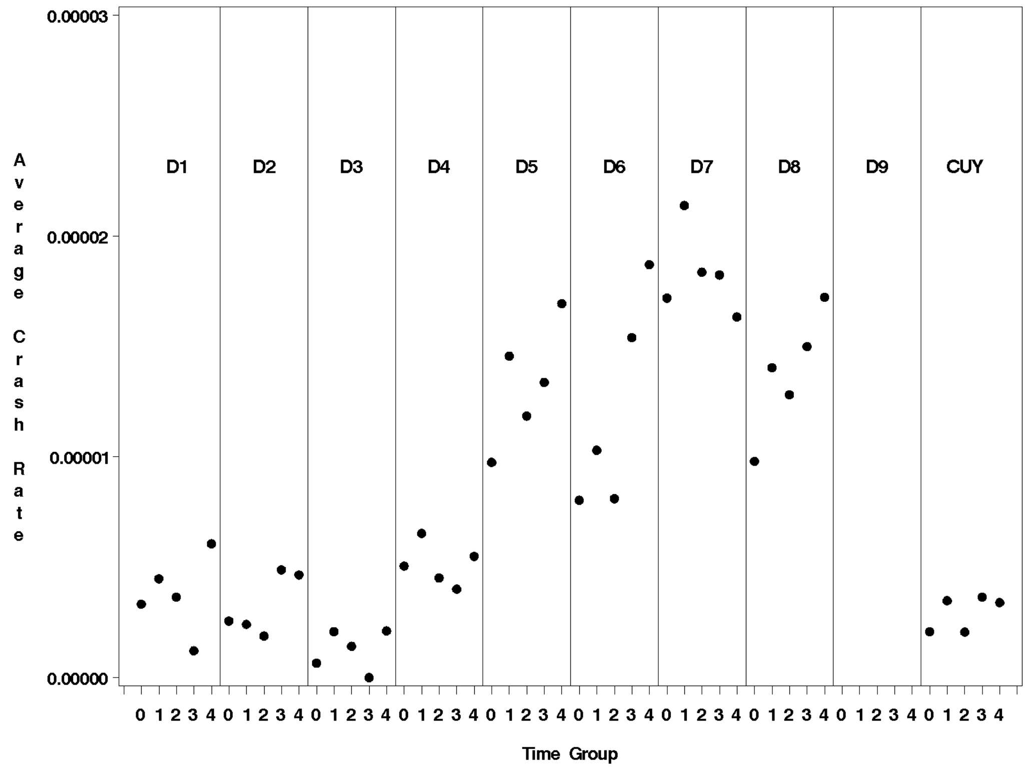

Figure 12. Average fatal and injury crash rate for speed-related crashes on interstates during different time groups in different districts.

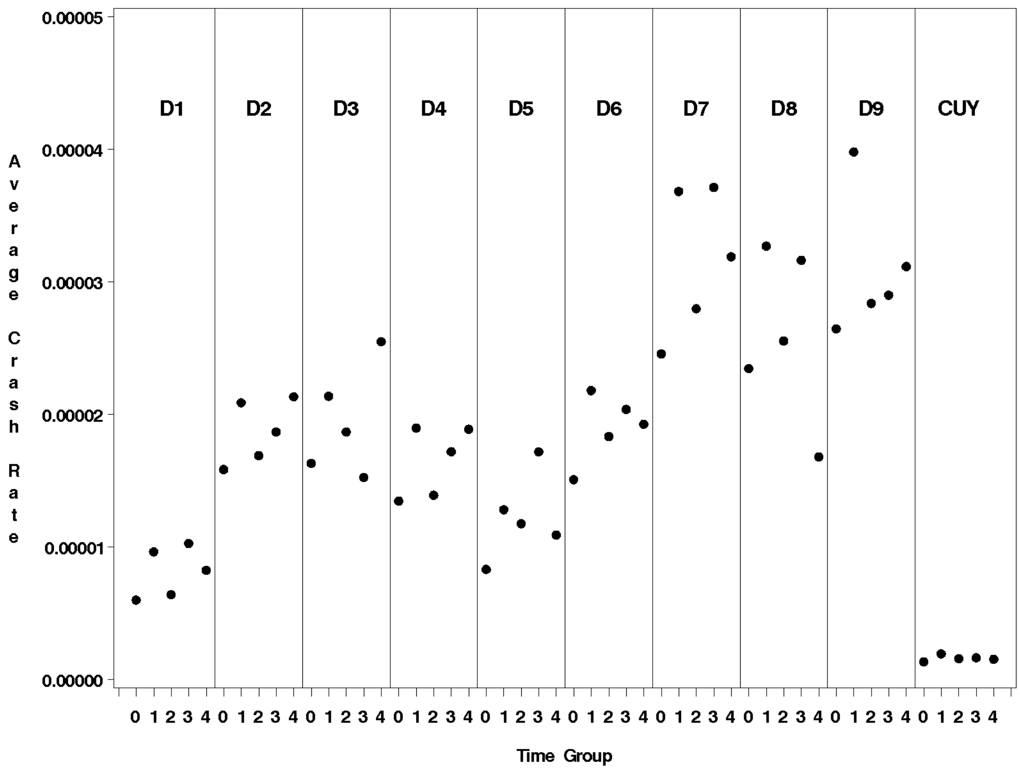

Figure 13. Average fatal and injury crash rate for speed-related crashes on US/State routes during different time groups in different districts.

The next six figures, Figure 14 through Figure 19 show the average crash rates for the three different age groups into which drivers were divided. For younger drivers, Districts 6 and 8 appear to have the highest crash rates on interstates. District 1 and Cuyahoga County have slightly lower crash rates on interstates for young drivers, but they still show higher crash rates than the remaining counties. On US/State routes, Districts 3, 4, and 8 appear to have the highest crash rates for younger drivers. For middle-age and older drivers, the crash risk patterns are very similar to the overall average crash rate patterns seen in Figure 8 and Figure 9.

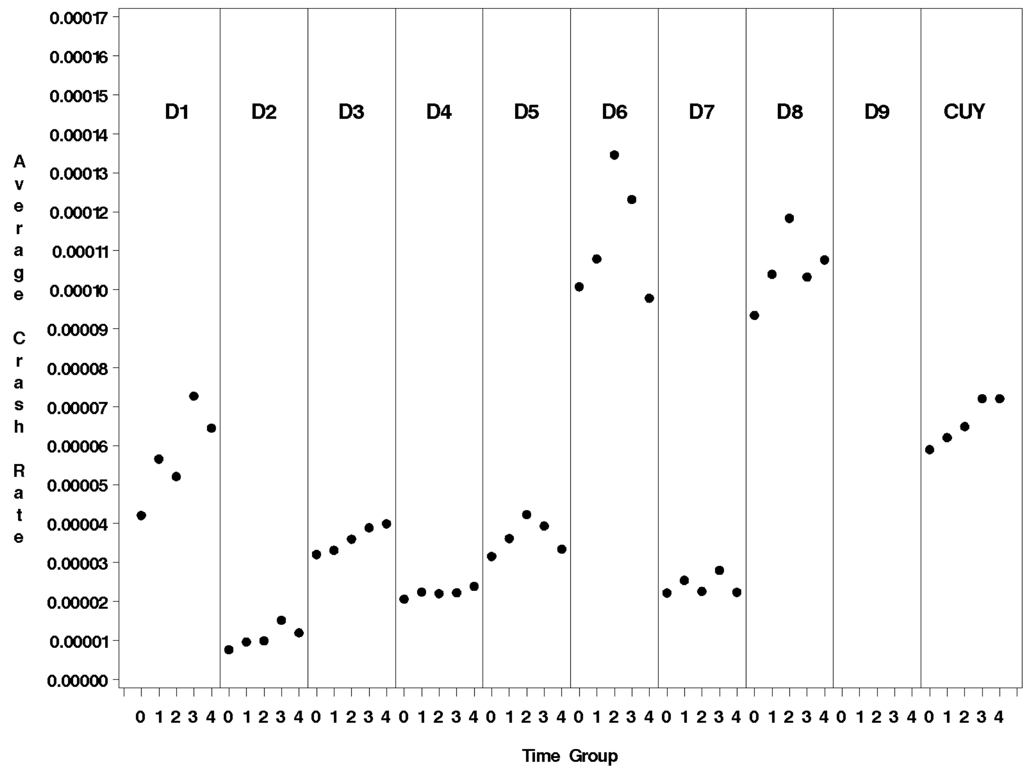

Figure 14. Average fatal and injury crash rate for youth-related crashes on interstates during different time groups in different districts.

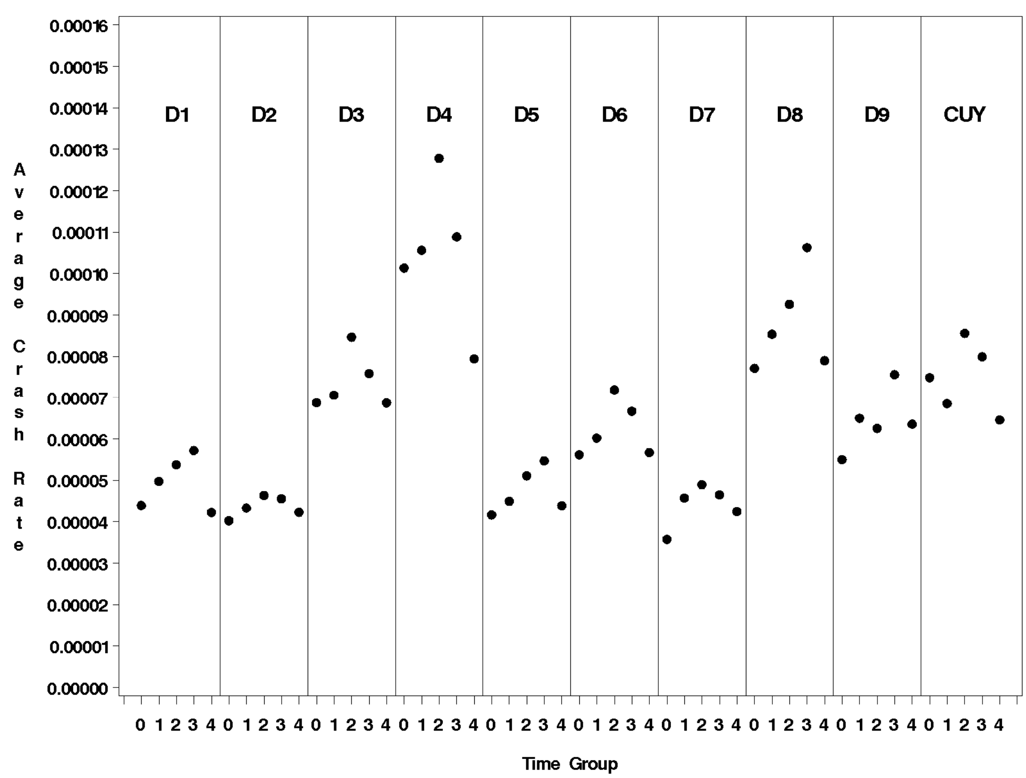

Figure 15. Average fatal and injury crash rate for youth-related crashes on US/State routes during different time groups in different districts.

