**Performance Measures for Prioritizing Highway Safety Improvements Based on Predicted Crash Frequency and Severity**

by

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## Abstract

The goal of this research was to develop highway performance measures that could be used to prioritize safety improvement projects by utilizing results from predicted crash frequency and crash severity for roadways the state of Alabama. The models used were derived from collected crash specific, roadway infrastructure, spatially related socio-economic and demographic, and roadway demand data and analysis of the derived performance measures. The research also implemented a novel approach at modeling crash frequency by using an ordered probit model, which has seldom been used in previous crash frequency studies, although frequently applied in crash severity studies. Growth trends for applicable demographic and roadway demand factors from both models were computed and forecast for a horizon year of 2025 to predict crash frequency and crash severity fifteen years into the future. Two different performance measure calculations were made based upon most likely and probabilistic scenarios for safest, median, and worst case observed crash severity scenarios for both 2010 and 2025. Results from the performance measure calculations, and their derived cartographic and graphical representations, suggest that the results of this research can be used as practical and integral tools for all persons working in the roadway safety realm.

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## 1. INTRODUCTION

According to the National Highway Traffic Safety Administration (NHTSA), more than 5.5 million reported motor vehicle crashes occurred in the United States in 2009, which is a slight decline from 5.8 million reported crashes in 2008 and 6.0 million reported crashes in 2007. Within these, over 33,000 people were killed and 2.2 million people were injured (Federal Highway Administration 2009). In fact, motor vehicle crashes are the leading cause of unintentional injury deaths and the predominant cause of death for people aged 1-34 years in the US (Miaou, *et al.*2003).Furthermore, traffic accidents often result in enormous costs to society, including excessive delay for roadway users and extensive damage to property (Chang and Chen 2005). The Centers for Disease Control and Prevention (CDC) estimates that motor vehicle crash deaths annually result in $41 million dollars of medical and work loss costs alone (Centers for Disease Control and Prevention 2011); for example, motor vehicle crashes result in over $2.8 billion dollars in annual costs in the state of Alabama (TRIP 2010). As a result, a number of US federal government agencies, including the US Department of Transportation, Federal Highway Administration, and the National Highway Traffic Safety Board, now emphasize reducing crashes as a top priority (Federal Highway Administration 2011). For example, the US Department of Transportation lists improving roadway safety as their top priority in their 2012-2016 Strategic Plan: Transportation for a New Generation (US Department of Transportation 2012), and is also a top priority for the Alabama Department of Transportation, and other state DOTs within the southeastern United States region (Alabama Dept. of Transportation 2012). Likewise, understanding how multiple factors affect crashes and roadway safety is a priority for many transportation agencies, including state and local departments of transportation, regional/metropolitan planning organizations, as well as independent non-profit agencies such as the Insurance Institute for Highway Safety (IIHS) (Milton, *et al.* 2008).

The need for roadway safety research is especially relevant to the southeastern United States, where crash occurrence and crash severity levels are often above the national averages (National Highway Traffic Safety Administration 2008). This could be due to a variety of contributing factors, such as, a high percentage of rural highways, lower levels of vehicle safety restraint usage, and large, isolated urban areas, among others (Stamatiadis and Puccini 1999). For example, in 2008 and 2009, Alabama roadways saw a total of 966 and 849 fatal crashes, respectively, which corresponded to roadway fatality rates of 1.63 and 1.41 fatalities per 100 million vehicle miles traveled, respectively (State of Alabama 2010). In comparison, the US national average fatality rate was 1.27 fatalities per 100 million vehicle miles traveled in 2008. What makes the Alabama statistics even more troubling (with respect to the national average) is that the 2008 and 2009 rates are significantly lower than prior Alabama state averages, and exceedingly lower than the decade high in 2006 of 2.00 fatalities per 100 million vehicle miles traveled (State of Alabama 2010). As a result, the state of Alabama, via Governor Dr. Robert J. Bentley (in cooperation with the Alabama Department of Transportation), has made it their vision to “create the safest surface transportation system in the Southeast by means of a cooperative effort that involves all organizations and individuals within the state who have traffic safety interests (State of Alabama 2010).” Furthermore, the state of Alabama has placed the identification and treatment of crash hot spots at the forefront of their roadway safety efforts (State of Alabama 2010).

In the past, much of the work done to reduce crash severity and frequency was focused on reacting to known crash locations; engineers would identify critical areas where a number of crashes occurred and reconfigure the roadway environment. Currently, practitioners are looking for proactive and cost-effective means of addressing crashes, even on roadways that are not yet built (Aguero-Valverde 2012). Identifying hazardous, 'high risk' locations on roadways is the first step of the highway safety management process (Montella 2010), however, this process is often challenging. The most common 'Hot Spot' or 'Black Spot' ranking techniques employed across the US aim to locate and identify segments of road where accidents are concentrated (Flahaut 2004), but, these methods often do not distinctly account for the severity of crashes, are often derived only from observed empirical data, and tend to only use a somewhat arbitrary binary ranking system (i.e., is a hazardous location, or is not a hazardous location) (Montella 2010). Techniques that utilize the effect of crash frequency and severity in order to discern hazardous locations, and are able to rank these locations in an ordinal manner for current and forecast scenarios, are still needed. Having such methods would allow for the development of comprehensive roadway safety maps that would enable transport agencies the ability to identify and rank potentially hazardous locations, establish a cost/benefit assessment of possible roadway safety improvement prescriptions, and be able to monitor and forecast the safety performance of their roadways over time (Miaou, *et al.* 2003).

In order to develop these needed methods, researchers require a deeper understanding of the factors influencing crashes (and their interactions). It has been shown that motor vehicle crashes occur as a result of a complex interaction between human factors, ambient traffic, environmental conditions, and the geometric characteristics of a roadway (Qi, *et al.*2007). Therefore, any efforts to improve roadway safety must be based on an investigation of <u>all</u> of these factors. However, past research has either focused on human factors (Lord, *et al.* 2005) or built environmental factors (Chang and Chen 2005). While both are important, how individuals react to the built environment needs to be considered. However, even with the empirically rich data available, not enough research has focused on the combined effect that all of the different factors have upon crash severity, frequency, and overall roadway safety.

The research presented in this thesis will incorporate crash frequency and crash severity models derived from comprehensive data comprised of factors from crash cases, roadway infrastructure, traffic demand, spatially related socio-economic and demographic data (from surrounding developments and nearest urban areas), and land use. Results will be modeled at a base year and a 15 year future forecast, and will be combined to create two different measures of overall roadway safety performance. Roadway performance measures will be represented in graphical and cartographical forms, which will allow roadway safety practitioners the ability to quickly and accurately reference roadway safety performance at varying levels of crash severity, temporal scales. The research seeks to provide essential tools to aid the state of Alabama in their efforts to identify and improve roadway locations associated with lower levels of roadway safety.

The rest of this paper is structured as follows: Section 2 discusses and defines the various models that have been utilized in crash frequency, crash severity, and safety ranking studies. The factors which influence crash frequency and severity, and the inherent data and methodological issues innate to subsequent modeling methods, will also be covered in Section 2. Section 3 introduces, and analyzes in full, the datasets compiled for the crash frequency and crash severity models developed for Alabama roadways; Section 3 also breaks down each step of the data compilation process. Section 4 gives an in-depth and comprehensive analysis of the modeling techniques utilized in this paper. Section 5 compares and evaluates the results of the crash frequency and crash severity models. This section also includes a thorough analysis of the effect that each variable has on roadway safety. Section 6 details the forecasting methods that were utilized to assess roadway safety at a horizon year of 2025. Section 7 introduces the derivation and analysis of the roadway safety ranking indices for both the base and forecast horizon years, this section also details the safety performance of the different Alabama Department of Transportation (ALDOT) divisions. Section 8 concludes the paper with a summary of the findings and thoughts for future research and developments.

## 2. LITERATURE REVIEW

The following section reviews the literature on measures of crash severity and frequency, factors influencing highway crashes, challenges in modeling these behaviors, frequently employed statistical models, and methods for identifying areas with crashes that require attention.

### 2.1 Measures of Crash Severity and Frequency

Crash severity and frequency are common measures in safety research. As such, a number of reoccurring methods for characterizing these values have been developed over the years. For example, Traffic Accident Damage scale (TAD) and Abbreviated Injury Scale (AIS) are common for characterizing crash severity. It is also common to have crash frequency datasets collected at different severity levels for relatively homogenous entities (a unit roadway designated for analysis) over a period of time (Chiou and Fu 2012).

Crash frequency also features common aggregations, such as over roadway segments (Jones, *et al.* 1999; Abdel-Aty, *et al.* 2004; El-Basyouny and Sayed 2006), intersections (Lord and Persaud 2000; Xie and Zhang 2008; Malyshkina and Mannering 2010), or large spatial units, such as traffic analysis zones (TAZ) (Pulugurtha, *et al.* 2012), census block groups (Pawlovich, *et al.* 1998), and counties (Miaou, *et al.* 2003; Noland and Oh 2004; Aguero-Valverde and Jovanis 2006) over a defined period of time (years, months, weeks, days, etc.).

While these common characterizations of severity and frequency assist researchers by increasing the ease of interpretation by roadway safety practitioners, their simplifications are not always appropriate for every situation or roadway environment. Therefore, researchers may find it beneficial to create a more finely tuned scale that directly accounts for the type of crash case or cause that they are modeling. It is sometimes in a researcher's best interest to breakdown, or augment, severity scales in order to better fit the model that is being used.

For example, Rosman, *et al.* (1995) took data classified in the AIS scale and turned it into a 12 point scale to better fit their modeling technique.

## 2.2 Factors Influencing Highway Crashes

*Environmental Factors*

A common category of factors that are relevant for crash frequency and crash severity are meteorological, environmental, and temporal characteristics (Kockelman and Kweon 2002; Eluru and Bhat 2007; Malyshkina and Mannering 2009; Azad and Tay 2010; Panagiotis, *et al.*2012).

Meteorological and environmental data are usually crash-time specific for crash severity studies, and are often used to model the time-dependent effect(s) that nature has upon crash severity. Previous crash severity studies have used factors, such as presence of precipitation, icy/wet roadway conditions, presence of fog, presence of lighting, and wind speed in their models. Jung, *et al.* (2009) dedicated their whole study to the effect that rainfall had upon crash severity and frequency; their findings suggested that wet roadway conditions have a positive correlation with crash frequency, yet a negative correlation with crash severity. Quddus, *et al.* (2009) corroborated this finding in their UK study when they found that fine weather, as opposed to rain, increased crash severity. Utilizing crash-time specific environmental and meteorological factors in crash severity studies enables researchers to account for both temporal heterogeneity and correlation, since crashes often exhibit spatial trends due to temporal changes in weather, i.e., snow, heavy rain, or fog (Lord and Persaud 2000).

Since crash cases are aggregated over a given time period in crash frequency studies, meteorological conditions must also be aggregated over the analysis time period. Aguero-Valverde and Jovanis (2006) used meteorological factors, such as mean total precipitation (in.), mean number of rainy days, mean total snowfall (in.), and mean number of days with snow, aggregated on a per year basis to determine that mean total precipitation (in.) had a positive relationship with the frequency of injury crashes in their base model, and also when accounting for time-trends.

Other researchers have employed much smaller aggregation levels in order to assess the temporally differing effects of meteorological factors. In their 2007 study on roadways in Virginia, Qi, *et al.* (2007) found that weather characteristics have a definite effect on the probability of being in a crash, with both presence of fog and rain during a day possessing positive associations. These results suggest that environmental, meteorological, and temporal characteristics, although defined differently, have a statistically significant effect on both crash frequency and crash severity.

### *Geometric and Operational Design*

One of the commonly discussed categories of factors influencing crash severity and frequency is that of geometric and operational roadway design (Abdel-Aty and Keller 2004; Milton, *et al.* 2008; Abhishek, *et al.* 2009; Panagiotis and Mannering 2010; Anastasopoulos, *et al.* 2012). Variables encompassing everything from posted speed limits to shoulder widths should be considered when attempting to improve the safety of a given roadway. Unfortunately, there is little consensus on the role that these factors have in crash severity and frequency, due in part to the inability to distinguish between whether these elements are involved in crash causation or simply affect vehicles once a crash has occurred.

A good example of this is higher speed limits. Garder (2005) found that higher posted speed limits are associated with more severe crashes, but Aguero-Valverde (2012) and Aguero-Valverde and Jovanis (2008) found that high speed limits had a negative effect on crash frequency.

Additionally Hu and Donnell (2010) found that “collisions with cable barriers increase the probability of a less-severe crash outcome relative to collisions with a concrete or guardrail median (Hu and Donnell 2010).” However, it has been found that the presence of median barriers, of any type, significantly increase the frequency of motor vehicle crashes (Xie and Zhang 2008). Moreover, researchers have found that smaller shoulder widths tend to increase both crash severity and crash frequency levels (Noland and Oh 2004; Chang 2005; Caliendo, *et al.* 2007; Aguero-Valverde and Jovanis 2008; Abhishek and Abdel-Aty 2010; Panagiotis and Mannering 2011).

Number of highway lanes is also a complex design element, as some research has shown that highways with more lanes experience an increase in crash frequency (Noland and Oh 2004; Yan, *et al.* 2005; Malyshkina and Mannering 2010), while other research has shown that the number of lanes either is not statistically significant (Jung, *et al.*2010) or has varying effects depending upon the class of roadway (Abdel-Aty and Keller 2005). It should also be noted that factors such as pavement type, or friction factors, have been more widely utilized in crash frequency studies, while often omitted from crash severity studies (Anastasopoulos and Mannering 2009; Malyshkina, *et al.* 2009; Anastasopoulos, *et al.* 2012).

Still, researchers do agree that the presence of curved sections has been shown to significantly increase crash severity levels as well as the likelihood for a crash (Caliendo, *et al.* 2007; Qi, *et al.* 2007; Chimba and Sando 2009; Barua, *et al.* 2010)

Overall, incorporating roadway geometric design factors into crash frequency and severity models has proved to be quite beneficial. These factors often assess and quantify improvable and correctable roadway features. When using roadway geometric factors, one item to take into consideration is their overall effect on roadway safety when compared to other possible causal factors. Using roadway geometric factors exclusively could potentially overstate or erroneously state the affect that a given geometric factor has upon either crash frequency or severity.

*Roadway Traffic Demand*

One of the most common factors utilized in crash frequency and crash severity studies is highway/roadway traffic and demand (Hu and Donnell 2010; Pande, *et al.* 2010; Christoforou, *et al.* 2010; Malyshkina and Mannering 2010; Anastasopoulos, *et al.* 2012). Traffic demand is most often modeled as average annual daily traffic (AADT), however, some studies have used crash-time specific traffic flow data in their models (Quddus 2008; Christoforou, Cohen, and Karlaftis 2010). In a similar respect to roadway geometric characteristics, traffic demand factors often have contradictory affects depending on whether the factor(s) is utilized in a crash frequency or crash severity study. In fact, previous research has suggested that traffic volume may be the leading cause of crash occurrence (frequency), but nearly negligible for crash severity (Wang and Abdel-Aty 2007). Noting this, many prior crash frequency studies, referred to as general average annual daily traffic models, have used traffic volume, or traffic exposure (in millions of vehicle miles traveled) as the *only* independent factor in their model (Xie and Zhang 2008; El-Basyouny and Sayed 2009; Malyshkina and Mannering 2010; Pulugurtha, *et al.* 2012; Zhang, *et al.* 2012). This is not surprising, as many studies point out that traffic demand increases the frequency of crashes simply because there is more opportunity for them to occur (Chang 2005; Aguero-Valverde and Jovanis 2008; Anastasopoulos and Mannering 2009; Malyshkina and Mannering 2010). However, crash frequency models that only utilize AADT, or exposure, will suffer from an omitted variables bias, since many non-demand related factors are known to affect the frequency of crashes (Lord, *et al.* 2008), and also may not be able to adequately capture the true relationship between crash frequency and travel exposure (Zhang, *et al.* 2012).

In contrast, prior crash severity studies have generally found traffic demand to reduce levels of crash severity, or to not have a statistically relevant effect at all (Kirolos and Abdel-Aty 2010). Quddus, *et al.* (2009) and Wang and Abdel-Aty (2008) both determined that elevated levels of AADT exhibited little to no statistically relevant effect on increasing crash severity. Whereas, after Christoforou, *et al.* (2010) incorporated a measure of speed, directly related to demand, into their model they found that low speeds and high volumes decreased severity, while high speeds and low volumes increased severity.

### *Human Factors*

Some of the most frequently used factors in crash severity modeling describe human factors (Malyshkina and Mannering 2009; Barua, *et al.* 2010; Hu, *et al.* 2010; Paleti, *et al* .2010; Xie, *et al.* 2012), including driver/passenger age, race, gender, failure to wear, or properly use, safety equipment (seat belts and airbags), failure to obey posted traffic safety measures, aggressive driving, driver distraction, and impaired driving (Holdrich, *et al.* 2005; Abhishek, *et* *al.* 2009). Of the above topics, aggressive driving, and most notably speeding, has been found to have the highest effect on crash severity, followed by impaired driving. Paleti, *et al.* (2010) found that speeding was the most common potentially aggressive action, making up about 31% of the total fatal crashes that they observed. Driver specific variables present an interesting problem for transportation engineers and law enforcement alike due to their unpredictable nature and the relative difficulty that they pose when attempting to control these variables.

*Spatially Related Demographic and Socio-Economic Factors*

Traditionally efforts have considered only crash data and roadway network attributes, and have not often modeled adjacent and surrounding demographics, socio-economic factors, land uses, and other non-roadway variables (Pawlovich, *et al.* 1998). However, many factors affecting crashes operate at a spatial scale, e.g., land uses and potential trip generations and attractions (Aguero-Valverde and Jovanis 2006, Levine, *et al.* 1995 a,b; Pawlovich, *et al.* 1998; Kim and Yamashita 2002; Pulugurtha and Sambhara 2011; Pirdavani, *et al.*, 2012; Pulugurtha, *et al.* 2012). Therefore, further research needs to be done to assess spatially related effects since they tend to change over time and play a key role in long distance pass-through trips, which are highly prevalent on interstates and highways (Kim, *et al.* 2006). For example, Levine, *et al.* (1995a,b), in two separate studies, developed statistical models in order to derive spatial patterns of crashes in Honolulu, HI based upon the spatial location of a crash, and census block group aggregate data on population, types of employment, and land area where the crash occurred. Common spatially referenced factors, other than population and employment metrics, include: income/poverty percentage (Aguero-Valverde and Jovanis 2006; Pirdavani, *et al.*, 2012), age or age groups of population (Aguero-Valverde and Jovanis 2006; Quddus 2008; Chen, *et al.* 2009), and gender (Aguero-Valverde and Jovanis 2006; Chen, *et al.* 2009).Kim and Yamashita (2002) introduced spatial correlation between crash frequency of different severity levels and surrounding land use variables by utilizing geographical information system (GIS) software. Later, Kim, *et al.* (2006) revisited the GIS technique and introduced population count and economic development data, in conjunction with land use data, for uniform grid sections in Hawaii, results from this study showed that population based metrics, by spatial units, are the most statistically significant predictors of crash occurrence, by severity level (Kim, *et al.* 2006).

Ultimately, it is important to decide which *combination* of different factors is most relevant for the goal(s) of the study. Some studies utilize a wide range of variables in their models; this enables them to report back results for a multitude of topics, while other studies have a far more acute range of observations and included variables, and focus on individual resultant categories, such as the general AADT crash frequency models. For crash frequency models, it is common to only utilize traffic, roadway characteristic, and environmental factors (Pawlovich, *et al.* 1998), and, often, these models are preferred due to their simpler functional forms, and ease of transferability (Zhang, *et al.* 2012). However, these models tend to omit numerous factor categories that may play an equal or greater role in determining crash frequencies. Crash severity models often incorporate numerous factors, including crash-case specific factors, but are often hard to interpret, and require copious amounts of data in order to transfer them to other roadways or settings. It is also apparent that there has not been enough work done considering the various spatially related factors affecting both crash frequency and crash severity. Further research needs to be performed that incorporates the combined effect that all of these various factors have on crash frequency and severity. In essence, a comprehensive model that models all factors, including spatially related demographics, and long distance travel characteristics, is still needed.

## 2.3 Data and Methodological Issues and Limitations

Data for crash frequency and crash severity studies generally originate from the same sources, including police crash reports, roadway geometric data, meteorological data, spatially related socio-economic and demographic data, and roadway travel demand data. With any data, there are innate issues and limitations that pose different modeling and procedural challenges. This section highlights a number of issues with data that need to be addressed when modeling this behavior.

### *Under-Reporting of Crash Data*

The under-reporting of crash cases has been well documented and discussed in crash frequency and crash severity literature for quite some time (Elvik and Mysen 1999). Daniels, *et al.* (2010) stated that crash severity is a crucial element in predicting the reporting rate of a crash, the more severe the crash the higher the reporting rate. The NHTSA estimates that 25% of minor injury crashes and 50% of non-injury crashes go unreported to the police, while nearly 100% of fatal crashes are reported (NHTSA 2009). Furthermore, in traditional crash databases some crashes are omitted, some states only report crashes that result in damage above a certain dollar amount, and other states require vehicle damage to be over a certain threshold value in order to be reported (Savolainen, *et al.* 2011). The inherent issue concerning crash under-reporting for crash frequency and crash severity studies is that statistical models are generally developed under the assumption that the sample data are randomly selected, and that each crash has an equal opportunity of occurring; this assumption is violated if large proportions of crashes go un- or under-reported. Hauer and Hakkert (1988) additionally determined that the probability that a crash will be reported is also based upon location and reporting agencies (city, state, local, etc.), and not simply a function of severity level. In regard to effect on crash frequency and crash severity, it has been shown that not accounting for some aspect of under-reporting may lead to biased estimates, false factors associated with crash severity, and unaccounted for crash causal factors, in the modeling procedure (Ma 2009).

*Unobserved Heterogeneity*

Another key issue that effects both crash frequency and crash severity studies has to do with unobserved heterogeneity, or the effect of omitted variable bias on model parameter estimates. This is relatively common for a number of reasons, including false /miss-reported data (Lord and Mannering 2010) or lack of available detailed data (Savolainen, *et al.* 2011). When forecasts of crash frequency and severity are conducted with limited explanatory variables, there is a strong potential that the forecasts can include marginally different effects and erroneous conclusions (Anastasopoulos and Mannering 2009).

Capturing spatial heterogeneity (or variety in environmental characteristics) is one of the most prevalent issues in crash frequency and crash severity modeling because, while many geometric characteristics are considered there are typically many unobserved human and/or roadway factors that are lost (Lee and Mannering 2002). Temporal heterogeneity (or capturing variety in time-based characteristics) is less prevalent in crash frequency studies since crash occurrences are typically averaged over larger time periods, but when ignored, can lead to inaccurate model results. Specifically, research has shown that including specific weather, time, and day factors can increase the precision of models, as these factors have a distinct temporal effect on both crash occurrence and severity (Lord, *et al.* 2010; Savolainen, *et al.* 2011).

Therefore, research suggests that model precision can be greatly improved if unobserved heterogeneity is accounted for by either introducing random parameter estimates, or by incorporating spatially related, temporally related, or crash-case specific factors.

*Unobserved Correlation*

Interstate crashes do not occur in isolation; in fact, one crash may be related to another crash by the simple fact that they were close to each other in time and/or space. These relationships, described with unobserved correlation, mean that the variables used to predict crashes are not wholly independent from each other (Quddus 2008). In fact, the same section of road or same storm may be influencing multiple crashes, and these crashes are all likely to share important unobserved effects (Savolainen, *et al.* 2011). Using aggregate averaged measures of crash counts over a given time period, e.g., the average number of crashes at a roadway segment/intersection per year for 3, 4, 5, etc. years of data, will help to alleviate some of the temporal correlation from unobserved factors. Recent research, however, has shown the importance of spatial correlation in roadway crash models at both the segment and intersection level (Aguero-Valverde and Jovanis 2010). Models that do not account for spatial dependence among observations produce high variance in their estimates, and, therefore, underestimated standard errors (Aguero-Valverde and Jovanis 2006). Whereas, models that do account for spatial correlation have shown significantly better statistical fit (Aguero-Valverde and Jovanis 2008). Researchers have begun to incorporate spatial and temporal correlation into model structures by using hierarchical methods (Miaou, *et al.* 2003; Aguero-Valverde and Jovanis

2006; Aguero-Valverde and Jovanis 2008; Aguero-Valverde and Jovanis 2010), general estimating equations (GEE) methods (Lord and Persaud 2000), classification regression tree (CART) methods (Chang and Chen 2005), or by assessing the effect of correlation at different spatial aggregation scales (Quddus 2008). Results from these different methods have all show an increase in statistical precision when spatial and/or temporal correlations are accounted for in the model.

*Endogenous Factors*

Another important issue is that of endogenous variables, which is tied to other factors and may be misinterpreted as causal when it is, in fact, not. Failing to account for potential endogenous variables can lead to erroneous conclusions about the true factors that influence frequency or severity. For example, airbag deployment should not be used an explanatory variable as they could also be misconstrued as a cause of higher vehicle damage crashes, since airbags do not deploy until a certain level of vehicle damage has already been attained (Savolainen, *et al.* 2010). Similarly, a geometric design characteristic like ice-warning signs are often placed at locations that have a previous history of ice related crash occurrence. If this endogeneity is ignored, then an erroneous conclusion that ice-warning signs lead to increased levels of crash frequency could be derived (Lord, *et al.* 2011). Accounting for, and removing, endogenous factors when modeling crash frequency or crash severity will greatly improve model results, and help to eliminate the possibility of reporting erroneous conclusions.

*Small Sample Sizes and Low Sample-Mean*

Small sample sizes may also present issues for roadway safety studies, as they invalidate many statistical model assumptions as well as render some methods invalid, such as maximum likelihood estimation (Lord, *et al.* 2010). Unfortunately, the detailed crash data required to address the other issues listed here is often costly and, as a result, much work on measuring factors is done with smaller datasets. In fact, Ye and Lord (2011), in their study comparing sample size effect on Multinomial Logit, Ordered Probit and Mixed Logit Models, concluded that small sample sizes significantly affect the development of crash severity models, no matter which type of model is used. Zhu and Srinivasan (2010) noted that their data set was too small to attain truly accurate results, and that a larger dataset should be considered in future research.

Furthermore, small sample sizes can also make it harder to describe the crashes that *are* included in the dataset. Crashes are inherently rare events, and when smaller spatial or temporal scales are used to collect data, the representativeness of the crashes captured is weakened (Lord, *et al.* 2005, Cameron and Trivedi 1998). Therefore, roadway entities influenced by small sample size, small spatial or temporal scales, and low roadway exposure will see a preponderance of zeros (no crash occurrence), which contributes to a low sample-mean, and displays over-dispersion (sample variance is greater than the sample mean) (Lord, *et al.* 2005).

As this section has described, there are numerous issues and limitations inherent to crash data that effect both crash frequency and crash severity studies. Failing to account for one or more of these issues can lead to biased and erroneous estimates and conclusions. Of the issues presented, not accounting for an omitted variable bias/spatial or temporal heterogeneity, endogenous factors, and small sample size/low sample-mean appear to be the largest culprits for degrading the precision of model results, and should continue to be addressed in future research.

This research will seek to account for limitations such as, the omitted variable bias, spatial and temporal correlation and heterogeneity, small sample size and low sample-mean, endogenous factors, and dependent variable structure, while attempting to mitigate the effects of other possible limitations.

## 2.4 Statistical Methods:

Due to the many similarities in the data required to analyze crash frequency and crash severity, there are numerous statistical models and methods available for both types of studies. A list of common models that have been used in the two types of studies can be seen in the Venn-diagram below, with crash frequency exclusive models on the left, crash severity exclusive models on the right, and models that have been employed in both types of studies populating the central portion. Of the models that have been employed in crash frequency and crash severity studies, two promising models have emerged, the Poisson regression model for crash frequency, and the logit/probit model for crash severity, each of which will be discussed in the following section.

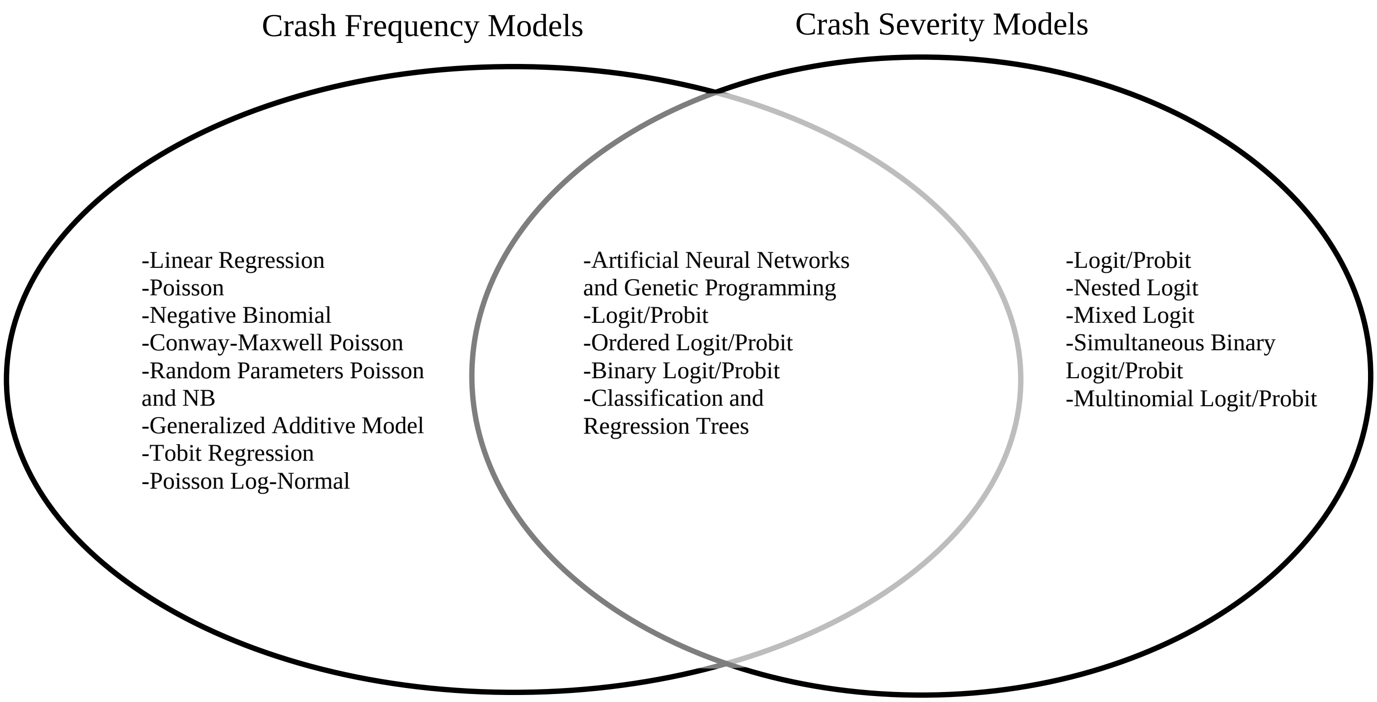


**Figure 2.1. Comparison of Statistical Methods.**

*Poisson Based Modeling Structures*

The first methods employed to model crash frequency were linear regression models. However, due to the discrete, non-negative integer nature of crash count data, the simple modeling structure of the ordinary least-squares linear regression models were determined to be inadequate for frequency modeling (Lord and Persaud 2000). Slightly more advanced Poisson distribution regression techniques soon developed into the preferred method to model crash frequency data, and still remain as the most common methods used, with varying generalizations (Lord 2006). The Poisson regression, often referred to as the Poisson log-linear model when the conditional mean is restricted to be greater than or equal to zero, is motivated by the usual considerations for regression analysis, but also seeks to preserve and exploit, as much as possible, the non-negative integer-valued aspect of the count data outcome. In other words, Poisson regressions can be thought of as a special type of non-linear regression that respects the discreteness of count data (Cameron and Trivedi 1998).

The Poisson regression model is derived from the Poisson distribution by allowing the intensity parameter, $\mu$, to depend on covariates (regressors, factors) (Cameron and Trivedi 1998). The Poisson regression, when applied to crash frequency data, consists of $n$ independent observations (crash counts for segments, intersections, etc.), the $i^{th}$ term of which is ($y_i$, $\boldsymbol{x}_i$). The dependent variable, $y_i$, is the number of crashes per entity over the specified time period, and $\boldsymbol{x}_i$ is the vector of linearly independent regressors (factors) that are thought to determine $y_i$. The regression model conditions the distribution of $y_i$ on a $k$-dimensional vector of factors, $\boldsymbol{x}_i$ = [$x_{1i},\ldots,x_{ki}$], and parameters $\beta$, through a continuous function $\mu$, with $\mu_i = \exp(\boldsymbol{x}_i\beta)$, to ensure that $\mu_i > 0$, for the log-linear version of the model (Cameron and Trivedi 1998). Therefore, $y_i$ given $\boldsymbol{x}_i$ is Poisson-distributed with density

$$f(y_i|\boldsymbol{x_i}) = \frac{e^{-\mu_i}\mu_i^{y_i}}{y_i!}, y_i = 0, 1, 2, \ldots \qquad (2.1)$$

with the function μ represented as:

$$\mu_i = \exp(\beta_0 + \boldsymbol{x}_i\beta + \varepsilon_i) \qquad (2.2)$$

where $\beta_0$ is a random intercept term, and $\varepsilon_i$ is the new dispersion parameter that seeks to account for the over-dispersion present within the data, which can either be fixed (same effect for all entities, or allowed to vary across entities (Malyshkina and Mannering 2010).

