Work Zone Crash Performance Data Measurement

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16. Abstract

The objective of this research was to utilize historical and archived crash data, maintained by TDOT, to closely analyze crash patterns in work zones, while considering crash, roadway geometry, environmental and several other characteristics and develop performance metrics for the work zones in Tennessee. The factors have important implications for education and training, traffic regulation and control, as well as planning and design of work zones safety measures. Identifying those factors and measures will ease the process of setting goals and actionable targets for the TDOT operations staff and manage their performance reporting process. This research determines, in close collaboration with TDOT, the appropriate set of measures for monitoring and evaluating Tennessee work zones performance in terms of safety, as well as for (monitoring and evaluating) the implemented strategies and the agency staff efficiency and awareness on safety issues.

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EXECUTIVE SUMMARY

Work zone safety is a major concern for Federal Highway Administration (FHWA), Departments of Transportation (DOTs), transportation industry, and the public. Work zones have significant impacts, both on traffic conditions, as well as on motorist and agency/contractor personnel safety. The growth of travel on the roadway system in the United States and recent adverse weather conditions has accelerated the deterioration of pavement, leading to constant pavement repairs and roadway rehabilitation. In the last three decades, the total lane miles available to meet the growing transportation demand have increased around 7.4% whereas the vehicles miles traveled (VMT) have increased by 86%. The presence of work zones on the roadway is hazardous to the motorists who drive through a complex arrangement of signs, barrels, and lane alterations, as well as for the work zone workers on the roadway. Roughly, more than 20,000 workers are injured in roadway construction work zone each year and 37,476 work zone related injuries were reported in in 2010, which equates to approximately four people injured every hour. Based on how severe a work zone crash can be, the associated fatalities, injuries and property damage, will lead in general to high costs, not to mention costs associated with damage in high value goods transported, and higher travel delays and relative cost impacts. TDOT has targeted the reduction of work zone crashes, at the administrative level, by incorporating it in the Individual Performance Plans of all operations staff.

The objective of this research is to utilize historical and archived crash data, maintained by TDOT, to closely analyze crash patterns in work zones, while considering crash, roadway geometry, environmental and several other characteristics and develop performance metrics for the work zones in Tennessee. The factors have important implications for education and training, traffic regulation and control, as well as planning and design of work zones safety measures. Identifying those factors and measures will ease the process of setting goals and actionable targets for the TDOT operations staff and manage their performance reporting process. This research determines, in close collaboration with TDOT, the appropriate set of measures for monitoring and evaluating Tennessee work zones performance in terms of safety, as well as for (monitoring and evaluating) the implemented strategies and the agency staff efficiency and awareness on safety issues.

The report is organized into eight sections. Section 1 outlines the introduction and background of work zone crashes and work zone performance measures that can accurately represent the effects of work zone crashes on the roadway facilities. Section 2 contains the Literature review related to some of the work zone crashes and performance measures studies done in the past. Section 3 contains the work zone crash data, work zone project data and roadway segment data collection procedure for all the 95 counties within Tennessee. Section 4 and 5 uses the data to present the methodology for the prediction of work zone crashes and calculation of appropriate set of performance measures and allowable targets for the Jurisdiction. Section 6 and 7 describes the results of the crash prediction and performance measures and allowable targets and section 8 concludes the report.

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1 INTRODUCTION

1.1 Background

Transportation in the U.S. is facilitated by well-developed road, air, rail, and water networks. A clear majority of the population travels by automobile for shorter and medium distances, along with a handful using this mode for long distances as well. Passenger transportation is dominated by personal vehicles that include cars, pickup trucks, vans, and motorcycles and some of the trips are handled by planes, trains, buses, walking, and biking. This predominant usage of the roadway system emphasizes the importance of proper planning, design, maintenance and rehabilitation of the highway network, making it more efficient, reliable and safer for road users. In this regard, Departments of Transportation of various states (and other agencies) must maintain the roads by proper standards and conditions. Government funding in the field of transportation exists at many levels. Federal funding for highway, rail, bus, and other forms of transportation is allocated by Congress for several years at a time. To sustain the aging U.S. roadway system, Federal and State government agencies have been allocating their funding on maintaining, expanding, and preserving the existing highway networks. As a result, road users often encounter an increasing number of work zones on the highways. Work zones have also significantly resulted in traffic safety problems. In the work zone areas, disruptions to regular traffic flow are inevitable due to partial closure of traffic lanes, poor traffic management within the work zone, general misunderstanding of the problems associated with work zones, and improper usage of traffic control devices. These kinds of disruptions often lead to work zone crashes and induce a heavy cost to transportation agencies as well as the users. The Moving Ahead for Progress (MAP-21) included a number of provisions emphasizing work zone safety for roadway and other work zone-related issues. The Federal Highway Administration (FHWA) and the American Association of State Highway and Transportation Officials (AASHTO) have played leading roles on this matter and have developed work zone safety guides and programs. Moreover, many state Departments of Transportation (DOTs) have been initiating research projects to improve work zone safety in their respective states.

Between 1982 and 2012, the total lane miles have hardly increased (7.4%), whereas vehicles miles traveled (VMT) grew by (86%) according to Bureau of Transportation

Statistics. According to FHWA ‘s Work Zone Injuries and Fatalities Facts and Statistics, VMT through work zones showed a similar growth pattern. The presence of work zones on the roadway is hazardous to the motorists who drive through a complex arrangement of signs, barrels, and lane alterations, as well as for the work zone workers on the roadway. According to FHWA facts and statistics, in 2013, 67,523 crashes occurring in work zones nationwide represent about 1.2% of all crashes. Approximately one quarter of work zone crashes resulted in injuries and less than 1 percent resulted in a fatality. Despite a trend towards fewer work zone crashes each year, the number of estimated work zone injuries was higher in 2013 compared to 2012. Specifically, 47,758 injuries were estimated to have occurred in work zone crashes during 2013. This equates to about 131 work zone injuries per day. Also, more than 20,000 workers are injured in road construction work zones each year, some of which are traffic related and some of which are limited to hazards within the construction activity area. Although these percentages may not seem alarming as numbers, the economic impact could be substantial. Based on how severe a work zone crash can be, the associated fatalities, injuries and property damage, will lead in general to high costs, not to mention costs associated with damage in high value goods transported, and increase in travel delays and relative cost impacts.

1.2 Problem Statement

TDOT has targeted the reduction of work zone crashes, at the administrative level, by incorporating it in the Individual Performance Plans of all operations staff. The objective of this research is to utilize historical and archived crash data, maintained by TDOT, to closely analyze crash patterns in work zones, while considering crash, roadway geometry, environmental and several other characteristics and develop performance metrics for Tennessee work zones. The factors have important implications for education and training, traffic regulation and control, as well as planning and design of work zones safety measures. Identifying those factors and measures will ease the process of setting goals and actionable targets for the TDOT operations staff and manage their performance reporting process.

Given the importance of work zone safety, and its unique traffic conditions with distinct traffic flow characteristics and environmental impact, research on work zone risk factors and crash prediction received special attentions (Bai et al., 2015; Bai and Li, 2007; Bourne et al., 2010; Carrick and Washburn, 2007; Chu et al., 2005). However, gaps exist in the past researches on efforts to precisely model and predict the causal factors and their corresponding economic consequences by work zone crashes. This study focuses on work zone crash prediction and development of performance measures at the County level to identify allowable targets of work zone crashes for decision makers to enforce. For the work zone crash prediction purpose, this study employs the most recently developed artificial intelligent techniques to perform pattern recognition and analysis of work zone crashes. The technique helps to: (1) identify the factors associated with work zone crashes, with a focus on system (non-behavioral) factors and determine predominant causal factors that essentially impact the overall performance of work zone safety, and (2) predict potential crash density at work zones, and the corresponding economic cost. Theoretically, modeling and predicting work zone crashes is a nonlinear multivariate prediction problem that involves multiple response and explanatory variables (Clark and Fontaine, 2015). Neural Networks (NN) have been widely and extensively used in pattern recognition and prediction where the true relationship between response and explanatory variables is unknown. Advantages of NN include: (1) no requirements on the pre-defined assumption of the underlying relationship between response and explanatory variables; (2) being insensitive to correlation between explanatory variables; and (3) capacity to model complex data environment such as mapping nonlinear multivariate to multivariate relationship. However, in the published traffic crash safety analysis literature, NN is criticized for being a black-box and over-fitting the training data (Clark and Fontaine, 2015).

In the field of prediction, new techniques are employed that advances NN paradigm to perform the following tasks: (1) open the black-box with a Neural Interpretation Diagram (NID) and graphically present Neural Network architecture with weight matrix such that the thickness of weight connections between neurons represents the strength of the connection; (2) use cross validation method and early stopping policy to determine the structure of a multi-layer perceptron Neural Network and overcome over-fitting problem; (3) use the Olden method (Akepati, 2010) to determine importance index or statistical significance of each explanatory variable; (4) use the Lek-profile method (Lek et al., 1996) to calculate the correlation between each response variable and explanatory variables.

1.3 Section Summary

The overall findings of this study are expected to help public agency and government officials to better understand the characteristics of work zone crashes, effectively prioritize work zone projects for budget allocation, financial programming, and to improve safety measures at work zones by reducing number of crashes, and lowering adverse social economic impacts caused by work zone crashes.

The report is organized into eight sections. Section 1 outlines the introduction and background of work zone crashes and work zone performance measures that can accurately represent the effects of work zone crashes on the roadway facilities. Section 2 contains the Literature review related to some of the work zone crashes and performance measures studies done in the past. Section 3 contains the work zone crash data, work zone project data and roadway segment data collection procedure for all the 95 counties within Tennessee. Section 4 and 5 uses the data to present the methodology for the prediction of work zone crashes and calculation of appropriate set of performance measures and allowable targets for the Jurisdiction. Section 6 and 7 describes the results of the crash prediction and performance measures and allowable targets and section 8 concludes the report.

2 LITERATURE REVIEW

This section presents a summary of the literature relevant to work zone crashes and performance measures. It is divided into three sub-sections namely: (1) work zone crashes and safety studies, (2) work zone performance measures studies, and (3) other work zone related studies.

2.1 Work Zone Crashes and Safety

There have been several studies on the topic of workzone crashes (ARTBA (2014); Bai et al. (2015); Clark and Fontaine (2015); Garber and Zhao (2002); Sun et al. (2014); Weng et al. (2014)). Garber and Zhao, (2002) conducted a study on characteristics of work zone crashes in Virginia occurring between 1996 and 1999. The main objectives of this study were to identify predominant locations within work zones where crashes occurred, to determine frequent types of crashes and distribution of severity at each location, and to study collision type and severity distribution with respect to different road types. In this study, the entire work zone was divided into different areas such as (i) warning area, (ii) transition area, (iii) longitudinal buffer area, (iv) activity area, and (v) termination area. All work zone crash locations were identified by careful examination of police accident reports, which included diagrams indicating locations of each crash within the work zone. Results showed that 70% of work zone crashes occurred in the activity area, which indicates the activity area is more susceptible to crashes regardless of the type of highway. For all crashes studied, Property Damage Only (PDO) crashes and rear-end collisions was more predominant in terms of crash severity and collision type. The clear majority (83%) of crashes occurring in the warning area were rear-end crashes; hitting a fixed object off the road was the second highest proportion of crashes accounting for 6% of overall work zone crashes. As one moves from the transition area to the work area, i.e., longitudinal buffer area and activity area, proportions of rear-end and sideswipe crashes decrease, and proportions of fixed-object and angle crashes increased. Clark and Fontaine (2015) also found the majority of the crashes occurred in the work area (combining the longitudinal buffer area and activity area), which was 44.7% of total work zone crashes. Weng et al. (2014) concluded that 39.1% and 16.6% of accidents occurred in the longitudinal buffer and activity areas, respectively. In another study by Sun et al. (2014), a different set of location categories was used: advance zone, taper zone, crossover zone, and bi-directional zone. Most of these crashes were found to have occurred in crossover and bi-directional (two-lane, two-way operation) zones.