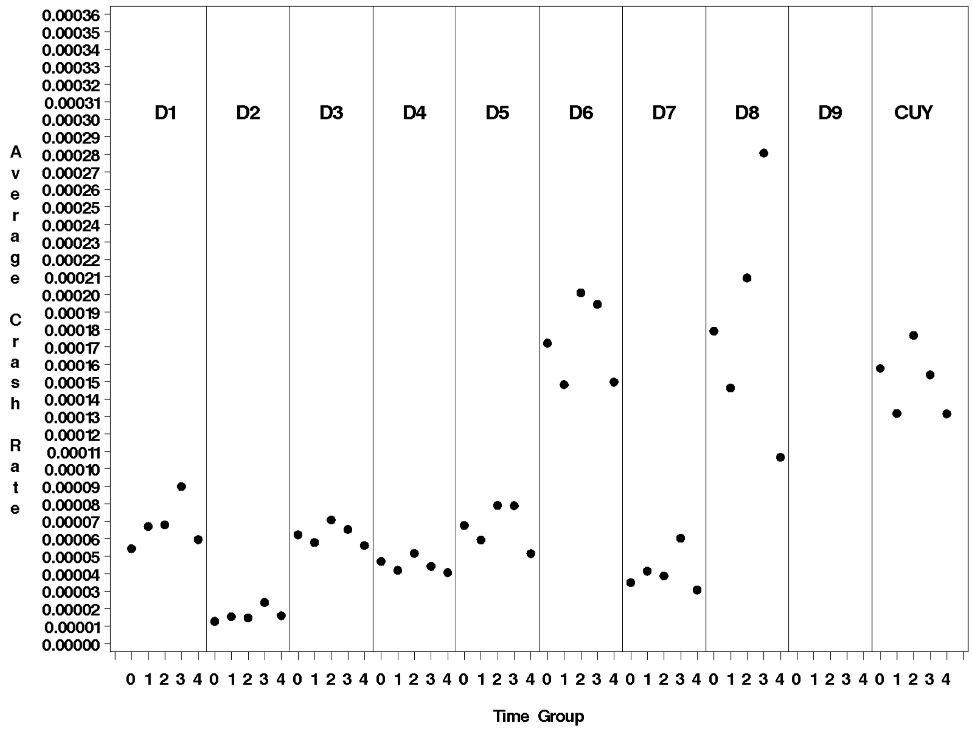

Figure 16. Average fatal and injury crash rate for middle age-related crashes on US/State routes during different time groups in different districts.

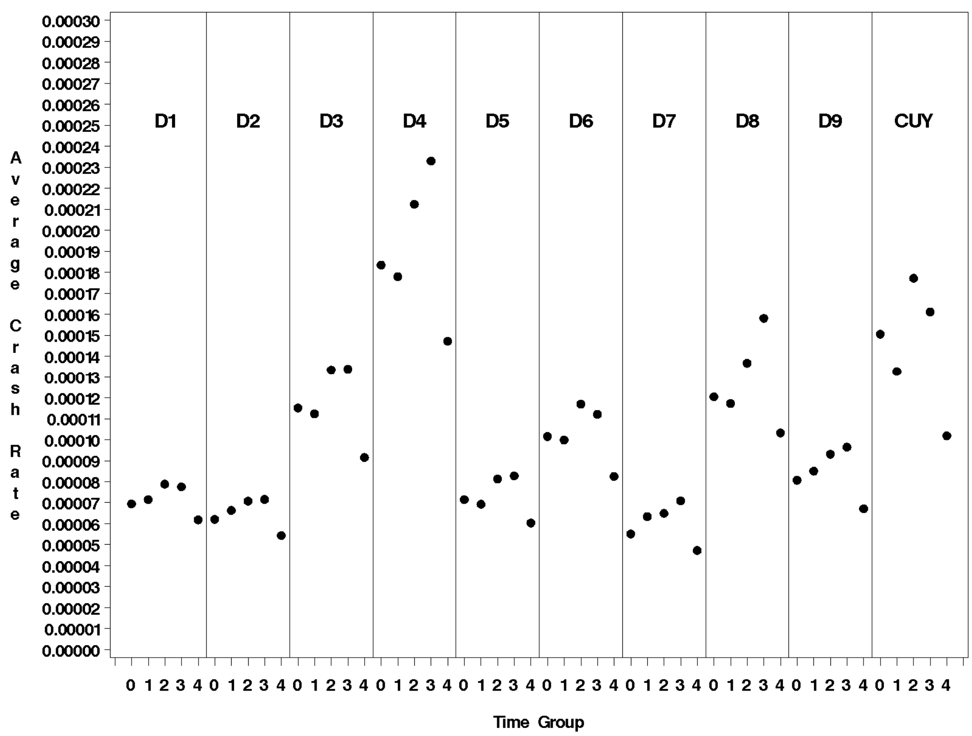

Figure 17. Average fatal and injury crash rate for middle age-related crashes on US/State routes during different time groups in different districts.

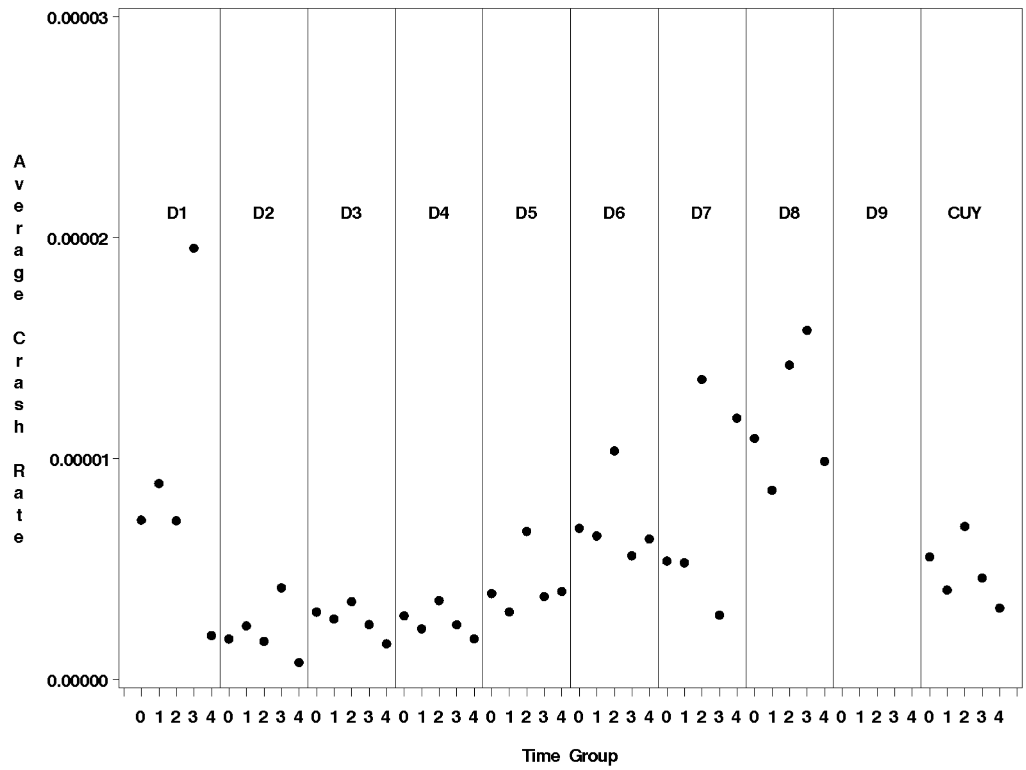

Figure 18. Average fatal and injury crash rate for older-related crashes on interstates during different time groups in different districts.

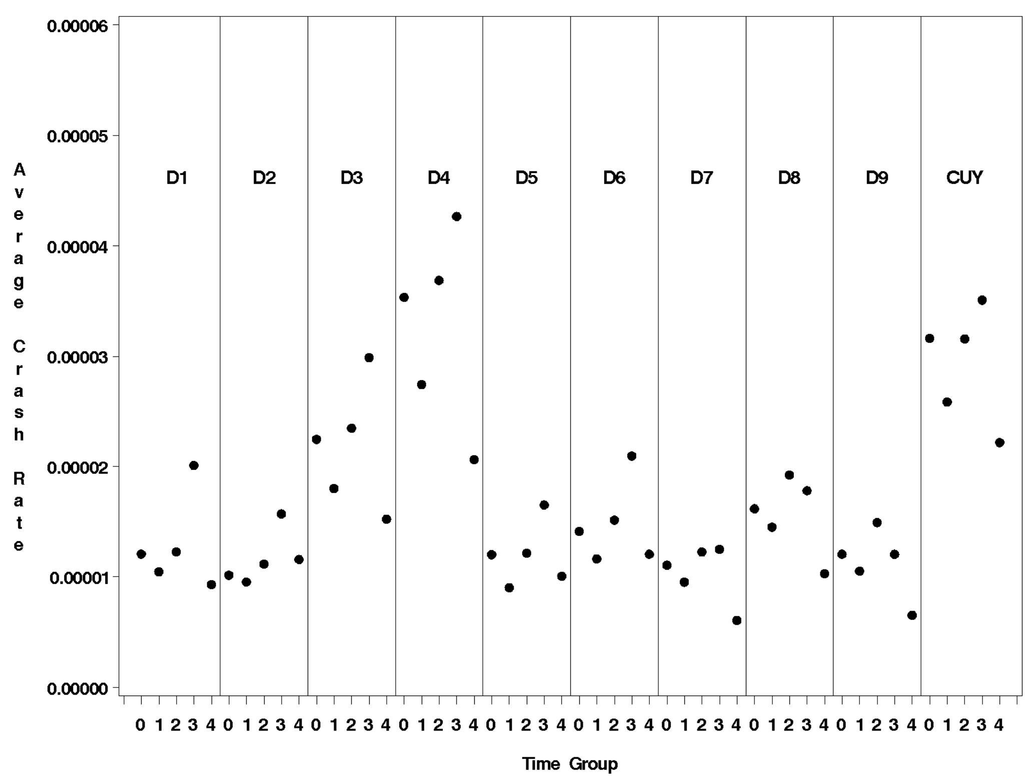

Figure 19. Average fatal and injury crash rate for older-related crashes on US/State routes during different time groups in different districts.

The final figures for examining crash rates in different cities and time groups, Figure 20 and Figure 21, show the average crash rate for commercial vehicle-related crashes. For these types of crashes, the crash rate appears to be the same on Monday – Thursday (time group 0), Friday (time group 2), and the day preceding a long weekend (time group 3). Crash rates are much lower for this group on holidays and weekends. There do appear to be some important differences across districts. On interstates, Districts 5, 6, and 8 stand out as having higher crash rates than other districts. On US/State routes, District 4 appears to have a higher crash rate for commercial vehicles than other districts.