One of the main limitations for all Poisson derived modeling structures is their innate inability to handle crash severity data realistically. The assumption of ordinal integer based count data is not valid for crash severity levels. Therefore, developing roadway performance measures for ranking roadway segments, based on both crash frequency and severity, must be performed using a separate modeling structure for crash severity. Recent research has sought to break down crash cases into severity level bins and to simultaneously model the crash frequency of these bins; this advanced modeling structure will be discussed in the application and ranking techniques section of the literature review.

*Logit and Probit Based Modeling Structures*

Instead, many researchers recognize that logit or probit models may be more appropriate for crash data analyses. In their most basic state these models effectively estimate the probability of a binary occurrence, 1-the event has occurred, versus 0-the event has not occurred. However, these models can be expanded to look at discrete choices from among a set of multiple options, e.g. a range of crash severity types of number of crashes along a stretch of roadway. As such, the use of logit/probit models for modeling outcome dependent variables is quite applicable, and widely used (Savolainen, *et al.* 2010). Logit and probit models are inherently very similar in that they both use a “link” function to transform a dichotomous variable into a continuous transformation of that variable (Train 2009). In this respect, the dichotomous dependent variable is transformed into a probability that ranges from zero to one. The probit model utilizes the cumulative normal distribution as its link function, whereas the logit model uses a logistic distribution (Train 2009). In effect, the logit and probit models, known as discrete choice models, examine ‘which’ factors contribute to a binary outcome (fatal crash or non-fatal crash, etc.), whereas a traditional regression function would ultimately examine ‘how much’ these factors contributed (Train 2009).

These discrete response models are generally used to explore the relationship between accident severity and its contributing factors, such as driver characteristics, roadway characteristics, etc. (Ye and Lord 2011). However, such models have also been used to determine the probability of a crash occurring, or probability of a certain crash severity level outcome in crash frequency studies (Milton, *et al.* 2008, Pei, *et al.* 2011). One of the main attractions for discrete outcome models, in particular the probit model, is that they are able to account for heterogeneity between observations, which has potential for use, and relevance, in both crash frequency and crash severity studies (Anastasopoulos and Mannering 2009).

Dependent variables in crash severity studies can also be represented as multiple response outcomes, which can either be identified as an ordered or unordered set of outcomes. When dependent variable outcomes are not assumed to have an order, then multinomial logit or probit models can be employed (Malyshkina and Mannering 2009; Hu and Donnell 2010; Ye and Lord 2011). The multinomial logit (MNL) is derived under the assumption that the unobserved factors are uncorrelated over the different outcomes or alternatives, this is also known as the independence from irrelevant alternatives (IIA) assumption (Train 2009). In this way, the multinomial logit model derives a latent variable and error term for each alternative independently. However, this is a large limitation for the model(s), since it can be assumed that there will exist some shared unobserved factors and effects between the outcomes, which may include factors such as injuries sustained, crash contributing circumstances, and/or crash time specific environmental characteristics (Ye and Lord 2011). Furthermore, crash data outcomes, for frequency and severity alike, exhibit an ordinal nature, and since multinomial logit models do not explicitly account for the ordered nature of the data, some would argue that said models are not ‘constrained’ by this assumption, they have a tendency to trace erroneous factors (Savolainen, *et al.* 2010). Therefore, models that explicitly account for the ordinal nature of crash data have frequently been employed.

Therefore, the most common models that are employed in crash severity studies have been the ordered logit and ordered probit models (Kockelman and Kweon 2002, Garder 2005; Zhu and Srinivasan 2011). These more advanced representations of logit/probit models explicitly account for the ordinal nature of crash severity outcomes (i.e., fatal, incapacitating injury, non-incapacitating injury, possible injury, property damage only), a slight variation of these models are referred to as sequential logit/probit models, however, they essentially derive the same results (Savolainen, *et al.* 2010). Similar to their multinomial counterparts, ordered logit and probit models derive a latent variable to disaggregate crash severity outcomes (Ye and Lord 2011). Ordered discrete models (logit/probit) treat the data as being generated by a continuous unobserved latent variable, which upon crossing a threshold value leads to an increase in severity by one level (Cameron and Trivedi 1998). The error term in ordered models again represents the effect of omitted or unobserved, factors, it is assumed to be independent of the included factors, constant over the different severity level outcomes, and logistically distributed for the ordered logit model and normally distributed for the ordered probit model.

As noted earlier, ordered logit and probit models have seen extensive use in crash severity modeling. However, in practice, ordered models have been rarely applied to count data, such as crash frequency data (Cameron and Trivedi 1998). This may be, in large part, due to past literature focusing on developing quantifiable measurements of factors, for use in determining a wide range of different safety alterations (Washington, *et al.* 2003). Ordered models will not allow for quantifying, they are only able to determine if it has a positive or negative effect. It is also difficult to quantify the middle threshold bins within an ordered model; probabilities for being in these bins are easily attainable (Washington, *et al.* 2003). Therefore, it is possible that ordered models have been omitted from crash frequency studies due to the ambiguous nature of their model parameter estimates (Washington, *et al.* 2003). It is worth mentioning, however, that ordered model results are easily applied for forecasting purposes, and are a valid alternative for modeling count data, since most observed counts take on discrete, ordered outcomes (i.e., 0, 1, 2…) (Cameron and Trivedi 1998). Therefore, the employment of ordered models, such as an ordered logit or ordered probit, should be considered and incorporated as an expansion upon the current work in the field of crash frequency modeling, since they will allow researchers the ability to forecast both crash frequency and severity using the same model, which will greatly increase the ease of derivation of roadway ranking performance measures.

One of the main limitations for the logit model, including their ordered versions, is that the effect of a given factor is fixed for all severity outcomes and for all observations, which, for example, would assume that the effect of speed on crash severity is the same for a property damage only crash as for a fatal crash (Xi, *et al.* 2012). Probit models differ from logit models in that they do not share the same three limitations as logit models: they can represent random taste variation, they are not bound by the IIA assumption, and they are able to account for unobserved correlated factors over time (Train 2009), therefore, a separate random parameters approach is not needed for probit models.

Previous research has primarily focused on altering and improving current models, or developing newer models in order to attain better statistical fit to crash frequency or crash severity data. However, it may be preferable to begin to develop models that consider the fundamental process of a crash, and avoid simply striving for 'best-fit' models in isolation (Lord, *et al.* 2005). Even with the various model adaptations that have been employed to account for the different issues and limitations associated with crash data, there still does not exist one singular model that adequately solves all of the issues at once. There is also the problem of possibly having to use different models to model crash frequency or crash severity. With that said, researchers may find it beneficiary to utilize similar models for both types of studies, even if one model has seen infrequent use in one type of study or the other. In this author's opinion, the use of ordered probit models for both crash frequency and crash severity could help to elucidate the various factors that affect both types of studies.

## 2.5 Performance Measure Application and Ranking Techniques

In order to constitute a full safety assessment of roadway elements (entities) a study needs to include investigations into the severity, as well as frequency of motor vehicle crashes (Das and Abdel-Aty 2011). The goal for roadway safety practitioners is to reduce the number of crashes, and mitigate the injury severity in the event that a crash does occur (Das and Abdel-Aty 2011). In order to do this, researchers need to identify the various factors that influence both crash frequency and crash severity, and be able to identify locations that should be considered dangerous due to possessing these factors. However, there does not yet exist a formal definition, that is universally accepted, of what should be considered 'dangerous' (Geurts, *et al.* 2006). Therefore, the success of safety improvement and identification programs depends on the availability of methods that give reliable estimates of a defined safety level associated with existing, and potentially future, road locations, so that plans and designs can be designated (El-Basyouny and Sayed 2006). A variety of roadway safety performance measure derivation methods have been used to determine what and where these 'dangerous' locations are. Previous literature often refers to these locations as "Hot Spots" or "Black Spots" to designate them as areas with increased likelihood for crash occurrence or severity (Montella 2010), and accurately identifying these locations is paramount in the roadway safety procedure. False identification of

Hot Spots or Black Spots is highly detrimental to roadway safety planning, since false readings cost money, and will put emphasis on roadway sites that do not truly require any improvements (Montella 2010). Previous literature has focused on three main genres of Hot Spot roadway safety performance measure ranking and identification methods, which include separate analysis of crash frequency and severity, simultaneous modeling of frequency and severity, and less computational methods for ranking observed trends in empirical data. However, more work is still needed in this field to assess the different causes, and levels, of roadway 'un-safety,' and also to generate real-time and forecasted maps depicting the different levels and areas in need of improvement (Miaou, *et al.* 2003).

The most common methods used for deriving roadway safety performance measures has been to model crash frequency and crash severity separately. Most of the models and studies identified previously in this literature review have depicted such cases, where separate models are run using crash frequency and crash severity data. However, there still is a need to assess the frequencies of different severity outcomes, and the factors that influence them (Milton, *et al.* 2008). Results from previous studies have shown that the factors affecting crash frequency and crash severity differ greatly (Chiou and Fu 2012). This fact is one of the reasons why separate frequency and severity models are often employed, and used in post derivation comparisons to determine roadway safety performance measures. Common practice for previous roadway safety studies has been to model crash frequency using a traditional frequency model, such as a Poisson model or a Negative Binomial model, to predict the number of crashes for a given entity, and then to use a traditional crash severity model, such a logit or probit model, to assess the proportion and probability of crashes at each of the included severity levels (Chiou and Fu 2012). In this way, researchers have been able to determine the frequency of different severity level crashes for roadway entities, which enables them to focus their efforts on locations with an exorbitant number of crashes, or locations that tend to have extremely severe crash cases. Separate modeling methods are also often employed due to the rather extensive set of data that is generally required for crash severity studies; such datasets make transferring model results difficult, are impossible to apply, as a whole to frequency models, and may not always be available for minor roadways (Chiou and Fu 2012). It has also been postulated that crash frequency and crash severity are fundamentally different phenomena, and that it would not be practical to constrain them to one singular model (Das and Abdel-Aty 2011). However, other researchers have noted that there is considerable appeal in developing some combination of frequency and severity models that are less data intensive than a traditional crash severity approach (Panagiotis and Mannering 2011).

Recent research has looked to combine the previous two-step process of predicting crash frequency and severity in order to streamline the performance measure derivation process, and the methods used to accomplish this goal are generally multivariate Poisson (MVP) or multivariate Poisson Log-Normal (MVPLN) models (El-Basyouny and Sayed 2009). One of the main limitations that researchers have stated for the separate modeling procedure is that these methods assume that the factors affecting crash frequency and crash severity are mutually independent (Chiou and Fu 2012). These methods also do not account for possible correlation between severity levels themselves (Park and Lord 2007). These two limitations are the main motivation behind the employment of MVP and MVPLN models, since these models are able to account for correlating factors, and correlation between severity levels (Park and Lord 2007). Bai, *et al.* (2007) validated these assumptions by concluding that the effects of factors significantly related to crash counts by severity level can be explored in the MVP/MVPLN model, crash related factors of different severity levels were not identical (some factors only effect certain severity levels), and correlations among crash counts of severity levels do exist, and should not be ignored in analysis. Essentially the simultaneous modeling of crash frequency and severity via MVP/MVPLN models has the same goal as the separate modeling methods, to predict the frequency of different severity level crashes at an entity over a given time period. However, proponents of simultaneous modeling suggest that separate methods are often inaccurate. El-Basyouny and Sayed (2009) concluded that some hazardous locations could be overlooked if only a univariate procedure is utilized, either by modeling crash frequency and severity separately, or by modeling the frequency of crashes that have been coded in different severity levels independently (since crash data are often collected in distinct severity level bins). In their study comparing property damage only crashes to injury/fatality crashes, El-Basyouny and Sayed determined that their MVPLN model was nearly twice as precise as their univariate PLN model (El-Basyouny and Sayed 2009). Conversely, other researchers have concluded that MVP/MVPLN models do not attain higher levels of accuracy, and that their complex estimation, requiring a subjectively present correlation matrix of severity levels, makes field validation of their results very difficult (Chiou and Fu 2012). Another observed limitation of the MVP/MVPLN models is that they are unable to differentiate between variables that exclusively effect severity, and those that exclusively effect frequency (Chiou and Fu 2012). Either way, the use of simultaneous crash frequency and crash severity modeling procedures appears to have numerous potential applications for future research.

There has been extensive literature focused on simple univariate methods for deriving roadway safety performance measures, with the ultimate goal of determining and ranking Hot Spots and Black Spots, referred to as Hot Spot Identification (HSID) methods. Often these methods are employed using only observed empirical data, and predictive models are never needed or employed. The most common of these methods is a simple ranking of crash frequency, or crash rate, in reverse order of magnitude; HSID methods have also assessed ranks based on crash cost equivalents, by proposing a crash “cost” for different severity level crashes, and assessing the total cost per entity over a certain observed time period (Montella 2010). Other methods have used difference methods that assess excess levels of observed-predicted crashes on an entity, or have based Hot Spots on whether they have excess proportions of higher severity crash cases than what would be seen on a “typical” safe roadway entity (Montella 2010).

In total, there are seven traditional methods that have commonly been used to rank Hot Spots: 1) crash frequency, 2) hazard potential ratio (crash rate), 3) joint-frequency and risk ratio, 4) confidence intervals, 5) crash severity ratio, 6) risk-rate method, and 7) inventory of risk causes (Geurts, *et al.* 2005). Often these methods only rank hazardous locations on a binary scale, 1-at risk location (Hot Spot), versus 0-safe location, and none of these methods truly account for the combined effect of crash frequency and crash severity. One method, utilized in Flanders, Belgium, uses a crash severity ratio method, where crashes are placed into an equation that converts all cases into similar scale, for the study being mentioned, the multiplicative factors were: one for a light injury crash, three for a serious injury crash, and five for a fatal injury crash (Geurts, *et al.* 2005). These factors were applied to each observed crash on each entity during a given year, and entities were classified as Hot Spots or Black Spots if they surpassed an arbitrary threshold value that was determined by the local governing agency (15 in the Flanders study) (Geurts, *et al.* 2005). However, methods such as the crash severity ratio and equivalent property damage method have adverse moral implications; can researchers really define a “price” for someone’s life in a fatal crash, or the injuries that they have sustained in an injury crash

(Montella 2010)? All of these methods also have the limitation that they do not explicitly allow for forecasting (usually only modeling observed trends and crashes), and they often rank hazardous locations in a binary manner, which leaves the determination of exact places and aspects in need of roadway improvements an ambiguous task. Therefore, there remains significant work for improving these ranking methods.

In all three genres of methods discussed in this section, there exist many limitations, and aspects that have yet to be covered. For example, a binary condition does not describe the difference between safe and unsafe sites, and, in fact, the difference in safety across all sites being compared may be continuous in nature (Cheng and Washington 2005). There is, perhaps a safety performance function that underlies roadway entities in an ordinal manner, and sometimes the difference between these sites may not be too large, therefore, an in-depth and comprehensive safety performance function, incorporating both crash frequency and crash severity, should be addressed (Cheng and Washington 2005). A predictive model that can assess the causal factors, and be precise when doing so, while incorporating various factors from all of the various areas influencing crash frequency and severity is also needed (Cheng and Washington 2005). Care must also be taken to assess the effect that demographic and land use characteristics have upon roadway safety, since these factors are the ones that are most likely to change over time (Noland and Oh 2004). Accounting for these limitations will facilitate the development of roadway safety and crash maps, which can be utilized by departments of transportation, highway safety planners and practitioners, and local governing agencies in order to identify dangerous locations, determine the causes and effects of various factors, and develop improvement strategies for roadway entities now, and into the future.

## 2.6 Conclusions

Although there has been extensive literature analyzing crash frequency and crash severity, and their underlying causal factors, there is still ample room for improvement. Previous studies have only utilized select groupings of variables, and in the case of crash frequency, simple general AADT models have become the model of choice. However, crash frequency and crash severity are generated by a litany of different causal factors, and omitting one or more groups of factors has the potential to bias estimates and report erroneous results. Therefore, comprehensive models that account for: environmental factors, roadway geometric factors, traffic demand factors, surrounding development demographic and land use factors, and long distance (trip attraction) demographic factors should be included in crash frequency models, with the addition of driver and passenger demographic data, and crash-case specific data for crash severity models. Only after all of these factors are included together, assessing their combined effect on crash frequency and severity, can researchers begin to more accurately model the factors that truly influence roadway safety.

Likewise, various statistical modeling procedures have been employed to assess the effect of different groups of crash causal factors. However, most work has focused on expanding upon models that are exclusive to one type of study or the other, and have not attempted to model crash frequency and severity by using the same type of model. Doing so would likely increase the accuracy of results, and ensure that a common scale and inferential pattern would be present. Using a common model, that is still flexible and powerful enough to account for most of the limitations present in crash data, could greatly expand current roadway safety modeling procedures, and could usher in a new paradigm for how the combined modeling of crash frequency and severity is performed. One such model that fits these specifications is the ordered probit model, which, in this author's opinion would allow for nearly seamless modeling of both crash frequency and crash severity, while being able to account for numerous crash causal factors, and output highly precise statistical results.

One facet of roadway safety that certainly has not seen enough work is that of the ranking of roadway entities. Improved ranking methods into comprehensive roadway safety performance measures that incorporate multiple strata would be able to discern sites that are only 'kind of' hazardous from sites that are in immediate need for roadway improvement projects or public awareness initiatives. Such methods should be derived as a joint scale comprised of crash frequency and crash severity levels for a given roadway entity, which is the only true way to completely assess roadway safety. It is also imperative that these models have the ability to forecast for a designated horizon period. Roadway improvement projects, and public awareness initiatives, are not completed overnight, therefore, having current roadway safety rankings, in conjunction with forecast roadway safety rankings, will enable roadway safety practitioners, departments of transportation, local planners and designers, and governing agencies the ability to plan for, and allot resources and efforts, in both remedial and preventative measures. These forecasts should also be developed into crash severity ranking maps, so that the crucial information, and scale, of these rankings can be easily delineated, analyzed, and bestowed upon any, and all, agencies that may benefit from having them.

Bringing all of these facets together, in a comprehensive manner, would greatly improve the accuracy and precision of identifying the factors contributing to motor vehicle crashes, and locations that are in need of roadway safety improvements, and they would certainly become invaluable tools for all persons involved in roadway safety. This, again, is the motivation behind the research presented in this thesis. This research seeks to account for many of the innate data and methodological limitations present in current roadway safety performance measure derivation procedures. A tabular list of important limitations and what this research did to account for them can be seen on the following page.

Before any modeling can be performed definitive, applicable dependent variables must be defined. In order to fulfill the goals of this research the dependent variable for crash frequency will be calculated by taking the average crash count over the eleven year time period and rounding all numbers up to their nearest whole integer value. For crash severity, nine distinct, ordered levels will be defined which ranged from property damage only: major and not disabling to fatal crash. Level of property damage, severity of highest injury level sustained, and percentage of persons in vehicle who sustained injuries will all be factors that will be used to derive the crash severity levels. These same principles, in conjunction with a large dataset that spans a vast temporal scale (11 years) and two different lower-end crash severity levels (property damage only: major and not disabling and property damage only: major and disabling), seek to account for possible underreporting of lower severity crash cases. Similarly, using the averaged, rounded up values for crash frequency in coordination with a large dataset comprised of over 15,000 crash cases should account for the small sample size/low sample-mean limitation. In order to account for unobserved heterogeneity and possible omitted variable bias a comprehensive dataset will be employed. This dataset will incorporate numerous different categories of factors simultaneously, which should reduce the likelihood of having omitted variables, and should better represent factors that could have been unobserved in previous research (with an emphasis on including long-distance travel characteristics). Also, the statistical structure of the ordered probit model includes an unobserved error term, which will

**Table 2.1. Synopsis of Important Topics.**

| Important Limitation Considerations | Thesis Research Counteractive Approach |
|---|---|
| Dependent Variable Structure | Crash frequency was defined as an average crash occurrence per year over the 11 year timeline |
| | Crash severity was broken into nine distinct levels based upon vehicle damage, level of injury, and percentage of occupants injured |
| Under-Reporting of Crash Data | Two distinct low-severity property damage only levels were defined, and an annual average of crash frequency from a large dataset over a vast temporal setting was employed |
| Unobserved Heterogeneity/Omitted Variable Bias | The statistical structure of the ordered probit model directly accounts for unobserved error |
| | A comprehensive set of factors from various different categories seeks to model many aspects traditionally not analyzed in pervious literature, with an emphasis on long distance travel characteristics |
| Small Sample Sizes and Low Sample-Mean | A large dataset comprised of over 15,000 crash cases was used |
| | Average crash frequency values were rounded up to their nearest whole integer |
| Crash Frequency and Severity Modeling Approach | Ordered probit models were used to model both crash frequency and severity, which will facilitate easier interpretation and account for each equally |
| Roadway Safety Performance Measures and Ranking | A combined approach using probit results for crash frequency and severity were used to derive two different performance measures, each with five distinct safety levels |
| | The above process was repeated for three ordered crash severity scenarios |
| Predictive Roadway Safety Performance Measures | Using applicable factors, factor forecasts were made for a 15 year horizon period based upon calculated Alabama state growth trends |
| Transferability of Performance Measure Rankings | Calculated performance measures were displayed in graphical and cartographic representations, which will facilitate simple, easy distribution |
| | The modeling structure, data needs, and graphical/cartographic representations can easily be generalized and recast for varying scenarios and/or settings |

account for a large portion of remaining unobserved heterogeneity. Having a similar modeling procedure for both crash frequency and crash severity is a facet that is often overlooked when deriving roadway safety performance measures; in order to account for this, this research will utilize ordered probit models for both crash frequency and severity, which should greatly increase the ease of interpretation for both studies, and facilitate the derivation of roadway safety performance measures. A combined approach using probit model results from both crash frequency and severity will be used to derive two different roadway safety performance measures, and this process will repeated for three distinct crash severity scenarios, which seek to emulate three different combinations of driver behavior and crash specific factors which will be observed from the data. Furthermore, the performance measures will be recalibrated for a 15 year horizon period based upon calculated growth trends for applicable factors in the state of Alabama; this process seeks to fulfill the need to develop predictive roadway performance measures. The calculated performance measures will then be represented in both graphical and cartographic settings, which will greatly increase their transferability. Lastly, the modeling structure, data needs, and the graphical/cartographic representations in this research can easily be generalized and/or recalibrated for various different scenarios and settings, which will make the methods applicable to numerous different agencies and roadway safety practitioners.

## 3. DATA SYNTHESIS

This study is based upon the Alabama interstate highway system and the areas it serves, which is comprised of 10 individual interstate roadways, totaling to 905 roadway miles and 3,935 lane miles (Alabama Dept. of Transportation 2009). The state also saw an increase in vehicular travel on its highways of 52% from just over 40,000 (million vehicles miles traveled) in 1990 to over 60,000 (million vehicle miles traveled) in 2010 (State of Alabama 2010; TRIP 2010).

Data describing roadway characteristics, urban zones and corridors, long distance travel, Alabama census information, Alabama interstate crash information, and Alabama interstate roadway infrastructure characteristics were collected from a variety of sources, which included the Alabama Department of Transportation (ALDOT), the US Census Bureau website database, and the Alabama State Water Program's website database. Once collected, the data synthesis comprised four parts: (1) defining the interstate segments, (2) compiling and assigning spatial characteristics, and (3) organizing and consolidating crashes to interstate segments. Finally, once all the data had been spatially compiled, it was organized into two different datasets to describe crash severity and frequency.

First, the data synthesis process began by breaking the state interstates into mile-long segments that could be used in analysis. This was accomplished by creating centerline data for every interstate, from GIS shapefiles provided by ALDOT, overlaid with points representing every mile marker posted on interstate highways, which were also provided by ALDOT. Since crashes were roughly identified by mile markers, each interstate centerline was subdivided into

½ mile segments centered on individual mile marker posts, which came to 1,810 highway segments. The table below shows the distribution of roadway segments per interstate in Alabama used in this research.

**Table 3.1. Roadway Segments per Interstate.**

| Interstate Number | Number of Roadway Segments |
|---|---|
| 10 | 131 |
| 20 | 169 |
| 59 | 482 |
| 65 | 732 |
| 85 | 159 |
| 165 | 10 |
| 359 | 7 |
| 459 | 67 |
| 565 | 44 |
| 759 | 9 |
| **Total** | **1810** |

Next, the shortest-path distance from each segment to its nearest urban area was calculated (the nearest urban area was identified based upon network distances from the ArcGIS Spatial Analyst and Alabama urban area point locations from the US Census TIGER Files database) in order to determine the name of, and proximity to, each segment's closest urban area. Finally, roadway infrastructure data (e.g. number of lanes, guardrail length, and median width, etc.) was assigned to each mile marker segment, which was compiled from extensive, raw roadway inventory data provided by ALDOT. Continuous variables, such as guardrail length, were proportioned accordingly, and assigned to their corresponding segments.

Second, spatial characteristics were assigned to each of the mile-long interstate segments. As such, socioeconomic and demographic data was compiled for all the 1,081 census tracts along the interstate system and the 494 urban areas within the state. SF1 2000 Census Tract data, including American Community Survey (ACS) data, was collected for a multitude of demographic variables, and was joined to the census tracts and urban areas(such as, total population, median age of population(s), number and percent of persons enrolled in school, etc., which were all gathered from the US Census Fact Finder database). Raster land development data, from the Alabama State Water Program online database, was then merged describing open space, low intensity, medium intensity, and high intensity development (Alabama State Water Program 2012). Table 3.2 shows descriptive statistics for statewide aggregate segment land uses, and, as one can see, there is a wide variety of land uses surrounding roadway segments.

**Table 3.2. Distribution of Land Uses.**

| State Wide Land Use Statistics for Interstate Roadway Segments | | | | |
|---|---|---|---|---|
| **Land Use Type** | **Mean (sq. mi.)** | **Median (sq. mi.)** | **Standard Deviation** | **Total (sq. mi.)** |
| Open Space | 0.469 | 0.341 | 0.362 | 849.6 |
| Lightly Developed | 0.360 | 0.137 | 0.470 | 649.8 |
| Moderately Developed | 0.167 | 0.044 | 0.260 | 247.3 |
| Heavily Developed | 0.100 | 0.029 | 0.180 | 95.0 |

In order to maintain a consistent scale for spatial data around each interstate segment, a 1-mile buffer was created around the centerline segments. It was assumed, for ease of compilation, that population, and other demographic variables, within each census tract were evenly distributed throughout the entire tract. As such, the tract data was scaled by area to calculate spatial data for the 1,810 buffered segments along the interstates (i.e. one buffer for each highway segment).

Third, crash data was organized and consolidated. To start, data on crashes occurring on Alabama interstate highways from 2000-2010, provided by ALDOT via their eCrash survey (a database containing copious amounts of crash case specific data from observed crashes on Alabama roadways), was cleaned. The crash data cleaning process consisted of removing all crash cases containing inconsistent, plausibly false, and/or incomplete data entries. The most common reason for removal in the cleaning process was due to a crash case having incomplete data entries, i.e., a crash case was missing one or more critical explanatory factors, followed by a crash case having inconsistent data, e.g., a crash case is reported as having no injures, yet also shows the presence of a fatality. The cleaning process resulted in a homogeneous dataset where all entries contained all of the necessary explanatory factors, which is essential for accurate statistical modeling. A crash severity level variable was created that ranges from 0 to 8, with 0 being the least severe and 8 being the most severe (fatal), and it was assigned to each crash case; the full list of crash severity variables is: 0) property damage only: major but not disabling, 1) property damage only: major and disabling, 2) possible injury: not 100% of occupants injured, 3) possible injury: 100% of occupants injured, 4) non-incapacitating injury: not 100% of occupants injured, 5) non-incapacitating injury: 100% of occupants injured, 6) incapacitating injury: not 100% of occupants injured, 7) incapacitating injury: 100% of occupants injured, and 8) fatal injury crash. These levels were chosen so that the subtle differences between crash severity outcomes could be modeled. In this way, the nine-level crash severity variable took vehicular damage, driver/occupant injury severity level sustained, and percent of occupants in vehicle that were injured into consideration. The last aspect considered in the crash severity variable derivation, percent of occupants in vehicle that were injured, seeks to take into account the difference in injury severity outcomes possibly due to different crash geometries and contributing circumstances, which may be present when vehicular occupants, other than the driver, are introduced. Crash characteristics were summarized as well, which consisted of replacing qualitative factors by dummy variables to represent situations where such factors were either present or not present during a crash. Examples of summarized crash characteristics would be: presence of rain, daylight condition, contributing circumstance was a DUI, causal vehicle was a heavy truck, etc. The resulting data table contained all relevant crash data for the 15,775 crashes (remaining after cleaning the crash data) that occurred on Alabama interstates during the eleven year (2000-2010) time period. Table 3.3 summarizes the proportion of crash cases having noteworthy crash case specific factors (as derived from previous research) can be seen below.

**Table 3.3. Summary of Noteworthy Crash Case Characteristics.**

| **Summary of Noteworthy Crash Case Characteristics** | |
|---|---|
| **Characteristic** | **Percent of Crash Cases Where Present/Average** |
| Was Dusk/Dark/Dawn | 11.33% |
| Was Raining/Snowing/Hailing | 15.84% |
| Average Number of Vehicles Involved | 1.5 Vehicles |
| Causal Vehicle was a Heavy Truck | 9.83% |
| Causal Vehicle was a Motorcycle | 0.97% |
| Alcohol Involved for Causal Vehicle Driver | 1.31% |
| Causal Unit was Speeding | 4.06% |
| Average Difference Between Posted and Impact Speeds | 10.12 (mi/hr) Below Posted Speed |
| Driver/Occupants Used Safety Equipment | 97.10% |

Then, the crashes were mapped to the mile-long interstate segments in which they occurred based on the nearest mile-marker recorded in the crash record. Of the original 134,510 crash cases present on Alabama interstate highways 118,223 (87.9%) were removed for having inadequate/inconsistent information, and another 512 (0.4%) were removed for having plausibly false information. All crash cases that occurred at either the absolute beginning or end of an interstate were classified as plausibly false data entries, since default mile marker entries are zero, the final mile marker for a given roadway, or ‘999’. Not removing these crash cases would have greatly biased results towards characteristics present at the extreme ends of interstate roadways, and would have potentially introduced erroneous conclusions. The cause for the removal of over 88 percent of crash cases could, most likely, be linked to inconsistent crash reporting practices across the state, however, given that crashes can be considered random events, independent of one another, all with the same distribution, the remaining dataset of 15,775 crash cases can be thought of as representative of the overall population.

Finally, two datasets were generated; one to describe crash severity and the other to describe crash frequency. The crash severity dataset, which describes the factors affecting each crash, needed to include all 15,775 crashes. As such, each crash was assigned the appropriate roadway infrastructure, buffered zones, and nearest urban area data based upon the milepost closest to where the crash occurred. The resulting table of crashes includes factors describing: crash specific characteristics, environmental characteristics, roadway geometric characteristics, demographic and socio-economic characteristics for surrounding developments and nearest urban areas, and roadway traffic demand. Table 3.4, describing the distribution of crash severity levels for all crash cases, can be seen below.

**Table 3.4. Distribution of Crash Severity Levels.**

| Distribution of Crash Severity Levels | |
|---|---|
| **Crash Severity Level** | **Percent of Crashes [Number of Crashes]** |
| Property Damage Only: Major but Not Disabling | 40.9% [6,454] |
| Property Damage Only: Major and Disabling | 35.9% [5,658] |
| Possible Injury: Less than 100% Injured | 2.8% [438] |
| Possible Injury: 100% Injured | 2.0% [316] |
| Non-Incapacitating Injury: Less than 100% Injured | 0.9% [145] |
| Non-Incapacitating Injury: 100% Injured | 1.4% [225] |
| Incapacitating Injury: Less than 100% Injured | 6.1% [962] |
| Incapacitating Injury: 100% Injured | 8.5% [1,338] |
| Fatal Crash | 1.5% [239] |

The second dataset, for crash frequencies, focuses on the number of crashes that occur per year within each mile-long interstate segment. Therefore, this dataset was organized around the 1,810 mile marker interstate roadway segments. Each segment contains factors representing:

roadway geometric characteristics, demographic and socio-economic characteristics for surrounding developments and nearest urban areas, and roadway traffic demand (noting that the crash case specific and environmental characteristics were not relevant for this model), and the average number of crashes per year. This value was calculated by summing all the crashes that occurred over the 11-year time period on each segment, dividing by eleven, and rounding up to the nearest integer. The resulting crash frequency variable, in crash cases per year, ranged from zero to ten, and the same crash frequency calculation process was repeated for each of the nine distinct ordered severity levels, which served to calculate the individual annual crash frequencies per severity level for each interstate roadway segment. Table 3.5, depicting the distribution of crash frequency values for interstate segments, can be seen below.

**Table 3.5. Distribution of Crash Frequency Values.**

| Distribution of Crash Frequency Values | |
|---|---|
| **Average Crashes per Year** | **Percent of Segments [Number of Segments]** |
| 0 | 4.6% [83] |
| 1 | 72.2% [1,307] |
| 2 | 16.6% [301] |
| 3 | 3.7% [67] |
| 4 | 1.7% [30] |
| 5 | 0.4% [7] |
| 6 | 0.2% [4] |
| 7 | 0.3% [5] |
| 8 | 0.1% [1] |
| 9 | 0.2% [4] |
| 10 | 0.1% [1] |

The most important aspect to take away from the data synthesis portion of this research is that the datasets created from the process represent novel, comprehensive approaches to modeling both crash frequency and crash severity. This is most prevalent with the inclusion of long distance travel characteristics (in the form of surrounding developments and nearest urban area demographics/land uses), which have seldom been included in crash frequency and severity datasets. It is also important to note that although a large proportion of crash cases occurring on Alabama interstates during the eleven year time period were removed, the dataset(s) retained are representative of the overall population, and are in accordance with prior crash severity and frequency studies.