Bai et al. (2015) compared the characteristics of fatal and injury work zone crashes that took place in Kansas for the period 1992-2004. The collected dataset was divided into six categories with each category consisting of different variables. These variable combinations were identified through statistical independence tests such as the Pearson Chi-Square test and the likelihood-ratio (LR) chi-square test. The study found that head-on collisions were the predominant type for fatal crashes (24%), and rear-end collisions were more predominant in injury crashes (46%). A large percent of fatal crashes involved trucks while most of injury crashes involved light-duty vehicles. Researchers also found that multiple-vehicle crashes and crashes occurring within the speed limit range of 51-60 mph were more predominant in both fatal and injury work zone crashes. Driver inattention was the leading cause for both fatal and injury work zone crashes. Results showed that 75% of fatal crashes and 66% of injury crashes involved male drivers, and those drivers aged 35 to 44 were involved in the highest percentage (24%) of fatal crashes among all age groups.

Ullman et al. (2011a) and Ullman et al. (2009) analyzed the effects of night work activity on crashes in two types of construction projects in Texas. The first project type involved both day and night work (hybrid project), whereas the other project type performed work only at night. Researchers determined the change in crash likelihood during periods of active night work, active day work (if applicable), and during periods of inactive work at day and night. Their analysis found that work activity at hybrid projects during both daytime and nighttime resulted in more crashes than during periods of inactive work. At the nighttime projects, a higher percentage of rear-end crashes did appear to occur on nights of work activity. More crashes at night were expected because the night work mostly involved more lane closure than the day work.

2.2 Work Zone Performance Measures

Cordahi et al. (2015a) mentioned the procedures and key findings of the impact assessment performed for two of three applications of incident work zone alerts for drivers and workers. They used performance measures of mainly three types of scopes, i) network wide, ii) incident zone level and, iii) individual user level performance measures. These performance measures are also categorized based on impact area, that is mobility/environmental and safety. Some of the performance measures used in the analysis are reduction in average delay, reduction in average speed, increase in section throughput, reduction in maximum deceleration, reduction in average sub-link speed, increase in average following distances and reduction in number of stops. (Cordahi et al., 2015b) developed an application called Incident Scene Work Zone Alerts for Drivers and Workers (INC-ZONE) which is a part of the application bundle, Response, Emergency Staging and Communications, Uniform Management, and Evacuation (R.E.S.C.U.M.E.). The authors described seven work zone performance measures produced by the above simulation model to quantify the objectives of the application which are decreasing congestion, shorten the evacuation clearance time and improve mobility. These performance measures are vehicle kilometers traveled, vehicle hours traveled, vehicle hours of delay, congested vehicle kilometers, congested vehicle hours, percentage of time congested, travel time difference, travel time to lodging facilities, unfulfilled fueling demand and average wait time.

Sun et al. (2014) have used crash modification factors as performance measures. Hallmark et al. (2013) identified and summarized the way the agencies collect, analyze and report various work zone traffic performance measures of three categories, exposure, mobility and safety measures. They developed a toolbox called Synthesis of Work-Zone Performance Measures to identify common safety and mobility performance measures which has been proposed or in use by several agencies nationwide. They define performance measure (PM) as sets of defined, outcome-based conditions or response times to evaluate success and their objective is to improve safety and mobility in work zones for the traveling public and highway workers. They also described in detail the data requirement and collection methodology for analyzing the aforesaid PMs and gave a detailed observation of how these performance measures are used by the Department of Transportation of several states. The exposure measures were categorized as volume-based, time-based and project-based. The mobility measures were categorized as queue, delay, capacity, speed, user measures and work-zone incidents. Finally, the safety performance measures were categorized as crashes by type, severity and contributing circumstances, speed, work-zone inspection, emergency management services (EMS) and surrogate measures.

Khattak et al. (2002) analyzed the effect of work zone duration due to the policy sensitivity the freeway work zones crash dataset of California. The author used Total Crash Rate (CR) as the performance measure in the study. This crash rate consists of non-injury and injury producing crashes. Ullman et al. (2011a) developed a primer to help the agencies in establishing and monitoring a useful set of work zone safety and mobility performance measures. This primer mentioned several work zone PMs, outlined methods and technologies to collect data and instructed the agencies on how to select and implement PMs for their own work zone programs. The authors also categorized the PMs based on safety, mobility and exposure. Ullman et al. (2009) identified the important safety and mobility PMs which the Texas DOR can use for their work zone monitoring program within a district, region or across state. This report identified the suitable safety and mobility performance measures, outlined the data requirement and collection procedures and explained the monitoring program. The report also showed analysis of pilot testing. Bourne et al. (2010) prepared a report of the best practices in work zone assessment, data collection and performance evaluation as part of NCHRP Project 20 68A. The report described the method by which the performance measures are used to ensure safety and minimize congestion in work zones. Like the above studies, the performance measure is also categorized as safety, mobility and exposure performance measures.

2.3 Other work zone Related Studies

There have been several studies done on work zone evaluation and various other topics related to work zone. Debnath et al. (2014) developed Tobit regression technique for modeling the probability and the magnitude of non-compliance with speed limits at work zones locations. Drum (2015) described the use of advance warning signs at work zones used by various state DOTs. Carrick and Washburn (2007) described methodology to improve collection system of work zone crash data. Chu et al. (2005) evaluated the effectiveness of automated work zone information system (AWIS) using vehicle count and speed data. Duffy and McAvoy (2009) used macro ergonomic approach to study work zone crashes and near crashes to validate driving simulator. Kang et al. (2004) developed an algorithm for speed limit control at highway work zones for crash minimization. There were also simulation based studies conducted to assess driver response at highway work zones (Morgan et al. (2010); Muttart et al. (2007)).

According to the State of Tennessee (FFY06) Highway Safety Performance Plan, improvement of work zone safety is one of the main emphasis areas. One of their many program goals (09-SC-Safe Community Projects and roadway safety) was to decrease work zone crashes by 5% in 2006. According to the Fatality Analysis Reporting System (FARS) 2014 ARF, NHTSA, a total of 962 fatal crashes occurred in the state of Tennessee out of which around 3% of these crashes occurred at work zone locations (ARTBA, (2014)). The table summarizing the literatures on work zone safety, work zone crashes and work zone performance measures is presented in detail in Appendix A.

Finley (2015) mentioned potential voluntary speed reductions for various work zone conditions mentioned in Table 1.

Table 1 Voluntary Speed Reductions for Various Work Zone Conditions (Finley, (2015))

Work-zone conditions	Potential Voluntary Speed Reduction
Work-zone reduced speed limit sign	0 to 3 mph
Barrier near inside travel lane	0 to 3 mph
Lane encroachment	1 to 5 mph
Lane closure	1 to 13 mph
Lane shift	3 to 8 mph
Temporary median crossover	4 to 17 mph
Construction vehicle access/egress location	5 to 6 mph
Two-lane, two-way barrier separated traffic	7 to 9 mph

2.4 Literature Review Summary

A detailed literature review on work zone safety-related topics was conducted. In this project, the literature review was primarily focused on work zone crashes, work zone safety and work zone performance measures studies. The reviewed materials are from various sources including journals, research reports, conference proceedings, and periodicals. From the available literature it can be concluded that various types of performance measures are widely used to evaluate work zones of various States and regions. The most commonly used types of work zone performance measures are exposure, safety, mobility, queuing, delay and reliability. In some cases, studies are done which used simple regression techniques to predict work zone crashes and establish thresholds and develop safety measures. Moreover, some studies used crash modification factors, crash rates and user satisfaction performance measures. The literature also revealed that hardly any study has used NN technique which is a considerably new technology in terms of crash prediction. Work zone crash performance measures, estimated using work zone crash data, can assist public and private stakeholders along with various transportation agencies to prioritize work zone projects and schedules, and efficiently allocate available resources for safety improvements at those roadway segments.

3 DATA COLLECTION AND PROCESSING

This section presents the study area and dataset used in this study. This section also explains the various types of data processed to create a comprehensive and rich data set.

3.1 Background

A comprehensive, complete and accurate data is essential to the conduct of meaningful research. Research on work zone safety mostly relies on data from traffic crash reports and work zone characteristics. In almost every state in the nation, crash report data elements have evolved in the form of crash data inventories to capture relevant information about location, vehicles, drivers, pedestrians, roadway or work zone conditions and causation. The data derived from these inventories are often the foundation of any kind of safety-related research. In this research, all the work zone related data sets are obtained from Tennessee Roadway Information Management System (TRIMS). It is a single integrated system that includes inventory of State and local roadways, structures, pavement, traffic, photo logs and crash data. Tennessee Department of Transportation (TDOT) implemented TRIMS as a mainframe database in 1972 and moved to a client server Oracle database in 1996. The development of a web-based application of the TRIMS database began in 2007. This application is map-centric and requires the use of query tool which comprises of digital Photo-log and GIS map-based application. This tool is available to TDOT, local agencies, contractors and universities. TRIMS database contains inventory data for more than 88,000 miles of roadways of the State of Tennessee which includes all Interstates, State routes and all other functionally classified routes. It also includes a variety of crash related data over the last two decades. The dataset can be downloaded and analyzed in four electronic formats (Text, Excel, GIS shapefiles and KML files) with the additional option

The primary TRIMS database table includes county and city data containing sub category data of highway, road segment, route feature, roadway description, roadway geometrics, intersection, structures, traffic, crash, maintenance feature, maintenance inventory and projects. Each data category has various attributes or columns. Road segment includes the road name, beginning lane-mile, end lane-mile, TDOT log mile, functional class of the segment, Government Control, Administration System, Incorporated Area, Urban Area and Special Systems. Route feature includes county boundary, city limit, urban boundary, underpass/overpass, structure, intersecting routes and traffic control. Roadway description includes pavement, shoulder, median, drainage, turn lane, parking lane and HOV lane. Roadway geometrics include number of lanes, through lanes, speed limit, truck speed limit, school speed limit, illumination and access control. The crash data is further categorized as crash feature, motorists/non-motorists, truck and bus, property owners and driver/vehicle. The TRIMS database has many functions that can be used for various purposes. The map layers embedded in the TRIMS system has all road by type, ramps, lakes and rivers, city boundaries, county boundaries, urban and state boundaries, surrounding states, TDOT districts and regions, Metropolitan Planning Areas, Rural Planning Organizations, railroads, hospitals, schools, churches, cemeteries and airports/runways. Finally, it has the option to produce reports like crash summary report, highway log, maintenance and traffic etc.