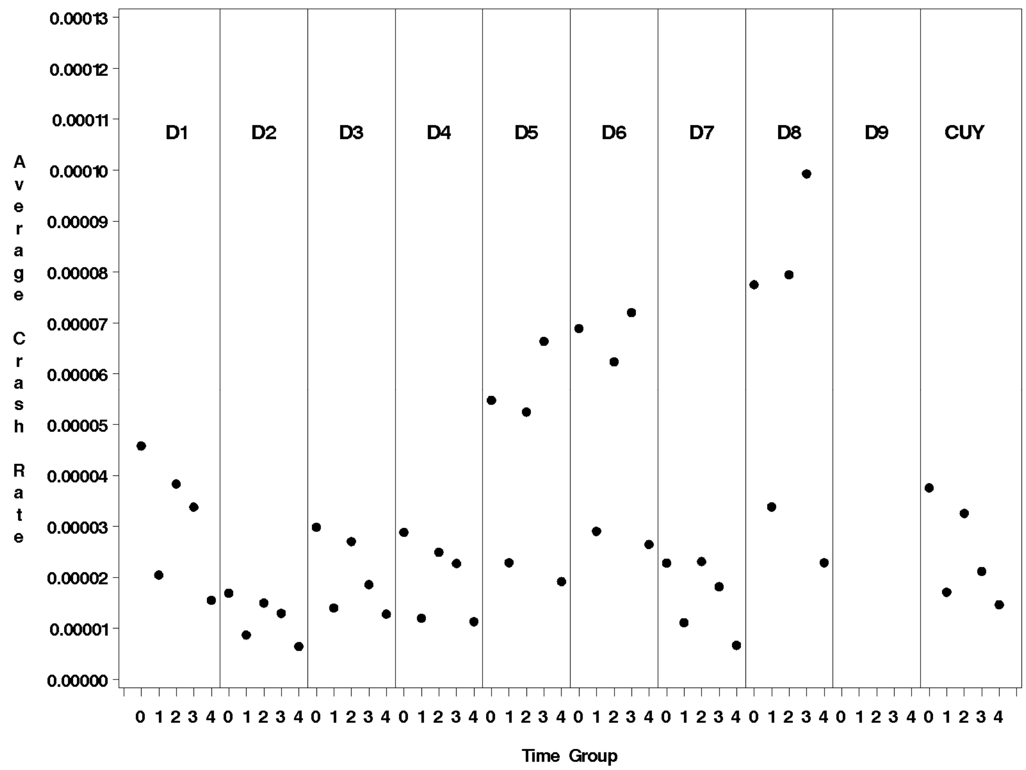

Figure 20. Average fatal and injury crash rate for commercial vehicle-related crashes on interstates during different time groups in different districts.

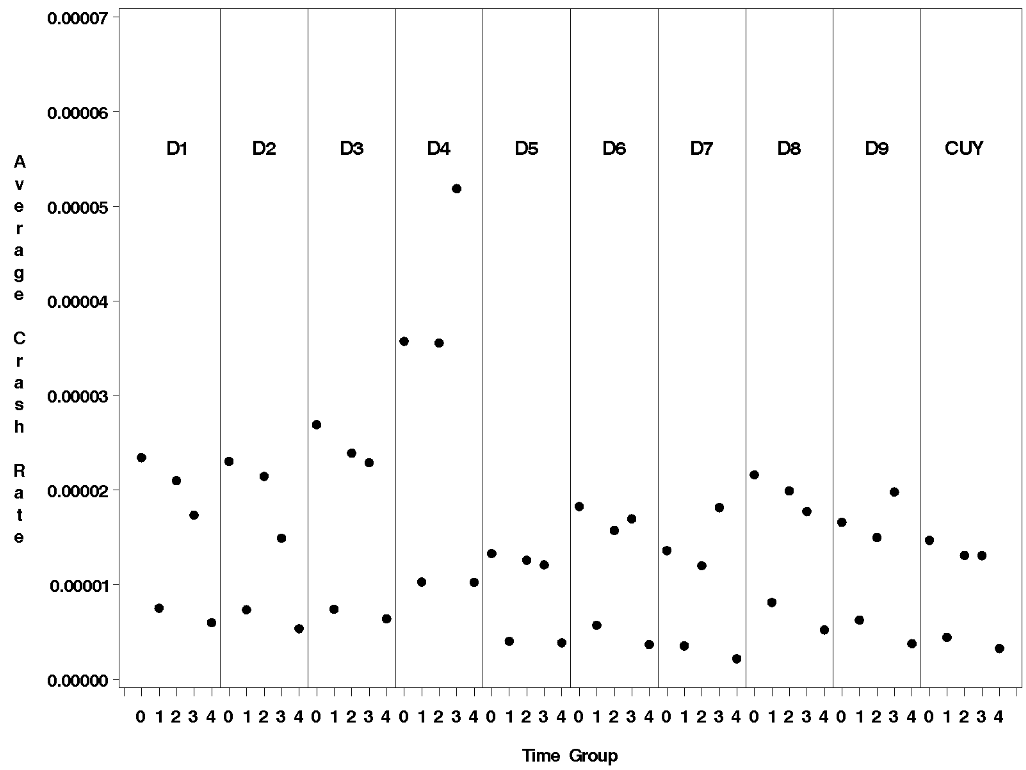

Figure 21. Average fatal and injury crash rate for commercial vehicle-related crashes on US/State routes during different time groups in different districts.

4.4.2. Crash Rate Over Time by Crash Type

In this section, the output of the model is summarized to show how crash rates vary throughout the day. Since the information is similar across districts and between interstates and US/State routes, information is combined for this analysis without regard to those divisions.

Figure 22 shows the fatal and injury crash rates across every road in Ohio by hour for each of the five different time groups in the analysis. As an example, consider the first panel of the figure. This panel corresponds to Monday through Friday (time group 0). The first peak is during the 8AM – 9AM hour, and the crash rate reaches approximately 3.6. This means that, on average, between 8AM and 9AM on an ordinary weekday there are predicted to be 3.6 fatal and injury crashes across all of the modeled roads in Ohio. Examining the other panels, we find that overall crash rates are similar on Monday through Thursday, Friday, and the day preceding a long weekend. Crash rates are lower on Saturday and Sunday and on holidays. Other noticeable patterns include increases in crash rates during the hours in which people typically commute to or from work, a spike during the early morning hours on Saturday and Sunday, and increased crash rates during the middle of the day on the day preceding a long weekend.

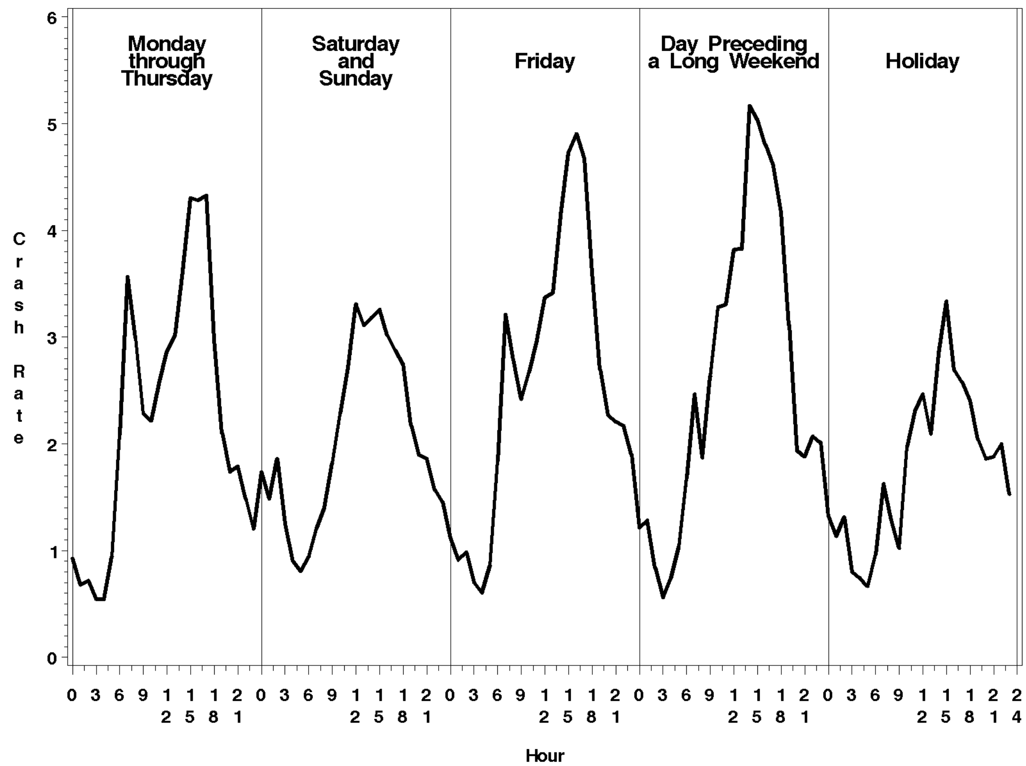

Figure 22. Fatal and injury crash rates over time, all roads.

Figure 23 shows the temporal pattern of fatal and injury alcohol-related crash rates across the entire state. On ordinary weekdays, the crash rate is highest during the early morning hours, drops during the middle of the day, and increases through the evening hours. On weekends, there is a big spike in the crash rate during the early morning hours, especially between 2AM and 3AM. Also, on these weekend days the alcohol-related crash risk increases steadily through the afternoon hours. On Fridays, the pattern of crash risk is similar to that observed on regular weekdays, but the increase in risk during the evening hours is more substantial. On the days preceding a long weekend, one interesting finding is the large spike in crash risk in the early morning hours. This risk extends later into the morning hours than on ordinary Fridays. Finally, the crash risk on holidays for alcohol-related crashes appears to be somewhat similar to the pattern observed for weekends.

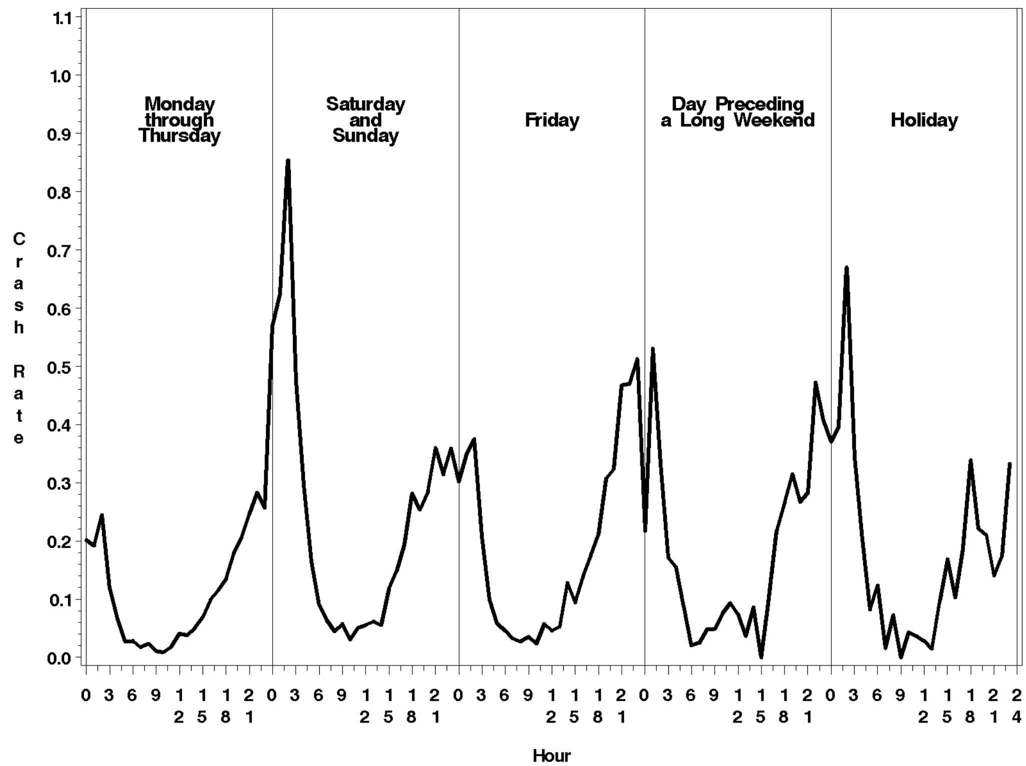

Figure 23. Fatal and injury alcohol-related crash rates over time, all roads.