# 4. METHODOLOGY

This study employs two ordered probit models for examining the likelihoods of experiencing different (a) levels of crash frequency and (b) levels of crash injury severity on any given interstate segment. The ordered probit model is an appropriate choice for evaluating these likelihoods because it supports multiple ranked dependent choice options that have an underlying continuous propensity (Yamamoto and Shankar 2004; Gray, *et al.* 2008), is able to incorporate and analyze numerous factors at once, and explicitly accounts for the ordinal nature of crash severity and crash frequency dependent variable outcomes.

Ordered discrete models, such as the ordered probit model, treat the data as being generated by a continuous unobserved latent variable, which upon crossing a threshold value leads to an increase by one level, either one crash severity level or one crash per year in this study (Cameron and Trivedi 1998). The error term in the ordered probit model represents the effect of omitted or unobserved factors, it is assumed to be independent of the included factors, constant over the different severity level outcomes, and normally distributed, which helps to account for any unobserved heterogeneity or correlation that may be present within the data. The ordered outcome value is broken into its *n* different outcomes by model derived threshold values, and the probability for a given observation to fall within one, or any, of the different outcomes can later be calculated by using the normal distribution function.

The statistical structure and performance of ordered probit models have been the driving force behind their extensive use in crash severity studies. Ye and Lord (2011), when assessing the effect of sample size on commonly used crash severity models, determined that ordered probit models possess the best goodness of fit to data, and are able to achieve high levels of fit at significantly lower levels of sample size than the other models tested (multinomial logit and mixed logit). In current practice, ordered probit models have rarely been employed in crash frequency studies. However, ordered probit models have a valid application in crash frequency studies, since the crash frequency dependent variable is classified as count data, and most observed counts take on discrete, ordered outcomes (i.e., 0, 1, 2…), which are best suited for ordered discrete choice models (Cameron and Trivedi 1998). Ordered probit models also offer distinct advantages over traditional logit and/or multinomial logit models in that they do not share the same three limitations as logit models: they can represent random taste (choice) variation, they are not bound by the independence-of-irrelevant-alternatives (IIA) assumption, and they are able to account for unobserved correlated factors over time (Train 2009).The lack of use of ordered probit models in crash frequency studies may be, in large part, due to past literature focusing on developing quantifiable measurements of factors, for use in determining a wide range of different safety alterations (Washington, *et al.* 2003). Ordered probit models do not allow for the definite quantification of effects, but assess a more general effect by way of an increase in likelihood or a decrease in likelihood (positive versus negative effect). Therefore, it is possible that ordered probit models have been omitted from crash frequency studies due to the more ambiguous nature of their parameter estimates, and the lack of directly interpretable single factor effects. Ordered probit models are, however, easily applied for forecasting purposes, which make them perfect model candidates for employment in this study for both crash frequency and severity.

In this study, as previously mentioned, the options for crash frequency were defined by eleven distinct ordered levels ranging from zero crash cases per year, to ten crash cases per year for a given segment in increments of one crash per year (0, 1, 2, …, 9, 10). The majority of segments were at the lower end of the scale, which can, again, be seen in Table 3.5 in the data synthesis section of this research. These eleven frequency levels adequately define the ordinal nature of per year crash frequency on Alabama interstate roadways, as derived from observed crash case data records. In this application, moving from the lowest rank (zero crash cases per year) to the highest (ten crash cases per year), the frequency associated with each increases continuously. Additionally, again, the options for crash severity are defined by nine distinct ordered levels: property damage only: major but not disabling, property damage only: major and disabling, possible injury: less than 100% of occupants injured, possible injury: 100% of occupants injured, non-incapacitating injury: less than 100% of occupants injured, non-incapacitating injury: 100% of occupants injured, incapacitating injury: less than 100% of occupants injured, incapacitating injury: 100% of occupants injured, and fatal crash. The majority of crash cases were at the lower end of the severity scale; severity level distributions can also be seen in the data synthesis portion of this research, in Table 3.4. These nine levels were selected because they demonstrated the practical variation within crash types with vehicular damage and injuries. The underlying continuous propensity, in this application, moved from the lowest rank (property damage) to the highest (fatal crash), and signifies that the risk/severity associated with each level will increase continuously.

The ordered probit model's continuous propensity function, which is underlying the different frequency/severity options, is written as:

$$Y^* = \beta' x_n + \varepsilon_n \tag{4.1}$$

Where $Y^*$ is the continuous, ordered propensity underlying different outcomes. In this study, $Y^*$ will represent increasing levels average annual crashes per year for a segment, and level of crash severity for a given crash, for the crash frequency and crash severity studies, respectively. The $x_n$ value is a column vector of observed factors affecting the utility of alternative $n$ (including a constant). In this study $x_n$ will be composed of crash case specific, environmental, roadway geometric, spatially related demographic/socio-economic, and roadway demand factors (excluding the crash case specific and environmental factors for the crash frequency study), and alternative $n$ will either be a given roadway segment in the crash frequency study, or a given crash case in the crash severity study. The $\beta$ term is a corresponding column vector of coefficients, which are model derived based on the effect that relevant factors have on overall crash frequency or crash severity values. Finally, the $\varepsilon_n$ error term is an unobserved random value that represents the idiosyncratic effect of omitted variables, which seeks to account for and assess the effect that unobserved heterogeneity and/or correlation have on crash frequency and/or crash severity studies, while mitigating the effect of an omitted variable bias. For probit models, the $\varepsilon_n$ term is assumed to be independent of the explanatory factors, $x_i$, and normally distributed. The ultimate value that the continuous, ordered propensity variable representing the underlying trend for an increase in average annual crashes per year or crash severity level, $Y_n$, is determined using the system of equations shown below, which, as an example, have been organized to represent the nine different crash severity levels (classified from zero to eight):

$$\begin{aligned} Y_n &= 0 \quad if \quad Y^* \leq \delta_1 \\ Y_n &= 1 \quad if \quad \delta_1 < Y^* \leq \delta_2 \\ Y_n &= 2 \quad if \quad \delta_2 < Y^* \leq \delta_3 \\ Y_n &= 3 \quad if \quad \delta_3 < Y^* \leq \delta_4 \end{aligned} \tag{4.2}$$

$$Y_n = 4 \quad if \quad \delta_4 < Y^* \leq \delta_5$$

$$Y_n = 5 \quad if \quad \delta_5 < Y^* \leq \delta_6$$

$$Y_n = 6 \quad if \quad \delta_6 < Y^* \leq \delta_7$$

$$Y_n = 7 \quad if \quad \delta_7 < Y^* \leq \delta_8$$

$$Y_n = 8 \quad if \quad Y^* > \delta_8$$

In this system, $Y_n$ = 0 represents the smallest order option (property damage only: major but not disabling crash), $Y_n$ = 8 represents the largest order option (fatal crash severity level), and the $\delta_i$ values represent the inherent thresholds between each propensity. These threshold values act as horizontal partitioning between the individual crash frequency or severity level propensities, and they separate the continuous $Y^*$value into distinct bins for each crashes per year value or crash severity level; the width of which, and relative probability of occurrence, are model derived, and are represented by the magnitude of the difference between concurrent threshold values. The model setup in the crash frequency study is nearly identical to the one described above, however the ordered levels, or bins, range from zero to ten, and represent average crashes per year values.

Once the coefficients of the ordered model are estimated, the model can then be used to determine the probability of being in a given bin (*x* number of crashes per year or *y* severity level) for a given set of parameters (the cumulative effect of all relevant factors). Whichever bin/level has the largest probability is assumed to be the most likely level of crash frequency or level of severity to occur for the given roadway segment or crash case, respectively. The system of equations below outlines the probability equations used in the model for the different crash frequency levels used in the crash frequency study. These probabilities utilize the cumulative normal distribution functions (represented by the Φ() in each equation), variable coefficients, and threshold estimations.

$$P(Y_0 = Zero\ Crash\ Case\ per\ Year) = \Phi(-\beta' x_n)$$

$$P(Y_1 = One\ Crash\ Case\ per\ Year) = \Phi(\delta_1 - \beta' x_n) - \Phi(-\beta' x_n)$$

$$P(Y_2 = Two\ Crash\ Case\ per\ Year) = \Phi(\delta_2 - \beta' x_n) - (\delta_1 - \beta' x_n)$$

$$P(Y_3 = Three\ Crash\ Case\ per\ Year) = \Phi(\delta_3 - \beta' x_n) - (\delta_2 - \beta' x_n) \quad (4.3)$$

$$P(Y_4 = Four\ Crash\ Case\ per\ Year) = \Phi(\delta_4 - \beta' x_n) - \Phi(\delta_3 - \beta' x_n)$$

$$P(Y_5 = Five\ Crash\ Case\ per\ Year) = \Phi(\delta_5 - \beta' x_n) - \Phi(\delta_4 - \beta' x_n)$$

$$P(Y_6 = Six\ Crash\ Case\ per\ Year) = \Phi(\delta_6 - \beta' x_n) - \Phi(\delta_5 - \beta' x_n)$$

$$P(Y_7 = Seven\ Crash\ Case\ per\ Year) = \Phi(\delta_7 - \beta' x_n) - \Phi(\delta_6 - \beta' x_n)$$

$$P(Y_8 = Eight\ Crash\ Case\ per\ Year) = \Phi(\delta_8 - \beta' x_n) - \Phi(\delta_7 - \beta' x_n)$$

$$P(Y_9 = Nine\ Crash\ Case\ per\ Year) = \Phi(\delta_9 - \beta' x_n) - \Phi(\delta_8 - \beta' x_n)$$

$$P(Y_{10} = Ten\ Crash\ Case\ per\ Year) = 1 - \Phi(\delta_9 - \beta' x_n)$$

The application of both equations 4.2 and 4.3 allow the ordered probit model the ability to predict not only the most likely crash frequency or crash severity level, but also probability for a given roadway segment or crash case to fall into any of the different frequency or severity bin levels, respectively. The multifaceted results structure can facilitate thorough analysis in later processes, such as the derivation of roadway safety performance measures.

For the final specification of the crash frequency ordered probit model the log-likelihood value at convergence is –1,289.1, and the log-likelihood value of the thresholds-only model is –1,493.3. The chi-squared value for comparing the two models is 408.3, which is substantially greater than the critical chi-squared value with 5 degrees of freedom at a two-tailed 95% level of significance (12.83).

Finally, crash severity model’s log-likelihood value at convergence, for the final ordered probit specification, is –20,741.1, and the log-likelihood value of the thresholds-only model is

–22,702.5.  The chi-squared test value for comparing the two models is 3,922.8, which is also substantially greater than the critical chi-squared value for this model, at 55 degrees of freedom and a two-tailed 95% level of significance (77.38).

The model fit results suggest that, for both studies, models including statistically relevant factors do a significantly better job representing the dependent variable than the naïve (thresholds only) models. This can be evidenced from both calculated chi-squared values being much larger than their 95% confidence critical chi-squared factors for each model respectively (tables containing model fit results can be seen in Appendix 1). What all this suggests is that the model results are statistically relevant, and warrant further analysis, which can be seen in the following section.

# 5. PREDICTION MODEL PARAMETER ESTIMATES

The results for the final probit specifications of the prediction models can be found in Tables 5.1 and 5.2. As was the goal, the estimations included a comprehensive set of infrastructure characteristics, land use characteristics, roadway traffic characteristics, and spatially related socio-economic and demographic characteristics for crash frequency, with the addition of crash specific characteristics and vehicle characteristics for crash severity. As such, there were many more factors originally considered in the specification that were not significant. Instead, the most relevant and significant factors were identified by utilizing a 95% significance level ($\alpha = 0.05$). The dependent variable for the crash frequency model was the average number of crashes on a roadway segment per year, and, for crash severity, the derived crash severity index, the threshold values for both models can be found at the end of each table respectively.

## 5.1. Crash Frequency Prediction Estimates

In total, ten predictive models for crash frequency were estimated, one for each of the nine different crash severity levels, and one estimating all crash cases together. For the purposes of this research only the cumulative, all crash cases model will be analyzed, and, later, utilized for further exploration. However, results for crash frequency predictive models at individual crash severity levels can be seen in Appendix 1 at the end of this research; the cumulative, all crash cases model table can be seen at the end of this subsection.

The first portion of the crash frequency model assessed the effect of roadway infrastructure characteristics on crash frequency. Model results show a very significant correlation between the presence of an exit or interchange and an increase in likelihood of a higher average crash frequency. This means that roadway segments that contain an exit or interchange are more likely to see higher levels of crash frequency than similar roadway segments without exits or interchanges. Similar results were found in a 2010 study by Malyshkina and Mannering (2010). It is worthwhile to note that certain roadway infrastructure factors commonly associated with crash frequency, such as number of lanes (Noland and Oh 2004; Yan, *et al.* 2005; Qi, *et al.* 2007) and posted speed limit (Yan, *et al.* 2005; Aguero-Valverde and Jovanis 2008; Malyshkina, *et al.* 2009), were not found to be statistically significant in this model. This could be due to the overwhelming influence of other factors in the model, or possibly from distinct, coordinated design standards for interstates in Alabama, which could have acted to temper the exacerbating affect that these factors have presented in previous research based in other states/settings.

The second portion of the crash frequency model encompasses spatially related socio-economic and demographic factors, and of these factors, only those from surrounding developments were found to be statistically significant. Three out of the four significant factors from this category increased the likelihood for a higher average crash frequency: percent of population over 60 years old, percent of households that are family households, and moderately developed land use type, while only the number of owner occupied housing units increased the likelihood to have a lower average crash frequency. These results suggest that segments with surrounding developments that contain high proportions of elderly persons, families, and moderately developed land will see an increased likelihood for a higher average crash frequency, whereas, segments with surrounding developments containing a large number of owner occupied housing units will tend to see lower levels of average crash frequency. Pawlovich, *et al.* (1998)

discovered similar findings when they determined that older populations were more prone to being in motor vehicle accidents. Aguero-Valverde and Jovanis (2006) also documented the effect of age on crash frequency at the spatial level; they concluded that those over the age of 64 increased crash frequency levels. Likewise, Kim, *et al.* (2006) and Pulugurtha, *et al.* (2012) found that moderately developed land uses of areas around schools/commercial districts and businesses/mixed use, respectively, increased crash frequency levels, thus corroborating the findings in this research.

The last factor assessed with regard to effect on crash frequency was roadway demand, in the form of Average Annual Daily Traffic (AADT), for the year 2000. Not surprisingly, an increase in AADT increased the likelihood of having a higher value of average crash frequency. What this result suggests is that as the traffic demand on a roadway segment increases, i.e., the number of cars traveling on a roadway per day, so does the likelihood for higher levels of crash frequency, possibly a function of increased vehicular exposure. This relationship has been documented for quite some time, and is almost unanimous across crash frequency studies. Similar results have been reported by Aguero-Valverde and Jovanis (2008), Malyshkina and Mannering (2010), Pulugurtha and Sambhara (2011), and Zhang, *et al.* (2012), among others.

The threshold values (model derived, to partition the continuous propensity dependent variable) for the crash frequency model, ten in total, were all found to be significant. However, the spacing between the threshold values depicts which frequency bins are more probable than others. The biggest spacing between threshold values is between one crash per year and two crashes per year, which suggests that there is a very large likelihood, with respect to the other frequency levels, to have an average of one crash per year. This result makes sense due to the way that the average frequency values were calculated (by rounding up), so that even segments that only had two or three crashes over the 11-year timespan will still have an average of one crash per year. There are also large spaces separating the frequency values of two and three crashes per year, as well as nine and ten crashes per year. These results suggest that there is a distinct, and significant, difference between factors that contribute to a two crash per year segment, and factors that contribute to a three crash per year segment. The results also suggest that factors contributing to a 10 crashes per year segment are significantly different from those affecting all other frequency levels, which would make sense, since one would expect/hope that a 10 crashes per year segment is a result of a set of unique exacerbating circumstances.

**Table 5.1. Crash Frequency Probit Model Results.**

| | All Crash Cases | |
|---|---|---|
| | Frequency[0-10] Crash/Year | |
| | **Coefficient** | **Significance** |
| **Roadway Infrastructure Characteristics** | | |
| Presence of Exit/Interchange | 0.382 | < 0.001 |
| **Surrounding Development Characteristics** | | |
| Percent of Population over 60 years (%) | 0.023 | 0.010 |
| Percent of Households that are Family Households (%) | 0.040 | < 0.001 |
| Owner Occupied Housing Units (1000's of housing units) | -0.160 | 0.037 |
| Land Use: Moderate Development (sq. miles) | 0.747 | 0.001 |
| **Roadway Demand** | | |
| Average Annual Daily Traffic 2000 (1000's of vehicles) | 0.025 | < 0.001 |
| **Threshold Values** | | |
| $\hat{\delta}_1$ | 2.450 | < 0.001 |
| $\hat{\delta}_2$ | 5.146 | < 0.001 |
| $\hat{\delta}_3$ | 6.119 | < 0.001 |
| $\hat{\delta}_4$ | 6.649 | < 0.001 |
| $\hat{\delta}_5$ | 7.164 | < 0.001 |
| $\hat{\delta}_6$ | 7.394 | < 0.001 |
| $\hat{\delta}_7$ | 7.589 | < 0.001 |
| $\hat{\delta}_8$ | 7.967 | < 0.001 |
| $\hat{\delta}_9$ | 8.069 | < 0.001 |
| $\hat{\delta}_{10}$ | 8.785 | < 0.001 |

### 5.2. Crash Severity Prediction Estimates

The first portion of the crash severity model assessed the effect of general, crash specific, conditions on severity. If a commercial motor vehicle was involved, it is likely to be a more severe crash. This makes sense because larger vehicles have the potential to cause more damage, both to vehicles and lives. Interestingly, the weather/lighting condition factors all reduce crash severity, relative to clear conditions. Perhaps under these conditions drivers are more aware of their surroundings, which will make them more reactive, and/or encourage them to drive slower. Still, they are in agreement with the findings of Shankar, *et al.* (1996) in their study on rural freeway accidents in Washington State; the authors found that icy or snow covered pavement decreased crash severity in single vehicle crashes. This finding is further validated by Quddus, *et al.* (2009) where it was found that snow played little to no role in determining crash severity. This category of explanatory factors also noted, in general crash terms, that if the cause of a crash is a cargo or load shift, there will be an increase in likelihood for a less severe crash.

The second set of factors described how the driver/vehicle that caused the crash affected its severity. First, the severity of the crash increases as the speed that the vehicle is traveling goes above the speed limit. The result for speed differential is consistent with a similar study by Lee and Abdel-Aty (2005), where they determined that higher vehicle speed, among other things, increased crash severity likelihood. The indicator variables in the causal unit section had mixed results; contributing circumstance variables of, for example, DUI, driver not in control, following too close, and improper lane change, or causal unit was carrying an attachment, all possessed negative coefficients, which suggests that if any, or all, of the above were present, the probability for a severe crash would decrease. Additionally, if the driver was fatigued or impaired the likelihood of having a severe crash decreases as well; however, if the causal unit driver is under the influence of alcohol explicitly (regardless of if a DUI was the contributing circumstance), there will be an increase in the likelihood for a more severe crash. Perhaps the reason for this is the focus on interstate highway travel, since drivers have slightly more space and time to react before crashing than they would on a small rural road, which would facilitate drivers being able to correct for fatigue or some type of impairment. However, this would not necessarily be true for alcohol impairment, since alcohol significantly increases reaction time, and even though drivers may have time and space to react before they crash, they may not be able to take advantage of this. Therefore, model results for alcohol use and impairment are technically in agreement with the findings from others, Zajac and Ivan (2002) found, in their study on rural Connecticut roadways, that the presence of alcohol increased the likelihood for a more severe crash; this same principle was reiterated by Wang and Abdel-Aty (2008) and Kim, *et al.* (2008). The positive coefficient for causal unit was a motorcycle condition is also noteworthy, since it is in agreement with findings from Wang and Abdel-Aty (2009), and Yamamoto and Shankar (2004). Rounding out the list of indicator variables for causal units, the results show that if a causal unit is carrying hazardous cargo there will be an increase in the likelihood for a more severe crash. It is also interesting to note that distractions such as cell phones and texting were not significant factors in this model, which might be due to cell phones and texting usage not being as widespread and prevalent in the beginning years of the dataset as they were towards the latter years.

The next section of the model, dealing with characteristics of second vehicles (non-causal vehicles) in an accident, saw similar impacts on crash severity. Higher differential in driving and posted speeds, motorcycles, and presence/influence of drugs increase the crash severity. Second vehicles are also influenced by whether or not they are carrying an attachment, which had a distinct increasing effect on crash severity, which, interestingly, is opposite of the effect that causal vehicles carrying an attachment had on crash severity. The second vehicle set of factors also introduced driver residence location factors, and even though all three factors decreased crash severity, having a residence distance under 25 miles away had the largest effect, which suggests that the closer that a second vehicle driver is to home, the less severe a crash will be. This could be due to driver familiarity with interstate roadways closer to home.

Some of the most important components for the analysis of crash severity are roadway infrastructure characteristics because they are aspects that transportation engineers have the best ability to control. Results show that higher posted speed limits and an increase in the number of vehicles involved in a crash will both increase the likelihood for a more severe crash. As noted in the crash frequency results, crashes are more likely to occur around interchanges, however, results indicate that these types of crashes are also less likely to be severe, since the presence of an exit or interchange decreases crash severity. This is perhaps due to the decreased speeds of people exiting/entering the interstate, the sign on the coefficient for presence of an exit or interchange is in agreement with the findings from Milton, *et al.* (2008), in a study on Washington state highway segments, using a mixed logit model. Both factors of ‘lane separation was a painted line’ and ‘roadway traffic control device (if applicable) was functioning’ had a decreasing effect on crash severity as well. A very interesting result is that accidents occurring in work zones tend to be less severe for the vehicle. This could be a bias towards the vehicular aspect of the study; if highway workers are hit in these situations, it can be fatal, or it could also be indicative of vehicles traveling slower in work zone locations. There are many other safety improvements that Alabama has implemented on the interstate system, including widening shoulders and adding rumble strips. These improvements are so widespread, however, that while they are known to improve safety, they may not show up in this analysis because they are too widespread, however, future work might find it advantageous to explicitly account for, and seek to determine a possible statistical relationship between such factors and crash severity/frequency, with an updated dataset.

Finally, the spatially related demographic and socio-economic factors in the crash severity model came from both surrounding development and nearest urban area characteristics, which, again, describe the type of travel that one can expect on a roadway. Interstates in rural areas are most likely to experience long-distance travel through the area; whereas interstates in metropolitan areas may experience more short work-based trips. Not surprisingly, there are a number of important factors in these categories. First, as one would expect, crashes occurring in rural areas are more likely to be severe, most likely due to possible driver inattention during a long trip, and a trend for increased vehicular speeds. Of all the surrounding land uses, crashes occurring near moderate development (e.g. associated with residential areas) are less likely to be severe, displaying the opposite effect on crash severity from crash frequency, which was also seen for presence of an exit or interchange. In terms of nearest urban area characteristics, crashes are more severe when the nearest urban area has a large proportion of small children (under five years old) or young drivers (15-24 years old). This follows from the fact that drivers may not have experience to react and reduce the severity of their crash. Areas with larger male populations are more likely to experience severe crashes. Men are often identified as more aggressive drivers; these results indicate that even if they aren't involved in a crash that cumulative behavior can influence an area. Results also indicated that urban areas with higher median ages will tend to have more severe crashes. This could likely be due to increased physical fragility, which is associated with old age. Last, it is not unexpected that areas that are more congested (i.e. have longer commute times) are less likely to experience severe crashes probably because traffic is much slower.

When analyzing the crash severity threshold values, one can see that the largest separations occur in the low (property damage) and high (fatalities) ends of the scale. This makes sense as those are rather definitive characterizations. It is worth noting, however, that the middle crash severity levels, save incapacitating crash with 100% injured, were all found to not be significant at a 95% confidence level. This suggests that the middle crash severity levels, including property damage only, major and disabling, may not be distinctly different from their adjacent severity levels. The results suggest the possibility (perhaps in a more practical sense) of grouping similar type crash outcomes (e.g. possible injury and non-incapacitating injury) into one group. However, for the purposes of this research the nine severity level distinctions were considered favorable. The table representation for the full crash severity probit model can be seen on the following four pages in Table 5.2.

**Table 5.2. Crash Severity Probit Model Results.**

| | Crash Severity Analysis | |
|---|---|---|
| | **Coefficient** | **Significance** |
| **General Crash Characteristics** | | |
| Commercial Motor Vehicle Involved | 0.216 | < 0.001 |
| The Weather was… | | |
| ...Clear | -0.850 | 0.003 |
| ...Cloudy | -0.882 | 0.002 |
| ...Foggy | -0.771 | 0.010 |
| …Some 'Other' Condition | -1.282 | 0.013 |
| ...Raining | -0.948 | 0.001 |
| ...Snowing/Hailing | -0.878 | 0.006 |
| ...Windy | -1.042 | 0.010 |
| Lighting Conditions were… | | |
| ...Daylight | -0.095 | < 0.001 |
| ...Dusk | -0.180 | 0.009 |
| The Contributing Circumstance was… | | |
| …A Cargo or Load Shift | -0.786 | < 0.001 |

**Table 5.2. Crash Severity Probit Model Results.** (Continued)

| | Crash Severity Analysis | |
|---|---|---|
| | **Coefficient** | **Significance** |
| **Causal Unit Crash Characteristics** | | |
| Difference Between Impact and Posted Speeds (mph) | 0.004 | < 0.001 |
| Contributing Circumstance was… | | |
| …A Cargo or Load Shift | -0.866 | < 0.001 |
| ...Defective Equipment | -0.596 | 0.002 |
| …A DUI | -0.626 | 0.007 |
| ...Driver not in Control | -0.496 | 0.004 |
| ...Following too Close | -0.756 | < 0.001 |
| …An Improper Lane Change | -1.199 | < 0.001 |
| ...Misjudging Stopping Dist. | -0.645 | 0.001 |
| …Some 'Other' Circumstance | -0.806 | < 0.001 |
| ...Speeding | -0.525 | 0.003 |
| ...Unobserved Object/Vehicle | -0.940 | < 0.001 |
| Causal Unit Driver was… | | |
| ...Fatigued | -0.410 | < 0.001 |
| ...Impaired in someway | -0.974 | 0.004 |
| …Apparently Normal | -0.907 | < 0.001 |
| ...Under the Influence of Alcohol | 0.205 | 0.017 |
| Causal Unit Vehicle was… | | |
| …Carrying an Attachment | -0.353 | < 0.001 |
| ...Carrying Hazardous Cargo | 0.319 | 0.028 |
| …A Heavy Truck | -0.409 | 0.012 |
| …A Light Truck | -0.322 | 0.041 |
| …A Mobile Home | -0.679 | 0.010 |
| …A Motorcycle | 0.666 | < 0.001 |
| …A Passenger Car | -0.344 | 0.029 |
| …A Van | -0.330 | 0.043 |

**Table 5.2. Crash Severity Probit Model Results.** (Continued)

| | Crash Severity Analysis | |
|---|---|---|
| | **Coefficient** | **Significance** |
| **Second Vehicle(s) Crash Characteristics** | | |
| Difference between Impact and Posted Speeds (mph) | 0.002 | 0.001 |
| Second Vehicle was… | | |
| …Carrying an Attachment | 0.136 | 0.007 |
| …A Motorcycle | 1.143 | < 0.001 |
| Second Vehicle's Driver… | | |
| …Was Under the Influence of Drugs | 2.036 | 0.006 |
| ...Residence Distance > 25 Miles Away | -1.028 | < 0.001 |
| ...Residence Distance < 25 Miles Away | -1.034 | < 0.001 |
| ...Residence Distance is Unknown | -0.880 | < 0.001 |
| **Roadway Infrastructure Characteristics** | | |
| Number of Vehicles Involved (Integer) | 0.480 | < 0.001 |
| Posted Speed Limit (mph) | 0.007 | < 0.001 |
| Lane Separation was: a Painted Line | -0.091 | 0.032 |
| Safety Equipment was Used | -0.727 | < 0.001 |
| Accident Occurred in/related to a Workzone | -0.238 | < 0.001 |
| Roadway Traffic Control Device was Functioning | -0.114 | 0.003 |
| Presence of Exit/Interchange | -0.047 | 0.018 |

**Table 5.2. Crash Severity Probit Model Results.** (Continued)

| | Crash Severity Analysis | |
|---|---|---|
| | **Coefficient** | **Significance** |
| **Surrounding Development Characteristics** | | |
| The Crash was Located… | | |
| …In Open Country | 0.065 | 0.048 |
| …In an 'Other' Area | 0.696 | 0.035 |
| Land Use: Moderately Developed (square miles) | -0.101 | 0.012 |
| **Nearest Urban Area Characteristics** | | |
| Percent of Population Under 5 Years (%) | 0.108 | < 0.001 |
| Percent of Population Between 15 and 24 Years (%) | 0.026 | < 0.001 |
| Median Age of Population (yrs.) | 0.044 | < 0.001 |
| Percent of Population that is Male (%) | 0.019 | 0.002 |
| Commuters Average Travel Time (minutes) | -0.006 | 0.026 |
| **Threshold Values** | | |
| $\hat{\delta}_1$ | 0.227 | 0.801 |
| $\hat{\delta}_2$ | 1.321 | 0.142 |
| $\hat{\delta}_3$ | 1.425 | 0.114 |
| $\hat{\delta}_4$ | 1.506 | 0.095 |
| $\hat{\delta}_5$ | 1.545 | 0.086 |
| $\hat{\delta}_6$ | 1.609 | 0.074 |
| $\hat{\delta}_7$ | 1.943 | 0.031 |
| $\hat{\delta}_8$ | 3.010 | 0.001 |

## 6. FORECASTING AND APPLICATION

The crash severity and crash frequency models derived in the previous sections were based on current and semi-current crash, spatially related demographic, infrastructure, and traffic demand data for interstate sections in Alabama. Generating pertinent models for predicting current crash severity and crash frequency levels are essential for analyzing where current at-risk locations throughout the state are located. Likewise, current data estimates are integral tools for identifying current, near-term roadway safety improvement locations, and can act as a catalyst for immediate roadway safety efforts and hazardous location mitigation. However, generating forecasts for future locations that are more likely to be prone to high levels of crash frequency and crash severity are of the utmost importance and utility for planners, engineers, and state officials. The Alabama Department of Transportation, and other regional planning associations, would be able to utilize forecasts in order to determine locations where crucial transportation improvement projects and public awareness objectives should be directed; forecasts will also allow them to be proactive in their efforts to mitigate, and reduce the likelihood and severity of motor vehicle crashes on interstate roadways. Also, contrasting current and forecast model prediction results will allow practitioners the ability to determine where/what are the high-risk populations and roadway scenarios on state-wide, system-wide, and individual section levels. Such methods and conclusions could be employed not only for interstate roadway segments and surrounding developments, but also could be extrapolated (to some extent) to smaller state and local roadways. Furthermore, forecasting efforts can be calibrated, and recalibrated for numerous different horizon years, scenarios, and changing growth trends, which offers nearly limitless opportunities to analyze roadway safety, via crash frequency and severity.

Different forecasting methods have been adopted and utilized by various different firms and government agencies for the purpose of predictive analysis. Common forecasting methods include: regression techniques, exponential and linear growth models, and artificial simulations. Since crash severity and crash frequency are dependent upon transportation, and transportation behavior, utilizing forecasting methods currently employed by local transportation planning associations will greatly increase the transferability and adoption of the predictive models. Out of the 13 metropolitan planning organizations (MPO's) in the state of Alabama (11 of them based exclusively within the state), the consensus has been to utilize linear and exponential growth models to predict and forecast transportation demand, generally via the traditional four-step method. In accordance with this practice, a linear growth model will be used in this research to forecast the relevant demographic variables from the crash severity and crash frequency models for the year 2025. In this way, the effect that changing demographics in the state of Alabama will have on crash severity and crash frequency over time, is sought to be modeled by this research.

The following sections will give an analysis of how factor forecasts were made for applicable factors in this research. The sections will analyze how growth rates were calculated, what their values were, and how the forecast factors were calculated from the growth rates. The diagram on the following page gives a visual aid as to which factors, and factor categories, were included in each model, and which factors were forecast for the horizon year of 2025. Lines denoted in orange represent factors that were not forecast, lines in green represent factors that were forecast, and lines in red represent individual model outputs into the generation of roadway safety performance measures.