3.2 Study Area

In this research, the study area included all 95 counties in the State of Tennessee (shown in table 2) with crash prediction and performance measure estimation performed at the county and regional level (shown in table 4).

3.3 Work Zone Crash Data Collection

A dataset consisting of work zone crashes over 15 years (2002-2016) from all 95 counties in the State of Tennessee was collected from TRIMS database. The dataset contains information on crash occurrence time, location, roadway condition, crash type, weather conditions, roadway segment attributes where the crash occurred such as the number of lanes, shoulder and median widths, illumination, traffic control, traffic flow characteristics such as annual average daily traffic (AADT), speed limit, and injury severity. The crash frequency data is collected for various years for all the roadway segments across the entire State of TN where work zone crashes have been reported. Once crash frequency is known, crash density can be calculated (as the ratio of crash frequency to work zone segment length). Crash severity data is also collected for all the segments from which crash cost is calculated. The crash cost is calculated by multiplying the comprehensive crash cost (as shown in Table 3) with the frequency of respective crash injury severity

Table 2 Counties of State of TN along with corresponding IDs

County ID	County name	County ID	County name	County ID	County name	County ID	County name
1	Anderson	25	Fentress	49	Lauderdale	73	Roane
2	Bedford	26	Franklin	50	Lawrence	74	Robertson
3	Benton	27	Gibson	51	Lewis	75	Rutherford
4	Bledsoe	28	Giles	52	Lincoln	76	Scott
5	Blount	29	Grainger	53	Loudon	77	Sequatchie
6	Bradley	30	Greene	54	McMinn	78	Sevier
7	Campbell	31	Grundy	55	McNairy	79	Shelby
8	Cannon	32	Hamblen	56	Macon	80	Smith
9	Carroll	33	Hamilton	57	Madison	81	Stewart
10	Carter	34	Hancock	58	Marion	82	Sullivan
11	Cheatham	35	Hardeman	59	Marshall	83	Sumner
12	Chester	36	Hardin	60	Maury	84	Tipton
13	Claiborne	37	Hawkins	61	Meigs	85	Trousdale
14	Clay	38	Haywood	62	Monroe	86	Unicoi
15	Cocke	39	Henderson	63	Montgomery	87	Union
16	Coffee	40	Henry	64	Moore	88	Van Buren
17	Crockett	41	Hickman	65	Morgan	89	Warren
18	Cumberland	42	Houston	66	Obion	90	Washington
19	Davidson	43	Humphreys	67	Overton	91	Wayne
20	Decatur	44	Jackson	68	Perry	92	Weakley
21	DeKalb	45	Jefferson	69	Pickett	93	White
22	Dickson	46	Johnson	70	Polk	94	Williamson
23	Dyer	47	Knox	71	Putnam	95	Wilson
24	Fayette	48	Lake	72	Rhea		

level for work zone segment. Along with the crash data set, roadway segment, roadway geometry, traffic characteristics and work zone projects data are also collected. These datasets and the descriptive statistics are explained in the following sub-sections.

Table 3 Crash Costs by injury severity level

Injury Severity Level	Comprehensive Crash Cost
Fatality (K)	$4,008,900
Disabling Injury (A)	$216,000
Evident Injury (B)	$79,000
Fatal/Injury (K/A/B)	$158,200
Possible Injury (C)	$44,900
PDO (O)	$7,400

Source: Highway Safety Manual, First Edition, Draft 3.1, April 2009.

Table 4 Regions in the State of TN

Region_1		Region_2		Region_3		Region_4	
County ID	**County name**	**County ID**	**County name**	**County ID**	**County name**	**County ID**	**County name**
1	Anderson	4	Bledsoe	2	Bedford	3	Benton
5	Blount	6	Bradley	11	Cheatham	9	Carroll
7	Campbell	8	Cannon	19	Davidson	12	Chester
10	Carter	14	Clay	22	Dickson	17	Crockett
13	Claiborne	16	Coffee	28	Giles	20	Decatur
15	Cocke	18	Cumberland	41	Hickman	23	Dyer
29	Grainger	21	DeKalb	42	Houston	24	Fayette
30	Greene	25	Fentress	43	Humphreys	27	Gibson
32	Hamblen	26	Franklin	50	Lawrence	35	Hardeman
34	Hancock	31	Grundy	51	Lewis	36	Hardin
37	Hawkins	33	Hamilton	52	Lincoln	38	Haywood
45	Jefferson	44	Jackson	56	Macon	39	Henderson
46	Johnson	54	McMinn	59	Marshall	40	Henry
47	Knox	58	Marion	60	Maury	48	Lake
53	Loudon	61	Meigs	63	Montgomery	49	Lauderdale
62	Monroe	67	Overton	64	Moore	55	McNairy
65	Morgan	69	Pickett	68	Perry	57	Madison
73	Roane	70	Polk	74	Robertson	66	Obion
76	Scott	71	Putnam	75	Rutherford	79	Shelby
78	Sevier	72	Rhea	80	Smith	84	Tipton
82	Sullivan	77	Sequatchie	81	Stewart	92	Weakley
86	Unicoi	88	Van Buren	83	Sumner		
87	Union	89	Warren	85	Trousdale		
90	Washington	93	White	91	Wayne		
				94	Williamson		
				95	Wilson		

3.3.1 Descriptive Statistics

Figure 1 highlights a sample work zone crash occurrence across the entire State of TN. Figure 2 highlights all 95 counties of the State of Tennessee where traffic crash data are collected for past 15 years. The traffic crash frequencies at work zones from the counties are color coded based on the number of crashes occurred. Davidson, Shelby, and Knox County are top three counties according to occurrence of trash crashes. Figures (13 – 16) in Appendix B show the frequency distribution of different types of work zone crashes by county.

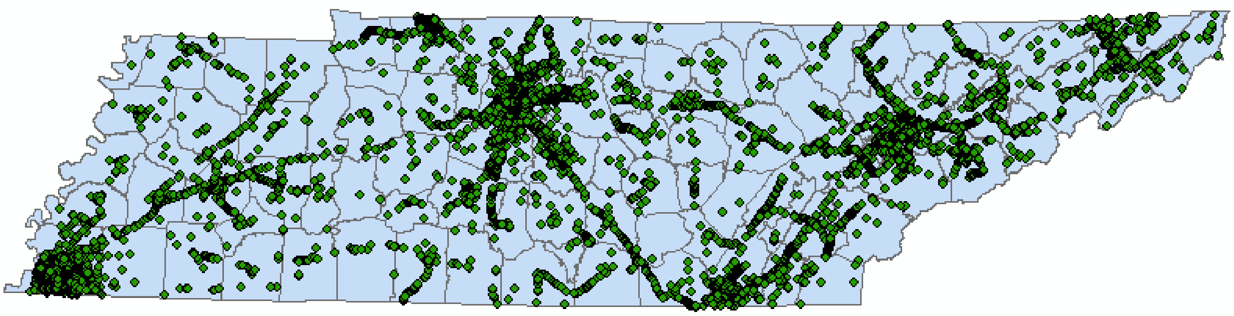


Figure 1 Sample workzone crash occurrence display

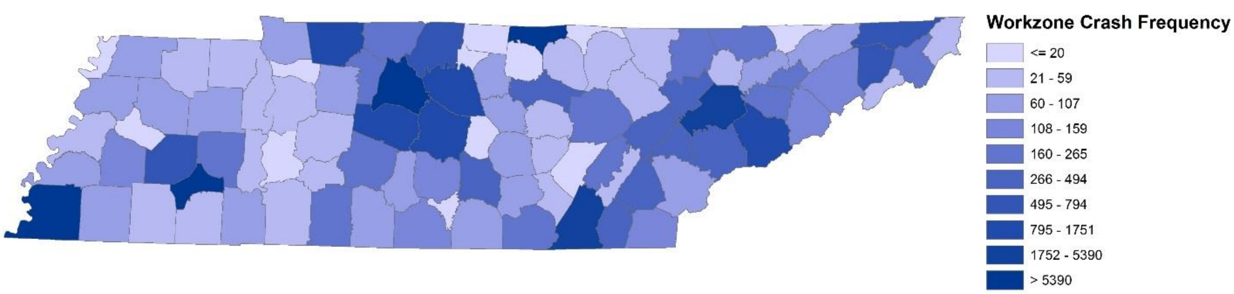


Figure 2 Data map of study area (2002 – 2015)

3.4 Workzone Project Data Collection:

The work zone project data is collected from the Program, Project and Resource management (PPRM) database. These dataset shows the active and future work zones, project type, project cost, project contractor and many other attributes across the entire State of TN. Figure 3 shows the frequency of workzone projects by project type. These workzone datasets have been merged with work zone crash dataset to identify how many crashes have occurred over the subsequent period of time at each work zone segments.

3.5 Roadway Segment, Geometry and Traffic Data Collection:

The roadway characteristics (segment and geometry) data set for each of the work zone roadway segment is collected from TRIMS database. Segment data includes functional classification of roadway such as freeways, arterials, collectors and locals, number of lanes, speed limit, type of terrain such flat or hilly, type of illumination of roadway, land use type and type of access control. The traffic data has also been collected from the same TRIMS database which includes AADT (annual average daily traffic) and percentage of passenger AADT and percentage of truck AADT.

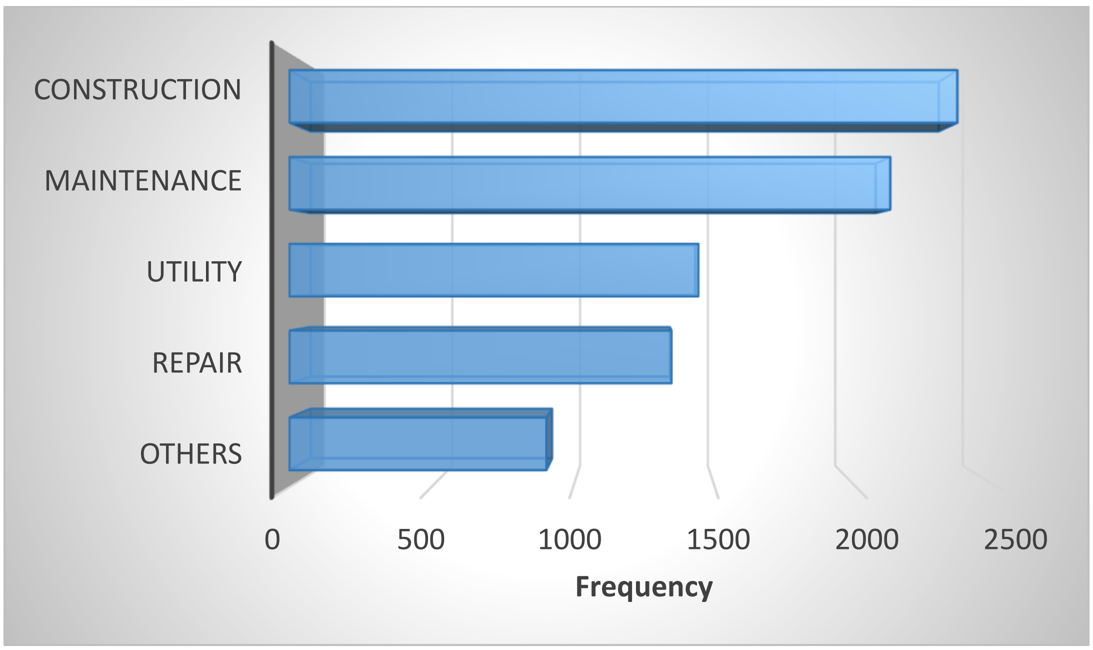


Figure 3 Work zone projects by type

3.6 Data Processing

For each of the County, the work zone data consists of all the current and past work zones which includes the work zone cost, work zone starting period, contractor, route number etc. The work zone crash data, road segment data as well as traffic data also has route number given by TRIMS. For each of those work zones, the route number is matched with the route numbers from the remaining data sets and all the data like number of work zone crashes, functional class of roadway of work zone, number of lanes, speed limit, AADT etc. are processed, merged and cleaned to create a rich source of data that has been used for crash prediction and development of work zone crash performance measurement. The dataset contains information on crash occurrence time, location, roadway condition, crash type, weather conditions, roadway segment attributes where the crash occurred such as the number of lanes, shoulder and median widths, illumination, traffic control, traffic flow characteristics such as annual average daily traffic (AADT), speed limit, and injury severity. For work zone crash prediction, 75% of the data is used for model training, 15% is used for cross validation, and 10% is used for prediction performance assessment.