Figure 24 shows the temporal pattern of fatal and injury speed-related crashes across Ohio. This figure shows the least discernable patterns of the figures presented in this section – it appears that the number of speed related crashes varies almost randomly across hours of the day. There are a couple of exceptions, however. In the Monday – Thursday and Friday time groups, there does appear to be a spike in speed-related crashes associated with the morning commuting hours. Also, on the day preceding a long weekend there appears to be a steadily increasing crash risk throughout the day, reaching very high levels in the evening hours.

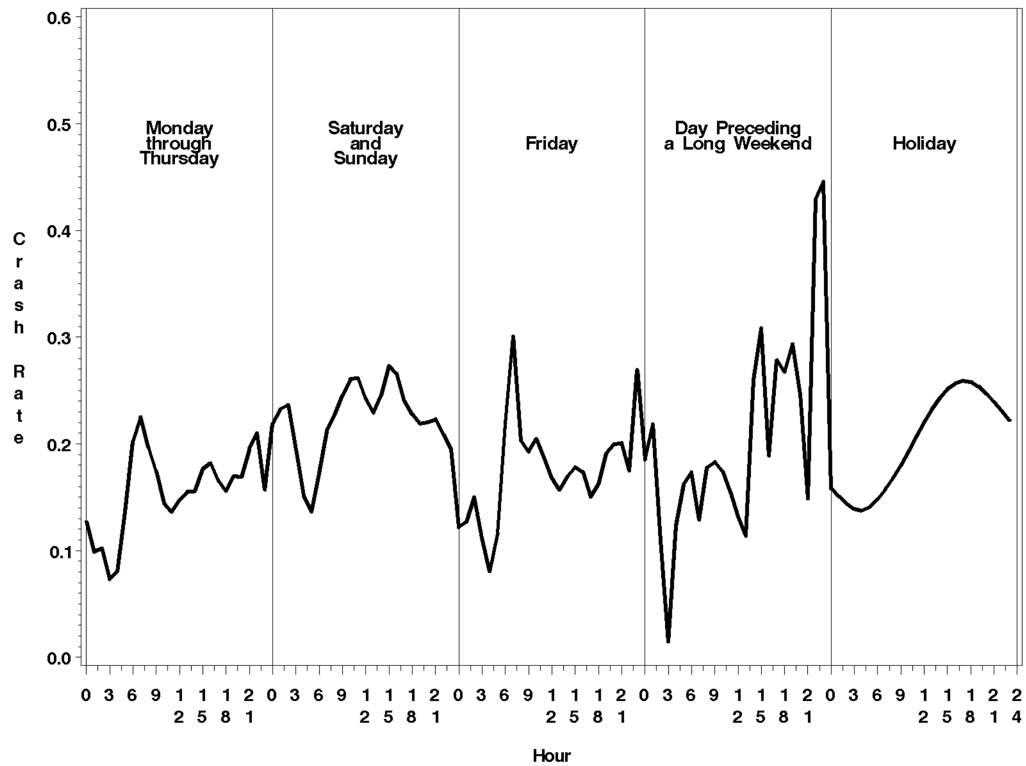

Figure 24. Fatal and injury speed-related crash rates over time, all roads.

Figure 25 shows the temporal pattern of fatal and injury crashes when a younger driver (under 25 years old) is at fault. The pattern for the Monday through Thursday and Friday time groups is similar with the highest spikes during the morning (7AM to 9AM) and afternoon (3PM to 6PM) commuting hours. The Friday afternoon commute appears to have a slightly higher risk than the afternoon commute on other weekdays. On Saturday and Sunday, the early morning spike (2AM to 3AM) is not very strong, but is still visible. On these weekend days the crash risk increases steadily during the later morning hours and persists until the early evening. On the day preceding a long weekend, this group shows a high crash risk during the afternoon hours, but this risk reduces quickly during the evening. Holidays show a pattern similar to weekends with increased risk of crashes during the afternoon and evening hours.

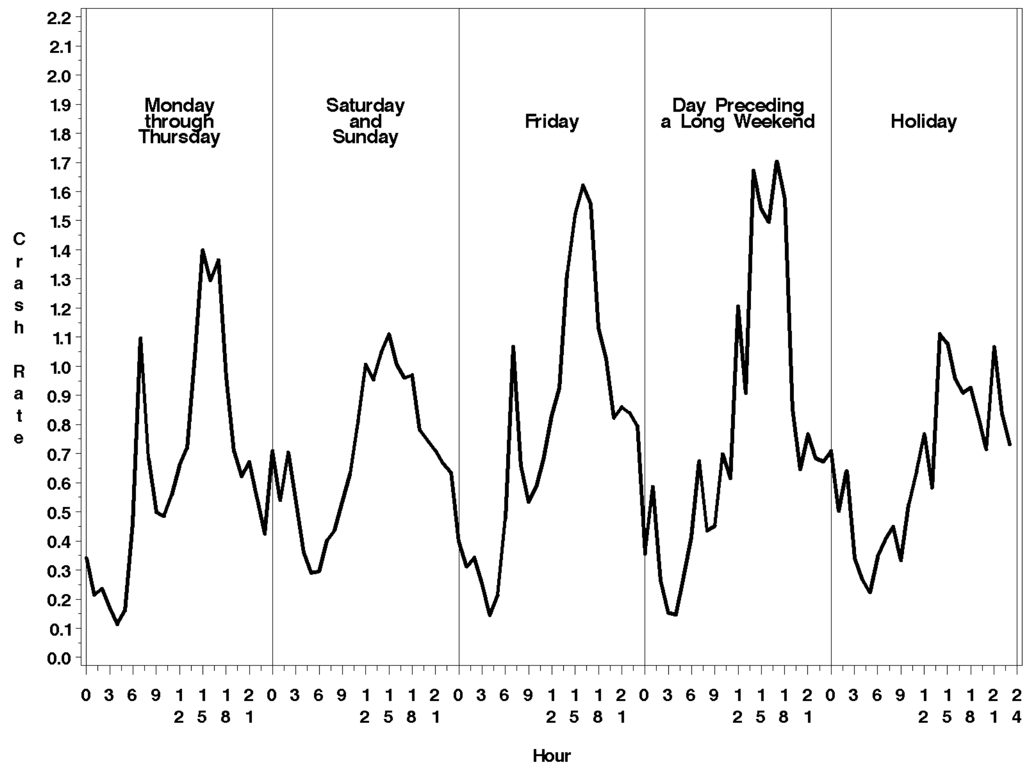

Figure 25. Fatal and injury youth-related crash rates over time, all roads.

Figure 26 shows the temporal pattern of fatal and injury crashes when a commercial vehicle is involved. Across all days, the pattern is essentially the same – crash risks are low during the night and increase during the daytime following a smooth curve. Crash risks are essentially the same on all weekdays. On weekends and holidays, crash risks are much lower throughout the day for these groups.

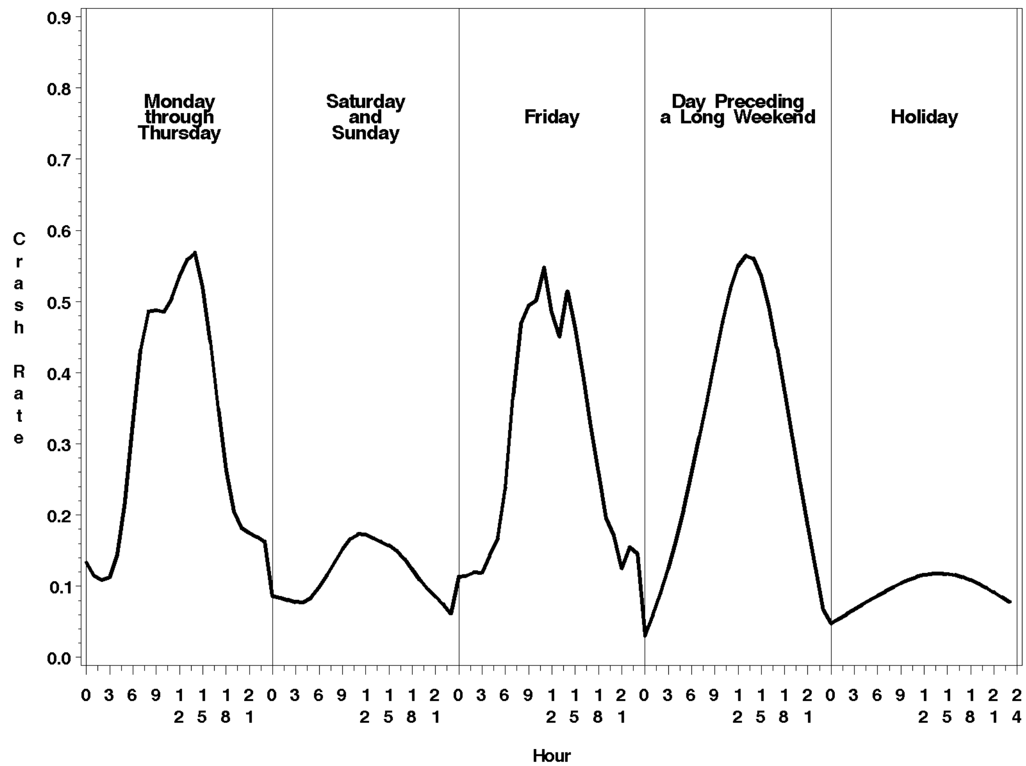

Figure 26. Fatal and injury commercial vehicle-related crash rates over time, all roads.

4.4.3. Geographic Crash Patterns

The analyses in the previous two sections established that crash rates are different across different districts, on different types of days, and at different times during the day. Those analyses were intended to provide some guidance in determining, on a large scale, where resources should be allocated and at what time those resources should be allocated. In the following subsections, geographic information is presented to help guide resource allocation decisions within District 2.

In each of the pictures in the following subsection, the roadways are presented in three colors: red, yellow, and green. These colors represent the risk associated with each portion of roadway relative to all other roadways of the same type (interstate or US/State route) in that district. The red roadways have the top 20% crash risk of all roadways in the district, the yellow roadways have the next 40% crash risk, and the green roadways have the lowest 40% crash risk. As a result, in each district 20% of the interstate segments and 20% of the US/State route segments are red, 40% of the interstate segments and 40% of the US/State route segments are yellow, and 40% of the interstate segments and 40% of the US/State route segments are green.

The following subsection contains 11 figures. The first figure shows the overall crash risk for all roads that were modeled in the district during the Monday through Thursday time group. The next two pictures show the exact same information, but one picture shows only the interstates and the next picture shows only the US/State routes. The fourth, fifth, sixth, and seventh pictures show the overall crash risk for each of the remaining time groups: Saturday and Sunday (time group 1), Friday (time group 2), the day preceding a long weekend (time group 3), and holidays (time group 4). These figures are, in general, very similar to the first figure in each section, but some differences can be observed in a few cases. For time groups 1 through 4, separate pictures are not presented for interstates and US/State routes. The remaining pictures show the levels of risk for different crash groups. These pictures show the risk for alcohol-related crashes, speed-related crashes, youth-related crashes, and commercial vehicle-related crashes.