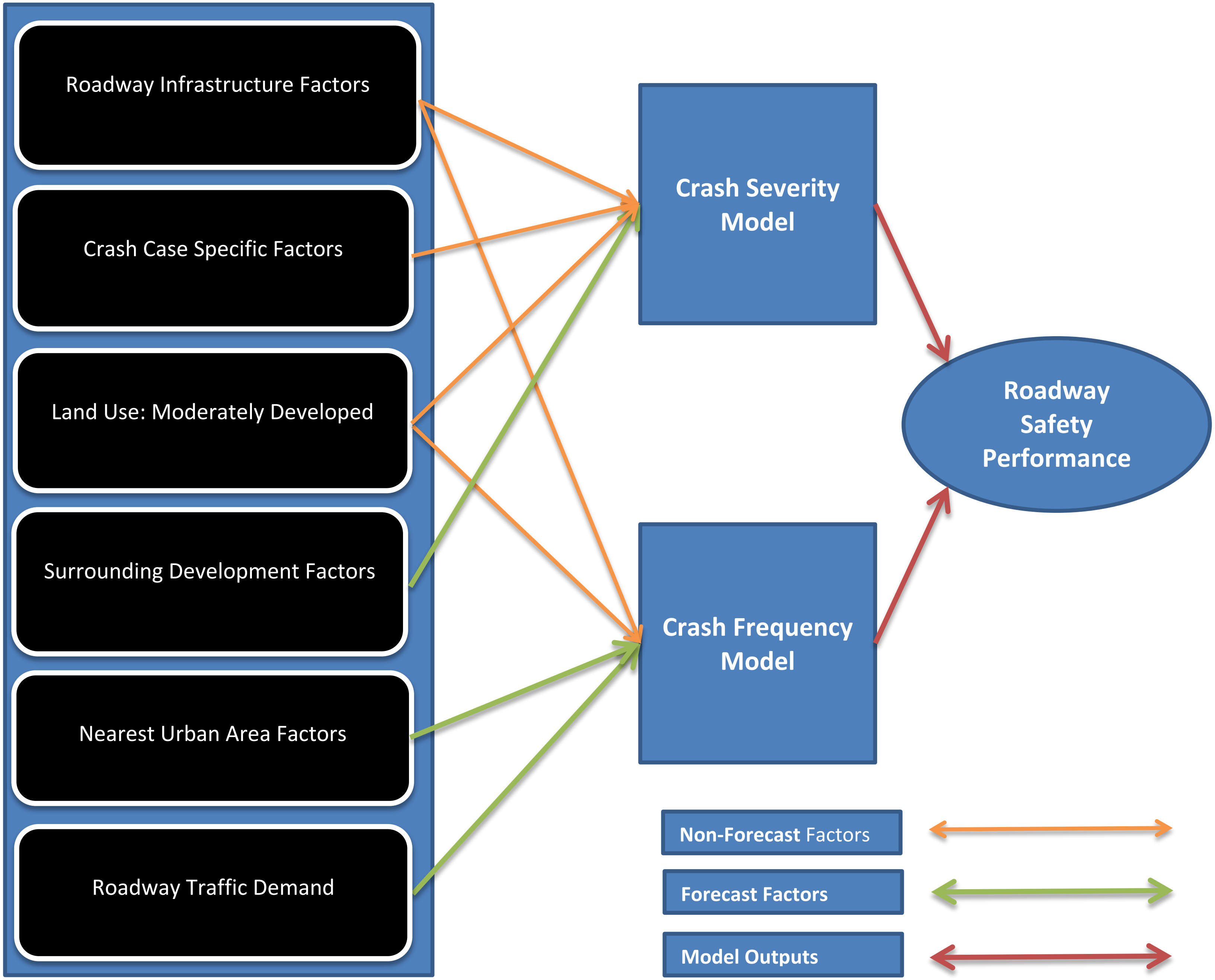


**Figure 6.1. Performance Measure Flowchart.**

## 6.1. Developing Growth Rates

In order to forecast the value of a variable for a given horizon period, one must first determine the timeframe, and rate, at which that variable's growth is to be based upon. For the purpose of this study, the time period from 2000 to 2010 was utilized for demographic variable growth in the state of Alabama. The horizon year for the forecasting methods was 2025; the initial demographic variables utilized in this study were derived from the 2000 US Census and American Community Survey (ACS). Given the nature of the exponential function, and its exaggerative forecasting behavior for horizon periods of over 20 years, exclusive use of a linear growth model was selected. In order to utilize a linear growth model, individual variable growth rates were obtained using the following equation:

$$AGR = \left(\frac{Var_{2010} - Var_{2000}}{Var_{2000}}\right)\left(\frac{100_{pct.}}{10_{years}}\right) \tag{6.1}$$

Where AGR is Annual Growth Rate, $Var_{2010}$ is the value of a variable for the year 2010, and $Var_{2000}$ is the value of a variable for the year 2000.

Equation 6.1 outputs the annual growth rate (AGR) of a variable (in linear form), with units of: percent of a variable's units per year. Therefore, for a percentage variable (such as percent of population that is male), the AGR output units would be (%/%/year). The percentage AGR will later be applied, in decimal form, to year 2000 demographic variables in order to forecast for 2025 values.

Of the statistically relevant variables present in the crash severity model, only five of them were applicable for forecasting into the year 2025. These five variables were: percent of population under five years old, percent of population between 15 and 24 years old, median age of population, percent of population that is male, and commuters' average travel time. A sixth variable, land use: moderately developed, was considered for forecasting, however, for the purposes, and limitations, of this study, the variable was considered to remain constant over time. The remaining variables from the crash severity model were attained from ALDOT via the eCrash survey, or roadway infrastructure data table, and, given the crash case or roadway segment specific nature of the variable(s), forecasting methods were found to be inapplicable. The five variables for forecasting in the crash severity model were all representative of their nearest urban areas, therefore, growth rates for these variables are all based on an urban scale. Data on urban areas for the state of Alabama were attained on an aggregate (state-wide) distinction from the US Census and American Community Survey (ACS) database website <fact2finder.gov> for the years of 2000 and 2010. The 2010 and 2000 Census and ACS 1-year estimates were used to determine the growth in select demographic variables from the year 2000 to the year 2010 in urban areas in the state of Alabama by utilizing equation 6.1.

The process for calculating growth rates for relevant demographic variables from the crash frequency model was very similar to that of the crash severity model; however, there were some nuances. The crash frequency model contained significantly less variables than the crash severity model, and of these variables, four out of six were applicable for forecasting. Once again, the land use: moderately developed variable was considered constant over time, as was the variable for presence of exit or interchange, a roadway infrastructure variable. The three demographic variables forecast in this section of the study were: percent of population over 60 years old, percent of households that are family households, and number of owner occupied housing units. A roadway demand variable, year 2000 Average Annual Daily Traffic (AADT) will also be forecast for the year 2025; however, the methodology for that procedure will be discussed in the ensuing subsection. Demographic variables in the crash frequency model were all representative of surrounding developments, whereas the demographic variables in the crash severity model were all representative of nearest urban areas, therefore, two different growth rates needed to be derived for each variable, one on an urban distinction, and one on a rural distinction. Utilizing the US Census and ACS database website, aggregate data for urban and rural areas in the state of Alabama were attained for both years 2000 and 2010 for each representative variable. Calculated growth rates using equation 6.1 for factors in both models can be seen below in Table 6.1.

**Table 6.1.Urban and Rural Alabama Demographic Growth Rates.**

| **Urban** | | | |
|---|---|---|---|
| **Variable Name** | **2010 Value** | **2000 Value** | **Linear Growth Rate** |
| Percent of population under 5 years old | 6.62% | 6.73% | **-0.1745** |
| | | | |
| Percent of population 15 to 24 years old | 15.81% | 15.13% | **0.4461** |
| | | | |
| Median age of Population | 35.8 Years | 35 Years | **0.2286** |
| | | | |
| Percent of population that is male | 47.43% | 47.22% | **0.0435** |
| | | | |
| Commuters' average travel time | 21.2 min. | 21.6 min. | **-0.1852** |
| | | | |
| Percent of Population over 60 years | 18.8 % | 17.3 % | **0.8671** |
| | | | |
| Percent of Households that are Family Households | 63.0 % | 66.4 % | -0.5120 |
| | | | |
| Owner Occupied Housing Units | 609,000 Units | 625,759 Units | **-0.2678** |

**Table 6.1. Urban and Rural Alabama Demographic Growth Rates.**(Continued)

| Rural | | | |
|---|---|---|---|
| **Variable Name** | **2010 Value** | **2000 Value** | **Linear Growth Rate** |
| Percent of Population over 60 years | 20.4 % | 17.3 % | **1.7919** |
| | | | |
| Percent of Households that are Family Households | 74.0 % | 75.6 % | **-0.2116** |
| | | | |
| Owner Occupied Housing Units | 679,000 Units | 632,927 Units | **0.7279** |

## 6.2. Applying Growth Rates

Linear growth rates assume a constant and consistent growth from one year to the next for a given variable. Even though the growth rates are given in percent per year, the rate is referenced to the zero, or initial, year of the growth rate calculation (the year 2000 in this study). Therefore, the amount of growth, or decay, of a variable is a constant fixed percentage of its year 2000 value, for every compounding period (year). The formula used to calculate linear forecasts of the demographic variables in this study is shown as equation 6.2.

$$Var_{2025} = \left(Var_{2000} \times \frac{AGR_i}{100_{pct.}} * 25_{years}\right) + Var_{2000} \tag{6.2}$$

Where $AGR_i$ is Annual Growth Rate for a given variable, $Var_{2025}$ is the forecast 2025 variable value, $Var_{2010}$ is the value of a variable for the year 2010, and $Var_{2000}$ is the value of a variable for the year 2000.

The year 2000 variable values used in this portion of the study were not the aggregate values utilized in the growth rate derivation process, individual segment demographic values from the 1,810 interstate segments were used to forecast their 2025 values. For the crash severity study the forecasting methodology was fairly simple, since all of the demographic variables were forecast using the urban distinction; in this way, the growth rates were applied to each segment demographic characteristic individually, and assigned to their corresponding crash cases.

Forecasting crash frequency study demographic variables required an additional step, since, depending on location, segment growth could fall under either an urban or rural distinction. An urban or rural identifier value, as denoted by ALDOT, was utilized to identify urban or rural classified zones. If a segment was located in an urban location, then urban growth rates were applied to its demographic variables, and, conversely, if a segment was located in a rural area, then rural growth rates were applied; this process was performed for each of the 1,810 segments. In order to forecast 2025 AADT, a traffic forecasting linear regression model formulated by LaMondia and Morgan (2012) in a previous study was utilized. For the purposes of this study, a full breakdown of the traffic forecasting model will not be included; however, a full citation to the traffic forecasting study has been included at the end of this paper.

For both crash severity and crash frequency, the variables that were deemed constant over time were retained from the 2010 datasets. For crash severity these included: all crash case, roadway infrastructure, and land use; for crash frequency these included: presence of exit or interchange, and land use. Forecast 2025 demographic and traffic demand variables were added to the retained constant variables for crash severity and frequency respectively, which resulted in the formulation of year 2025 datasets for all 15,775 crash cases (crash severity), and 1,810 interstate roadway segments (crash frequency).

### 6.3. Limitations

Forecasting has proven to be a cogent and tested method for predicting future values, however, there are unique challenges and limitations innate to any forecasting method, and one can never be 100% assured of results being precise five, ten, or fifteen years into the future. There are two main areas where error, and lack of confidence, may come into play when performing forecasts, data accumulation and unforeseen deviations of growth trends over time.

The data utilized in this portion of the study came from the 2000 and 2010 US Census and ACS; it can be assumed that the US Census data is accurate, to a certain confidence level, based upon survey response rates, however, ACS data is performed on a much smaller scale, and has higher intrinsic levels of uncertainty associated with it. The scale of the data collection took place on aggregate urban and rural levels, which are much lower levels of refinement than individual census tracts or buffer sections, which were the scales used to determine interstate section demographics in this study. It was assumed, for this portion of the study, that growth trends on urban and rural levels would remain constant and analogous over the entire state during the forecasting period; in effect, omitting unique regional, city, or town characteristics that may influence the growth of select variables in those locations.

Another assumption made in this portion of the study was that growth, and the rates thereof, will remain constant over the entire forecasting period. This assumes that the factors and patterns influencing growth seen across the state from 2000 to 2010 would remain valid over the next 15 years. However, this may be an imperfect assumption, and one need not look any further than to note the recent economic recession as an example of the volatility of demographic growth. Therefore, utilizing linear growth models and rates may not take into account economic and/or population vicissitudes as a whole, it is very possible that the population and economy of Alabama could see continued stagnant growth due to prolonged recession, however, it is also possible that the state could encounter an economic resurgence, and spike in growth, should the economy begin to recover rapidly. One must also consider the composition of the population in the state. From 2000 to 2010 Alabama saw a median age increase of 0.80 years and an increase in percentage of population over the age of 60 in both the urban and rural distinctions of 1.50% and 3.10% respectively. As we progress further in time the “baby boomer” generation will continue to age, and a larger proportion of these individuals will enter into the over 60 age demographic, a demographic that plays an important role in modeling crash frequency in this study. Reproduction and total population also, generally, follow an exponential growth model, therefore, factors such as population between zero and five years, and population between 15 and 24 years of age, may not be precisely forecast by a linear growth model over a long forecast period. Furthermore, general immigration trends within for a state are known to fluctuate as well, and Alabama could easily see a net decrease in immigration over the suspect time period.

## 7. PERFORMANCE MEASURE INDICES

As referenced numerous times in this research, roadway safety is not a one dimensional problem or solution. Roadway safety, is, in fact, a multifaceted quandary that requires the assessment of numerous different factors in order to fully analyze, which, in the case of this research, corresponds to crash frequency and crash severity, and the factors which influence either, respectively. However, analyzing frequency and severity separately is a process, and a methodology that streamlines the two studies together into a singular measure of roadway safety would be quite advantageous. This had led to the derivation of performance measure indices, which allow roadway safety practitioners the ability to quickly, and accurately, assess roadway safety for various different roadway sections and corridors. Performance measure indices also allow practitioners the ability to develop cartographic models that can increase the ease of understanding and transferability of said data.

Two different performance measure index values (both novel approaches using both crash frequency and severity to define roadway safety) were calculated from the data in this research, each having a distinctly different methodological form, and practical usage/implication. The first performance measure indices (called the likely crash severity index) were calculated by taking the product of multiplying the predicted crash frequency by the predicted crash severity for a given segment. This was done for each of the 1,727 interstate roadway segments in Alabama (83 interstate roadway segments did not have a crash case over the 11-year time period, and were removed from the performance measure derivation process), for both 2010 and 2025 at the median, safest, and worst case crash severity scenarios, and its corresponding equation can be seen below.

$$Index_{Li} = \ Crash\ Severity\ Score_i\ \times\ Crash\ Frequency\ Score_i \tag{7.1}$$

This equation numbered roadway segments as integers from one through 90 (the maximum values for crash frequency and severity were ten and nine, respectively). The second performance measure indices (probabilistic crash severity index) were calculated by multiplying likely crash severity index values by the probability for each roadway segment to possess its predicted individual crash severity level (as derived from the normal distribution probability function, ranging from 0-1.00). The probabilistic crash severity index equation numbered roadway segments from zero through 90 (again, only the 1,727 relevant segments), however, all probabilistic crash severity index values are dependent on the likelihood of a certain crash severity level, and have the ability to be non-integer values; the probabilistic crash severity index equation can be seen below.

$$Index_{Pi} = Crash\ Severity\ Score_i\ \times\ Crash\ Frequency\ Score_i\ \times\ Probability\ of\ Crash\ Severityity\ Score_i \tag{7.2}$$

Even though the two index value calculations are fairly similar in their equations, there is a distinct and essential practical difference between the two. The likely crash severity index categorizes segments based upon their absolute predicted crash frequency and crash severity. In this way, likely crash severity index values assume that the probability, or likelihood, for a random crash on segment *i* to have predicted severity level *j* is 100 percent, and, likewise, that the likelihood for segment *i* to have *x* number of predicted motor vehicle crashes per year is also 100 percent. Results from this type of calculation can be quite reliable, and their precision increases as the accuracy and reliability of the prediction process increases. However, since no prediction model is absolute, i.e., no model is 100 percent accurate; one may find it advantageous to incorporate a probability measure into the index calculations. The probability measure, in the case of the probabilistic crash severity index, the probability that roadway segment *i* will fall into predicted crash severity level *j*, with severity level *j* being the most probable severity level for segment *i*, assesses the effect of the likelihood for a crash severity level on a roadway segment in terms of overall roadway safety. Therefore, the probabilistic crash severity index is not constricted to the same 100 percent likelihood principle that the likely crash severity index is. This is felicitous due to the possibility that a roadway segment could have similar probabilities for multiple severity levels. In effect, the probabilistic crash severity index penalizes roadway segment safety performance measures by the derived crash severity level probability, in addition to the predicted frequency and severity values themselves. This is useful for roadway safety practitioners since it allows them to assess roadway safety based not only upon crash frequency and severity, but also the likelihood that a roadway segment is going to have a certain level of crash severity, since crash severity levels with higher probabilities will significantly increase calculated performance measure index values.

To better graphically, and cartographically, represent the performance measure indices, definitive groupings of similar index values were derived. Natural breaks, using the supplied equation and derivation in ArcMap, were used to determine four interior break point values (creating five distinct levels) for each index on an entire-state level (all 1,727 segments) for the median crash severity scenario for the year 2010. What the natural break process does is use a mathematical function to determine the inherent multimodality for the observed, calculated data. In this way, the natural breaks process seeks to partition the distributions of the index values into groups based upon their natural clustering; this process developed the break point values represented on the following page.

**Table 7.1. Break Point Calculation Criteria.**

| Break Point Calculations | | |
|---|---|---|
| **Level** | **Likely** | **Probabilistic** |
| **1** | 1.00 | min-0.81 |
| **2** | 1.01-2.00 | 0.82 |
| **3** | 2.01-3.00 | 0.83 |
| **4** | 3.01-4.00 | 0.84-1.11 |
| **5** | 4.01-max | 1.12-max |

The median crash severity scenario for the year 2010 was utilized to derive break points since said data represents the $50^{th}$ percentile of predictions based upon the most recent data available. These values, as described in the methodology section of this paper, represent the median crash severity scores for individual roadway segments over the eleven year time period, and serve as the best representation of mid-point severity scenarios available. Therefore, the above break point values can be considered representative for any type of spatial or temporal subset(s) of data that could be derived from this research, such as, the 2025 index predictions, or different spatial subsets of roadway segments, which could include entire interstates, or simply roadways running through towns/cities. Likewise, the break points will facilitate the application and evaluation of the performance measure indices for any of the various possible spatial and temporal settings.

## 8. PERFORMANCE MEASURE EVALUATION

Practical use of interstate segment performance measures dictated the incorporation of a known and applicable spatial scale. In the state of Alabama the Department of Transportation (ALDOT) is broken into nine divisions, each of which considers and develops plans for the transportation needs within their division, while all reporting back to the central office in Montgomery, Alabama. Since these divisions are already in place in a working environment, it was deemed applicable to mimic these divisions for the spatial scales of the interstate segment performance measures (and their associated cartographic references). Eight out of the nine divisions in the state contained interstate roadways within their boundaries (division 7 was devoid of interstate roadways). Performance measure maps were developed for the likely crash severity index and the probabilistic crash severity index for both 2010 and the forecast horizon year of 2025. The performance measure maps were fabricated using ArcMap, and they consist of all of the pertinent geographical data (division, counties, interstate roadway centerlines, datum, projection, etc.), as well as a graphical representation of the distribution of the performance measure indices for each division, index type, and year. Each map assesses all three crash severity scenarios simultaneously (safest, median, and worst case), which gives practitioners the ability to compare roadway safety performance at varying degrees of previously observed driver/crash behavior and circumstances.

Assessment of the maps provides proof of a definite difference between results for the likely crash severity index and the probabilistic crash severity index. Further review shows common trends over all eight of the relevant ALDOT divisions: the probabilistic crash severity index is significantly more dispersed than the likely crash severity index, with the likely crash severity index showing a definite right-skewed distribution towards the safer side; generally speaking, unsafe sections (denoted in red) tend to be similar for the worst case crash severity scenarios in both of the indices; major urban areas (Birmingham, Huntsville, Mobile, Montgomery, etc.) tend to display elevated (less safe) values for roadway safety performance; and there often are clusters of very safe, or less safe, roadway segments. It is also important to note that, on average, roadway segments became less safe when forecast for 2025, with respect to their 2010 values (for both index calculations).

Division 1 of ALDOT, encompassing Blount, Cherokee, Cullman, Dekalb, Etowah, Jackson, Madison, Marshall, and St. Clair counties, was chosen as a representative county for map analysis purposes. Division 1 was chosen since it contains numerous important aspects that were the focus of this research, these include: five different interstates (I-20, I-59, I-65, I-565, and I-759), two large cities, including one major urban area (Huntsville and Gadsden), a shared border to two different states (Georgia and Tennessee), which should increase the likelihood of seeing long distance travel, and the maps clearly display the distinct trends of/between the likely crash severity index and the probabilistic crash severity index that were mentioned prior. Full 2010 maps for the likely and probabilistic indices of division 1 can be seen on the following two pages. The remaining set of maps for the ALDOT divisions can be seen at the end of this section, prior to Section 9.

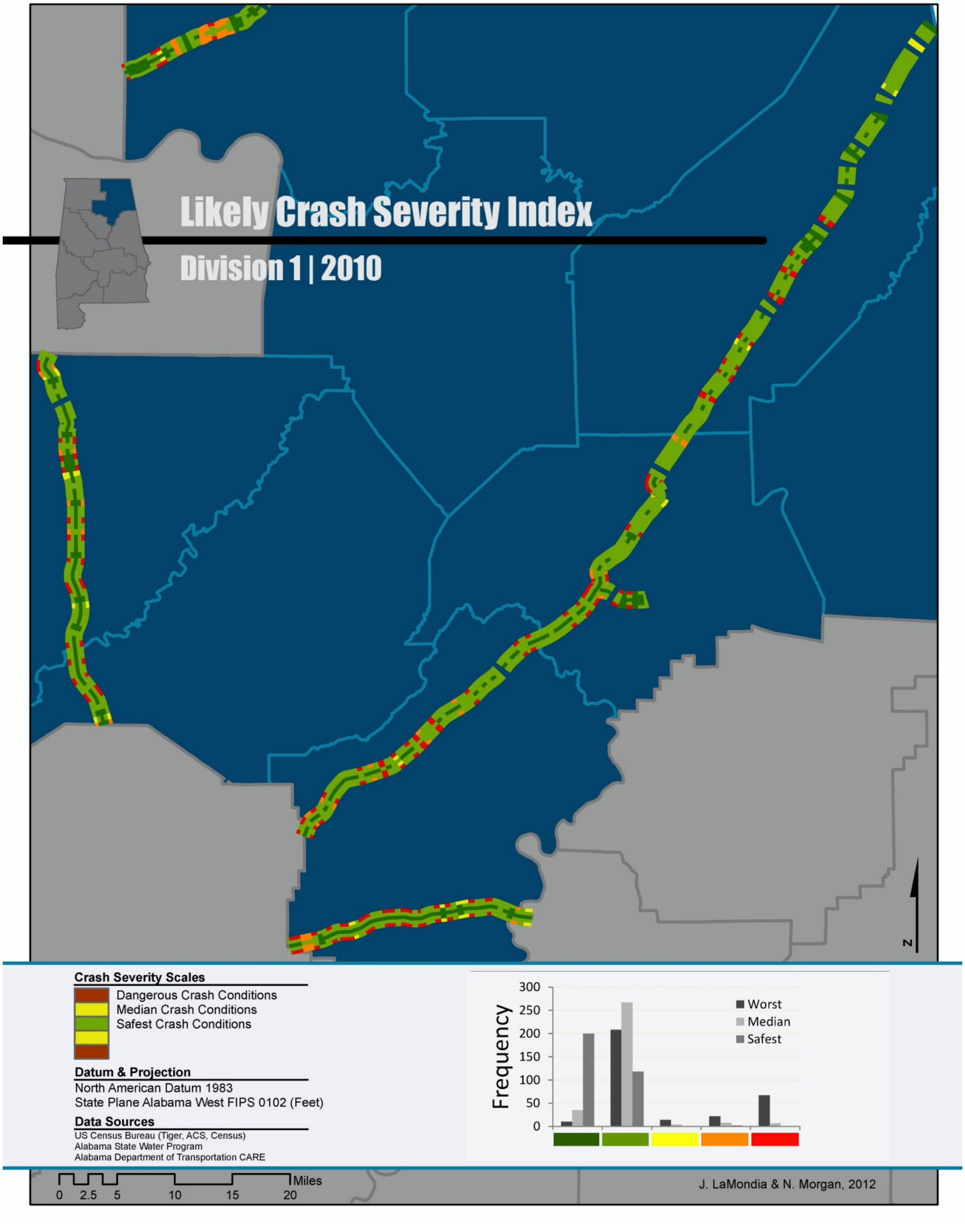


**Figure 8.1. Division 1: Likely Crash Severity Index 2010.**

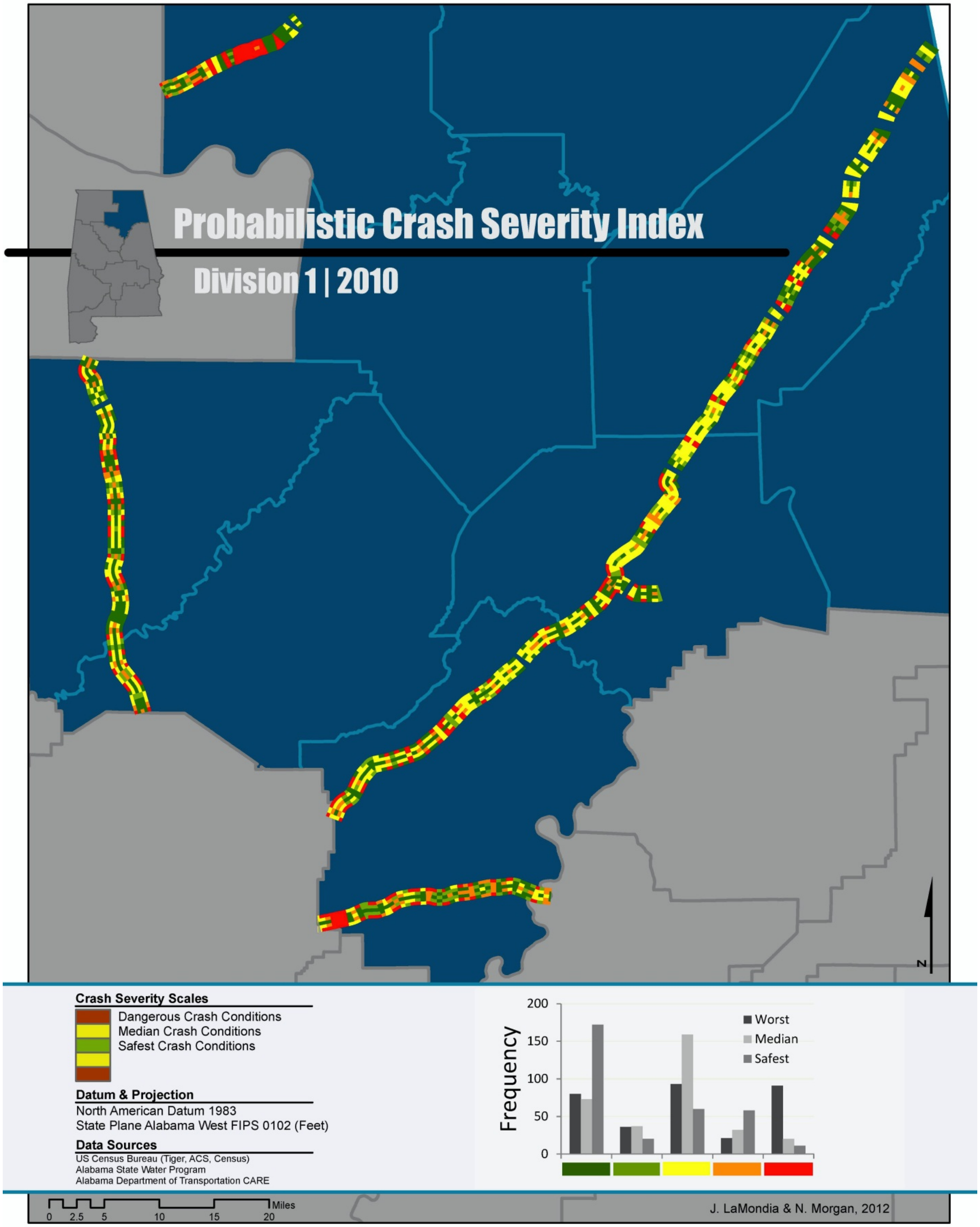


**Figure 8.2. Division 1: Probabilisitc Crash Severity Index 2010.**

For analysis purposes, a closer look at the North-West portion of Division 1 can be seen in the snap-shot below.

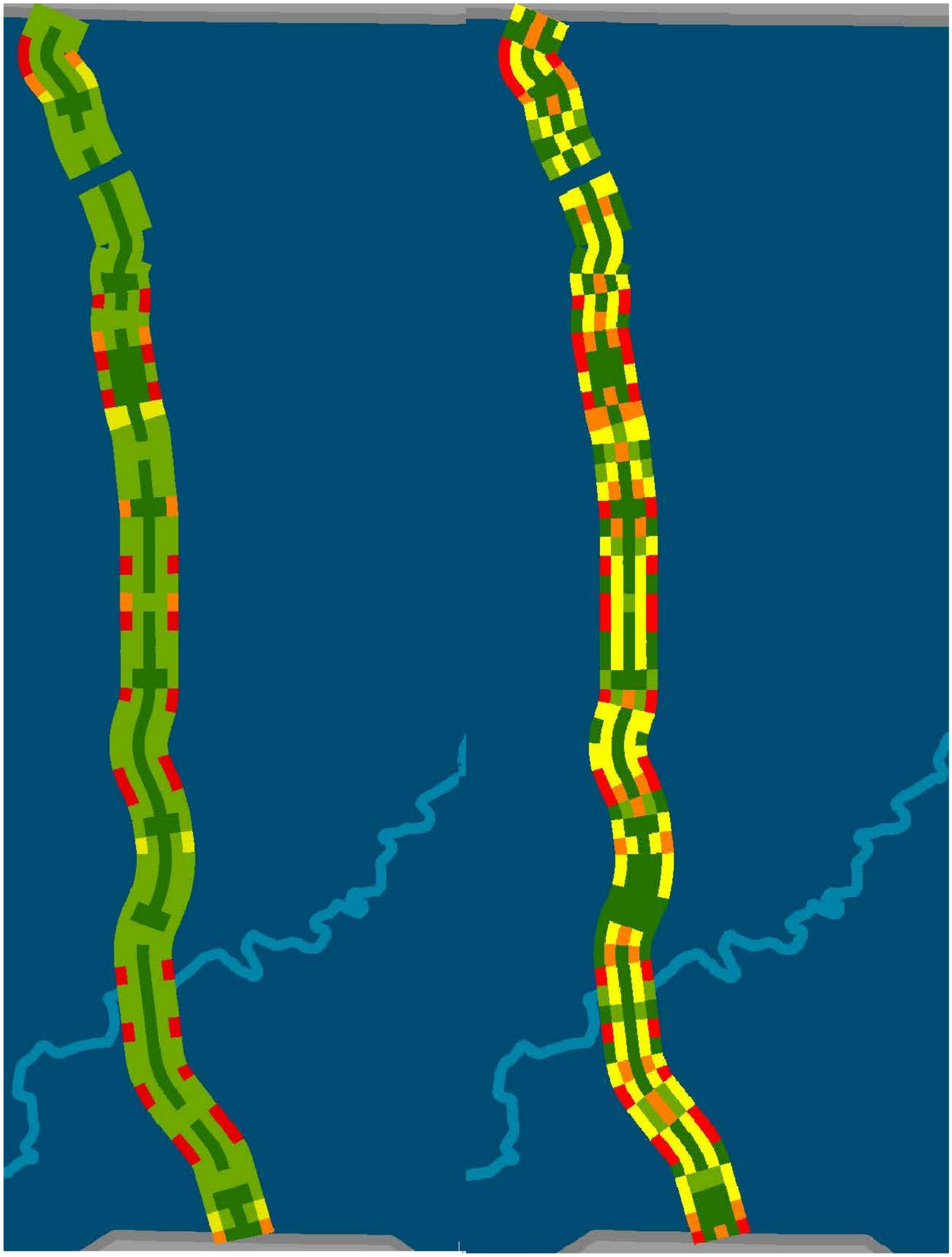

**Figure 8.3. Division 1: Interstate 65 Snap-Shot.**

The roadway assessed in the snap-shot above is interstates 65 (running north/south towards Tennessee/Birmingham). The left side of the snap-shot displays the likely crash severity index values, while the right side of the snap-shot displays the probabilistic crash severity index values. Analysis of the snap-shot corroborates the general map trends denoted previously. The probabilistic crash severity index values for Interstate 65 shows a fairly large proportion of yellow and orange roadway performance levels (denoting median and mildly unsafe conditions, respectively), whereas the same section for the likely crash severity index values is predominantly green, which gives a general sense of roadway safety. In this snap-shot, red sections for the likely crash severity index for the worst case crash severity scenarios are mirrored in the probabilistic crash severity index results, which is good, since it shows that inherently dangerous circumstances (crash case, roadway, and spatially related) will be viewed as such no matter which analysis technique is applied. There are also examples of similar performance measure level clustering in both index values. Examples of this are: the clustering of red levels for the worst case crash severity scenario in the probabilistic crash severity index, clusters of dark green (safest level) levels for both indices throughout the safest crash severity scenario (much more pronounced for the likely crash severity index), and large clusters of light green or yellow (moderately safe and median levels) for the likely crash severity index and probabilistic crash severity index respectively.

Overall, results for the likely crash severity index and the probabilistic crash severity index depict somewhat similar situations for roadway performance; however, there are some unique and inherently different aspects innate to each. Both performance measure derivation techniques display relatively safe conditions for the safest crash severity scenario, moderately safe and median safe levels for the median crash severity scenario, and similar moderately unsafe levels for the worst crash severity scenario. However the distribution for the likely crash severity index is much more right-skewed than the probabilistic crash severity index. The skewed nature of the likely crash severity index results (towards the safer side) may give users and roadway safety practitioners a false sense of roadway safety. Conversely, the increased number of unsafe locations depicted in the probabilistic crash severity index might also give users and roadway safety practitioners an ominous, and perhaps somewhat unwarranted, depiction of overall roadway safety. However, when accounting for the methodological differences between the derivations of either index, it becomes this author's opinion that the probabilistic crash severity index is the superior performance measure. The reasoning behind this selection is due to the added probability aspect in the probabilistic crash severity index, which incorporates a level of likelihood and probability for a certain crash severity level to be present, an aspect that is missing from the likely crash severity index. In this way, the probabilistic crash severity index performance measures may be better at displaying the subtle differences in roadway safety that unobserved factors may have. The more dispersed distribution for the probabilistic crash severity index values also may help roadway safety practitioners better prioritize areas that may be in need of future roadway safety improvements, such as segments denoted in yellow or orange, which could be completely overlooked in the likely crash severity index map, since the same segments have a high probability of being dark or light green in the likely crash severity index map. However, both performance measures can be extremely valuable to all persons involved in roadway safety, and practitioners may find it propitious to assess both when prioritizing roadway safety improvements.