3.7 Summary

Despite the rich source of dataset, there has been several caveats regarding the data collection procedures. Pickett County did not have any work zone crash record in the TRIMS dataset and hence crash prediction and performance measures cannot be calculated for this county. Moreover, although the work zone (WZ) crash data has been obtained from TRIMS, the active duration of WZ is not known from the PPRM database of TRIMS. Some of the WZ segments have crash information missing from the data base. The only information about the work zone from the crash data obtained from TRIMS database is the type of work zone. The next section describes the methodology employed for crash prediction in detail.

4 METHODOLOGY: CRASH PREDICTION

In this section, the developed methodology for crash prediction based on Artificial Neural Network is described:

4.1 Artificial Neural Network Model (ANNM)

Artificial neural networks (ANNs) are extensively utilized for variety of applications including pattern recognition, sequence recognition, data mining, process control, financial application, and prediction. Multi-Layer Perceptron – Neural Network (MLP-NN) is a class of commonly used feed-forward NN architecture with full connection between neurons. Mathematically, an MLP-NN model can be written as Equation (1).

$$y_t = \phi_0 + \sum_{j=1}^{n} \phi_j f\left(\sum_{i=1}^{m} \theta_{i,j}\, y_{t-i} + \theta_{0,j} \right) + \varepsilon_t \qquad (1)$$

where y_t represents a response variable in the output layer, y_{t-i} $\{i=1,\ldots,m\}$ represents explanatory variables in the input layer, m denotes the number of neurons in the input layer, n denotes the number of neurons in the hidden layer, f is a sigmoid transfer function (e.g., logistic, $f(x)=\frac{1}{1+\exp(-x)}$), ϕ_j $\{j=1,\ldots,n\}$ is a vector of weights from the hidden to the output neurons and $\theta_{i,j}$ $\{i=1,\ldots,m;\ j=1,\ldots,n\}$ are weights from the input to the hidden neurons. ϕ_0 and θ_0 denote the bias terms equivalent to the intercept in a linear model.

The MLP-NN is chosen among others because it is a class of universal approximators (Hornik, K et al. (1989)), which can approximate any nonlinear relationship between crash risk factors and predictive variables such as crash density and economic cost. However, there is no consistent guidance available in literature for specification of NN but many rules of thumb are adopted by various researchers. In this study, cross validation and early stopping techniques are chosen to construct a NN (more discussion in the empirical study section).

4.1.1 Determination of Number of Input Variables, and Output Variables

The number of neurons in the input layer is determined by the number of crash risk factors considered, and the output layer contains the number of neurons equivalent to the number of variables to be predicted. There is no specific limitation in number of explanatory and response variables and their nature (i.e., discrete or continuous).

4.1.2 Determination of Number of Hidden Layers

Cybenko (1989) proved that a single hidden layer MLP feed-forward NN can approximate any bounded continuous and multivariate function with arbitrary precision. Hornik et al. (1989) also provided substantial proof that a standard multilayer feed-forward network with one hidden layer can approximate any measurable function to any desired degree of accuracy such that multilayer feed-forward networks are a class of universal approximators. Therefore, one hidden layer is employed for the architecture of MLP in the sense that networks with more than one hidden layer can be converted to an equivalent network with just one hidden layer. Kolmogorov (Tikhomirov et al. (1991)) theorem provides a solid theoretical basis in this regard.

Theorem: *For any integer* $n \geq 2$ *there are continuous real functions* $\psi^{p,q}(x)$ *on the closed unit interval* $E^1 = [0;1]$ *such that each continuous real function* $f(x_1, \cdots, x_n)$ *on the* $n-dimensional$ *unit cube* E^n *is representable as*

$$f(x_1, \cdots, x_n) = \sum_{q=1}^{q=2n+1} \chi_q \left[\sum_{p=1}^{n} \psi^{pq}(x_p) \right] \qquad (2)$$

Where $\chi_q(y)$ *are continuous real functions.*

4.1.3 Determination of Number of Iterations

An intelligent choice of the number of hidden neurons depends on what form of regularization is being used (Sarle W. et al. (1997)). In this study, the cross-validation technique with an early stopping policy is employed to find the near optimal number of neurons in the hidden layer and the number of training iterations for weight matrix optimization. The dataset is partitioned into three complementary subsets including training, validation, and testing set. The training set is used for model estimation with different numbers of neurons in the hidden layer. The number of neurons in the hidden layer is increased by one at a time during training process. The generalization error is periodically estimated from the validation set. The test set is used for evaluation of prediction performance of the trained model. Early stopping policy prevents the network from over-fitting the model. Early stopping criterion is to monitor the generalization error to decide when to stop the training. If the generalization error shows no further improvement or increase after a certain number of iterations, then the training process stops from further optimization. The number of neurons in the hidden layer and the number of iterations that yield the minimum generalization error determine NN architecture.

4.1.4 Training Algorithms

Training algorithms commonly used to optimize weight matrix include three nonlinear optimization routines, i.e. Standard Backward Propagation (BP), Scaled Conjugate Gradient (SCG), and the Broyden-Fletcher-Goldfarb-Shannon quasi-Newton method (BFGS). These algorithms are available in RSNNS and NNET packages in open source software R. In this study, SCG is used for training the NN.

4.2 Section Summary:

This section demonstrated the methodology implemented for the determination of significant factors affecting work zone crashes and the prediction of work zone crashes. In this research, ANN model is proposed to establish the empirical relationship between work zone crashes and risk factors by exploring a broad range of variables including highway geometry, traffic and environmental characteristics, and provides insight into the underlying relationship. The neural network (NN) method is favored upon conventional statistical models due to its efficiency and accuracy. The results of this study may be applicable to work zone crash analysis and prediction for transportation corridor.

5 METHODOLOGY: PERFORMANCE MEASURES

5.1 Background

Work zone performance measures are metrics that help to quantify how work zones impact travelers, residents, businesses and workers. Work zones can cause significant impacts on traffic congestion and safety. Every work zone is unique, and the combined effects of design decisions, work phasing and sequencing operations, and impact mitigation strategies implemented at a site can be challenging to predict beforehand. Work zone performance measures help improve the understanding of how the decisions during planning, design, and construction affect work zone safety and mobility, and thus can help improve how the decisions are made for future work zones. These performance measures help to utilize resources more effectively and improve the quality of service to the road users. Moreover, they help to accomplish agency goals and objectives, strengthen accountability and enhance decision making. In some cases, the performance measures also assess the difference in effectiveness of new and existing policies, practices, or procedures allowing comparisons to identify unacceptable or unsafe situations that need to be corrected.

Performance monitoring of work zones is highly subjective and influenced by several factors. An important statistic for work zone of an area may not necessarily be important for the work zone of another area. It can be recognized that some sort of standardization of measures is necessary, as well as stratification of measures of various work zones on variables such as average daily traffic (ADT) or roadway characteristics. Decision makers care about performance measures for work zones in a quantitative sense but are also concerned that efforts to monitor and measure work zone performance does not require field personnel to collect a large amount of additional data that will not be useful to them in how they manage day-to-day operations of the work zone.

5.2 Identification of Performance Measures

One of the biggest challenges in the selection of suitable performance measures is data availability or the lack of available data set required for the calculation or corresponding performance measures. In the case of safety performance measures at a work zone project level, method involving estimation of changes in crash frequency due to the work zone (and during various periods within the overall duration of the project) are very commonly known, if the project is of sufficient length and duration that adequate numbers of crashes are available for analysis. Methods of combining the performance measures of multiple work zones in an area due to crashes based on work zone type and work activity (e.g., periods of work activity with and without lane closures required, periods of work inactivity, etc.) are also common. However, it has been noted that work zone operations officials desire to use crash data as a way of assessing the effectiveness and safety of work zone design elements and/or operating strategies.

FHWA is currently supporting initiatives to monitor work zone performance on major roadways in various regions. As part of implementation support of the new work zone safety and mobility rule, FHWA has been looking into appropriate performance measures to suggest to states, both output and outcome-based measures. An initial preliminary list of measures among the safety categories are:

- Safety
    - Total fatalities
    - Total injuries
    - Highway workers killed and injured
    - Crash rates per 100 million VMT
    - Crash rates per work zone
    - Increase in rates relative to non-work zone conditions
    - Speed and enforcement surrogates
        - Percent of vehicles exceeding speed limit
        - Speed variability

Several of these measurement categories are interrelated. There must also be justification for the inclusion of a work zone performance measure in terms of usability, data availability and improvement. Not all the measures will be equally available or calculable, depending on the location, data availability and type of a project. However, researchers believe that the measures recommended below will provide decision-makers with the type of information needed to evaluate agency processes and procedures. In addition, the available data could be combined in other ways to aid tracking of underperforming entities (with regard to traffic impacts generated) and identify those whose scheduling may need to be scrutinized in greater detail. In this research, five types of work zone performance measures are used, namely:

1. Average number of work zone crashes by year
    - This is the most common form of performance measure that is often used to set achievable goals or targets for the agencies. In this research, the arithmetic mean of work zone crashes from 2002 – 2016 for each County in the State of TN are calculated using the following equation:

$$Average\ number\ of\ work\ zone\ crashes\ = \frac{1}{n}\sum_{i=1}^{n} C_i$$

$$where,$$
$$n = Number\ of\ years$$
$$C = Number\ of\ work\ zone\ crashes\ in\ year\ i$$

2. Median of yearly work zone crashes
    - This is another common performance measure used. The median is a commonly used measure of the properties of a data set in statistics and probability theory. The median is the value separating the higher half of the number of work zone crashes per year for each County from the lower half. The basic advantage of the median in terms of performance measure compared to the mean or average is that it is not skewed so much by extremely large or small value of the number of crashes per year, and so it may give a better understanding in terms of setting of actionable targets for the agencies. Because of this, the median is of central importance in robust statistics, as it is the most resistant statistic. To calculate the Median, first the number of yearly crashes for each County is arranged in an ascending order. Then the Median is calculated using the following equation:

$$Median\ of\ work\ zone\ crashes$$
$$= \left(\frac{n+1}{2}\right)^{th}\ value\ of\ work\ zone\ crashes$$
$$where, n = 15\ (Total\ 15\ years\ between\ 2002$$
$$- 2016, both\ inclusive)$$

3. Standard deviation of yearly work zone crashes
    - The standard deviation is a measure that is used to quantify the amount of variation or dispersion of a set of data values which in this case is the yearly work zone crashes. A low standard deviation indicates that the yearly work zone crashes tend to be close to the mean or average of the set, while a high standard deviation indicates that the yearly work zone crash are spread out over a wider range of values. A useful property of the standard deviation is that it is expressed in the same units as the data. In addition to expressing the variability of a population, the standard deviation is commonly used to measure confidence in statistical conclusions. Since in this research 15 years of crash data was utilized, the standard deviation of the sample was calculated using the following equation:

$$Standard\ deviation = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(c_i - \bar{c})^2}$$

$$where,$$

$$N = number\ of\ years$$

$$c_i = Crash\ in\ year\ i$$

$$\bar{c} = Mean\ of\ yearly\ crash$$

4. 85th percentile of yearly work zone crashes
    - A percentile (or a centile) is a measure used in statistics indicating the value below which a given percentage of observations in a group of observations fall. In general, percentiles are specific types of quantiles. If the number of work zone crashes is at the 85th percentile, where 85 is the percentile rank, it is equal to the value below which 85% of the yearly work zone crashes may be found. Therefore, the 85th percentile value of yearly work zone crashes means that 85% of the time, the work zone crashes do not exceed this value at a county.
5. 95th percentile of yearly work zone crashes
    - Similarly, 95th percentile value of yearly work zone crashes means that 95% of the time, the work zone crashes do not exceed this value at a county.