4.4.3.1 Geographic Crash Patterns – District 2

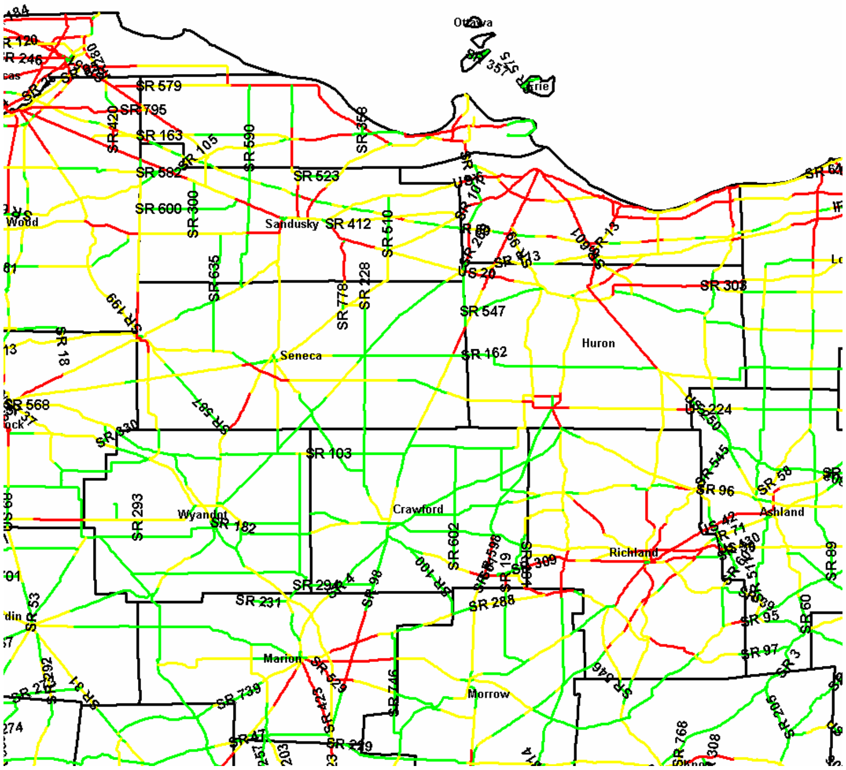

Figure 27. District 2 overall fatal and injury crash rate for all roads, Monday-Thursday.

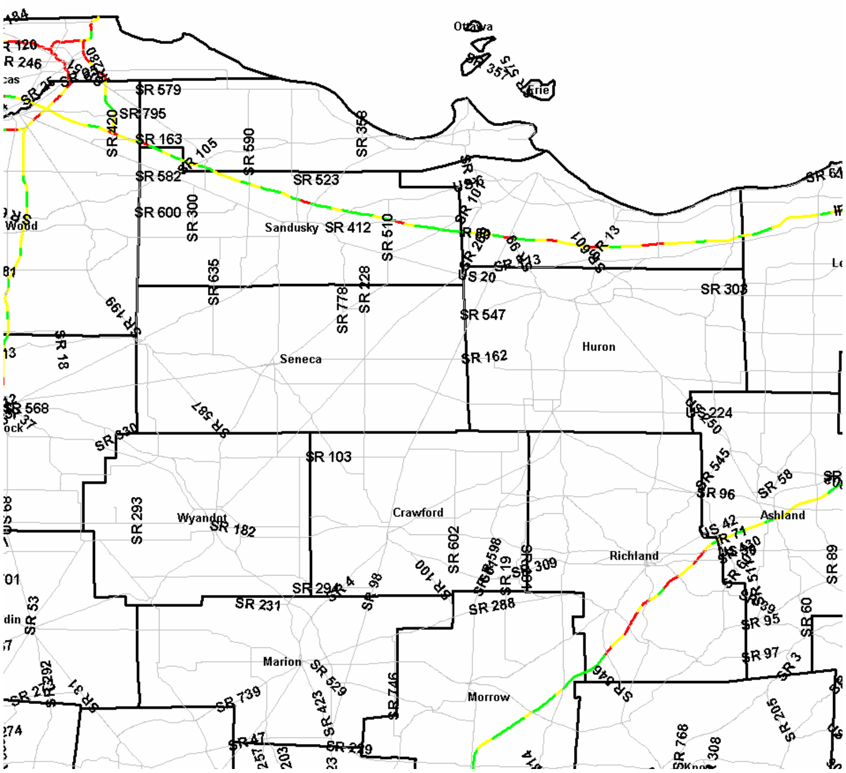

Figure 28. District 2 overall fatal and injury crash rate for interstates, Monday-Thursday.

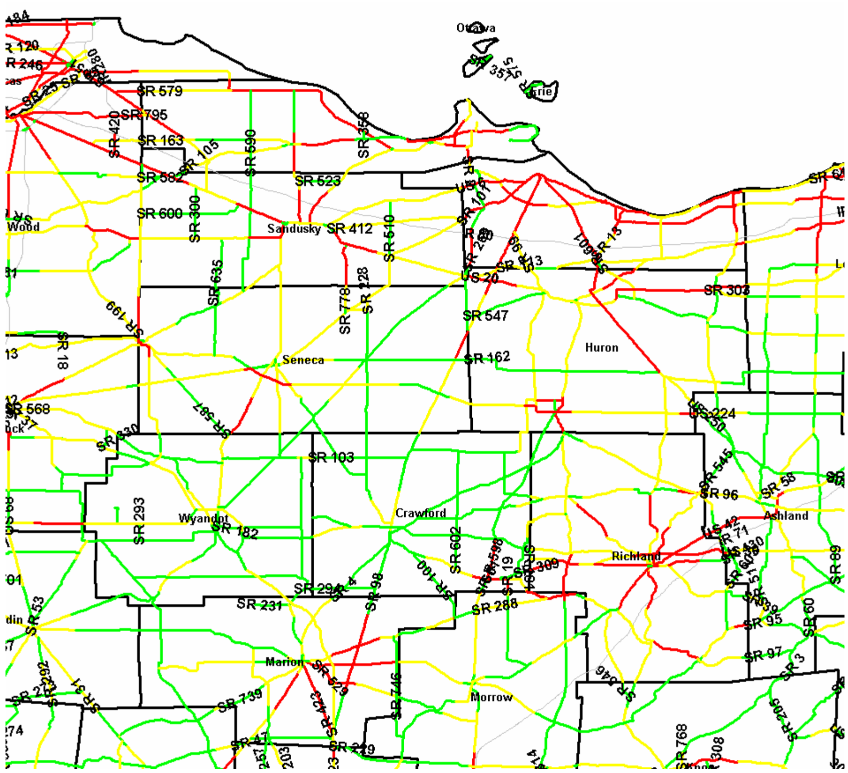

Figure 29. District 2 overall fatal and injury crash rate for US/State routes, Monday-Thursday.

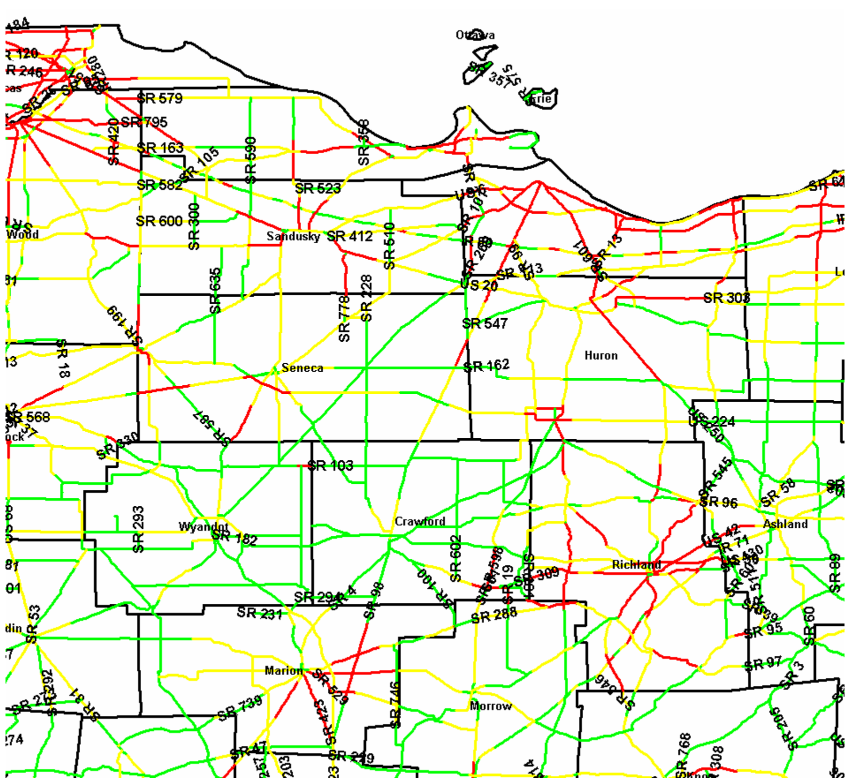

Figure 30. District 2 overall fatal and injury crash rate for all roads, Saturday and Sunday.

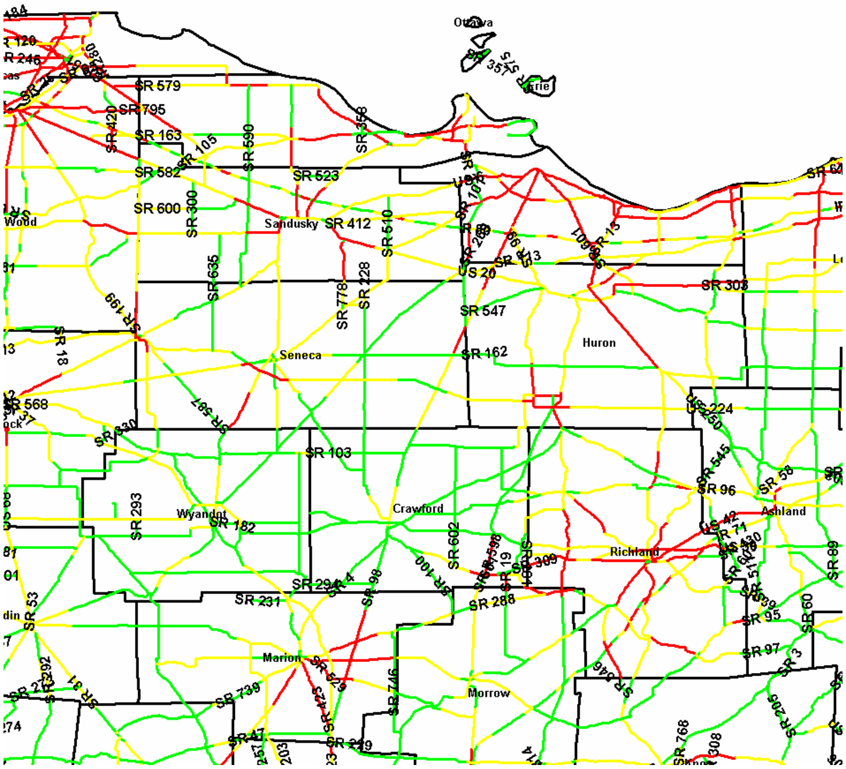

Figure 31. District 2 overall fatal and injury crash rate for all roads, Friday.