The remaining maps for all ALDOT divisions for 2010 and 2025 can be seen on the ensuing pages.

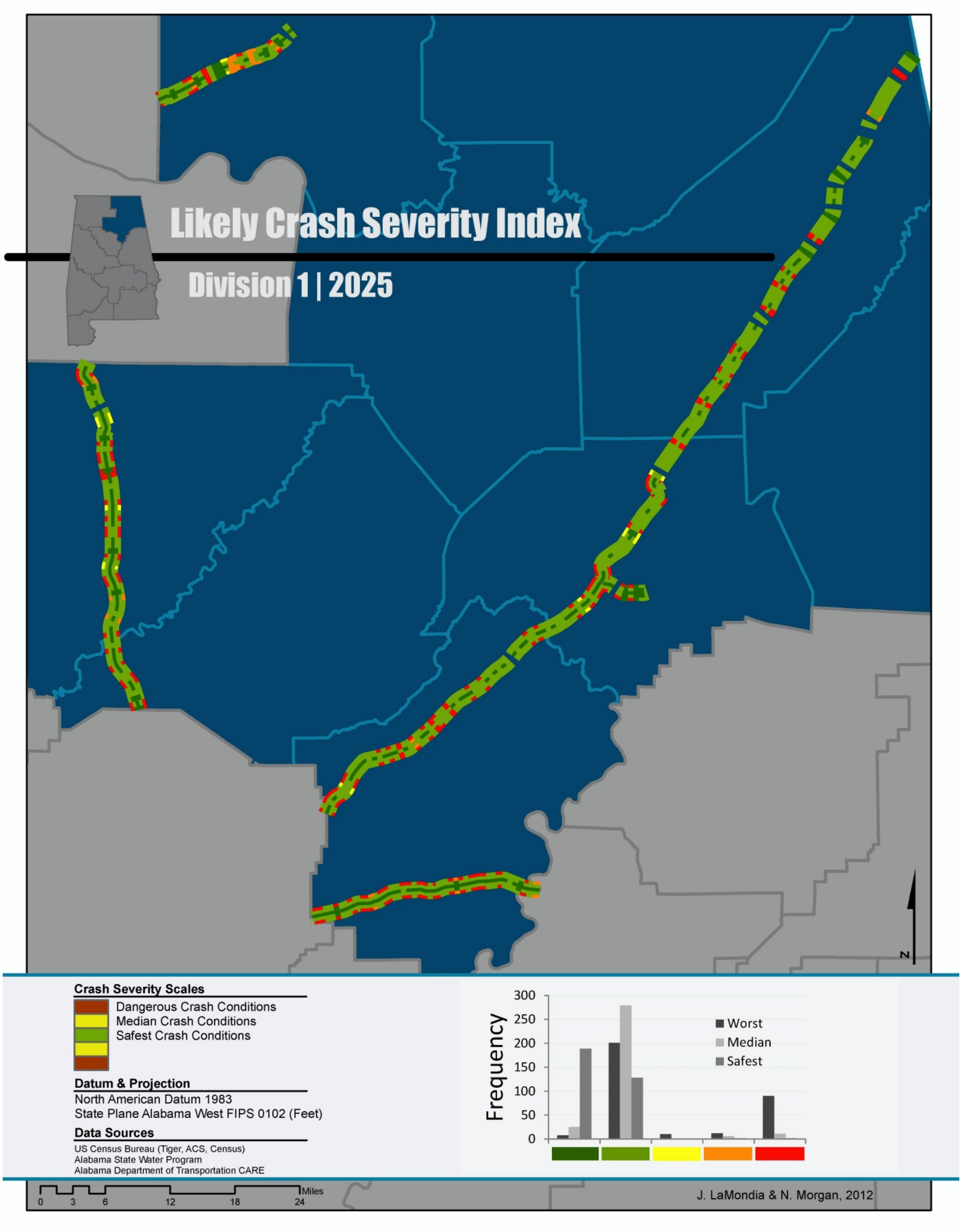


**Figure 8.4. Division 1: Likely Crash Severity Index 2025.**

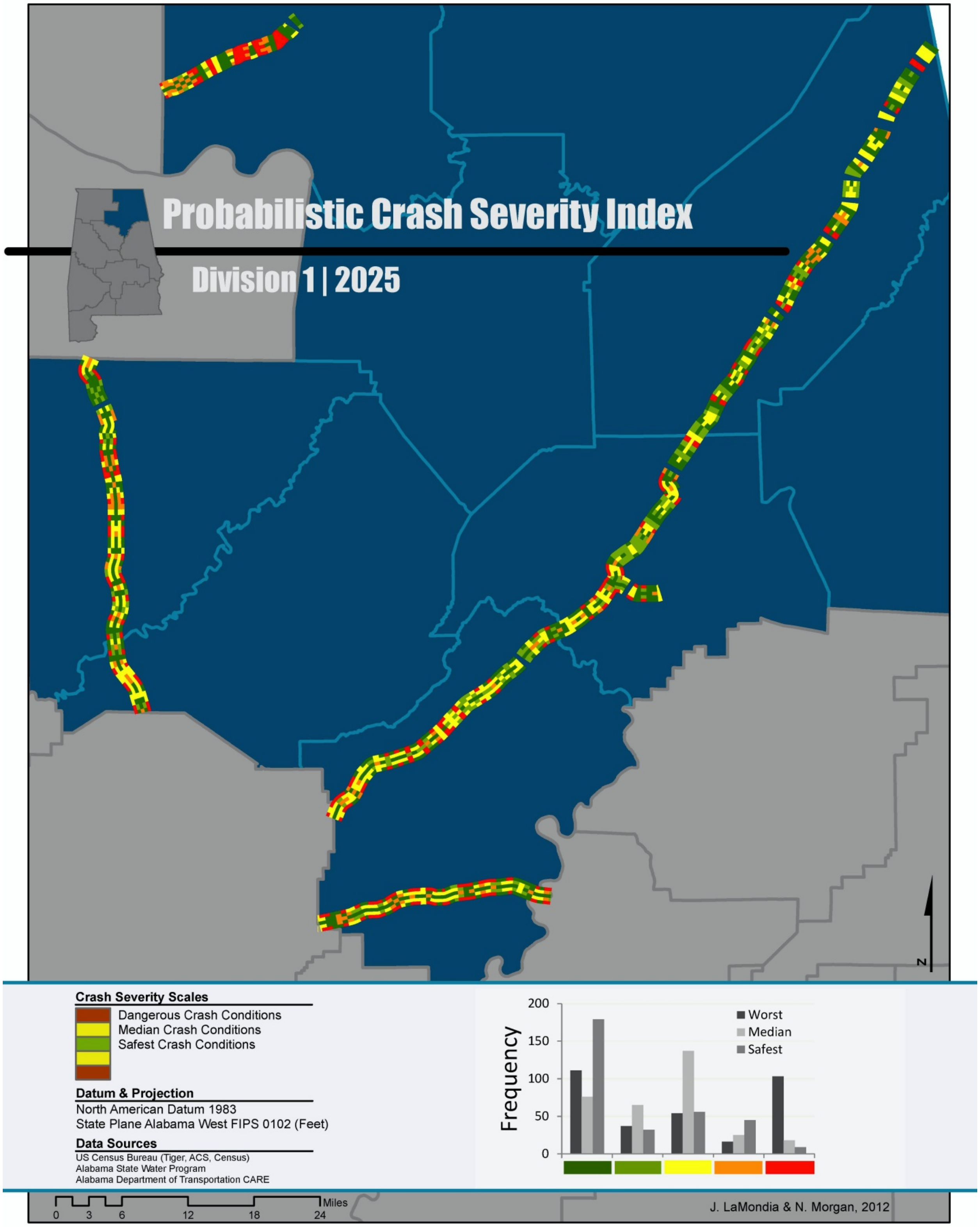


**Figure 8.5. Division 1: Probabilistic Crash Severity Index 2025.**

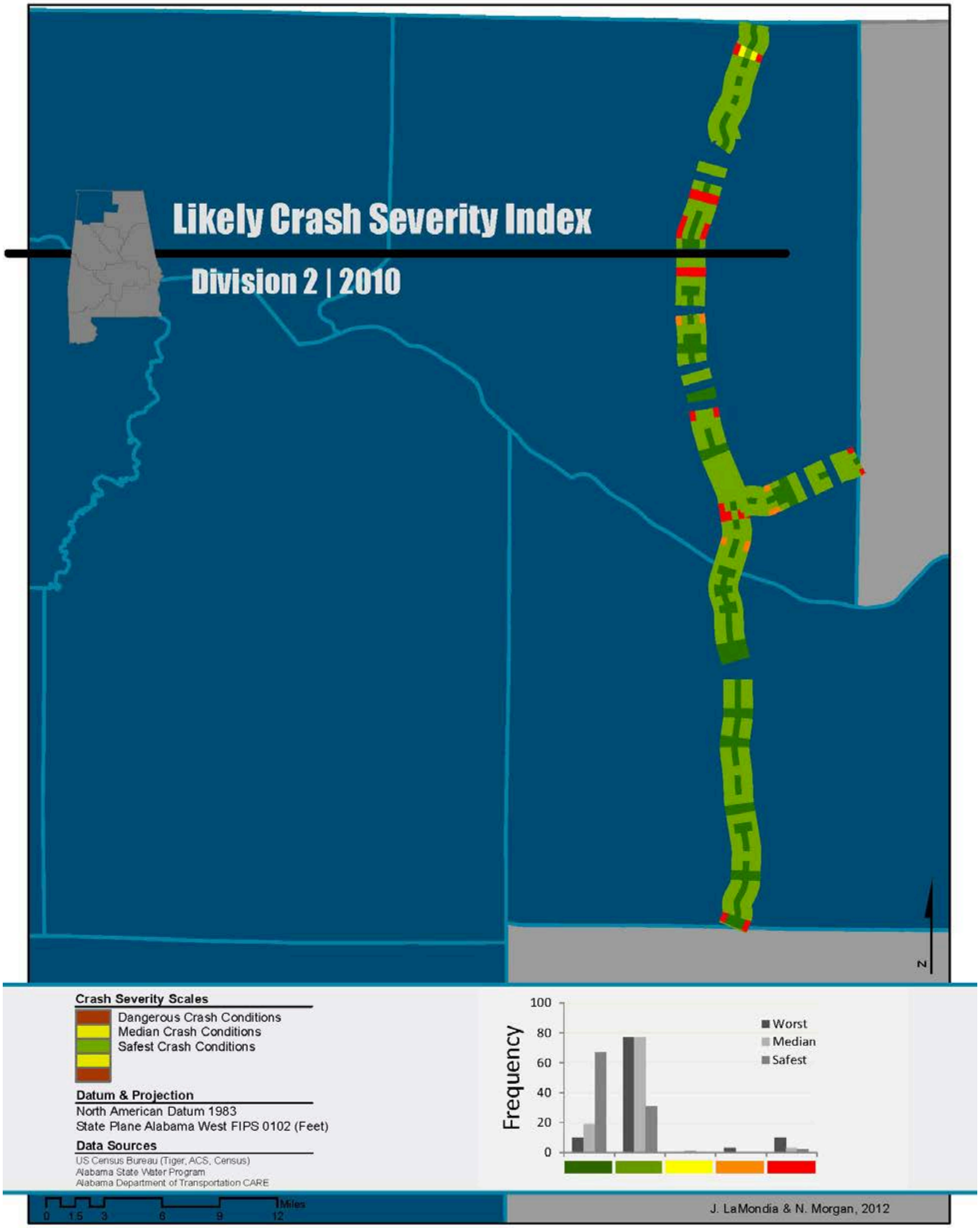


**Figure 8.6. Division 2: Likely Crash Severity Index 2010.**

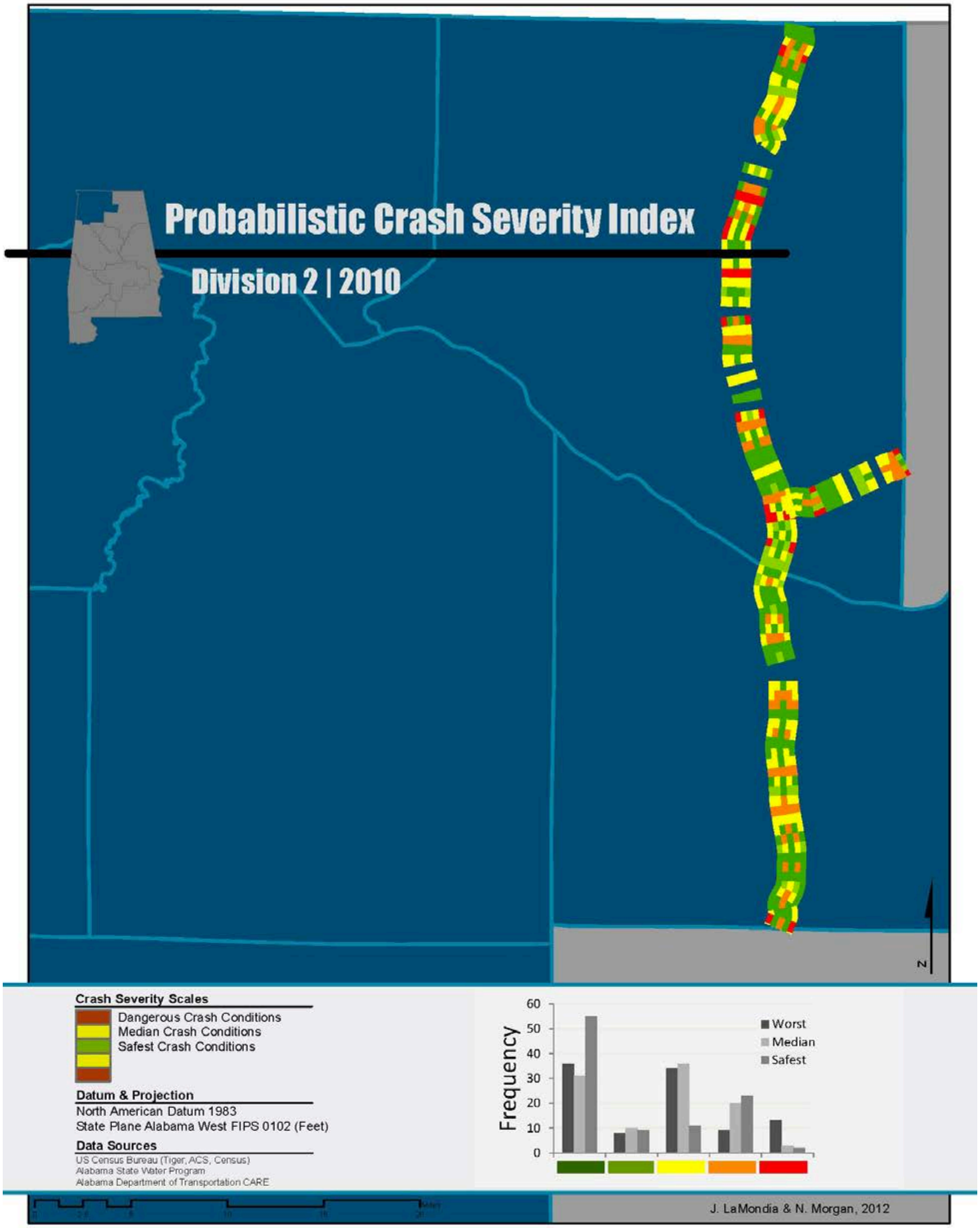


**Figure 8.7. Division 2: Probabilistic Crash Severity Index 2010.**

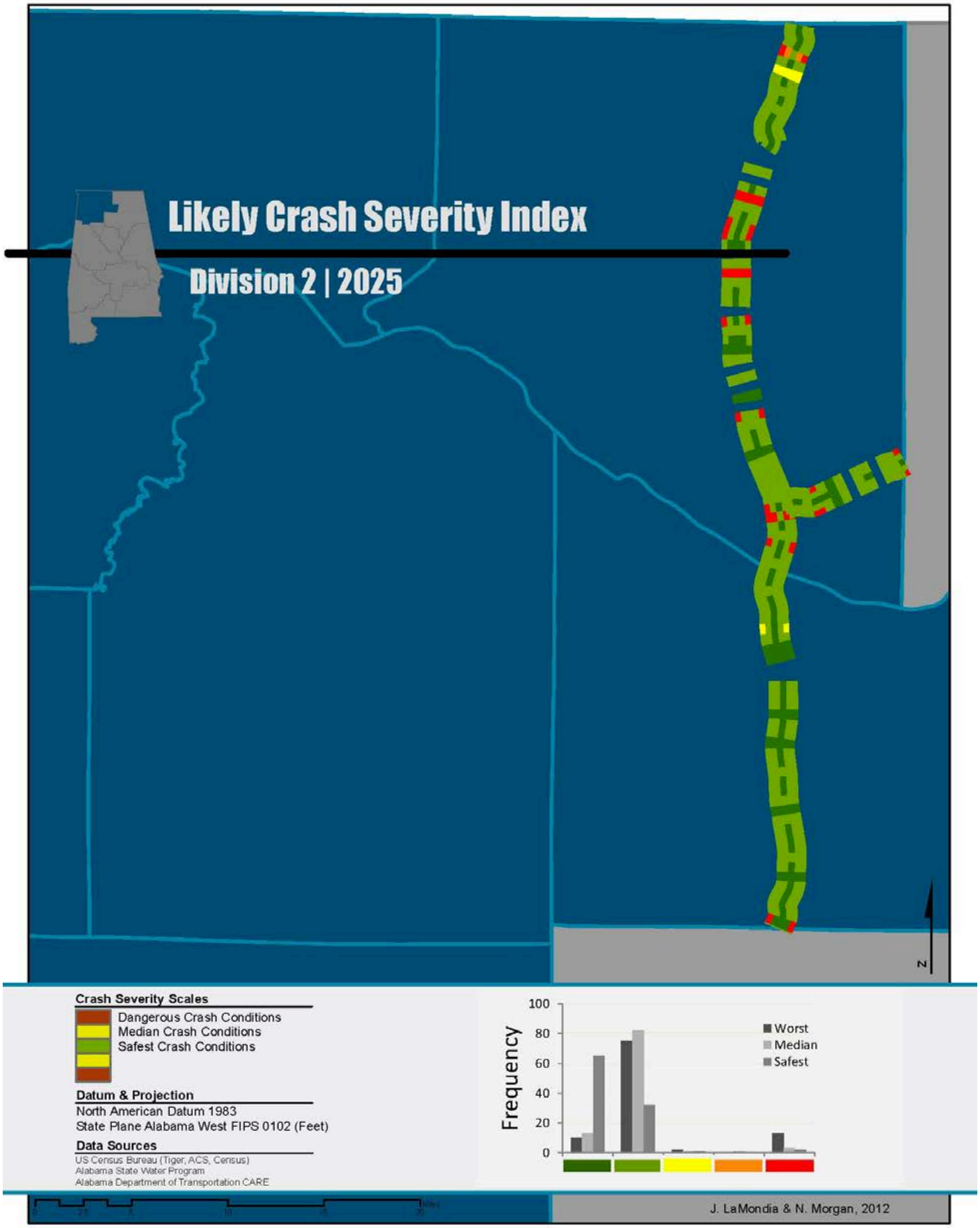


**Figure 8.8. Division 2: Likely Crash Severity Index 2025.**

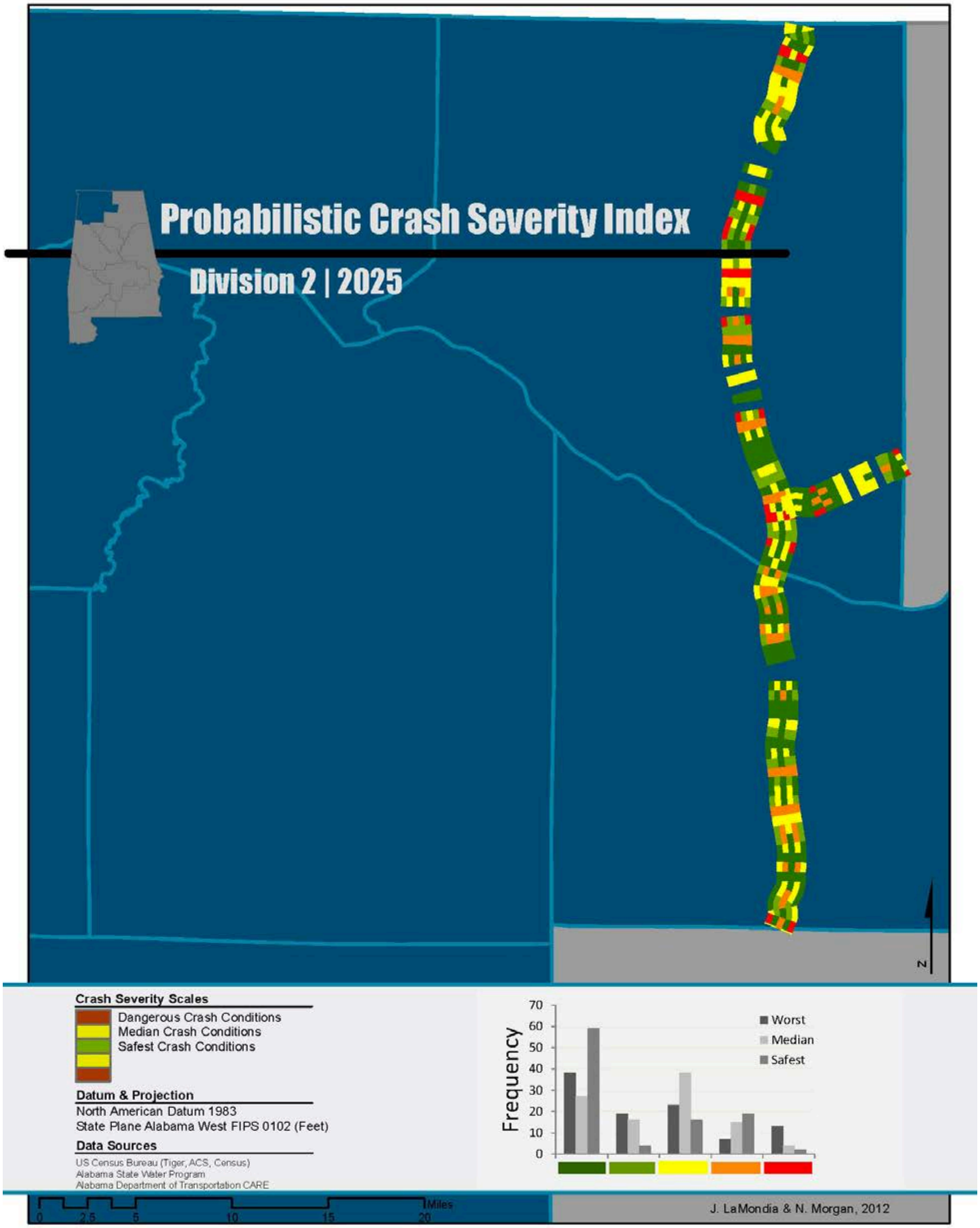


**Figure 8.9. Division 2: Probabilistic Crash Severity Index 2025.**

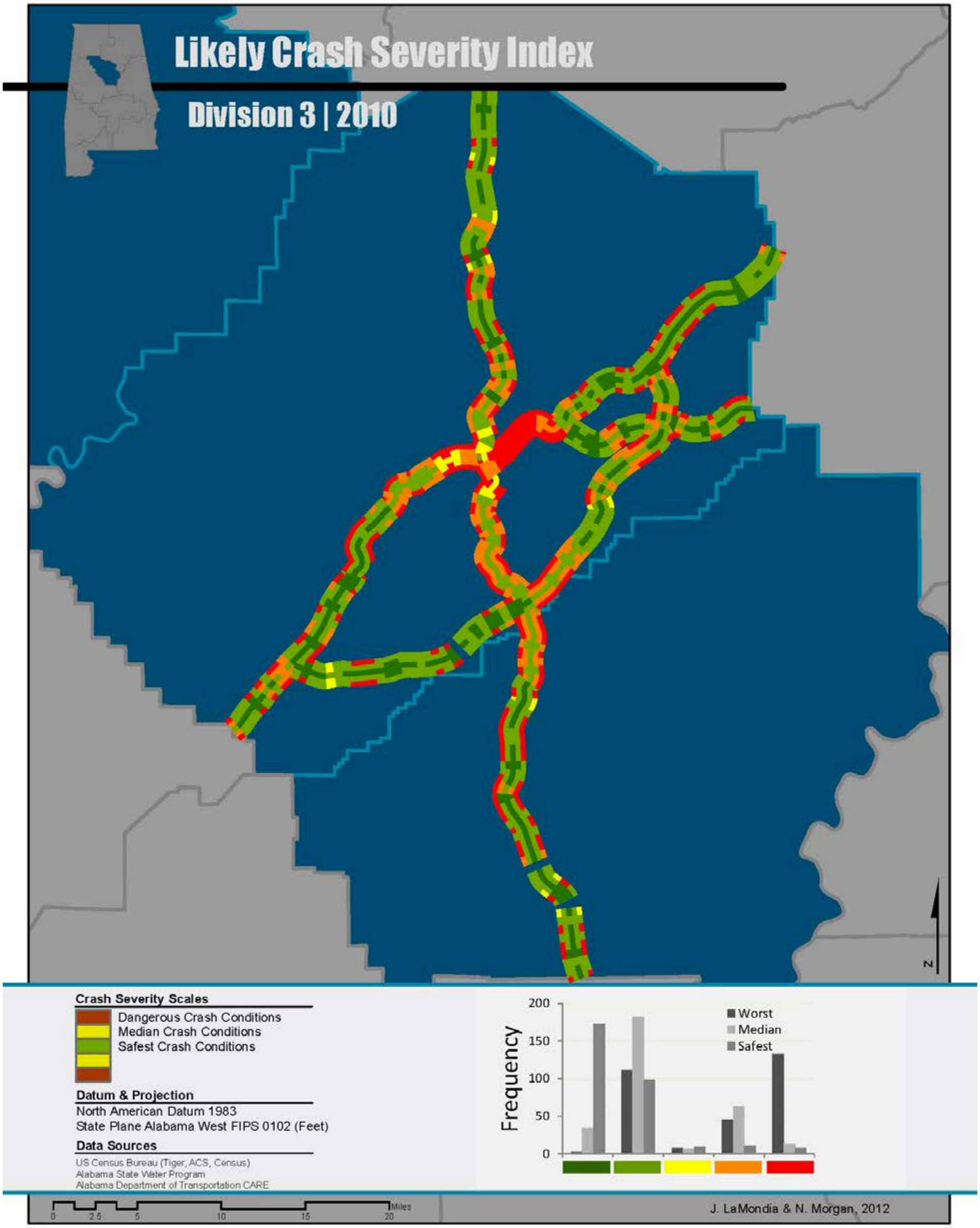


**Figure 8.10: Division 3: Likely Crash Severity Index 2010.**

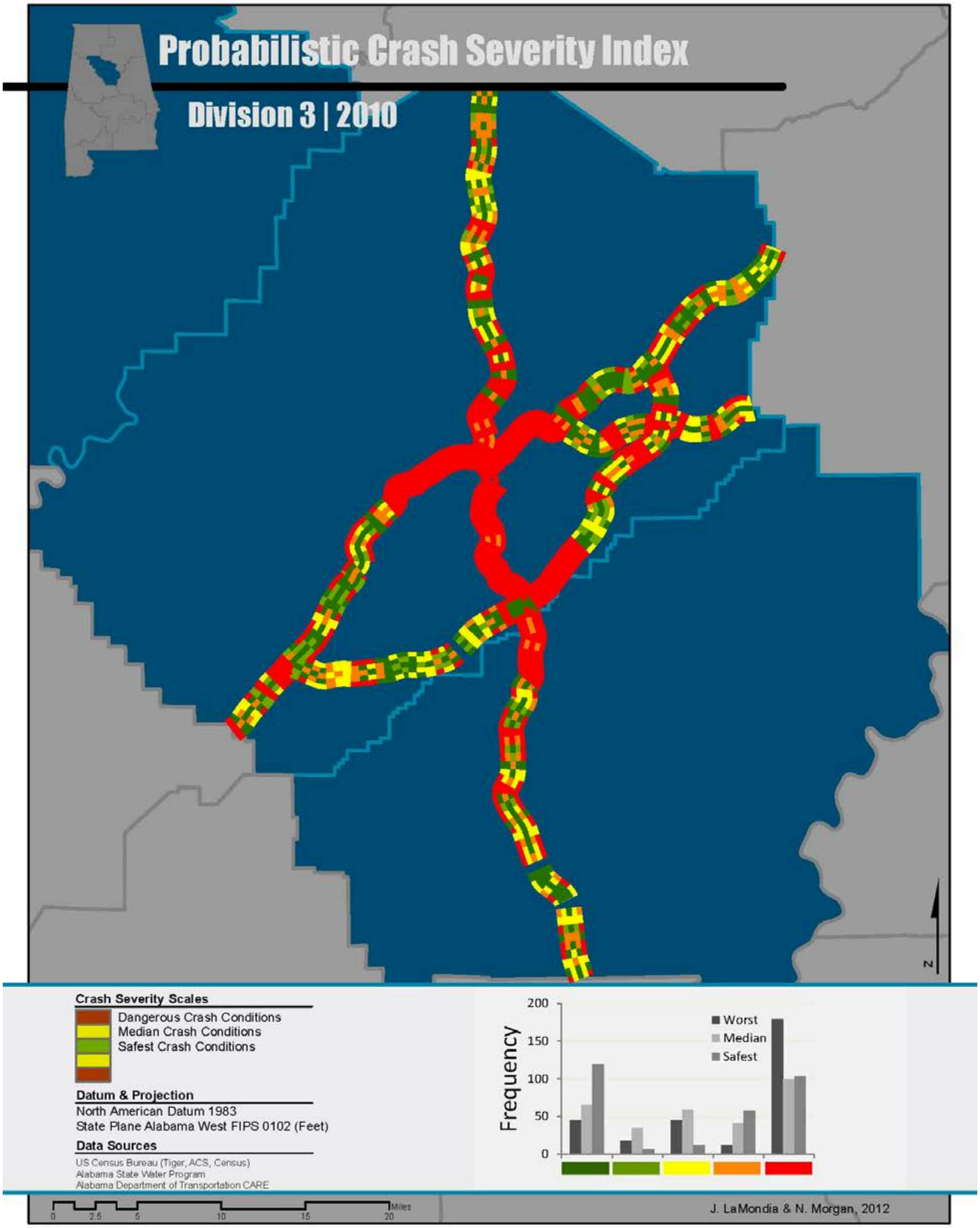