Most of the above performance measures are self-explanatory. These performance measures are selected in this research because of their least data requirements, simple to explain, infer or interpret and easy to use.

5.2 Section Summary

Performance measurement can significantly improve work zone safety and operations. Although based on literature, there are several workzone crash performance measures that could be implemented to assess the impacts at work zones but due to the limitation in dataset and increased emphasis on crashes, the performance measures used in this research are solely based on safety, simplicity and usability. These performance measures will help the decision makers to take ample safety measures at work zones to minimize the number of crashes.

6 RESULTS: CRASH PREDICTION

6.1 Prediction of work zone crashes

This section focuses on finding the significant factors by using the above explained methodology, predicting the crashes and estimating the performance measures using the crash dataset obtained from TRIMS.

6.1.1 Implementation of Neural Network

The MLP feed-forward NN is developed for analysis of predominant causal factors contributing to traffic crashes at work zones. Figure 4 shows a NID indicating the NN architecture and the strength of the weight connections between neurons that are constructed for this research. There are 15 neurons included in the input layer, 39 in the hidden layer, and 2 in the output layer. The nodes I1 – I15 represent explanatory variables that might cause traffic crashes at work zones including length of road segment, year, functional class of roadway, number of lanes, speed limit, nature of land use, illumination, traffic control, AADT, percentage of passenger vehicle, and truck. The nodes H1 – H39 represent neurons in the hidden layer and O1 and O2 denote crash density and economic cost respectively in the output layer. Crash density is defined as total work zone crashes a roadway segment experienced during the period normalized by its length, and economic cost represents the societal cost of crashes that incorporates cost by severity levels defined in highway safety manual.

Figure 5 shows how to determine the number of neurons in the hidden layer and training iterations for the Neural Network model using cross validation and early stopping techniques. A neuron is added to the hidden layer one at a time and the weight matrix is iteratively optimized until the generalization error of the validation set stops improving or begins to climb up. The optimal number of neurons in the hidden layer is identified as 39 with 43 training iterations to produce minimum error 0.0547. The network is trained, and its weight matrices are optimized via the Scaled Conjugate Gradient (SCG) algorithm.

6.1.2 Predominant Factors

Factors that are considered as explanatory variables in this research are system factors, i.e., non-behavioral factors including length of road segment, year, functional class of roadway, number of lanes, speed limit, nature of land use, illumination, traffic control, AADT, percentage of passenger vehicle, and truck. The relative importance index of explanatory variables for a single response variable in the NN is estimated by Olden method (Olden et al., 2004) to show significance of each explanatory variable.

To establish a generalized methodology to identify true importance of the explanatory variables in Neural Network, (Olden et al., 2004) compared nine methodologies for assessing variable importance using a Monte Carlo simulation experiment with data exhibiting predefined numeric relationships between a response variable and a set of explanatory variables. The results show that a Connection Weight Approach that uses raw input-hidden and hidden-output connection weights in the NN provides the best methodology for accurately quantifying variable importance and outperform the other approaches.

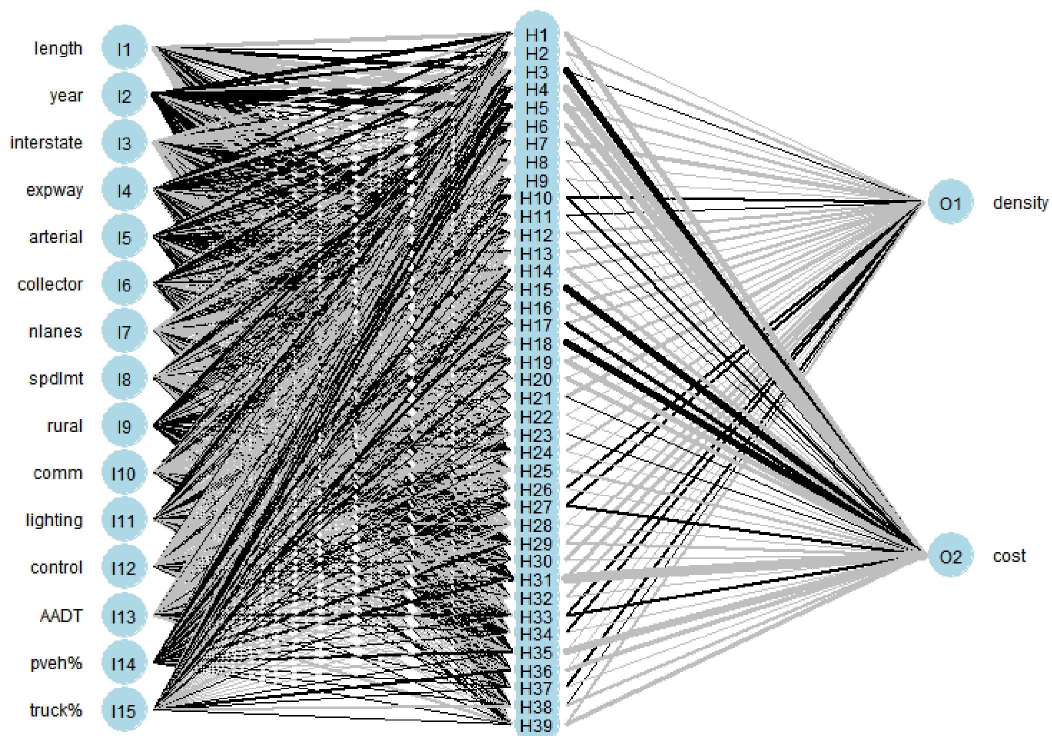


Figure 4 Architecture of MLP feed forward neural network

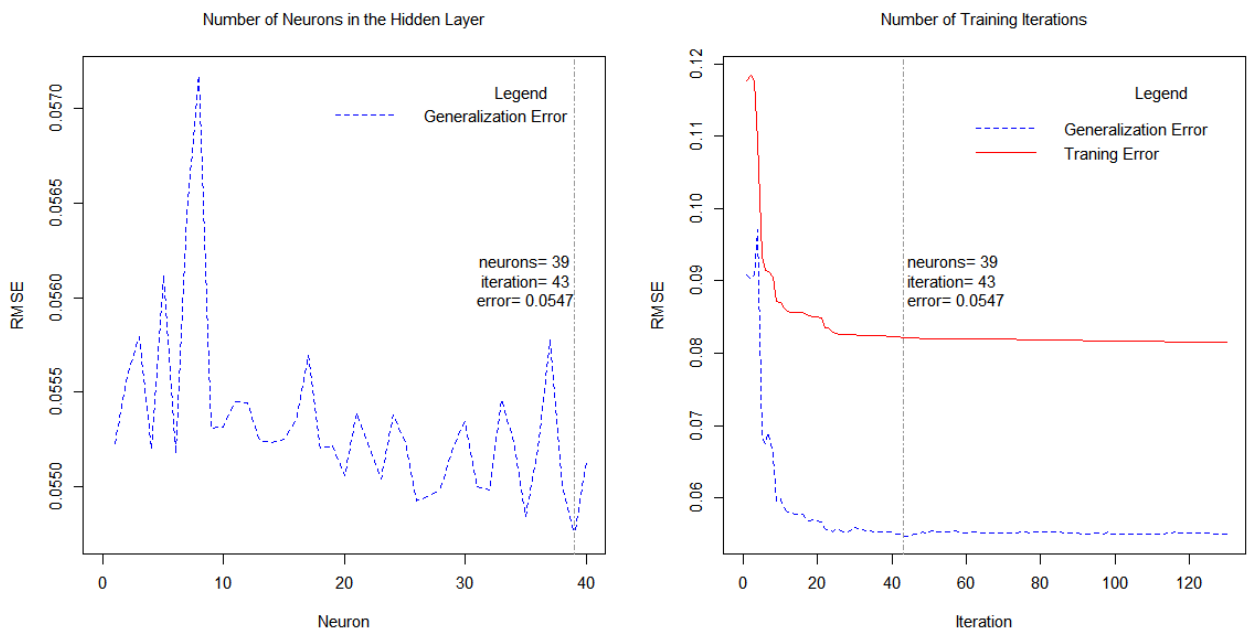


Figure 5 Chosen number of neurons in the hidden layer and training iterations using cross validation and early stopping techniques

This Olden method calculates relative importance of input variables in Neural Networks as the sum of the product of the raw input-hidden and hidden-output connection weights between each input and output neuron. An advantage of this approach is that both magnitude and sign of each connection weight are maintained such that opposite effect between the input-hidden and hidden-output layers would be cancelled out in the relative importance. In addition, Olden method can evaluate NN with multiple hidden layers.

Figure 6 shows the relative importance of explanatory variables corresponding to two outcome variables, i.e. crash density and economic cost. It is noteworthy that the magnitude and order of relative importance among explanatory variables are different for each response variable. The upward and downward bars in Figure 6 respectively represent the relative importance of the explanatory variables to each response variable proportionally in opposite direction.