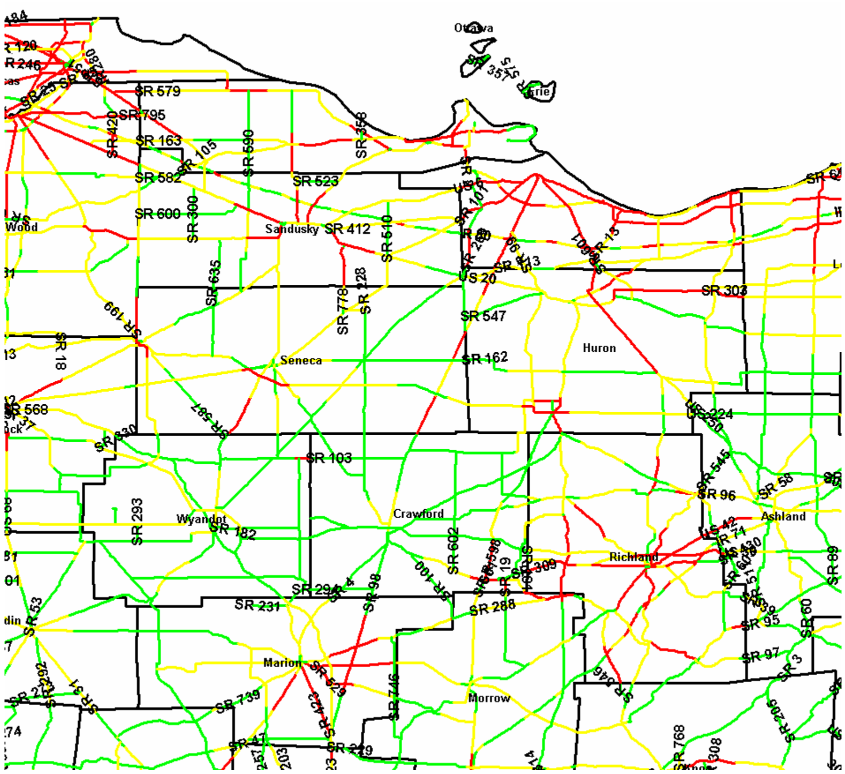

Figure 32. District 2 overall fatal and injury crash rate for all roads, day preceding a long weekend.

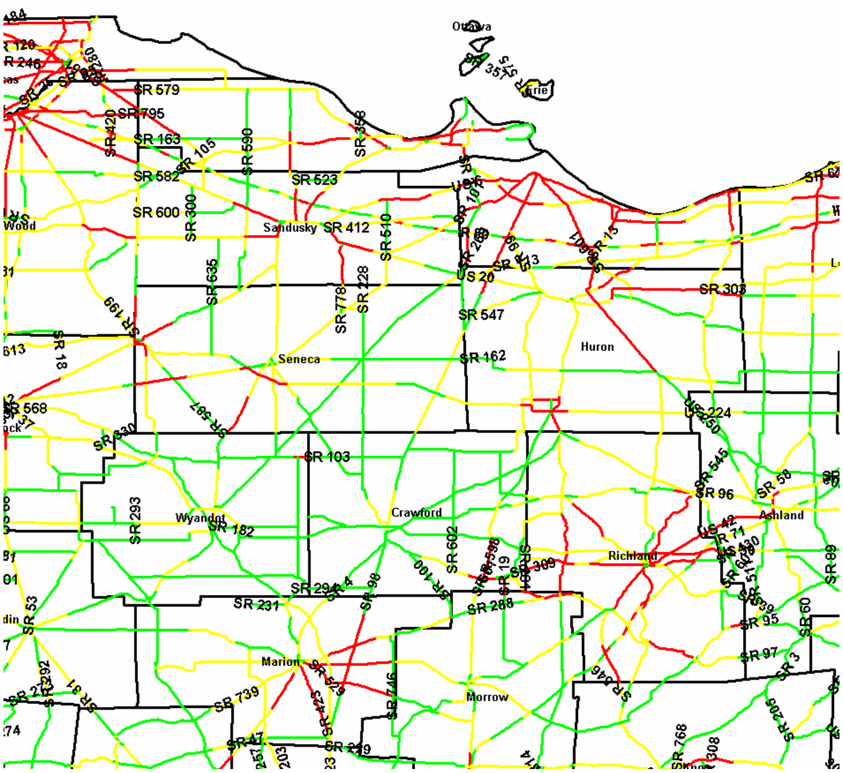

Figure 33. District 2 overall fatal and injury crash rate for all roads, holiday.

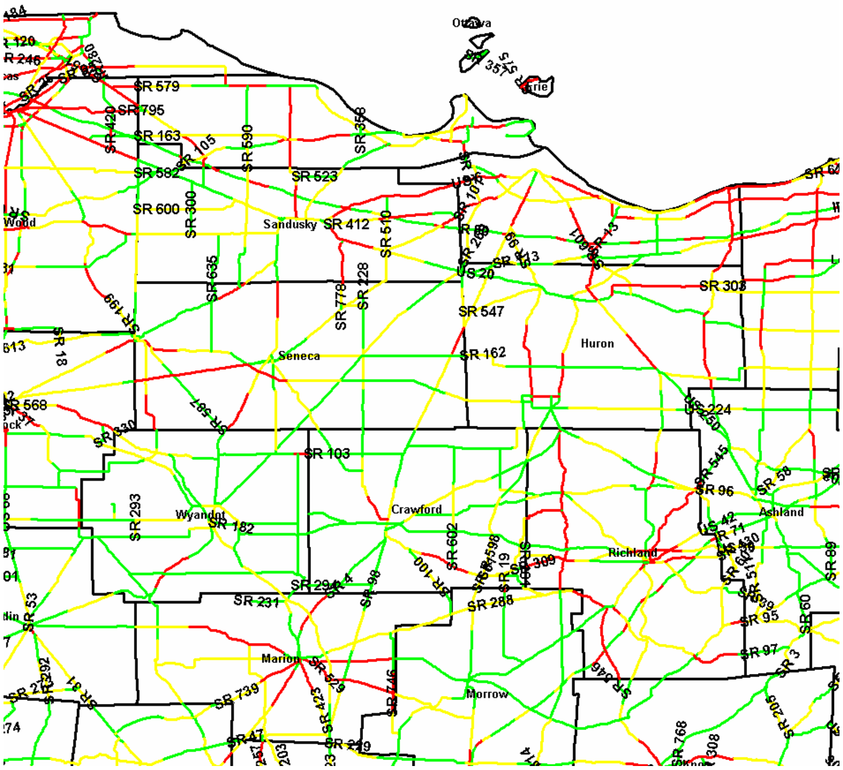

Figure 34. District 2 alcohol-related fatal and injury crash rate for all roads.

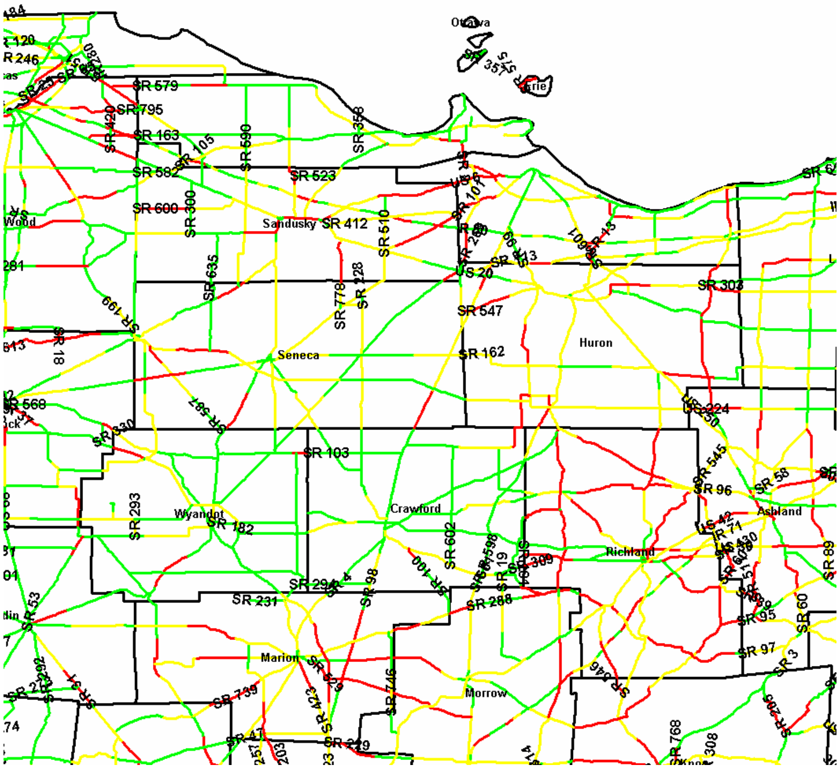

Figure 35. District 2 speed-related fatal and injury crash rate for all roads.

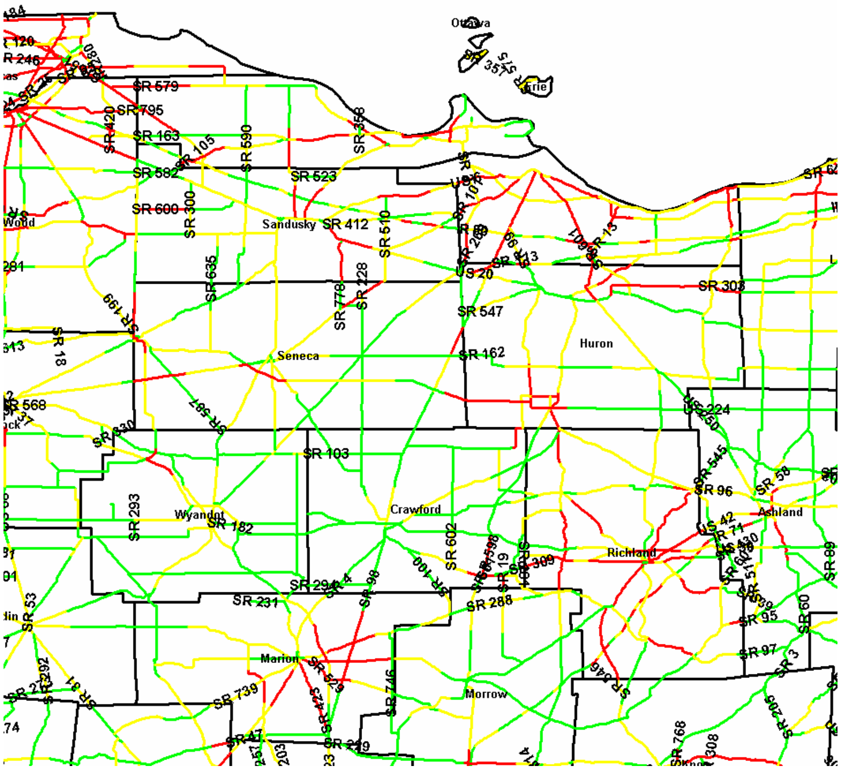

Figure 36. District 2 youth-related fatal and injury crash rate for all roads.

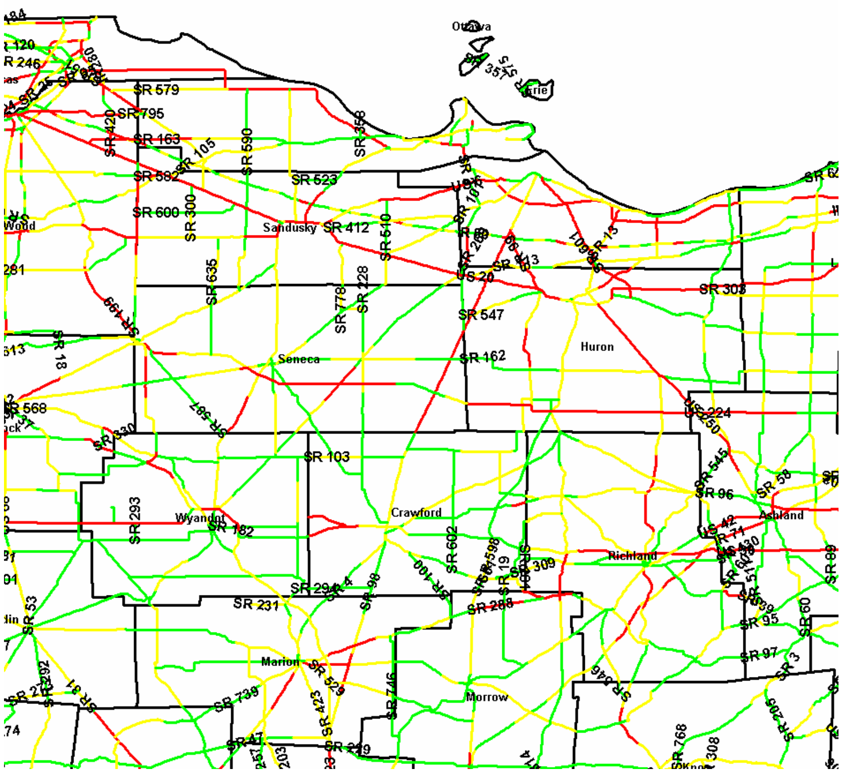

Figure 37. District 2 commercial vehicle-related fatal and injury crash rate for all roads.