**Figure 8.11. Division 3: Probabilistic Crash Severity Index 2010.**

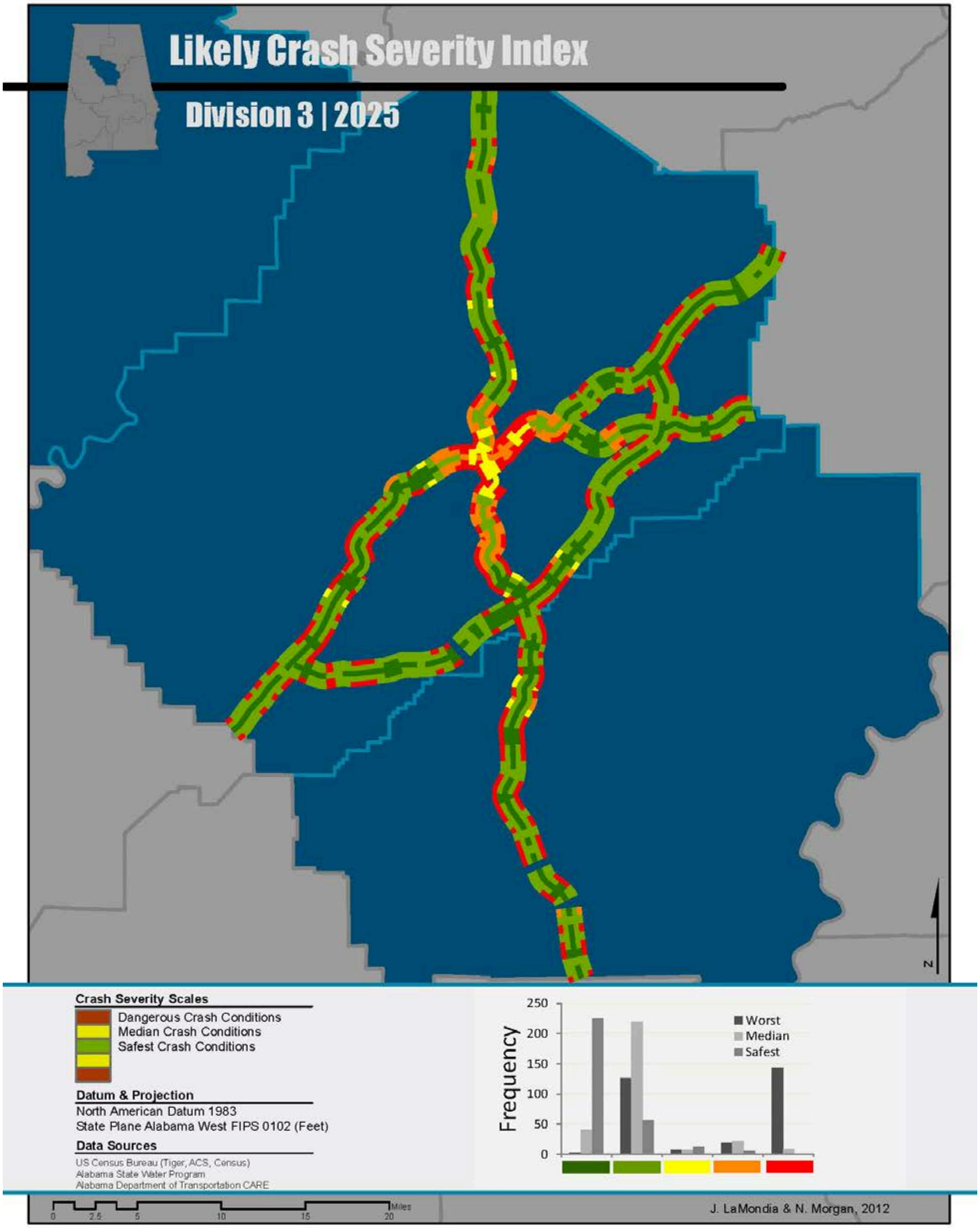


**Figure 8.12. Division 3: Likely Crash Severity Index 2025.**

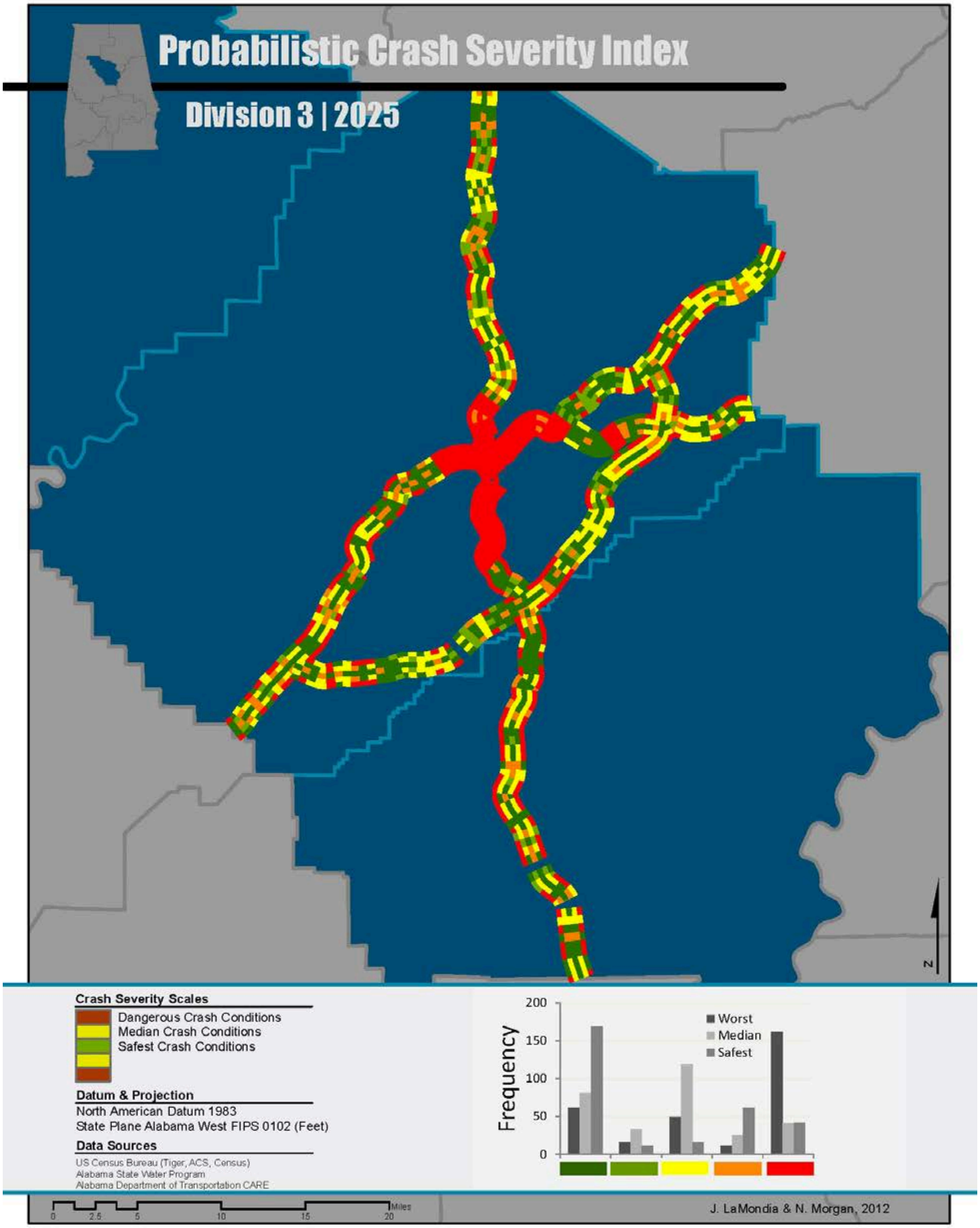


**Figure 8.13. Division 3: Probabilistic Crash Severity Index 2025.**

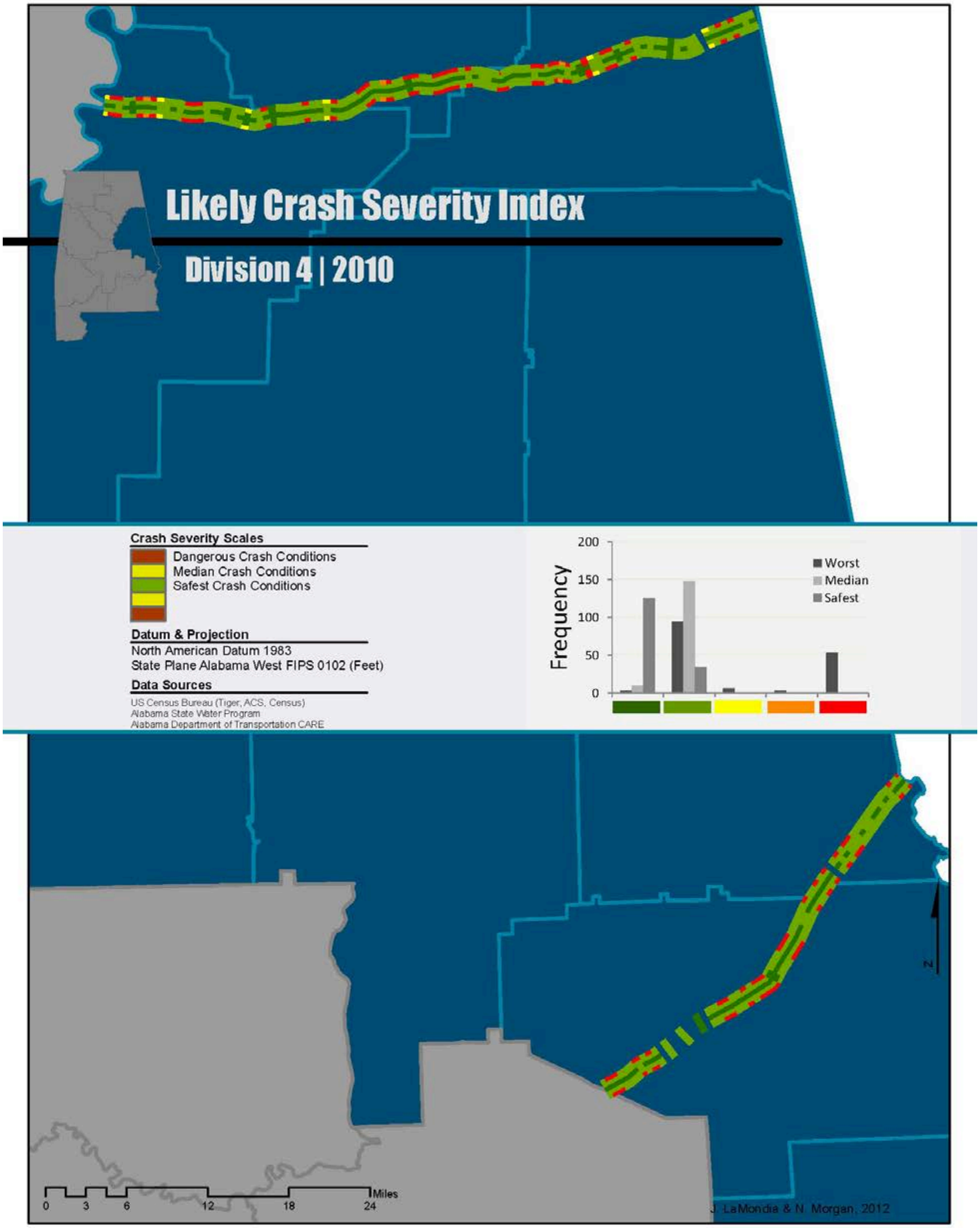


**Figure 8.14. Division 4: Likely Crash Severity Index 2010.**

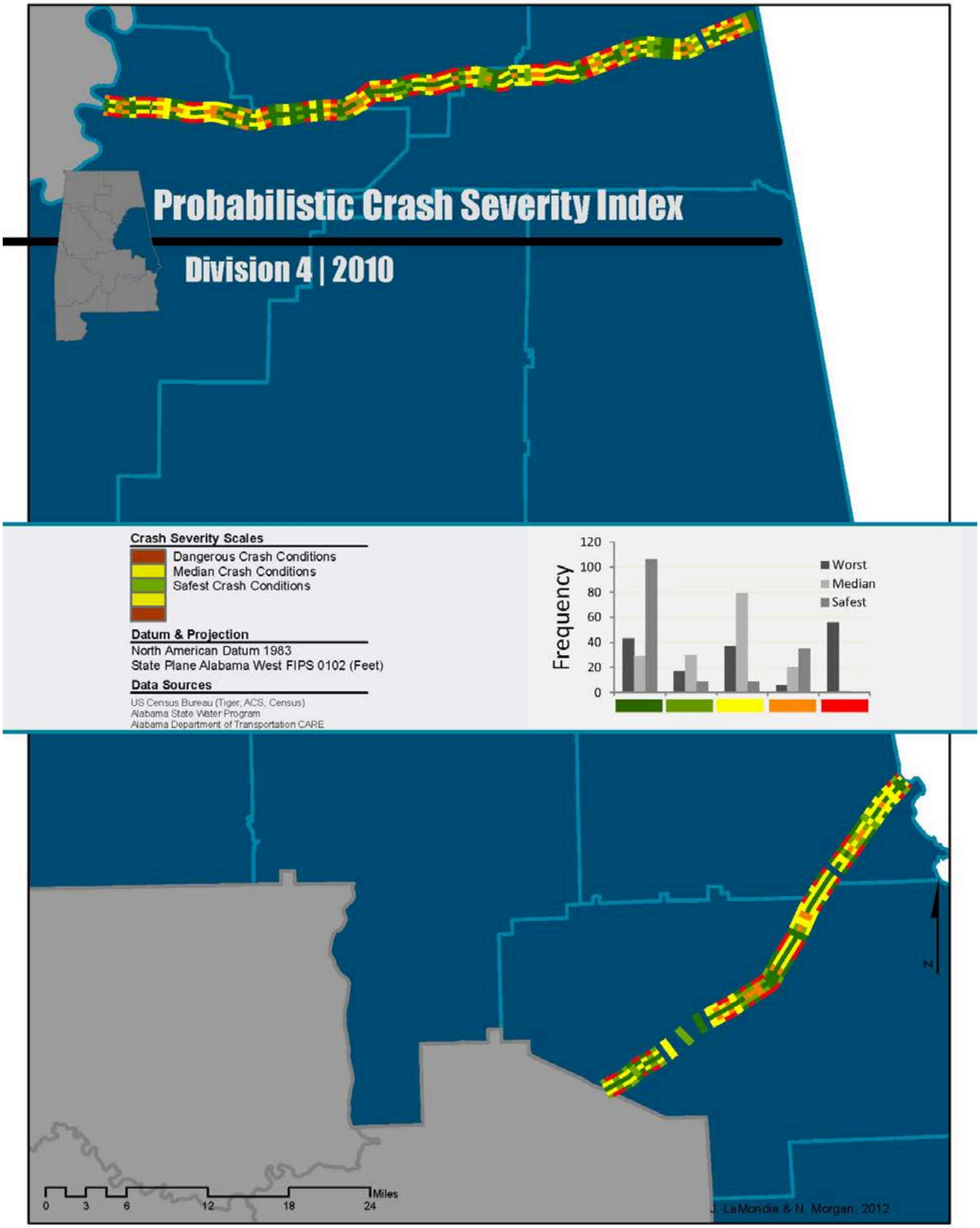


**Figure 8.15. Division 4: Probabilistic Crash Severity Index 2010.**

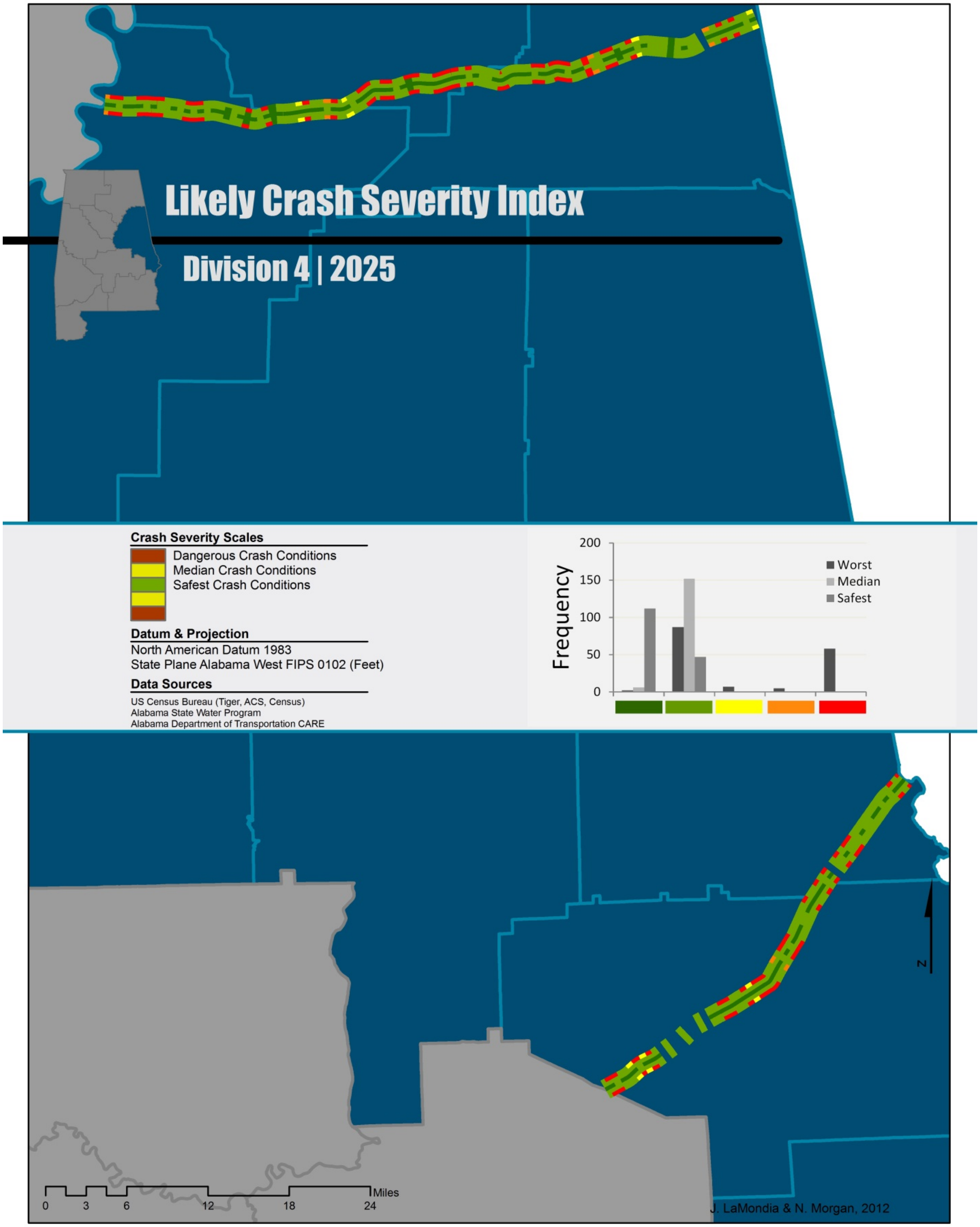


**Figure 8.16. Division 4: Likely Crash Severity Index 2025.**

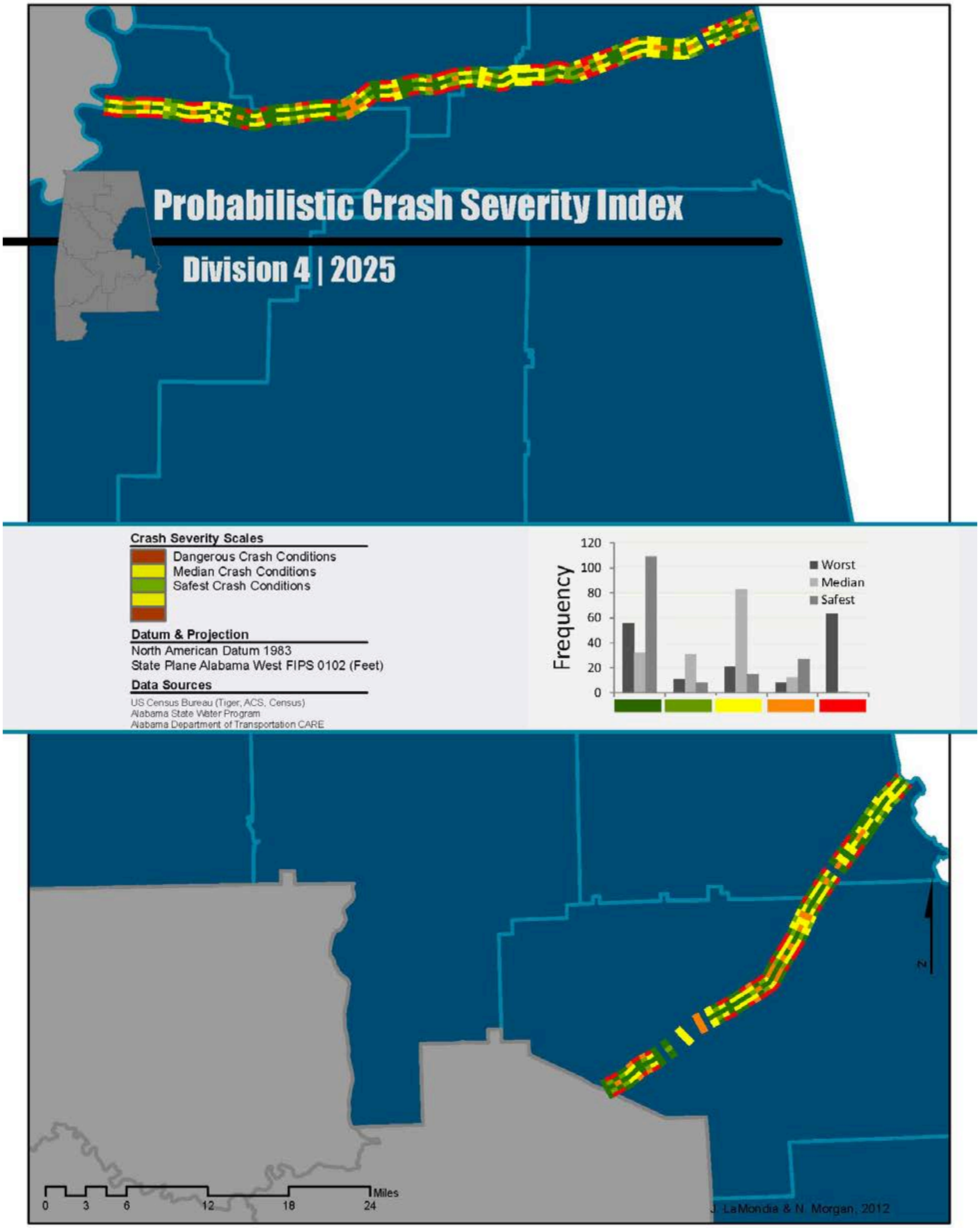


**Figure 8.17. Division 4: Probabilistic Crash Severity Index 2025.**

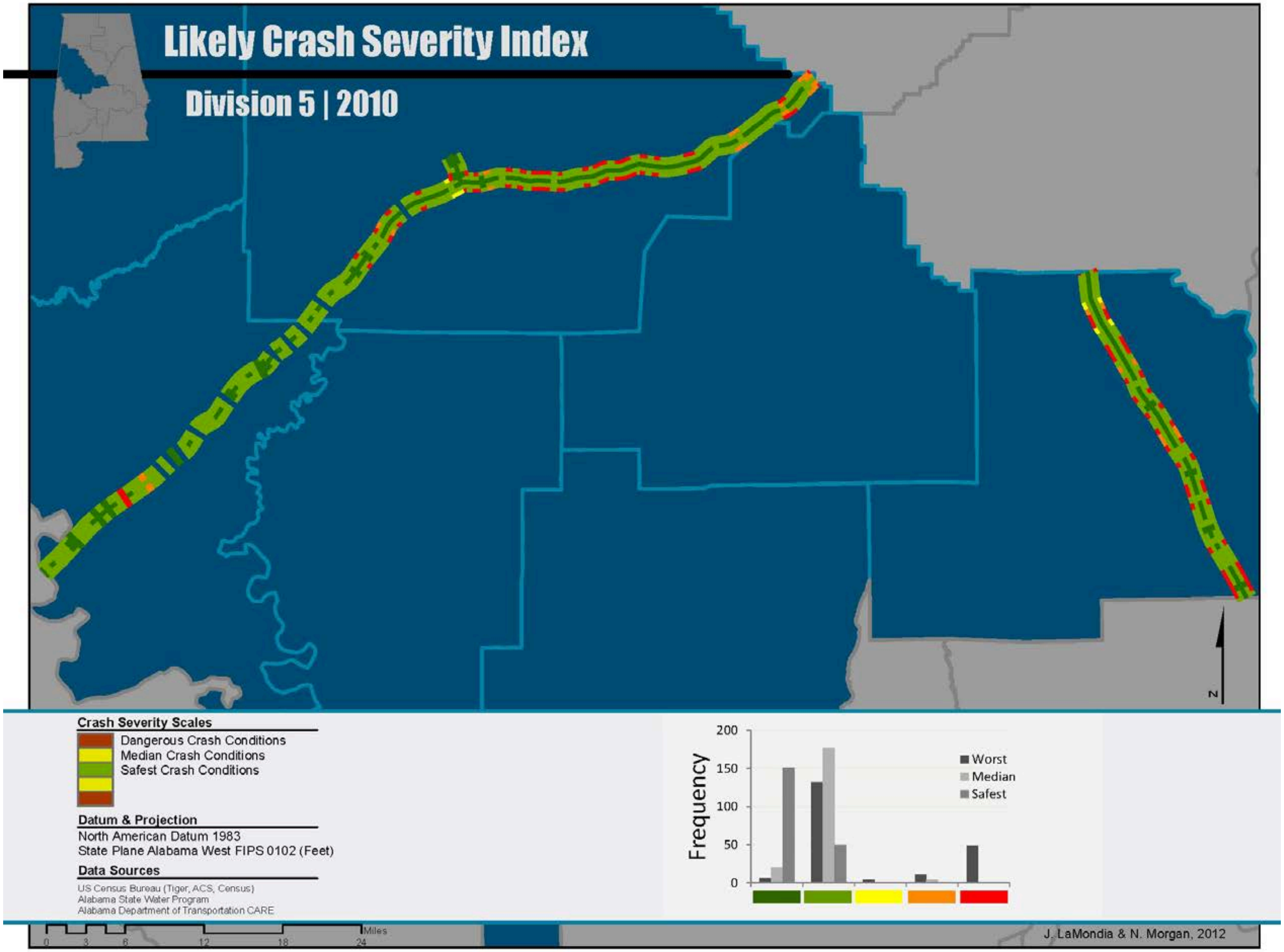


**Figure 8.18. Division 5: Likely Crash Severity Index 2010.**

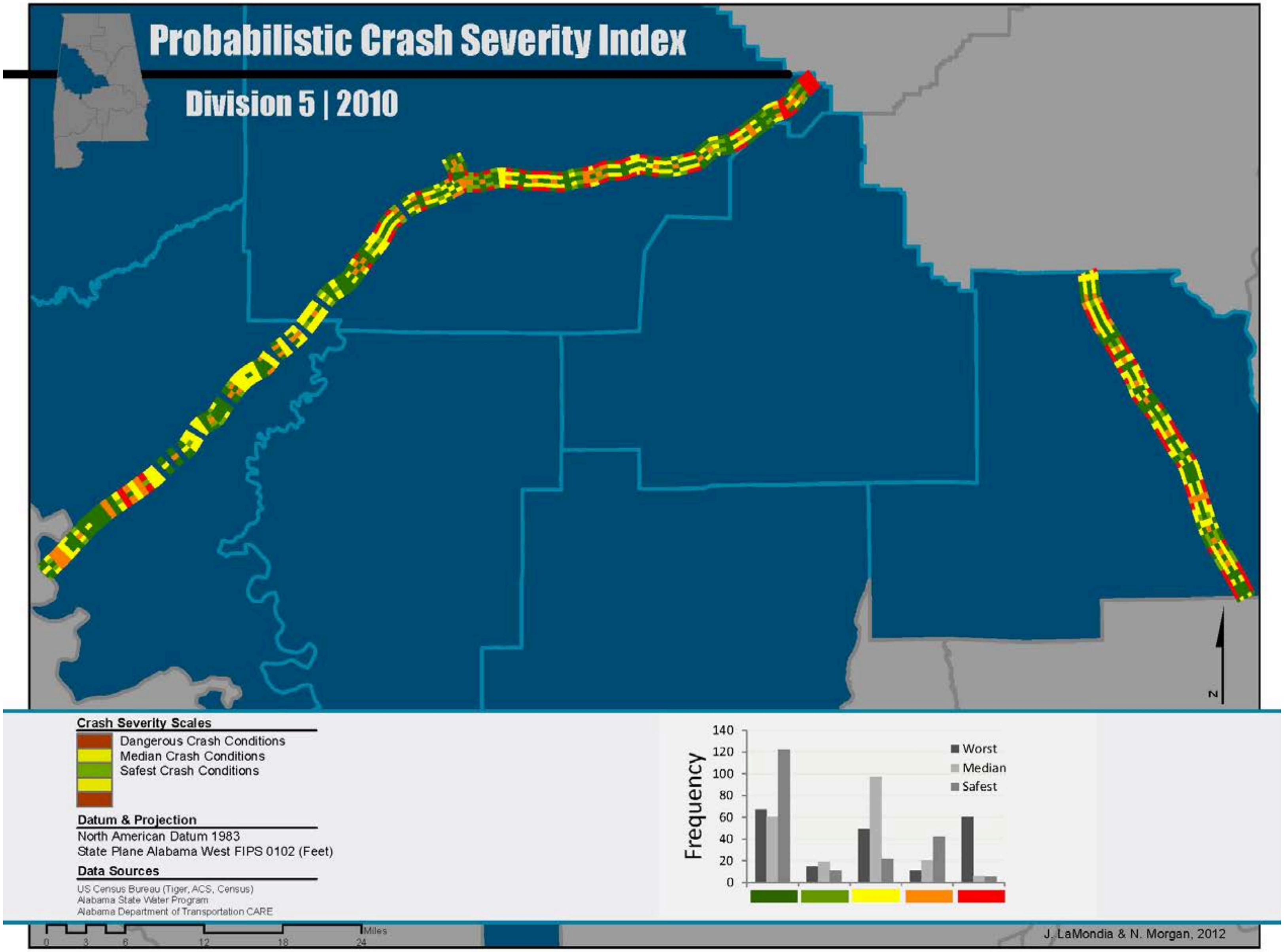


Figure 8.19. Division 5: Probabilistic Crash Severity Index 2010.