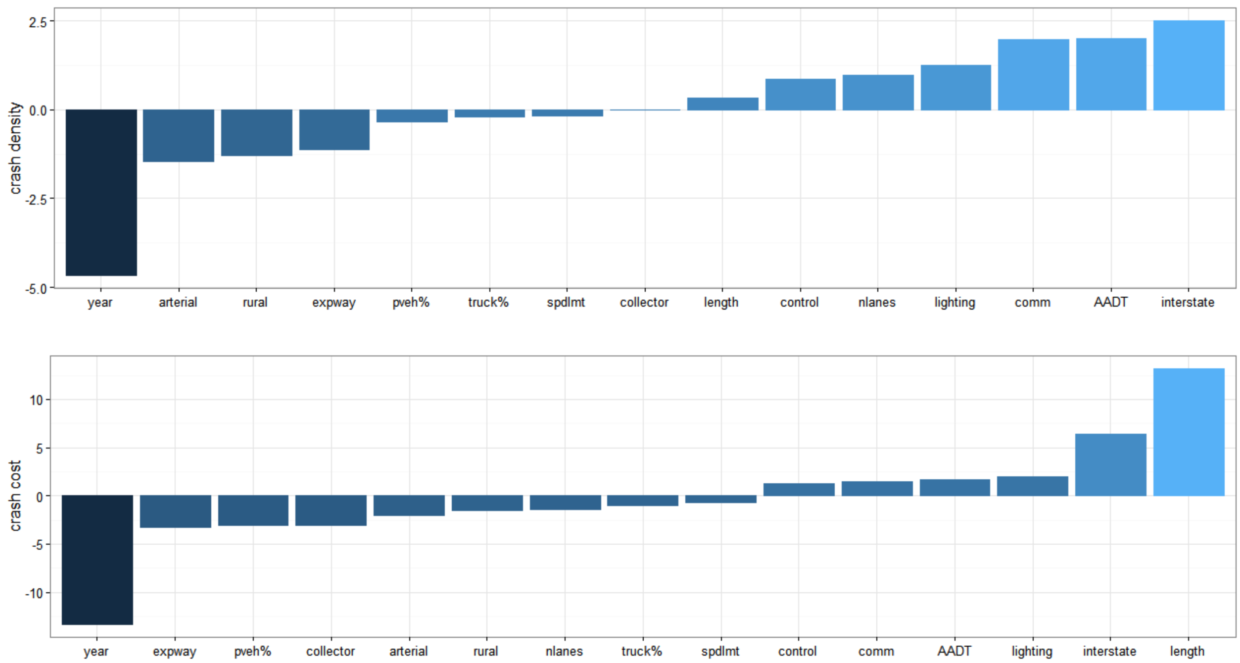


Figure 6 Relative importance of explanatory variables

6.1.3 Correlation and Elasticity

The weights that connect neurons in a Neural Network may be analogous to those coefficients in a standard regression model and its elasticity analysis that can be used to describe relationships between variables. The weights assigned to explanatory variables may have either positive or negative associations with a response variable. In contrast to a regression model, an obvious advantage is that Neural Network may have as many number of weights as desired by adjusting the number of neurons in the hidden layer(s). This flexible structure enables Neural Networks to map nonlinear relationship between multiple response variables and explanatory variables, and well absorb noises of dataset. However, interpretation of the effects of a specific weight is challenging.

Figure 7 show the correlations between explanatory variables (i.e. I1 ¬I15) and response variables (i.e. O1, and O2). For all plots, the colors in the legend indicate the corresponding quantile groups defined by the user where unevaluated explanatory variables were held constant. The x-axis represents percent variation of each the explanatory variable and y-axis illustrates the percent increase or decrease of response variable. For instance, 25% increase in AADT contributes to 4.8% increase in crash density. Similar interpretation can be done for all significant explanatory variables. It is noteworthy to observe the degree of linear or nonlinear nature of explanatory variables associated with each response variable.

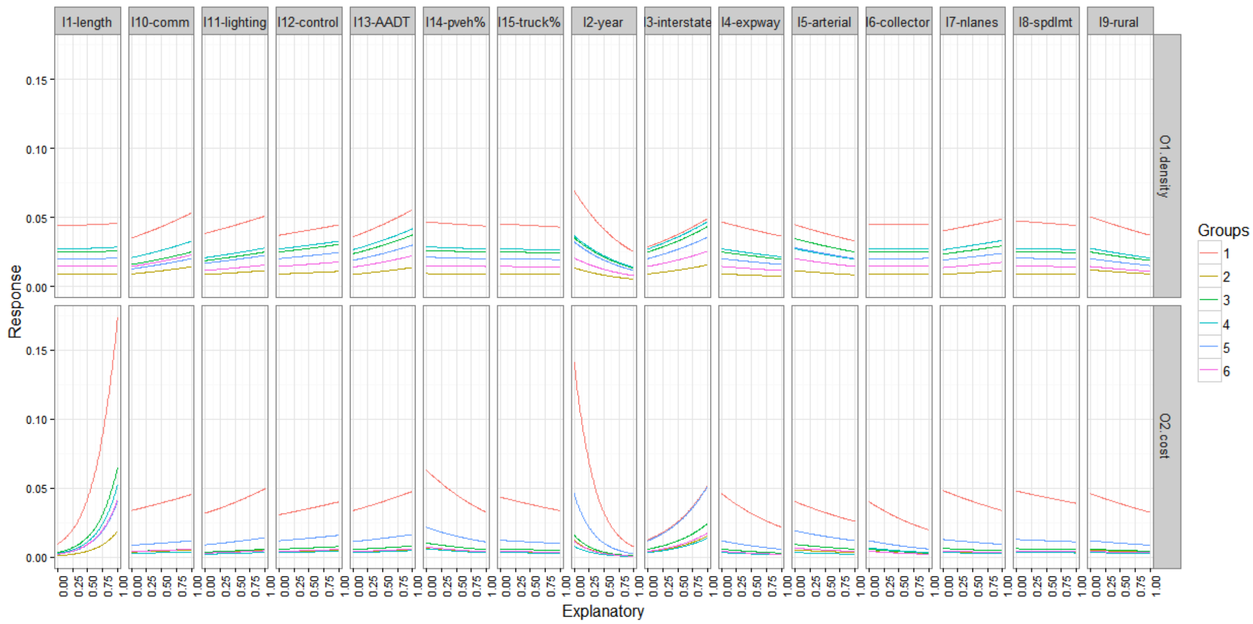


Figure 7 Correlation between input variables and output variables

6.1.4 Work Zone Crash Prediction

This section demonstrated the prediction of work zone crash density and crash cost. Figure 8 shows prediction of work zone crash density and cost respectively for 2015 and 2016 in 10 most populous counties. The prediction for the rest of the counties can be presented upon request. The prediction includes 141 records of work zone crashes. Both crash density and cost predictions follow the general trend of the observed frequencies. However, the overall prediction of crash density is higher than observation. The possible reasons for this discrepancy include that the NN model is trained with a relatively smaller dataset of 2,315 observations from 2002 to 2014 such that it cannot fully capture the crash patterns of 2015 and 2016, especially, sparse historical data is visible in counties such as Wilson, Sevier, and Madison, and the comparison shown in Figure 8 is performed at individual crash site level. The discrepancy of prediction may be complemented by (1) performing comparison at aggregated level, (2) expanding the dataset used for model training, and (3) including additional variables in the input layer of Neural Network. However, these complement measures require more data available.

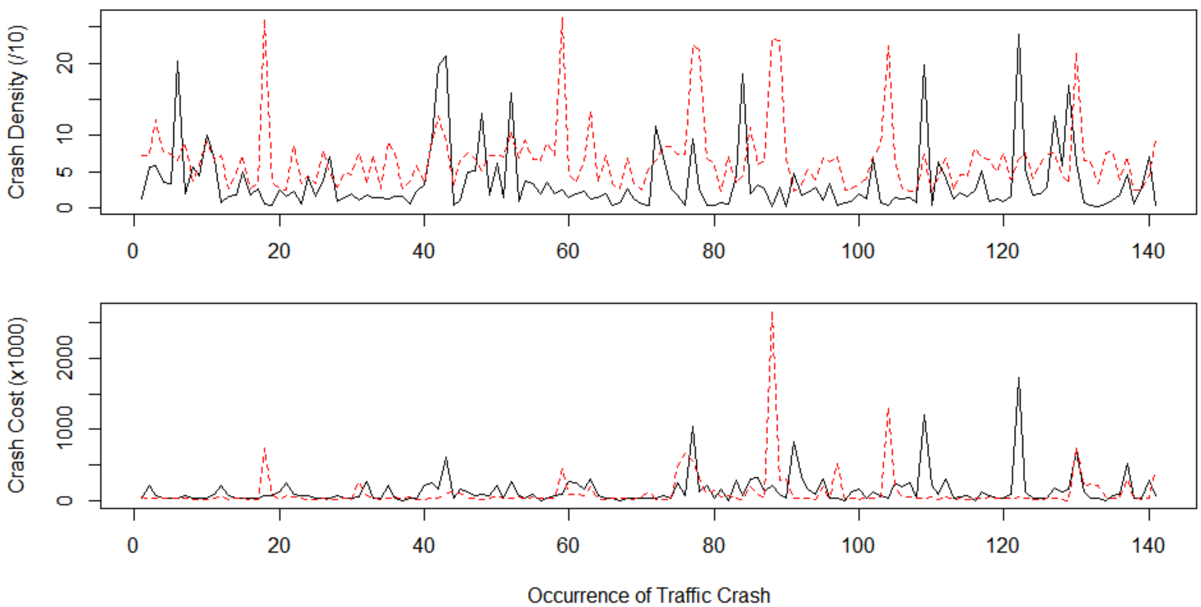


Figure 8 Prediction of crash density and cost at work zones in 10 counties

6.1.4.1 Crash Density and Cost

Figure 8 shows prediction of work zone crash density and cost respectively for 2015 and 2016. Both crash density and cost predictions follow the general trend of the observed frequencies. However, the overall prediction of crash density is higher than observation. The possible reasons for this discrepancy include that the NN model is trained with a relatively smaller dataset from 2002 to 2014 such that it cannot fully capture the crash patterns of 2015 and 2016, especially, sparse historical data is visible in counties such as Wilson, Sevier, and Madison, and the comparison shown in Figure 8 is performed at individual crash site level. The discrepancy of prediction may be complemented by (1) performing comparison at aggregated level, (2) expanding the dataset used for model training, and (3) including additional variables in the input layer of Neural Network.