4.4.4. Top Crash Risk Roadways

The information in the previous section can be used to locate sections of roadway where attention should be focused to reduce the occurrence of fatal and injury crashes at certain times and from certain causes. However, the figures can be somewhat difficult to interpret at a small scale since it is difficult to see exactly what sections of road are highlighted in red. To present the information in a different format, the table in this section presents the top 5 segments of interstate and US/State routes in District 2 for alcohol-, speed-, youth-, and commercial vehicle-related crashes.

For each road segment, the table presents the PrimaryLRS code (the code used by ODOT to identify roads), the beginning mile, and the ending mile. For US/State routes, the ending and beginning miles correspond to the mile markers on the actual roadway. For interstates, the beginning and ending mile numbers in the table start over at the county borders. To find the corresponding mile marker on the actual roadway the values in the table must be added to the mile marker on the actual roadway at which the interstate enters the county.

Table 1. District 2, Top 5 road segments in each category and for each road type.

Road Type	PrimaryLRS	Beginning Mile	Ending Mile	Category	Rank
IR	SRICIR00071**C	10	11	alcohol	1
IR	SERIIR00080*KC	4	5	alcohol	2
IR	SSANIR00080*KC	3	4	alcohol	3
IR	SRICIR00071**C	20	20.64	alcohol	4
IR	SERIIR00080*KC	9	10	alcohol	5
US/SR	SSENSR00019**C	20	20.26	alcohol	1
US/SR	SERISR00113**C	20	20.91	alcohol	2
US/SR	SOTTSR00053**C	5	6	alcohol	3
US/SR	SHURSR00060**C	15	15.96	alcohol	4
US/SR	SERISR00002**C	30	30.56	alcohol	5
IR	SRICIR00071**C	18	19	commercial	1
IR	SOTTIR00080*KC	0	1	commercial	2
IR	SRICIR00071**C	14	15	commercial	3
IR	SRICIR00071**C	17	18	commercial	4
IR	SRICIR00071**C	13	14	commercial	5
US/SR	SHURSR00004**C	5	8.38	commercial	1
US/SR	SRICUS00030**C	10	15	commercial	2
US/SR	SHURUS00250**C	5	10	commercial	3
US/SR	SOTTSR00002**C	0	5	commercial	4
US/SR	SERIUS00250**C	10	12.47	commercial	5
IR	SRICIR00071**C	10	11	speed	1
IR	SRICIR00071**C	18	19	speed	2
IR	SOTTIR00080*KC	3	4	speed	3
IR	SRICIR00071**C	14	15	speed	4
IR	SRICIR00071**C	7	8	speed	5
US/SR	SSENSR00019**C	20	20.26	speed	1
US/SR	SHURSR00060**C	15	15.96	speed	2
US/SR	SSANSR00019**C	0	5	speed	3
US/SR	SRICSR00545**C	0	5	speed	4
US/SR	SRICSR00545**C	5	10	speed	5
IR	SRICIR00071**C	10	11	youth	1
IR	SERIIR00080*KC	17	18	youth	2
IR	SRICIR00071**C	3	4	youth	3
IR	SRICIR00071**C	6	7	youth	4
IR	SERIIR00080*KC	12	13	youth	5
US/SR	SMARSR00095**C	15	20	youth	1
US/SR	SSANSR00053**C	10	15	youth	2
US/SR	SERIUS00250**C	0	5	youth	3
US/SR	SERISR00004**C	10	12.22	youth	4
US/SR	SRICUS00042**C	10	15	youth	5

4.4.5. Parameter Estimate Summary

In developing the model for OSHP, it was determined that crashes should be modeled in thirteen different groups. These groups comprised the twelve possible combinations of alcohol-related (yes or no), speed-related (yes or no), age category of the driver at fault (under 25, 25 to 64, and 65 and over), and a separate category for commercial vehicle-related crashes. For each of these categories, the model produces parameter estimates that can then be interpreted in terms of the effects of inclement weather and month of the year on crash rates over all districts.

Table 2 shows the thirteen crash groups for which modeling was performed. Information was averaged across all districts to produce estimates of the effects of inclement weather and month of the year for each of these groups.

Table 2. Thirteen crash groups for modeling.

Group Number	Commercial Vehicle Involved	Unsafe Speed	Alcohol Related	Age
1	No	No	No	Under 25
2	No	No	No	25 to 64
3	No	No	No	65 and Over
4	No	No	Yes	Under 25
5	No	No	Yes	25 to 64
6	No	No	Yes	65 and Over
7	No	Yes	No	Under 25
8	No	Yes	No	25 to 64
9	No	Yes	No	65 and Over
10	No	Yes	Yes	Under 25
11	No	Yes	Yes	25 to 64
12	No	Yes	Yes	65 and Over
13	Yes	Any	Any	Any

Within each of these groups, the interpretation of the parameters is presented in Table 3 through Table 27. The first line in each table presents the increase in risk of a crash on a segment of roadway resulting from inclement weather, as compared to conditions in which weather is not inclement. For example, Table 3 indicates that interstates are about 20 times as likely to have a fatal or injury crash for drivers under 25 who are not traveling at an unsafe speed and not alcohol impaired during inclement weather as they are during good weather. The remaining lines in the table show the change in crash rate compared to December. For example, in Table 3 crashes seem to be 1.5% less likely in January than December for this group of drivers. The safest month appears to be March, and the least safe month appears to be July.

Some tables, or parts of tables, are missing due to the fact that there was not enough data available to estimate the parameters.

Table 3. Crash group 1 (under 25, no unsafe speed, no alcohol) parameter interpretations for interstates.

Parameter	Level	Percentage Increase from Baseline
Inclement Weather		2024.98%
Crash Month	1	-1.57%
Crash Month	2	-9.39%
Crash Month	3	-11.06%
Crash Month	4	13.85%
Crash Month	5	5.53%
Crash Month	6	22.55%
Crash Month	7	37.25%
Crash Month	8	26.21%
Crash Month	9	8.69%
Crash Month	10	11.27%
Crash Month	11	13.83%
Crash Month	12	0.00%

Table 4. Crash group 1 (under 25, no unsafe speed, no alcohol) parameter interpretations for US/State routes.

Parameter	Level	Percentage Increase from Baseline
Inclement Weather		3143.37%
Crash Month	1	-10.50%
Crash Month	2	-10.43%
Crash Month	3	-5.90%
Crash Month	4	8.76%
Crash Month	5	24.54%
Crash Month	6	42.16%
Crash Month	7	35.42%
Crash Month	8	33.87%
Crash Month	9	22.68%
Crash Month	10	14.33%
Crash Month	11	4.88%
Crash Month	12	0.00%

Table 5. Crash group 2 (25 to 64, no unsafe speed, no alcohol) parameter interpretations for interstates.

Parameter	Level	Percentage Increase from Baseline
Inclement Weather		1803.86%
Crash Month	1	-3.70%
Crash Month	2	-1.65%
Crash Month	3	-4.37%
Crash Month	4	10.92%
Crash Month	5	9.61%
Crash Month	6	24.68%
Crash Month	7	29.35%
Crash Month	8	21.72%
Crash Month	9	12.97%
Crash Month	10	10.68%
Crash Month	11	7.56%
Crash Month	12	0.00%

Table 6. Crash group 2 (25 to 64, no unsafe speed, no alcohol) parameter interpretations for US/State routes.

Parameter	Level	Percentage Increase from Baseline
Inclement Weather		2700.95%
Crash Month	1	-3.03%
Crash Month	2	-2.63%
Crash Month	3	-3.45%
Crash Month	4	7.35%
Crash Month	5	14.16%
Crash Month	6	25.29%
Crash Month	7	23.06%
Crash Month	8	22.65%
Crash Month	9	20.71%
Crash Month	10	16.75%
Crash Month	11	9.09%
Crash Month	12	0.00%

Table 7. Crash group 3 (65 and over, no unsafe speed, no alcohol) parameter interpretations for interstates.

Parameter	Level	Percentage Increase from Baseline
Inclement Weather		1409.20%
Crash Month	1	-15.35%
Crash Month	2	-2.32%
Crash Month	3	15.04%
Crash Month	4	24.39%
Crash Month	5	25.10%
Crash Month	6	42.51%
Crash Month	7	68.60%
Crash Month	8	74.97%
Crash Month	9	35.02%
Crash Month	10	22.96%
Crash Month	11	34.75%
Crash Month	12	0.00%

Table 8. Crash group 3 (65 and over, no unsafe speed, no alcohol) parameter interpretations for US/State routes.

Parameter	Level	Percentage Increase from Baseline
Inclement Weather		1994.89%
Crash Month	1	-17.58%
Crash Month	2	-14.73%
Crash Month	3	-11.88%
Crash Month	4	-3.58%
Crash Month	5	16.54%
Crash Month	6	22.62%
Crash Month	7	23.33%
Crash Month	8	21.05%
Crash Month	9	31.03%
Crash Month	10	10.48%
Crash Month	11	7.02%
Crash Month	12	0.00%

Table 9. Crash group 4 (under 25, no unsafe speed, alcohol) parameter interpretations for interstates.

Parameter	Level	Percentage Increase from Baseline
Inclement Weather		1471.05%
Crash Month	1	-38.53%
Crash Month	2	-26.62%
Crash Month	3	19.39%
Crash Month	4	30.12%
Crash Month	5	4.22%
Crash Month	6	52.22%
Crash Month	7	58.56%
Crash Month	8	-3.91%
Crash Month	9	33.33%
Crash Month	10	18.49%
Crash Month	11	28.86%
Crash Month	12	0.00%

Table 10. Crash group 4 (under 25, no unsafe speed, alcohol) parameter interpretations for US/State routes.

Parameter	Level	Percentage Increase from Baseline
Inclement Weather		5726.75%
Crash Month	1	-17.28%
Crash Month	2	27.85%
Crash Month	3	6.31%
Crash Month	4	10.57%
Crash Month	5	49.77%
Crash Month	6	69.29%
Crash Month	7	55.55%
Crash Month	8	49.41%
Crash Month	9	63.57%
Crash Month	10	20.65%
Crash Month	11	14.80%
Crash Month	12	0.00%

Table 11. Crash group 5 (25 to 64, no unsafe speed, alcohol) parameter interpretations for interstates.

Parameter	Level	Percentage Increase from Baseline
Inclement Weather		1059.34%
Crash Month	1	-4.21%
Crash Month	2	19.76%
Crash Month	3	-5.50%
Crash Month	4	13.18%
Crash Month	5	-3.78%
Crash Month	6	-4.68%
Crash Month	7	28.01%
Crash Month	8	-7.17%
Crash Month	9	9.52%
Crash Month	10	18.50%
Crash Month	11	25.69%
Crash Month	12	0.00%

Table 12. Crash group 5 (25 to 64, no unsafe speed, alcohol) parameter interpretations for US/State routes.