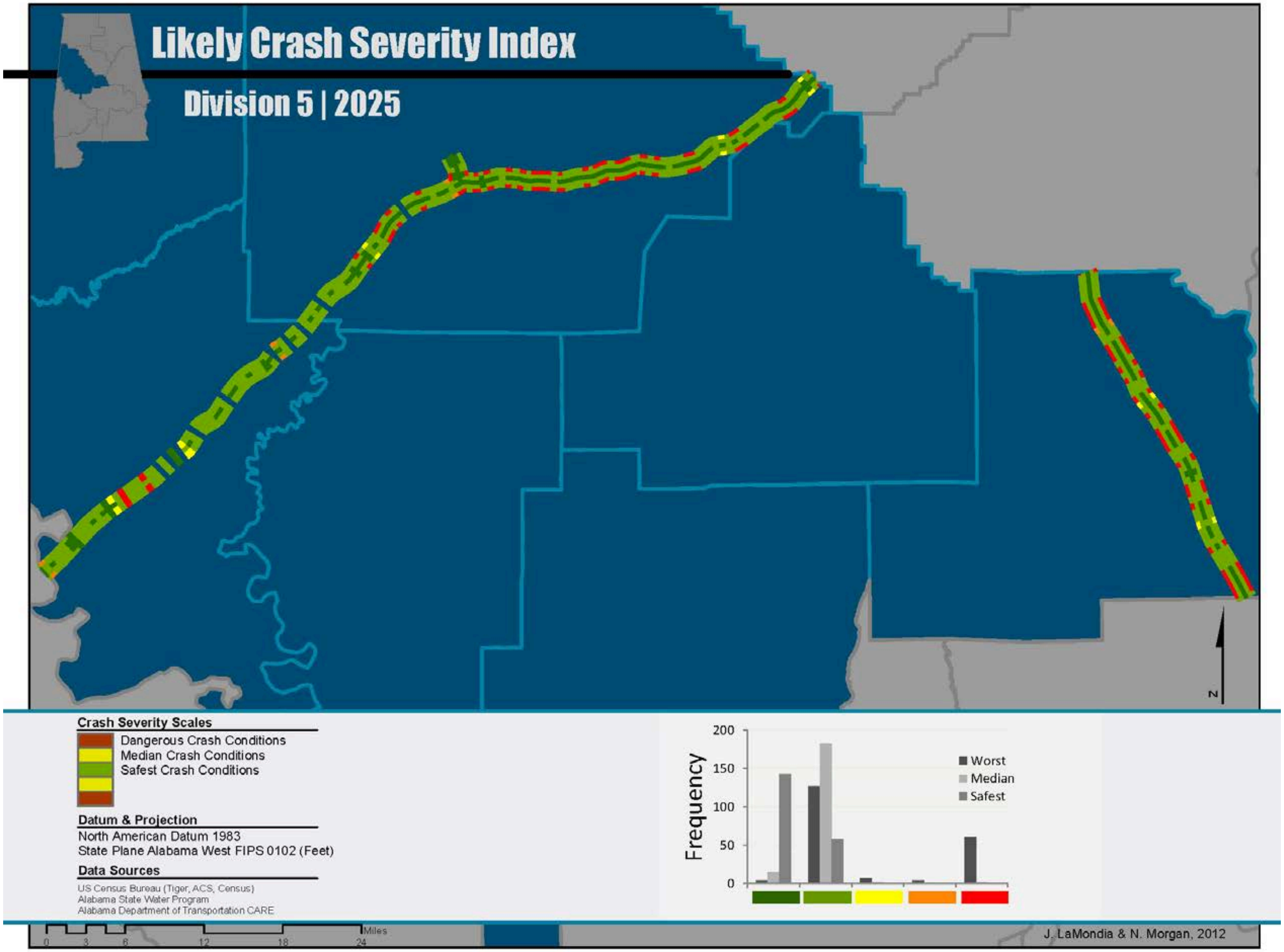


**Figure 8.20. Division 5: Likely Crash Severity Index 2025.**

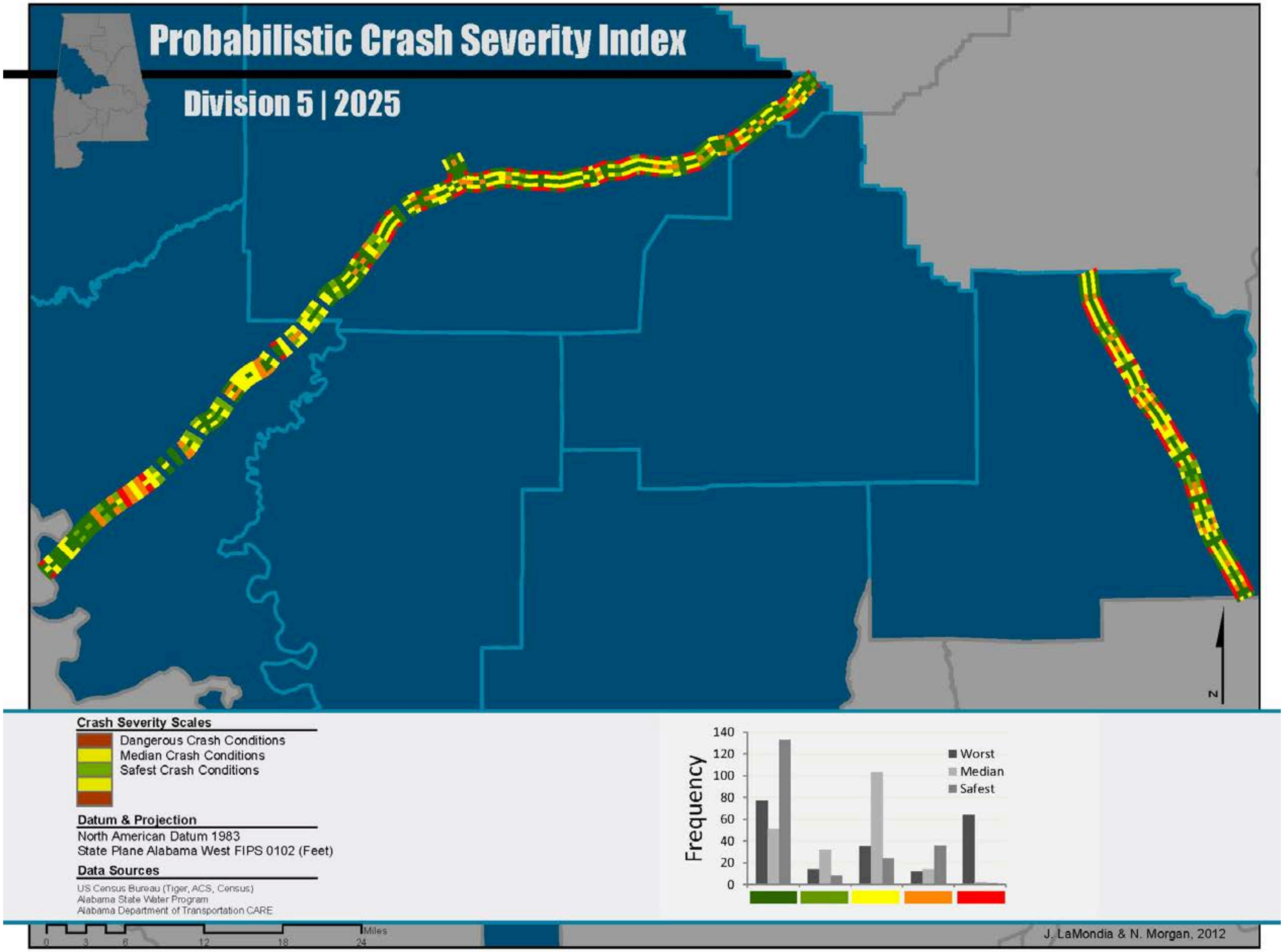


**Figure 8.21. Division 5: Probabilistic Crash Severity Index 2025.**

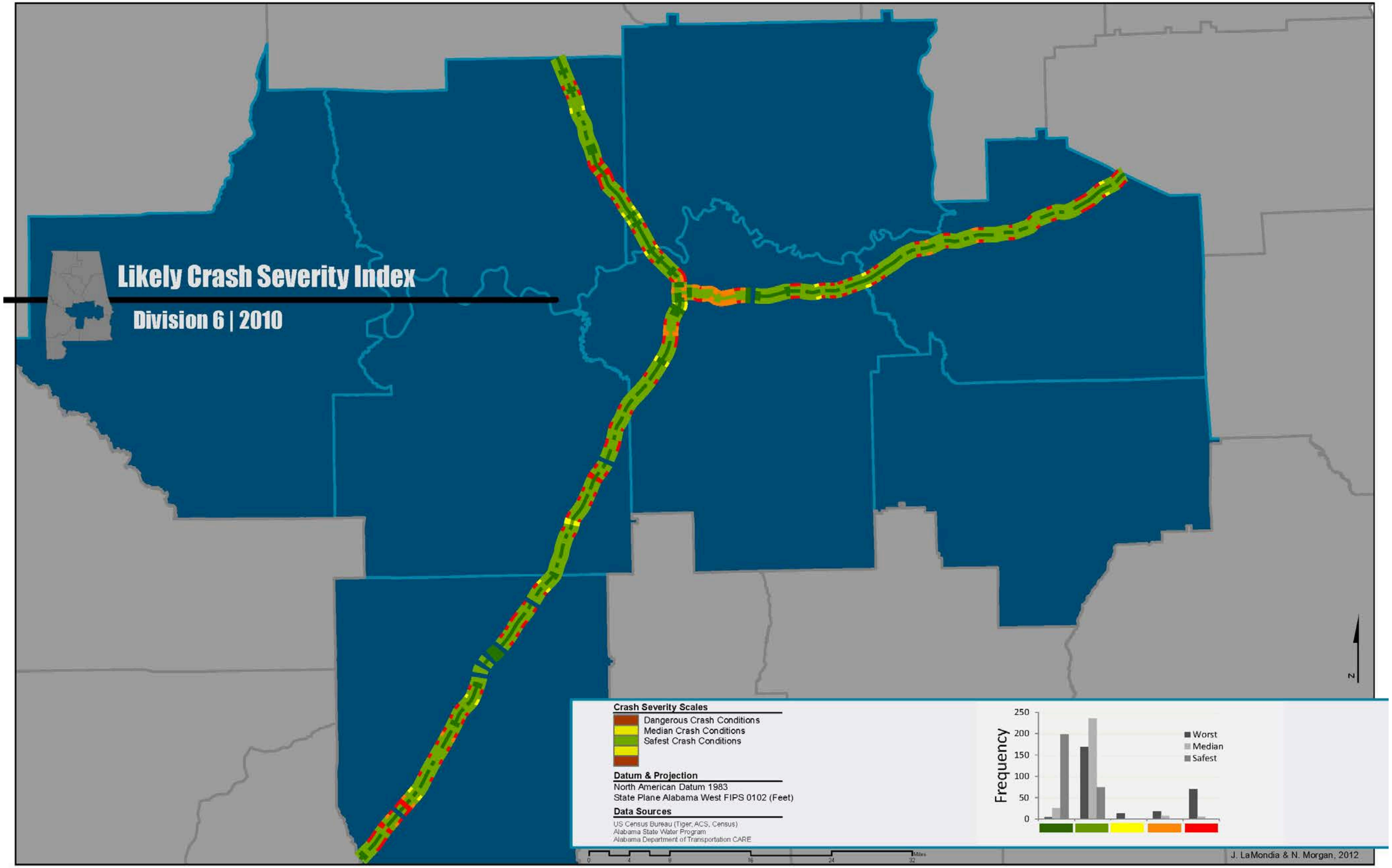


**Figure 8.22. Division 6: Likely Crash Severity Index 2010.**

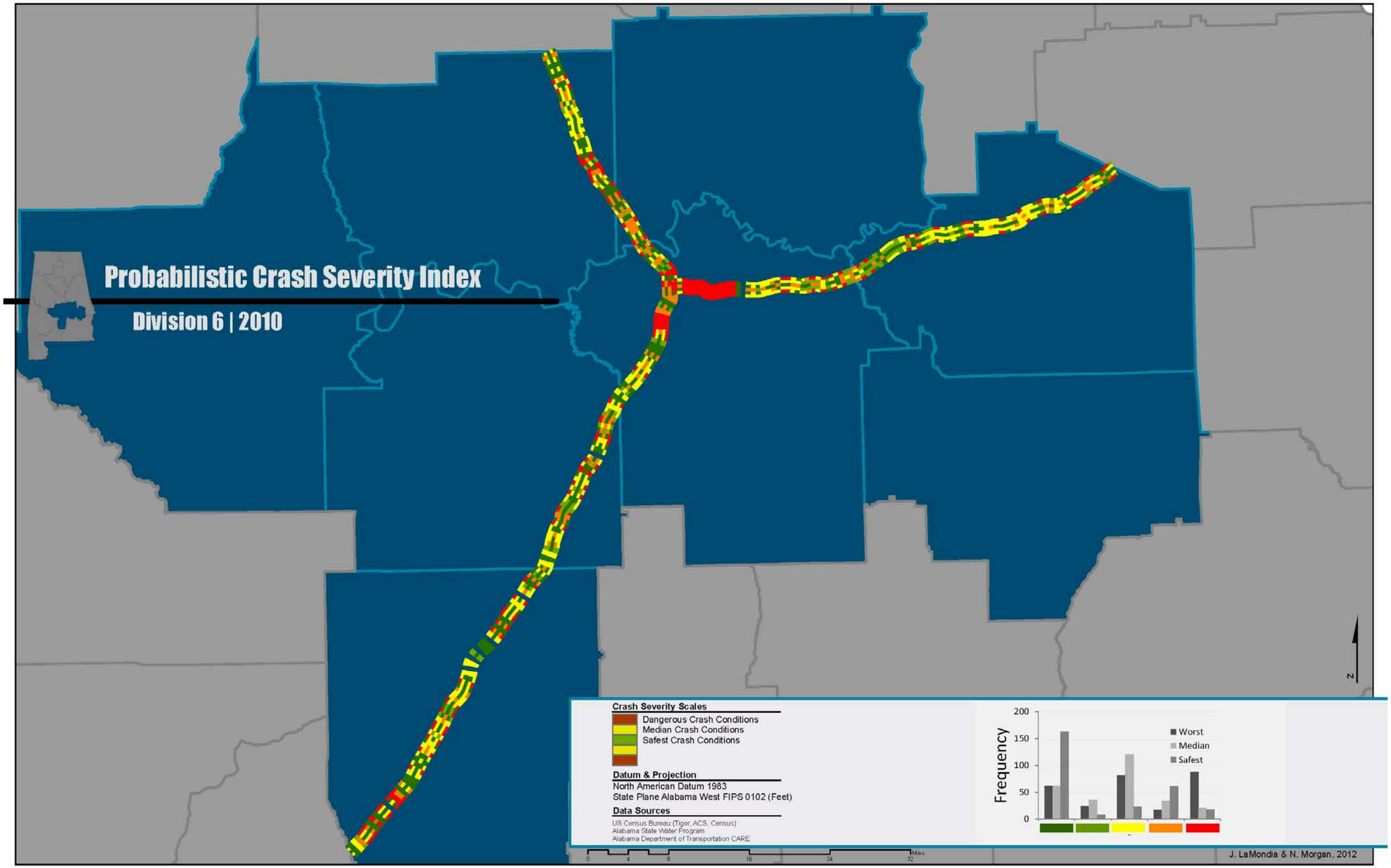


**Figure 8.23. Division 6: Probabilistic Crash Severity Index 2010.**

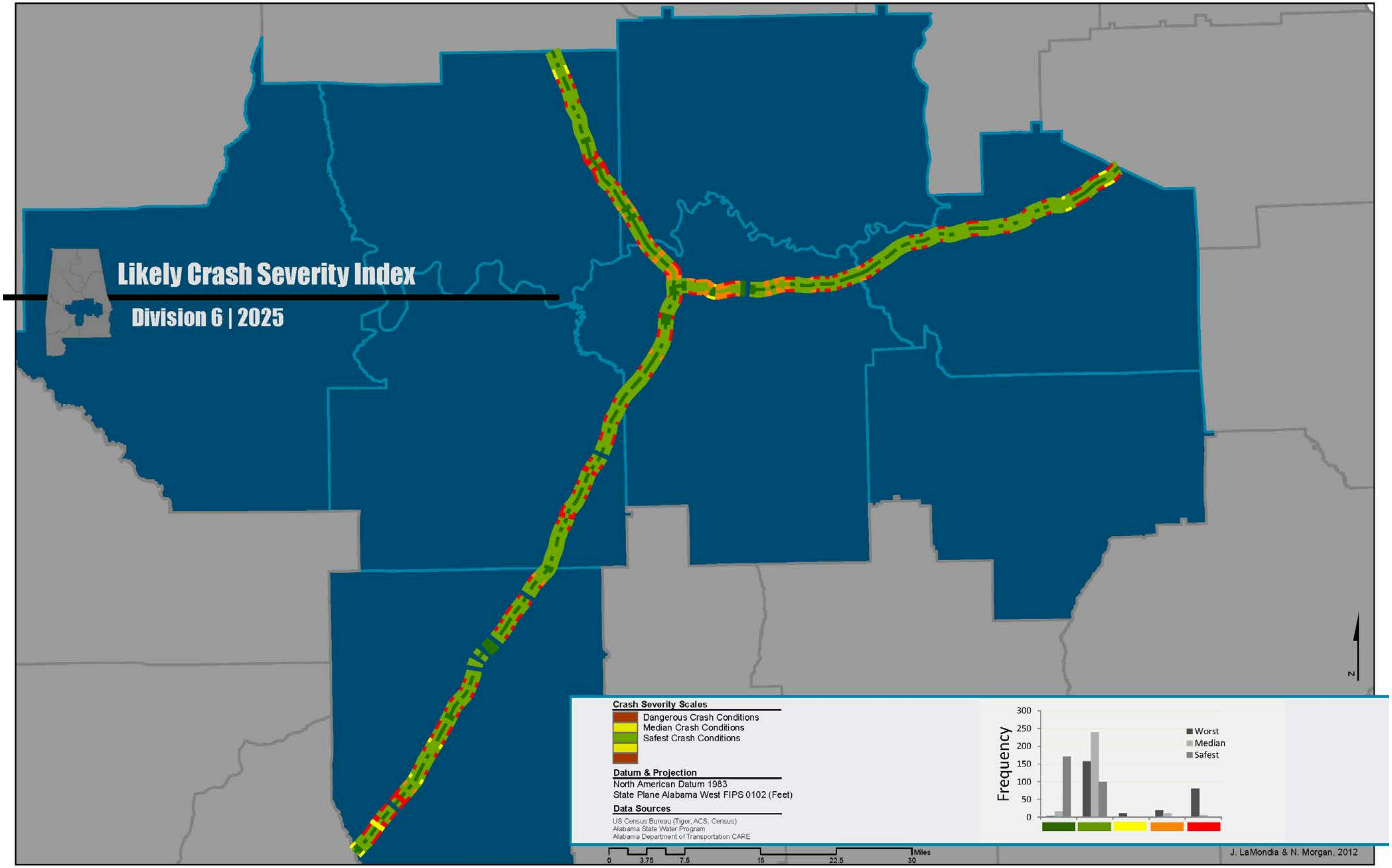


**Figure 8.24. Division 6: Likely Crash Severity Index 2025.**

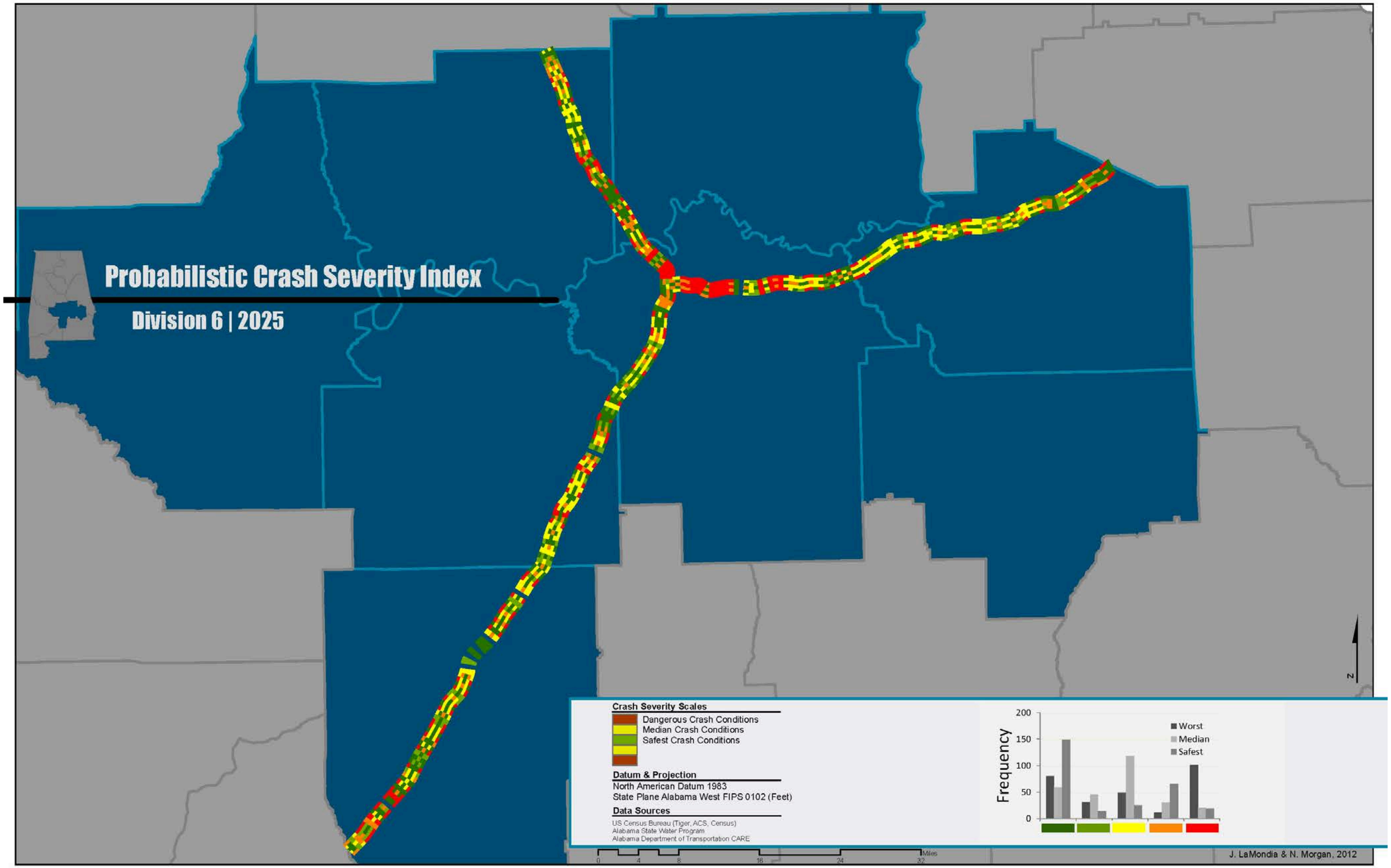


Figure 8.25. Division 6: Probabilistic Crash Severity Index 2025.