Table 5 show comparisons of observed and predicted crash density and cost for the year 2016 - 2018 at the county level, respectively. The comparison at county level appears more reasonable than the comparison at individual level shown in Figure 8. In addition, 2016 work zone data does not represent the complete year yet. It can be seen that Shelby, Davidson, Hamilton and Knox County has comparatively higher predictions than the other counties which is expected due to the large size of the Counties in terms of population. The other counties have prediction values significantly lower due to the

Table 5 Comparison of Observed and Predicted Crash Density and Cost (2016 – 2018)

County	Observed Crash Density (x0.1)	Predicted Crash Density (x0.1)	Observed Crash Cost (x1000)	Predicted Crash Cost (x1000)
1	0.190	0.518	1,727	2,517
2	0.307	0.235	4,679	2,751
3	0.034	0.382	135	1,050
5	0.070	0.266	1,196	920
6	1.030	1.082	5,110	2,318
7	0.433	0.190	2,231	271
10	0.069	0.155	22	159
11	0.907	0.276	4,558	392
12	5.369	5.513	6,176	5,662
13	0.044	0.225	214	627
14	3.680	1.782	2,765	3,430
15	0.265	0.273	5,485	770
16	0.148	0.217	1,131	230
18	0.108	0.528	564	1,364
19	7.044	3.736	9,166	9,499
20	0.030	0.116	237	223
21	0.032	0.126	135	513
24	0.049	0.271	214	670
25	0.055	0.151	237	172
26	0.010	0.127	45	240
30	0.086	0.267	225	646
32	0.198	0.553	1,652	925
33	2.486	1.802	2,532	2,501
36	0.791	1.201	970	2,527
37	0.484	0.588	135	403
38	0.070	0.175	417	519

Table 5 (Continued)

43	0.036	0.159	237	169
45	0.146	0.204	641	200
46	0.017	0.064	124	388
47	0.806	1.076	2,741	3,000
49	0.041	0.212	316	675
51	0.020	0.053	269	581
52	0.010	0.048	45	173
53	0.448	0.975	1,690	2,265
54	0.030	0.138	135	484
55	0.080	0.336	372	921
57	0.054	0.072	1,391	825
58	0.118	0.212	962	306
60	0.052	0.243	348	938
62	0.104	0.311	440	478
63	0.478	0.425	4,028	1,357
67	0.020	0.046	432	169
68	0.004	0.020	79	348
70	0.119	0.339	485	807
71	0.140	0.476	1,223	431
73	0.640	0.519	4,139	1,092
74	0.715	0.838	810	1,354
75	0.346	0.566	5,669	6,491
78	1.222	0.451	672	711
79	6.441	5.786	15,403	20,412
82	0.648	1.701	3,076	2,740
83	0.254	1.535	1,137	2,469
84	0.010	0.137	79	266
86	0.031	0.114	135	163
88	0.050	0.180	135	380

Table 5 (Continued)

90	2.263	3.069	7,823	3,548
91	0.074	0.170	269	441
92	0.048	0.443	282	410
93	0.034	0.147	135	452
94	1.237	0.401	876	979
95	0.000	0.100	237	575

higher differences compared to the larger Counties. These crash density and crash cost prediction values are used to calculate the work zone crash performance measures for each of the Counties and for the four regions in the State of TN. The next section explains the calculation and interpretation of performance measures. In some counties, no work zone crash record could be found (for example, Pickett). Hence, for these counties, neither the prediction procedure nor the calculation of performance measurement could be carried out.

6.2 Conclusion

In this section, the implementation of neural network methodology to find relations between work zone and roadway factors and work zone crashes are determined. Moreover, the crash density and crash cost prediction results are demonstrated and discussed. The data set was divided into model training, cross-validation and prediction data. The MLP feed-forward NN is developed for analysis of predominant causal factors contributing to traffic crashes at work zones. The number of neurons in the hidden layer and training iterations for the NN model using cross validation and early stopping techniques were determined. The results are applicable to work zone crash analysis and prediction for transportation corridor. The relative importance of explanatory variables corresponding to two outcome variables, i.e. crash density and crash cost were identified. Also, the correlations between explanatory variables and response variables were determined. The findings indicate the influential factors that contribute to crashes at work zones include number of lanes, AADT, higher speed limit, and length of roadway, etc. The interstate highways have significant influence on vehicle crashes. This research demonstrates that ANN with new techniques introduced in this study is a consistent alternative and an important methodology for analyzing and predicting work zone crashes. The prediction results for both the work zone crash density and crash cost suggested that there are significant differences in prediction values between counties and the overall prediction of crash density is higher than observed crash density.

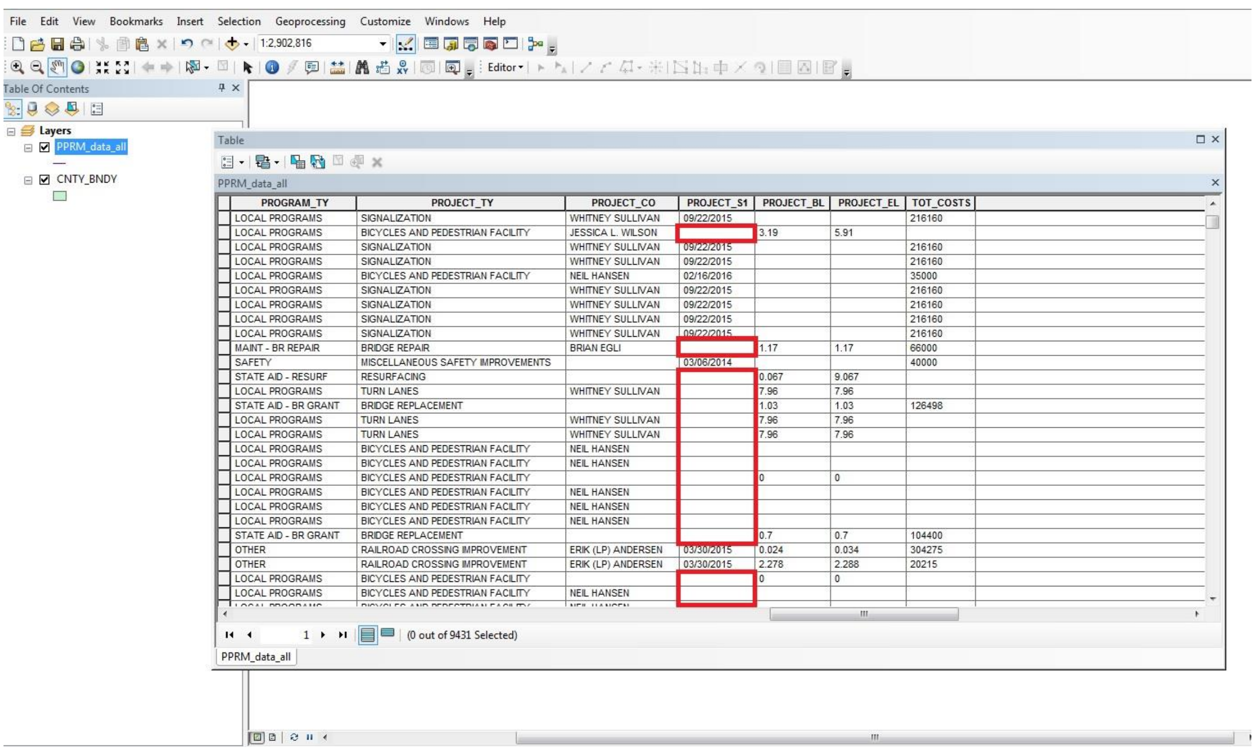
7 RESULTS: PERFORMANCE MEASURES

In this section, the calculation of crash performance measures is explained, and the results of those performance measures are interpreted for Shelby County. The crash performance measures for the remaining Counties and regions are presented in the Appendix C, D, E and F.

7.1 Performance measure calculation

Figure 10 shows the work zone crash frequency and performance measure analysis of Shelby County. Similarly, subsequent analysis is also done for the rest of the counties and four regions as can be found in the appendix section (Appendix C and Appendix D). Figure 10 contains four sub-figures. The first figure shows the number of work zone crashes and the number of work zones in each successive year for Shelby County. There are two y-axes in this graph. The left y-axis represents the number of work zone crashes from 2002 to 2016 and the y-axis on the right represents the number of work zone crashes for the Shelby County. The x-axis represents the years spanning from 2002. The blue bars show the work zone crash frequency trend in subsequent years. The horizontal blue line in the graph represents the yearly average work zone crashes frequency for the County. Now, the red dots indicate the number of work zones present in those subsequent years and the red line indicates the trend. It can be observed that with passing years and with increase in the number of work zones, the work zone crash frequency have reduced. This may be due to ample safety measures taken at work zones. Even in the appendices, most of the County and regional figures show a decrease in number of crashes by year. This reduction explains the improvement in workzone safety measures by the Transportation agency through the years. Another trend that can be observed is that, in the past years (especially from 2002 – 2010) the number of work zone crashes are significantly higher compared to the number of work zones for the same year. For example, in the year 2002, about 750 crashes are found whereas the number of work zone crashes are just 5. This difference is due to discrepancy in the work zone PPRM data sets. In the work zone PPRM data sets, for each county, a significant number of work zones have active date and time missing as can be seen in figure 9. This means that there are higher number of work zones for each year than the number shown in the graph. The number of work zones for the years since 2010 are significantly higher in number and this shows that the work zone data is more updated for these years than the previous years.

The second figure in figure 10 shows the trend of work zone crashes against the work zone lane miles for each of the functional class of roadway. This figure, like the first figure, also contains two y-axes. The left side y-axis represents the number of work zone crashes and the right y-axis represents the total work zone lane miles. The x-axis represents all the different functional classification of roadway in the County. The bar plot in blue shows the number of work zone crashes that took place in each of the functional class of roadway. The bar plot in green shows the total work zone lane miles present on that functional class of roadway. From this graph, it can be observed that for Shelby County, most of the work zone crashes took place at Interstates. If the blue bar is higher than the green bar, it shows that the number of work zone crashes in higher compared to the total number of work zone lane miles for that functional class of roadway. This is the case of interstates for Shelby County. All the other functional class of roadway like arterials, collectors and locals have higher work zone lane miles compared to number



PROGRAM_TY	PROJECT_TY	PROJECT_CO	PROJECT_S1	PROJECT_BL	PROJECT_EL	TOT_COSTS
LOCAL PROGRAMS	SIGNALIZATION	WHITNEY SULLIVAN	09/22/2015			216160
LOCAL PROGRAMS	BICYCLES AND PEDESTRIAN FACILITY	JESSICA L. WILSON		3.19	5.91	
LOCAL PROGRAMS	SIGNALIZATION	WHITNEY SULLIVAN	09/22/2015			216160
LOCAL PROGRAMS	SIGNALIZATION	WHITNEY SULLIVAN	09/22/2015			216160
LOCAL PROGRAMS	BICYCLES AND PEDESTRIAN FACILITY	NEIL HANSEN	02/16/2016			35000
LOCAL PROGRAMS	SIGNALIZATION	WHITNEY SULLIVAN	09/22/2015			216160
LOCAL PROGRAMS	SIGNALIZATION	WHITNEY SULLIVAN	09/22/2015			216160
LOCAL PROGRAMS	SIGNALIZATION	WHITNEY SULLIVAN	09/22/2015			216160
LOCAL PROGRAMS	SIGNALIZATION	WHITNEY SULLIVAN	09/22/2015			216160
MAINT - BR REPAIR	BRIDGE REPAIR	BRIAN EGLI		1.17	1.17	66000
SAFETY	MISCELLANEOUS SAFETY IMPROVEMENTS		03/06/2014			40000
STATE AID - RESURF	RESURFACING			0.067	9.067	
LOCAL PROGRAMS	TURN LANES	WHITNEY SULLIVAN		7.96	7.96	
STATE AID - BR GRANT	BRIDGE REPLACEMENT			1.03	1.03	126498
LOCAL PROGRAMS	TURN LANES	WHITNEY SULLIVAN		7.96	7.96	
LOCAL PROGRAMS	TURN LANES	WHITNEY SULLIVAN		7.96	7.96	
LOCAL PROGRAMS	BICYCLES AND PEDESTRIAN FACILITY	NEIL HANSEN				
LOCAL PROGRAMS	BICYCLES AND PEDESTRIAN FACILITY	NEIL HANSEN				
LOCAL PROGRAMS	BICYCLES AND PEDESTRIAN FACILITY			0	0	
LOCAL PROGRAMS	BICYCLES AND PEDESTRIAN FACILITY	NEIL HANSEN				
LOCAL PROGRAMS	BICYCLES AND PEDESTRIAN FACILITY	NEIL HANSEN				
LOCAL PROGRAMS	BICYCLES AND PEDESTRIAN FACILITY	NEIL HANSEN				
STATE AID - BR GRANT	BRIDGE REPLACEMENT			0.7	0.7	104400
OTHER	RAILROAD CROSSING IMPROVEMENT	ERIK (LP) ANDERSEN	03/30/2015	0.024	0.034	304275
OTHER	RAILROAD CROSSING IMPROVEMENT	ERIK (LP) ANDERSEN	03/30/2015	2.278	2.288	20215
LOCAL PROGRAMS	BICYCLES AND PEDESTRIAN FACILITY			0	0	
LOCAL PROGRAMS	BICYCLES AND PEDESTRIAN FACILITY	NEIL HANSEN				

Figure 9 Missing Data from Workzone PPRM Dataset

of work zone crashes. Similar graphs in Appendix C could be explained for each of the County and the four regions.