Parameter	Level	Percentage Increase from Baseline
Inclement Weather		3879.53%
Crash Month	1	1.36%
Crash Month	2	0.61%
Crash Month	3	6.13%
Crash Month	4	4.34%
Crash Month	5	12.21%
Crash Month	6	41.63%
Crash Month	7	24.16%
Crash Month	8	42.07%
Crash Month	9	37.43%
Crash Month	10	36.25%
Crash Month	11	2.54%
Crash Month	12	0.00%

Table 13. Crash group 6 (65 and over, no unsafe speed, alcohol) parameter interpretations for interstates.

Parameter	Level	Percentage Increase from Baseline
Inclement Weather		1097.63%
Crash Month	1	-28.73%
Crash Month	2	8.60%
Crash Month	3	-50.17%
Crash Month	4	-37.15%
Crash Month	7	61.09%
Crash Month	8	53.12%
Crash Month	12	0.00%

Table 14. Crash group 6 (65 and over, no unsafe speed, alcohol) parameter interpretations for US/State routes.

Parameter	Level	Percentage Increase from Baseline
Inclement Weather		3389.41%
Crash Month	1	5.36%
Crash Month	2	-34.06%
Crash Month	3	18.12%
Crash Month	4	85.60%
Crash Month	5	22.26%
Crash Month	6	12.42%
Crash Month	7	77.31%
Crash Month	8	20.73%
Crash Month	9	101.66%
Crash Month	10	104.65%
Crash Month	11	-22.03%
Crash Month	12	0.00%

Table 15. Crash group 7 (under 25, unsafe speed, no alcohol) parameter interpretations for interstates.

Parameter	Level	Percentage Increase from Baseline
Inclement Weather		23059.83%
Crash Month	1	8.28%
Crash Month	2	-15.51%
Crash Month	3	-22.94%
Crash Month	4	-37.67%
Crash Month	5	-30.70%
Crash Month	6	-49.12%
Crash Month	7	-20.13%
Crash Month	8	-8.97%
Crash Month	9	-14.44%
Crash Month	10	-27.95%
Crash Month	11	-35.80%
Crash Month	12	0.00%

Table 16. Crash group 7 (under 25, unsafe speed, no alcohol) parameter interpretations for US/State routes.

Parameter	Level	Percentage Increase from Baseline
Inclement Weather		28740.66%
Crash Month	1	32.48%
Crash Month	2	6.20%
Crash Month	3	-9.75%
Crash Month	4	-27.78%
Crash Month	5	-20.32%
Crash Month	6	-20.51%
Crash Month	7	-17.20%
Crash Month	8	-26.49%
Crash Month	9	-31.47%
Crash Month	10	-25.16%
Crash Month	11	-27.09%
Crash Month	12	0.00%

Table 17. Crash group 8 (25 to 64, unsafe speed, no alcohol) parameter interpretations for interstates.

Parameter	Level	Percentage Increase from Baseline
Inclement Weather		28855.41%
Crash Month	1	16.07%
Crash Month	2	7.39%
Crash Month	3	17.37%
Crash Month	4	-39.51%
Crash Month	5	-43.69%
Crash Month	6	-31.01%
Crash Month	7	-25.40%
Crash Month	8	-14.65%
Crash Month	9	-34.56%
Crash Month	10	-54.40%
Crash Month	11	-32.92%
Crash Month	12	0.00%

Table 18. Crash group 8 (25 to 64, unsafe speed, no alcohol) parameter interpretations for US/State routes.

Parameter	Level	Percentage Increase from Baseline
Inclement Weather		36621.58%
Crash Month	1	33.58%
Crash Month	2	19.52%
Crash Month	3	-1.99%
Crash Month	4	-35.89%
Crash Month	5	-52.47%
Crash Month	6	-43.03%
Crash Month	7	-37.56%
Crash Month	8	-38.66%
Crash Month	9	-36.04%
Crash Month	10	-54.47%
Crash Month	11	-35.75%
Crash Month	12	0.00%

Table 19. Crash group 9 (65 and over, unsafe speed, no alcohol) parameter interpretations for interstates.

Parameter	Level	Percentage Increase from Baseline
Inclement Weather		24060.42%
Crash Month	1	-59.15%
Crash Month	2	-29.30%
Crash Month	3	-56.79%
Crash Month	4	-60.51%
Crash Month	5	-56.48%
Crash Month	6	-25.88%
Crash Month	7	-19.59%
Crash Month	8	-26.86%
Crash Month	9	-34.20%
Crash Month	10	-67.11%
Crash Month	11	-75.79%
Crash Month	12	0.00%

Table 20. Crash group 9 (65 and over, unsafe speed, no alcohol) parameter interpretations for US/State routes.

Parameter	Level	Percentage Increase from Baseline
Inclement Weather		27237.90%
Crash Month	1	-11.57%
Crash Month	2	-8.56%
Crash Month	3	-66.50%
Crash Month	4	-67.06%
Crash Month	5	-51.74%
Crash Month	6	-53.76%
Crash Month	7	-55.77%
Crash Month	8	-47.42%
Crash Month	9	-63.70%
Crash Month	10	-38.16%
Crash Month	11	-71.84%
Crash Month	12	0.00%

Table 21. Crash group 10 (under 25, unsafe speed, alcohol) parameter interpretations for interstates.

Parameter	Level	Percentage Increase from Baseline
Inclement Weather		4928.06%
Crash Month	1	4036.99%
Crash Month	2	2412.95%
Crash Month	3	115147.86%
Crash Month	4	158476.65%
Crash Month	5	28.44%
Crash Month	6	39.53%
Crash Month	7	135.27%
Crash Month	8	0.82%
Crash Month	9	12.19%
Crash Month	10	89.97%
Crash Month	11	22.13%
Crash Month	12	0.00%

Table 22. Crash group 10 (under 25, unsafe speed, alcohol) parameter interpretations for US/State routes.

Parameter	Level	Percentage Increase from Baseline
Inclement Weather		14859.56%
Crash Month	1	-8.19%
Crash Month	2	90.24%
Crash Month	3	43.34%
Crash Month	4	67.18%
Crash Month	5	28.73%
Crash Month	6	83.19%
Crash Month	7	47.76%
Crash Month	8	95.44%
Crash Month	9	46.87%
Crash Month	10	69.39%
Crash Month	11	4.18%
Crash Month	12	0.00%

Table 23. Crash group 11 (25 to 64, unsafe speed, alcohol) parameter interpretations for interstates.

Parameter	Level	Percentage Increase from Baseline
Inclement Weather		3876.91%
Crash Month	1	-29.49%
Crash Month	2	-54.90%
Crash Month	3	17.23%
Crash Month	4	-56.98%
Crash Month	5	-1.42%
Crash Month	6	2.00%
Crash Month	7	30.08%
Crash Month	8	-3.33%
Crash Month	9	-12.46%
Crash Month	10	-30.67%
Crash Month	11	-29.54%
Crash Month	12	0.00%

Table 24. Crash group 11 (25 to 64, unsafe speed, alcohol) parameter interpretations for US/State routes.

Parameter	Level	Percentage Increase from Baseline
Inclement Weather		10095.37%
Crash Month	1	60.83%
Crash Month	2	37.81%
Crash Month	3	63.58%
Crash Month	4	33.01%
Crash Month	5	45.14%
Crash Month	6	73.30%
Crash Month	7	67.04%
Crash Month	8	95.40%
Crash Month	9	63.91%
Crash Month	10	48.74%
Crash Month	11	79.35%
Crash Month	12	0.00%

No estimates are available for crash group 12 (65 and over, unsafe speed, alcohol) on interstates.

Table 25. Crash group 12 (65 and over, unsafe speed, alcohol) parameter interpretations for US/State routes.

Parameter	Level	Percentage Increase from Baseline
Inclement Weather		53637.75%
Crash Month	1	20.46%
Crash Month	2	-16.30%
Crash Month	4	-36.19%
Crash Month	6	55.05%
Crash Month	7	55.07%
Crash Month	9	11.01%
Crash Month	10	155.85%
Crash Month	11	17.91%
Crash Month	12	0.00%

Table 26. Crash group 13 (commercial vehicles) parameter interpretations for interstates.

Parameter	Level	Percentage Increase from Baseline
Inclement Weather		2691.65%
Crash Month	1	27.93%
Crash Month	2	14.59%
Crash Month	3	16.64%
Crash Month	4	7.85%
Crash Month	5	24.96%
Crash Month	6	29.85%
Crash Month	7	26.87%
Crash Month	8	34.18%
Crash Month	9	23.67%
Crash Month	10	15.42%
Crash Month	11	12.41%
Crash Month	12	2691.65%

Table 27. Crash group 13 (commercial vehicles) parameter interpretations for US/State routes.

Parameter	Level	Percentage Increase from Baseline
Inclement Weather		3878.30%
Crash Month	1	16.75%
Crash Month	2	6.32%
Crash Month	3	12.84%
Crash Month	4	16.96%
Crash Month	5	23.49%
Crash Month	6	39.81%
Crash Month	7	45.92%
Crash Month	8	33.21%
Crash Month	9	46.80%
Crash Month	10	40.40%
Crash Month	11	13.82%
Crash Month	12	0.00%

5. Recommendations and Conclusions

The main purpose of this project was to extend the OSHP forecasting model from the metro roadways on which it was developed to the interstates and US/State routes throughout the state. Ultimately, the goal is to use the output of the model as a quantitative basis for making informed decisions about where and when The Ohio State Highway Patrol should allocated its resources. In general, this model can be used as a tool to supplement the methods the Highway Patrol already uses to allocate resources – past quantitative analyses and the years of experience and expertise of officers.

Most of the statistical work required for creating the model was conducted for a previous project – this report seeks only to extend that model to more roadways. However, some exploratory analysis was conducted to determine whether the model could be extended to all interstates, US routes, and State routes in Ohio. This analysis found that all interstate routes could be modeled, but that US/State routes in nine counties would have to be excluded due to large amounts of missing geolocation data.

Fitting the statistical model required substantial computing power, so resources from the Ohio Supercomputer Center were used. The model was fit over a two-week period. Model diagnostics suggested that the model fit the data well. The model fitting produced a large amount of output that can be used in several ways.

The main strategy for using the output is to synthesize the information presented in Section 4.4. First, the comparisons between districts over time periods presented in Section 4.4.1 can be used to determine problem areas and make allocation decisions between districts. Those districts with higher crash rates may require more resources and attention in the future. Next, the time-series charts of Section 4.4.2 can be used to determine the times during the day when crash rates are at their highest. These charts can also be used to determine the relative rates of alcohol-, speed-, and commercial vehicle-related (among other types of) crashes. Once the temporal allocation of resources has been determined, the maps in Section 4.4.3 can be used to determine what locations officers should patrol. Finally, the information on the most dangerous roadways in Section 4.4.3.1 can be used to obtain more precise information on which roadways should receive the most attention.

Overall, the forecasts provided by the model serve as a useful guide in determining the best use of limited resources. By allocating officers to the locations where crashes are most likely to occur, efforts to reduce crash rates can be conducted with a high level of efficiency.

6. Acknowledgements

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7. References

Holloman, C. (2006) *Predicting Crashes and Crash Causes on the Ohio Sub-metro Roadways*. Report to The Ohio State Highway Patrol. June 30.