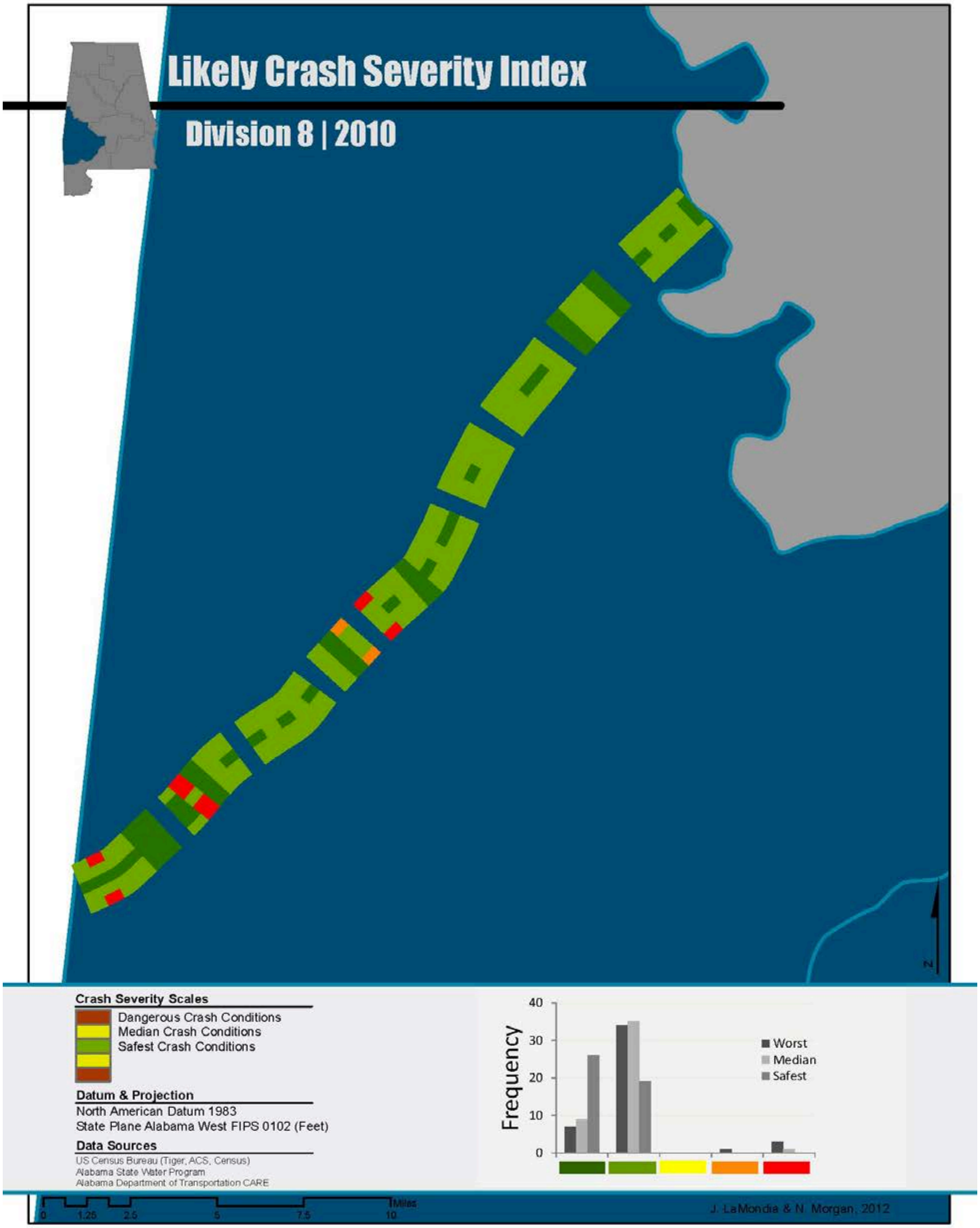


**Figure 8.26. Division 8: Likely Crash Severity Index 2010.**

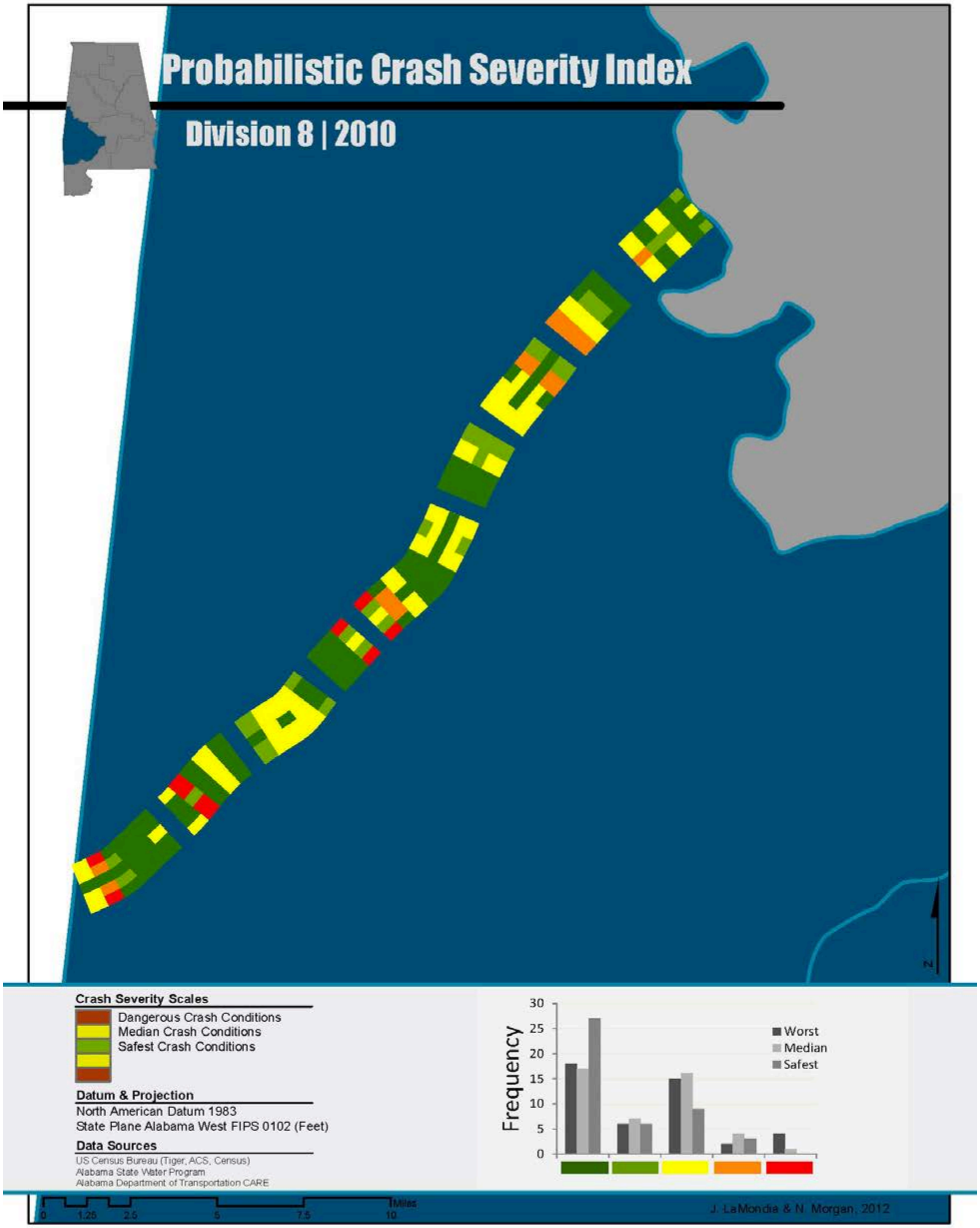


**Figure 8.27. Division 8: Probabilistic Crash Severity Index 2010.**

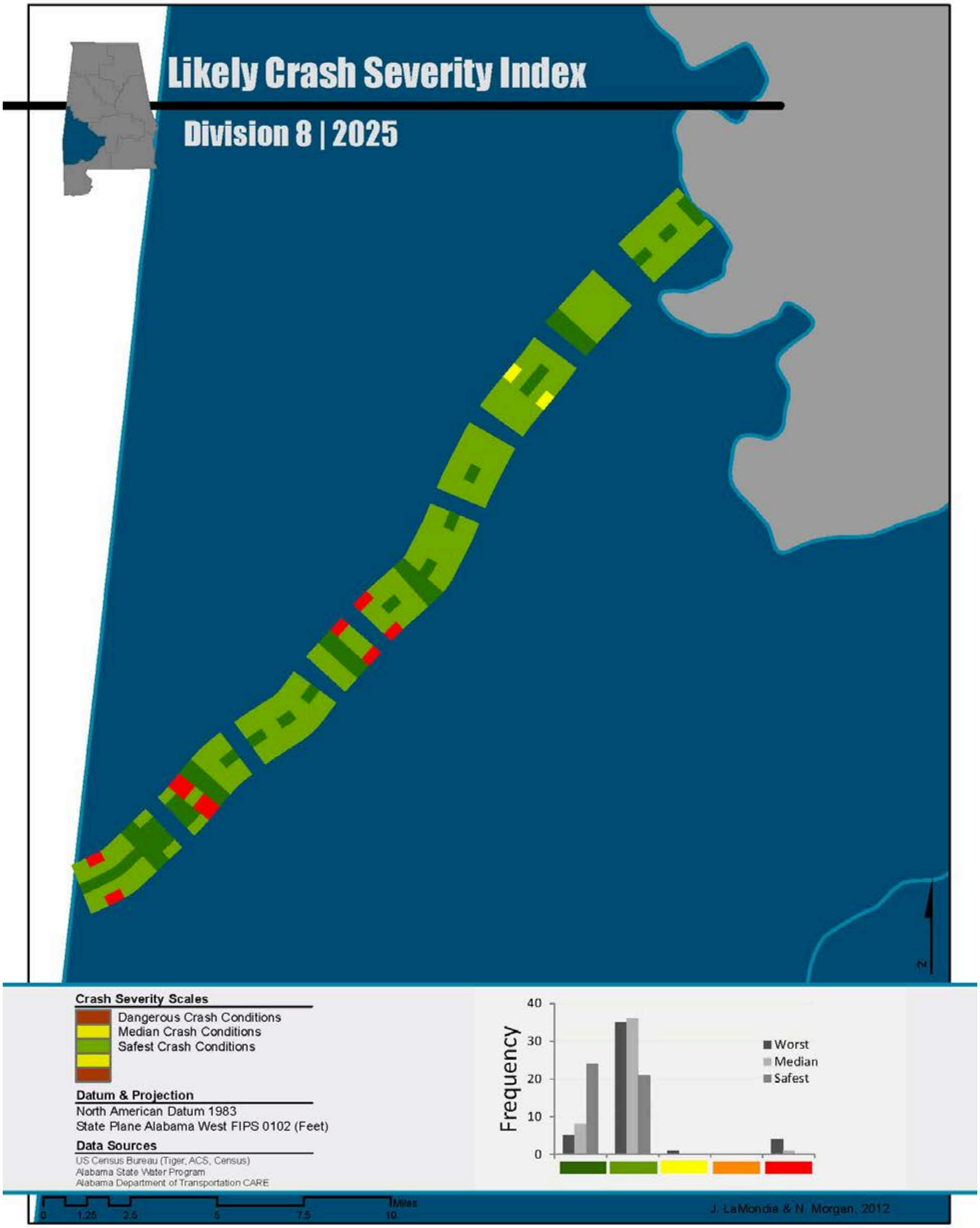


**Figure 8.28. Division 8: Likely Crash Severity Index 2025.**

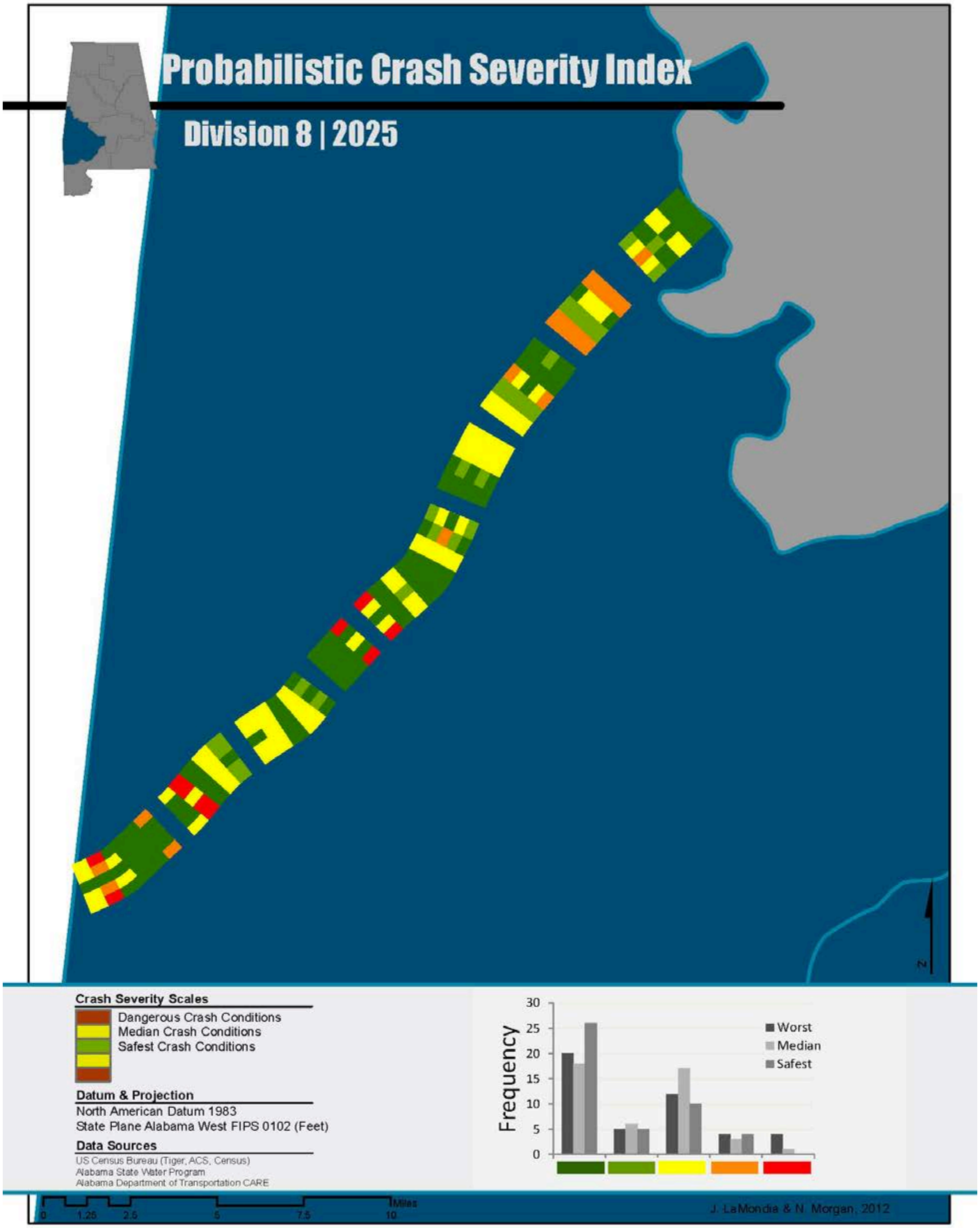


**Figure 8.29. Division 8: Probabilistic Crash Severity Index 2025.**

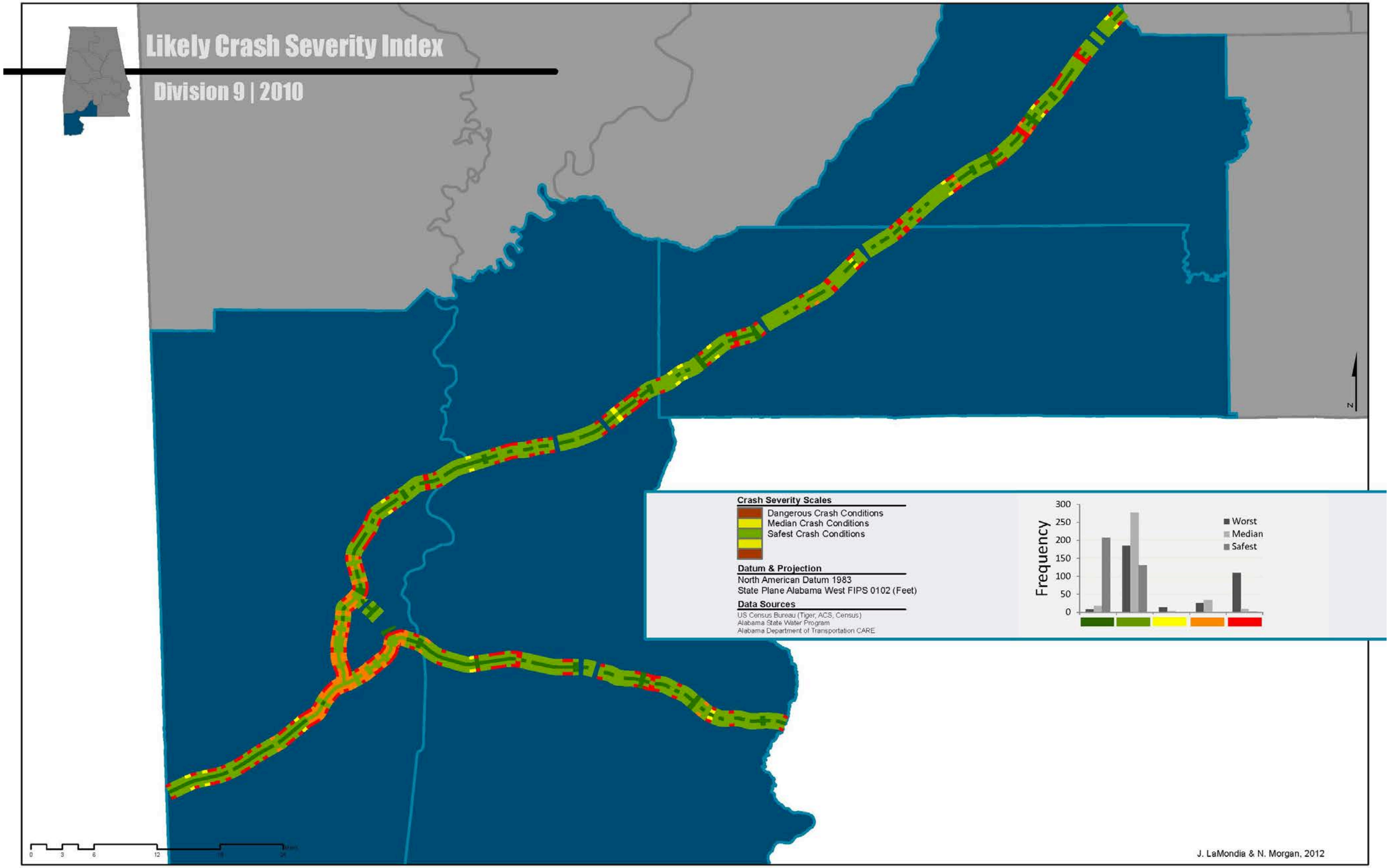


**Figure 8.30. Division 9: Likely Crash Severity Index 2010.**

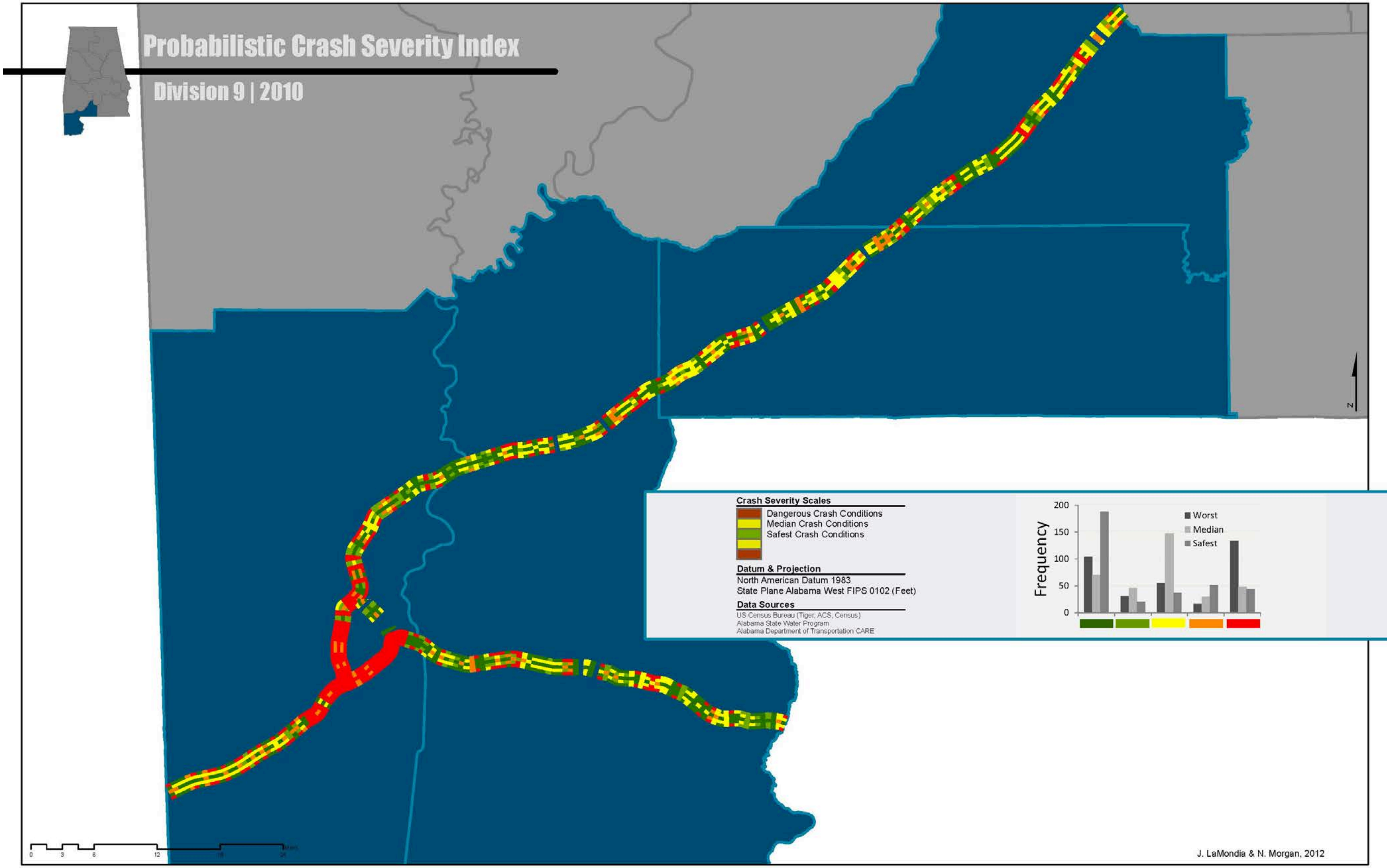


**Figure 8.31. Division 9: Probabilistic Crash Severity Index 2010.**

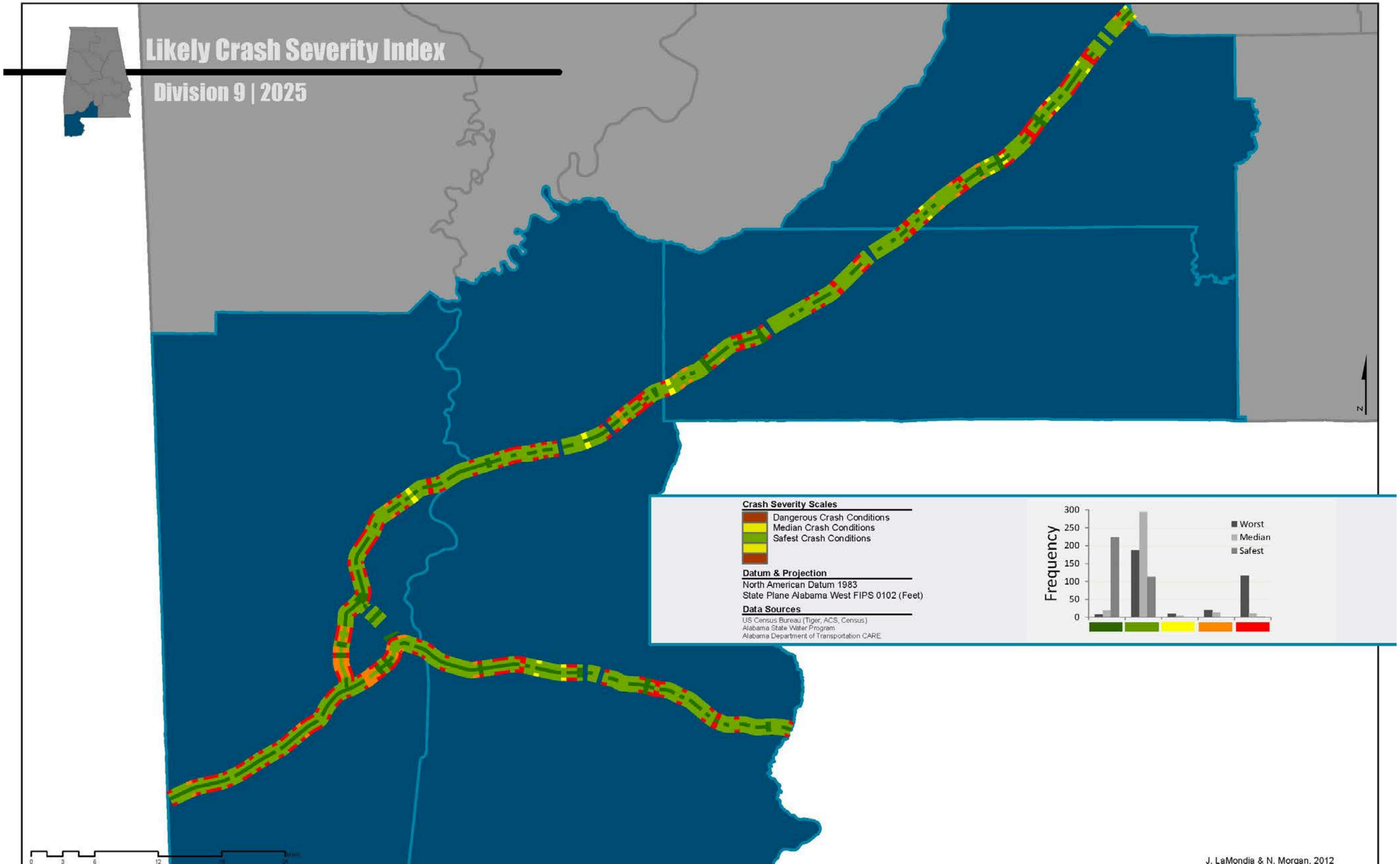


**Figure 8.32. Division 9: Likely Crash Severity Index 2025.**

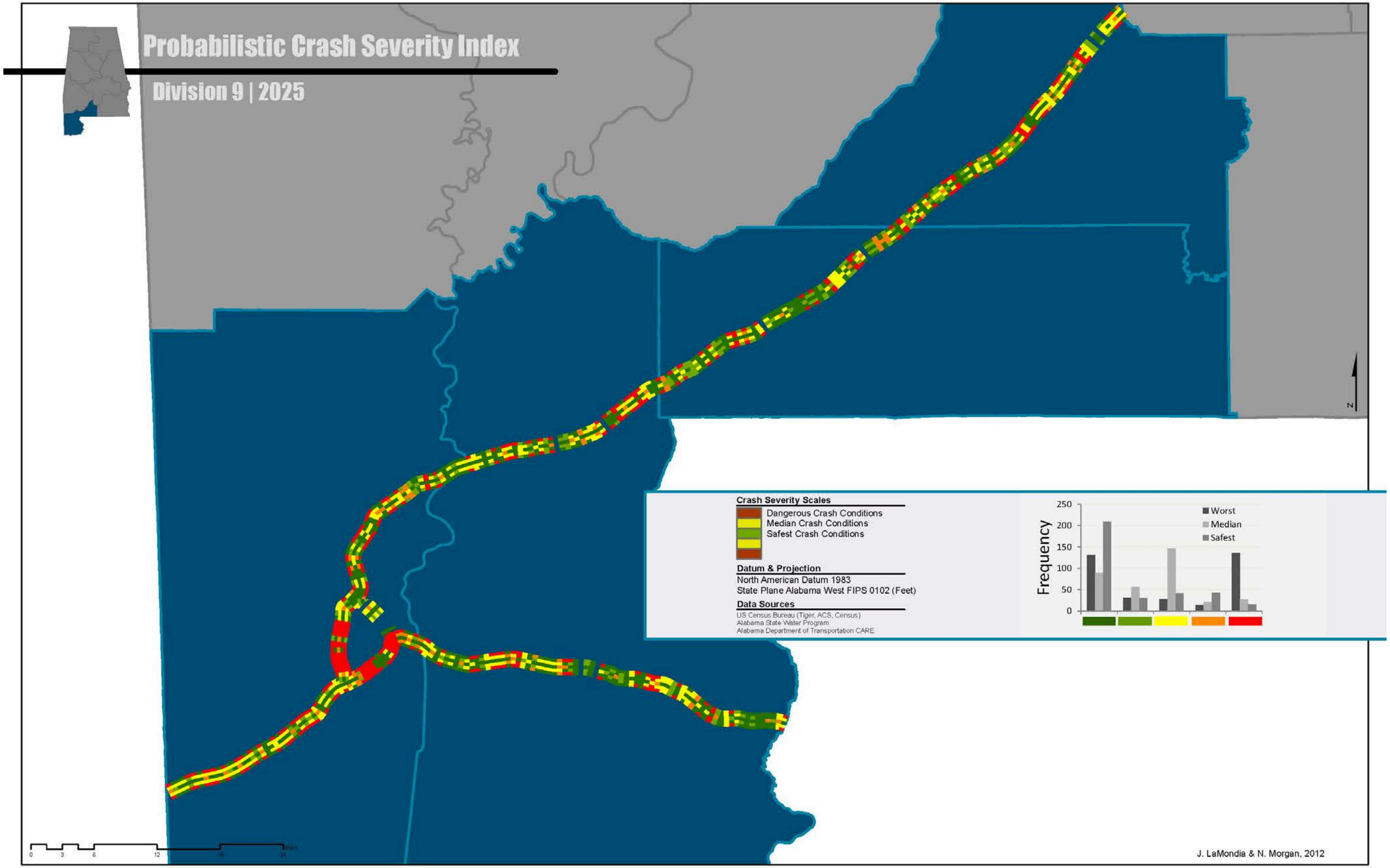


**Figure 8.33. Division 9: Probabilistic Crash Severity Index 2025.**

# 9. SUMMARY AND CONCLUSIONS

The goal of this research was to develop highway performance measures that could be used to prioritize safety improvement projects by utilizing results from predicted crash frequency and crash severity for roadways the state of Alabama. The models derived from collected crash specific, roadway infrastructure, spatially related socio-economic and demographic, and roadway demand data and analysis of the derived performance measures suggest that the results of this research can be used as a practical and integral tool for all persons working in the roadway safety realm.

Data from various sources, including the Alabama eCrash survey, the American Community Survey, US Census, Alabama State Water Program, and Alabama Department of Transportation, were used to formulate comprehensive models for crash frequency and crash severity using an ordered probit statistical model. The multifaceted, comprehensive set of factors used in the two models is unique in that it is one of the first of such studies to incorporate the effect all of the factors simultaneously. Previous research has sought to model some, or all, of the different factor categories independently, but few have ever attempted an approach that assesses the combined effect that these categories have on crash frequency or severity together. In this way, the research presented attempted to model the true, underlying factors associated with crash frequency and severity as would be encountered in the built environment by roadway users. The research also implemented a novel approach at modeling crash frequency by using an ordered probit model, which has seldom been used in previous crash frequency studies, although frequently applied in crash severity studies. Using the same statistical model for crash frequency and crash severity introduces a less confusing approach to joint modeling of both studies, and will reduce the computational time required for roadway safety practitioners to develop, manipulate, and update both studies. The single statistical model approach also significantly increases ease of interpretation of results, since the same inferential logic can be applied to results for both the crash frequency and crash severity models.

Growth trends for applicable demographic and roadway demand factors from both models were computed and forecast for a horizon year of 2025. The resultant data was used to predict crash frequency and crash severity for Alabama interstate roadway segments fifteen years into the future. Results from both the 2010 and 2025 analyses were applied in two different methodological approaches to derive current and forecast roadway safety performance measures, which can be used by pubic/private agencies to monitor and assess roadway safety performance at a segment-by-segment level. For ease of interpretation and increased transferability, the performance measures were converted into cartographic and graphic representations. The resulting maps give a clear, visual interpretation of roadway safety performance for interstate roadway segments for each of the eight applicable ALDOT divisions.

Results from the crash frequency study mirrored closely what previous researchers have found in terms of important and influential factors. Most notably, the results of this model show a distinct increase in crash frequency on a roadway segment due to the presence of an exit or interchange, or for an increase in average annual daily traffic; both relationships have been corroborated numerous times in past research. The crash frequency model also notes a distinct effect from spatially related data. Factors such as, percent of population over 60 years of age, percent of households that are family households, number of owner occupied housing units, and area of moderately developed land use, in surrounding developments, all represent statistically relevant factors effecting the average predicted crash frequency on roadway segments. These factors offer new insight into causal factors affecting crash frequency, since extensive work modeling factors at this scale has seldom been accomplished.

The crash severity model incorporated additional factor categories that were not relevant/applicable to the crash frequency study (crash specific factors such as driver and vehicle characteristics, etc.), while also still accounting for the factors present in the frequency model. As such, the crash severity model reported a higher number of statistically relevant variables. The most important characteristics to take away from this model had to do with driver behaviors and vehicle types. Factors such as, differential between posted and collision speed, driving under the influence of alcohol (for the causal vehicle) and driving under the influence of drugs (for the second vehicle, if applicable) showed distinct, often drastic, increases in the potential for being in a more severe crash. Also, the involvement of a commercial motor vehicle or motorcycle in a crash significantly increases the potential for being in a more severe crash. Of those two, the presence of a motorcycle, represented in both causal vehicle and second vehicle characteristics, displayed an alarmingly high potential to increase crash severity, which has been noted in previous crash severity research. There were also a number of spatially related factors significant in the crash severity model; roadway segments located in rural areas significantly increased crash severity. A large set of demographic variables related to nearest urban areas were also significant in this model; these included factors such as, percent of population under five years of age, percent of population between 15 and 24 years of age, median age of population, percent of population that is male, and the average commute time, all of which, except for average commute time, increased the likelihood of being in a more severe crash. These results definitively suggest a statistical importance for representing long distance spatially related demographic factors when assessing crash severity.

Modeling both crash frequency and severity using the same statistical structure allowed for the comparison and contrast of influential factors between the two, and also the ability to derive general conclusions about factors that possess a distinct detrimental influence on roadway safety and performance. Two factors were present in both models: presence of an exit or interchange, and area of moderately developed land use for a surrounding development. The most interesting thing presented by these two factors is the opposite effect that either has on crash frequency and severity. For crash frequency, presence of an exit or interchange has an increasing relationship, whereas for crash severity, the same factor presents a decreasing effect on crash severity. This presents an interesting conundrum for roadway safety practitioners, since clearly the presence of an exit or interchange has an effect on roadway performance, but could/should this be considered a beneficial effect (due to the reduction in overall crash severity)? Or a detrimental effect (due to the increase in crash frequency)? Such are questions that may need to be asked/assessed before the possible construction of new exits/interchanges. These questions also may invoke a moral perspective in roadway safety performance analysis and assessment; can one morally improve crash severity while simultaneously increase the likelihood of users being in motor vehicle crashes? The same positive for frequency, yet negative for severity relationship was also present for area of moderately developed land use, and, again, the same question about the tradeoff between frequency and severity must be addressed; a sensitivity analysis to quantify the effect of presence of an exit/interchange and land use: moderately developed for crash frequency versus crash severity could help to elucidate the answer to the proposed roadway safety improvement morality question  proposed above. It was also very interesting to find distinctly different statistically significant scales for spatially related factors between the two models; the crash frequency model was highly influenced by local, surrounding development characteristics, while the crash severity model was highly influenced by more long distance, nearest urban area characteristics. This lends to the notion that overall roadway safety and performance is tied to both spatial scales, however, contributing circumstances may be exclusive to one scale or the other depending upon which type of study is being performed.

One of the most interesting things to take away from both models is the apparent lack of traditionally relevant roadway infrastructure variables for both crash frequency and crash severity. Factors such as, presence of curvature or grade, width of medians, shoulders, etc., and pavement types, to name a few, are commonly noted as significant variables in crash frequency and crash severity studies. However, in both studies in this research, predominantly for the crash frequency study, such roadway infrastructure factors were not found to be relevant. As mentioned in the results section, the lack of roadway infrastructure factors could likely be due to stringent, widespread roadway design standards in the state of Alabama, or for the Interstate roadway system in general, which might help to diminish the effect of these factors. It is also possible that, with respect to the other factor categories assessed, since the models presented in this research are comprehensive in nature, roadway infrastructure factors do not play an overly significant role. The results are somewhat troubling in terms of potential roadway safety improvements, since the bulk of possible improvements available to roadway safety agencies and practitioners reside in the roadway infrastructure realm. However, in regard to crash severity, there were still some roadway infrastructure factors present (posted speed limits, painted line lane separations, a functioning roadway traffic control device, if applicable) that could be considered when formulating/proposing roadway infrastructure safety improvements. There are also a number of driver behavior and traffic composition related factors that could be improved through public awareness and driver training, which roadway safety practitioners may find invaluable for improving roadway safety performance into the future.

Cartographically and graphically representing the roadway performance measures introduced a more comprehensive analysis of overall roadway safety performance, especially with respect to neighboring roadway segments. There was a distinct difference in results between the likely crash severity index and probabilistic crash severity performance measures, which can be directly contributed to the inclusion of a probability, or likelihood, factor in the probabilistic crash severity index calculations. One thing that stood out from the performance measure maps was that roadway segments running into or through highly developed urban areas tended to be significantly less safe than those in more rural areas; perhaps this is related to a profound increase in crash frequency in these areas, which, likewise, may be attributed to an increase in roadway demand. It was also interesting to note clustering of similar level roadway performance values, many of the divisions showed clusters of very safe or fairly unsafe segments of roadways. The clustering of unsafe segments could allow roadway safety practitioners the ability to narrowly focus in on certain areas, and designate an entire ‘group’ of sections as a high priority roadway safety environment. It is also worth noting that overall roadway safety performance declined for roadway segments from 2010 to the forecast year of 2025. Since the forecast measures reflect differences in demographic and traffic demand related factors, roadway safety practitioners have insight into which groups of demographics are more ‘at risk,’ and they can then implement public awareness initiatives, or propose roadway safety improvements to areas that are expected to see a significant increase in said populations/factors.

One of the main limitations and concerns for implementing comprehensive roadway safety performance analyses is the transferability of such methodologies and techniques. Often when referring to transferability one is referencing data collection limitations and issues. To this end, the models used in this research, specifically the crash severity model, have fairly extensive sets of factors, which make them somewhat data intensive. This type of structure, and data dependence, is applicable for Interstate roadways since comprehensive and extensive data is often readily available, which may not be the case for smaller roadways such as state/local highways or local rural roads. However, given the relative ease of implementation of the ordered probit model, a more generalized form of crash severity model could easily be attained. Such models could seek to omit certain factors if they were not available. Luckily, for the spatially related factors, extensive data from the American Community Survey and US Census are readily available, and can often be found at very fine scales, such as census tracts or census block groups. Corroboration with local law enforcement, in order to generate a set standard for reporting practices, also could easily facilitate the immediate transferability and/or generalization of the methods presented in this research. Likewise, cartographic representations of roadway performance measures can easily be transferred in physical or electronic form to any agency or persons who could see benefit from their possession.

The models and results in this research could also be applied individually, or as a group. Different agencies could use different aspects of the research to assess different issues. For instance, Division 2 of ALDOT could use the crash frequency model to predict what the crash frequency will be on one of their roadway in five years, while Division 5 of ALDOT could use only a crash severity study to assess crash severity levels for a certain segment(s) of roadway, while ALDOT, as a whole, could also apply the entire study to all of its divisions. In this way, the applications for the research presented are numerous, and extensive. The dual application approach for the individual models (current and predictive) could be used by local agencies, state agencies, and/or consulting firms to assess the current state of roadway performance, crash frequency, and crash severity. These same models could then be used for countless forecasts, under varying expected conditions, to assess what roadway safety performance might be *x* years into the future. Therefore, these models, and the general research results, can be assessed on a nearly constant basis, while utilizing and incorporating up to date data as soon as it becomes available.

Although this research is a comprehensive approach to deriving roadway performance measures there were still some limitations and applications for future research. With regard to model specification and derivation, it is worthwhile to note that even in current practice not all of the inherent data and statistical modeling structure limitations can be accounted for at once. Items such as an omitted variable bias, lending to unobserved heterogeneity between segments/observations, spatial and temporal correlation, and low sample mean and/or size can all have an effect on the precision of crash frequency and crash severity model estimates. This research employed an exhaustive list of factors as an attempt to account for some of the omitted variable bias, however, it is difficult, if not impossible, to account for every possible causal factor present in the built environment. It is recommended that future research use the structure presented in this research, while including and even vaster array of factors, time and money, limitations notwithstanding, to *further account for potential omitted variable bias*. Future researchers might also find it useful to *implement spatial correlation factors* when deriving performance measures, since the cartographic results from this research showed clustering of similar levels of roadway performance on many occasions.

The main goal of this research was to develop cartographic files that would enable all types of roadway safety agencies and practitioners to quickly and easily assess the roadway safety performance of highways within their jurisdictions. On a practical standpoint, future researchers may find it valuable to *generalize the models* in order to facilitate the replication of these results on varying scales of roadway and design criteria. Simplified crash frequency or crash severity models could be applied where some of the more data intensive factors are omitted or unavailable, for example, detailed crash case specific factors may not be readily available to all agencies. Furthermore, some researchers may find it applicable to *reduce the overall scale* of the study from a statewide model to jurisdictional settings such as counties, metropolitan areas, or local cities/towns. This would enable individual jurisdictions to assess specific factors which may be exclusive only to their locations. It would also be possible for researchers to use the models derived in this research in a *planning type approach*, where certain factors, such as area of land use, traffic demand, populations, and presence of an exit or interchange, could be modified to see what their effect their augmentation would have on roadway safety performance. Similar methods could also be used to determine what the roadway performance, crash frequency, and crash severity would be for a new, proposed roadway by using average values for crashes on similar type roadways in conjunction with existing, proposed, or forecast values for roadway geometries, traffic demand, and spatially related factors. A relevant application for this type of study would be the proposed Interstate 22 connection from Birmingham, Alabama to Memphis, Tennessee.

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## APPENDIX 1

**Table A1.1. Crash Frequency Model Fit Statistics.**

| Metric | Value |
|---|---|
| Log-likelihood of Estimation | -1,289.1 |
| Log-likelihood of Thresholds only | -1,493.3 |
| Degrees of Freedom | 5 |
| Chi-Squared | 408.3 |
| Critical Chi-Squared (95% CI) | 12.83 |

**Table A1.2. Crash Severity Model Fit Statistics.**

| Metric | Value |
|---|---|
| Log-likelihood of Estimation | -20,741.1 |
| Log-likelihood of Thresholds only | -22,702.5 |
| Degrees of Freedom | 55 |
| Chi-Squared | 3,922.8 |
| Critical Chi-Squared (95% CI) | 77.38 |

**Table A1.3. Recommendations for Implementation.**

| |
|---|
| Adapt models for target roadway |
| Generalize model inputs for available data |
| Use as analytical and predictive approaches |
| Adjust model scale as necessary |
| Recalibrate for varying scenarios, as desired |

**Table A1.4. Recommendations for Future Research.**

| |
|---|
| Re-run models in other real world settings |
| Further analyze long distance travel characteristics |
| Further account for omitted variable bias |
| Include spatial/temporal correlation factor(s) |
| Utilize recent/updated data as available |

**Table A1.5. Crash Frequency Probit Results: Per Crash Severity Level.**

| | Major Not Disabling | | Major and Disabling | | Possible Injury [Not 100% Injured] | | Possible Injury [100% Injured] | | Non-Incapacitating Injury [Not 100% Injured] | | Non-Incapacitating Injury [100% Injured] | | Incapacitating Injury [Not 100% Injured] | | Incapacitating Injury [100% Injured] | | Fatal Crash | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Frequency[0-6] Crash/Year | | Frequency[0-4] Crash/Year | | Frequency[0-1] Crash/Year | | Frequency[0-1] Crash/Year | | Frequency[0-1] Crash/Year | | Frequency[0-1] Crash/Year | | Frequency[0-1] Crash/Year | | Frequency[0-1] Crash/Year | | Frequency[0-1] Crash/Year | |
| | Coeff. | Sig. | Coeff. | Sig. | Coeff. | Sig. | Coeff. | Sig. | Coeff. | Sig. | Coeff. | Sig. | Coeff. | Sig. | Coeff. | Sig. | Coeff. | Sig. |
| **Roadway Infrastructure Characteristics** | | | | | | | | | | | | | | | | | | |
| Width of Left-hand Shoulder (feet) | — | — | — | — | — | — | — | — | — | — | — | — | -0.043 | 0.000 | — | — | — | — |
| Guardrail Length on Left (feet) | — | — | — | — | — | — | — | — | — | — | — | — | — | — | — | — | 0.882 | 0.008 |
| Bridge Length (miles) | — | — | — | — | — | — | — | — | — | — | — | — | — | — | — | — | -1.618 | 0.029 |
| Roadway Material was Concrete | — | — | — | — | -0.765 | 0.020 | — | — | — | — | — | — | — | — | — | — | — | — |
| Roadway Material was Asphalt | — | — | — | — | -0.789 | 0.015 | — | — | — | — | — | — | — | — | — | — | — | — |
| Presence of Bridge Protector | — | — | — | — | — | — | — | — | -0.267 | 0.027 | — | — | — | — | — | — | — | — |
| Presence of Exit/Interchange | 0.249 | 0.001 | 0.269 | 0.001 | 0.278 | 0.001 | — | — | — | — | — | — | — | — | — | — | — | — |
| **Surrounding Development Characteristics** | | | | | | | | | | | | | | | | | | |
| Population Under 5 Years (1000's of persons) | — | — | -1.184 | 0.000 | — | — | — | — | — | — | — | — | — | — | — | — | — | — |
| Population between 25 and 59 Years (1000's of persons) | — | — | — | — | — | — | — | — | — | — | — | — | -0.159 | 0.000 | — | — | — | — |
| Percent of Population between 25 and 59 Years (%) | — | — | — | — | — | — | — | — | — | — | -0.139 | 0.003 | — | — | — | — | — | — |
| Percent of Population Under 9th Grade Education (%) | — | — | — | — | — | — | — | — | — | — | — | — | — | — | — | — | -0.019 | 0.049 |
| Percent of Population Under 12th Grade Education (%) | — | — | — | — | — | — | 0.022 | 0.003 | — | — | — | — | — | — | — | — | — | — |
| Percent of Population Graduated High School (%) | — | — | — | — | 0.044 | 0.000 | — | — | — | — | — | — | — | — | — | — | — | — |
| Family Households (1000's of households) | — | — | — | — | — | — | -0.811 | 0.001 | — | — | — | — | — | — | — | — | — | — |
| Percent of Households that are Family Households (%) | — | — | 0.025 | 0.000 | — | — | — | — | — | — | — | — | — | — | — | — | — | — |
| Owner Occupied Housing Units (1000's of housing units) | — | — | — | — | — | — | 1.017 | 0.000 | — | — | — | — | — | — | 0.315 | 0.040 | — | — |
| Median Household Income (1000's of dollars) | — | — | — | — | 0.015 | 0.001 | — | — | — | — | — | — | — | — | — | — | — | — |
| Blue Collar Jobs (1000's of jobs) | — | — | — | — | — | — | — | — | — | — | — | — | — | — | -0.328 | 0.003 | — | — |
| Land Use: Open Space [Undeveloped] (sq. miles) | — | — | — | — | — | — | — | — | — | — | 0.521 | 0.000 | — | — | — | — | — | — |
| Land Use: Moderate Development (sq. miles) | — | — | 0.768 | 0.000 | — | — | — | — | — | — | — | — | — | — | — | — | — | — |
| **Nearest Urban Area Characteristics** | | | | | | | | | | | | | | | | | | |
| Percent of Population between 5 and 14 Years (%) | — | — | — | — | 0.094 | 0.023 | — | — | — | — | — | — | — | — | — | — | — | — |
| Percent of Population between 15 and 24 Years (%) | — | — | — | — | 0.031 | 0.004 | — | — | — | — | — | — | — | — | — | — | — | — |
| Population under 9th Grade Education (1000's of persons) | — | — | — | — | -0.217 | 0.023 | — | — | — | — | — | — | — | — | — | — | — | — |
| Population with a College Degree (1000's of persons) | — | — | — | — | — | — | — | — | — | — | — | — | — | — | -0.012 | 0.008 | — | — |
| Average Household Size (persons) | — | — | — | — | -0.887 | 0.041 | — | — | — | — | — | — | — | — | — | — | — | — |
| Blue Collar Jobs (1000's of Jobs) | — | — | — | — | 0.032 | 0.016 | — | — | — | — | — | — | — | — | — | — | — | — |
| **Roadway Demand** | | | | | | | | | | | | | | | | | | |
| Average Annual Daily Traffic 2000 (1000's of vehicles) | 0.025 | 0.000 | 0.023 | 0.000 | 0.020 | 0.000 | 0.014 | 0.000 | 0.007 | 0.000 | 0.019 | 0.000 | 0.025 | 0.000 | 0.014 | 0.000 | — | — |
| **Threshold Values** | | | | | | | | | | | | | | | | | | |
| $\delta_1$ | -0.236 | 0.008 | 1.433 | 0.003 | 3.870 | 0.000 | 2.075 | 0.000 | 1.996 | 0.000 | 2.125 | 0.000 | 0.928 | 0.000 | 0.487 | 0.000 | 1.023 | 0.000 |
| $\delta_2$ | 2.627 | 0.000 | 4.649 | 0.000 | — | — | — | — | — | — | — | — | — | — | — | — | — | — |
| $\delta_3$ | 3.504 | 0.000 | 5.680 | 0.000 | — | — | — | — | — | — | — | — | — | — | — | — | — | — |
| $\delta_4$ | 3.866 | 0.000 | 6.470 | 0.000 | — | — | — | — | — | — | — | — | — | — | — | — | — | — |
| $\delta_5$ | 4.350 | 0.000 | — | — | — | — | — | — | — | — | — | — | — | — | — | — | — | — |
| $\delta_6$ | 4.968 | 0.000 | — | — | — | — | — | — | — | — | — | — | — | — | — | — | — | — |