The third graph in figure 10 shows the trend in total crash cost (in y-axis) with subsequent years (in x-axis). Like the number of work zone crashes, the work zone crash cost also reduces with passing years. Finally, the fourth graph shows the total work zone crash cost in terms of severity of work zone crashes. The y-axis represents the total crash cost and the x-axis represents the severity. The graph for Shelby County shows that severity level C has induced higher cost followed by severity level K and B whereas severity level A and O has significantly induced lower cost due to work zone crashes in Shelby County.

Figure 11 displays two graphs, the first shows the trends of total crash density with years and the second shows the total crash cost with years. Both graphs show five horizontal bars with different color codes which represent work zone crash performance measures. The solid red horizontal line shows the mean yearly crash density in the first figure and mean yearly crash cost in the second figure. The green small stripped line shows the median of yearly crash density in the first graph and median of yearly crash cost in the second. The grey dotted line shows the standard deviation of yearly crash density in the first and yearly crash cost in the second. The orange dotted stripped line shows the 85th percentile of yearly work zone crash density in the first and yearly crash cost in the second. Finally, the purple large stripped line shows the 95th percentile of yearly crash density in the first graph and 95th percentile of yearly crash cost in the second graph. The crash performance measurement for the rest of the counties and regions can be found in Appendix E.

Figure 12 also displays two graphs which is like figure 11 but the only difference is that figure 12 shows the crash performance trends for all the Counties during the year 2015 whereas figure 11 showed the crash performance trends by years for each County. The first graph in figure 12 shows the trends of total crash density for year 2015 with Counties at the x-axis and the second figure shows the trend of total crash cost with Counties for the year 2015. Both graphs shows five different values in the legend which represent work zone crash performance measures. The mean crash density for the year 2015 across all Counties of TN is 6.936 crashes per work zone lane mile in the first figure

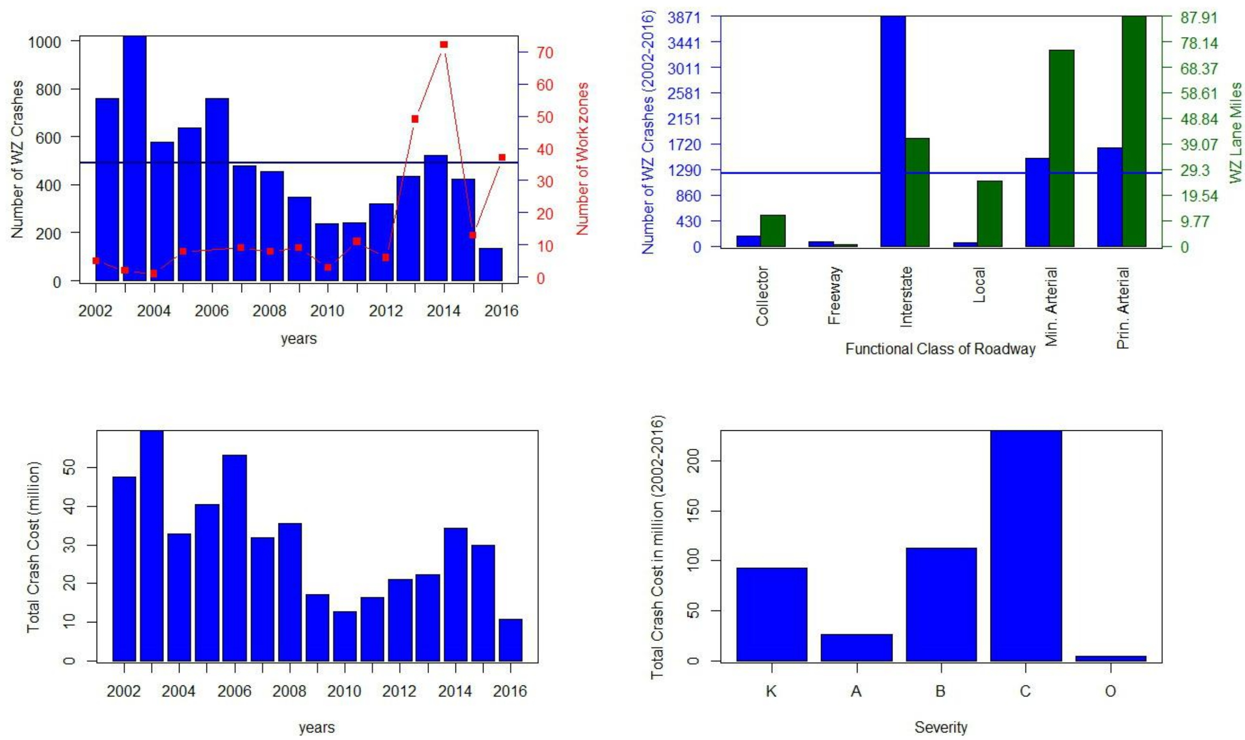
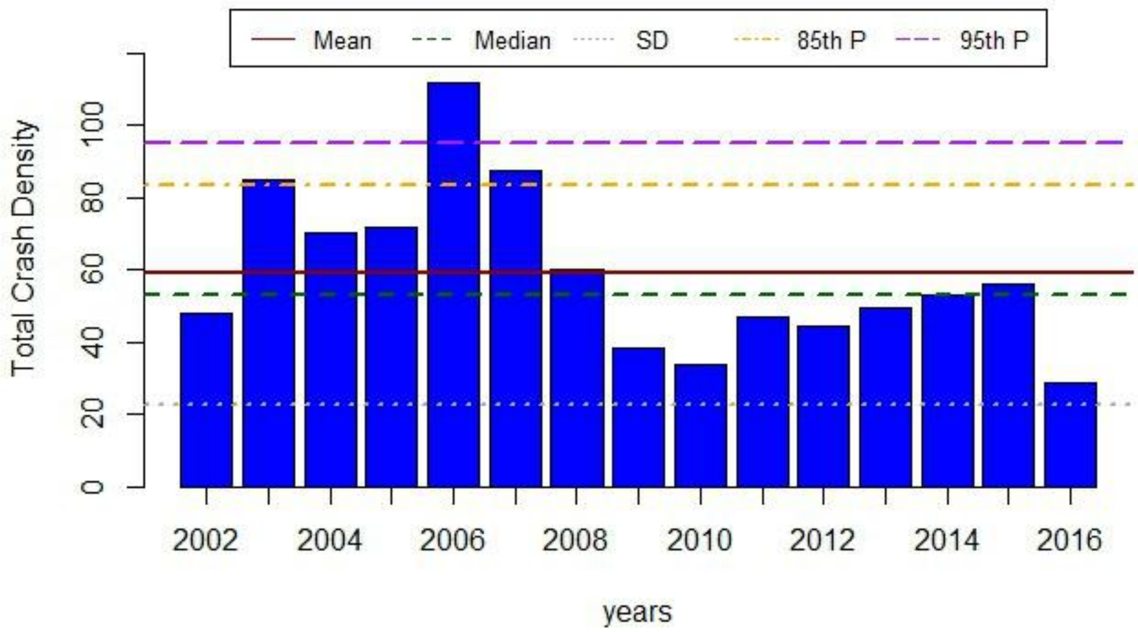


Figure 100 Work zone crash analysis - Shelby County

and mean crash cost for the year 2015 across all Counties is 2.727 million in the second figure. The median of crash density across all Counties for the year 2015 is 0.487 in the first graph and median of crash cost across all Counties for the same year in the second graph is 0.216. The standard deviation of crash density across all Counties for 2015 is 25.954 in the first and 7.907 in the second. The 85th percentile of work zone crash density across all the Counties shows a value of 4.324 in the first and crash cost of 2.58 in the second. Finally, the 95th percentile of crash density in the first graph shows the value of 21.559 and 95th percentile of crash cost in the second graph shows the value of 15.753. In addition, it can be observed from figure 12 that for the year 2015, for the Counties: Chester, Clay, Davidson, Shelby and Washington, the crash density values are higher than the mean whereas for the Counties: Chester, Clay, Davidson, Knox, Sevier and Shelby, the crash cost values are higher than the mean. The crash performance measurement for the rest of the years from 2002 to 2014 can be found in Appendix F.



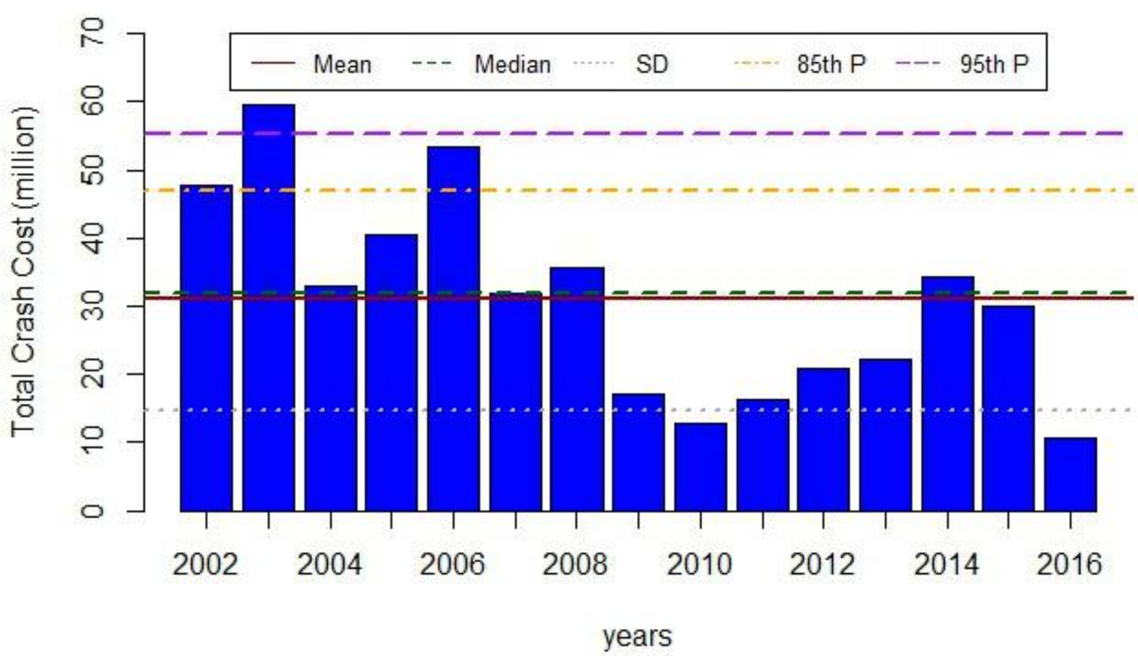


Figure 111 Crash Performance Measure: Shelby County

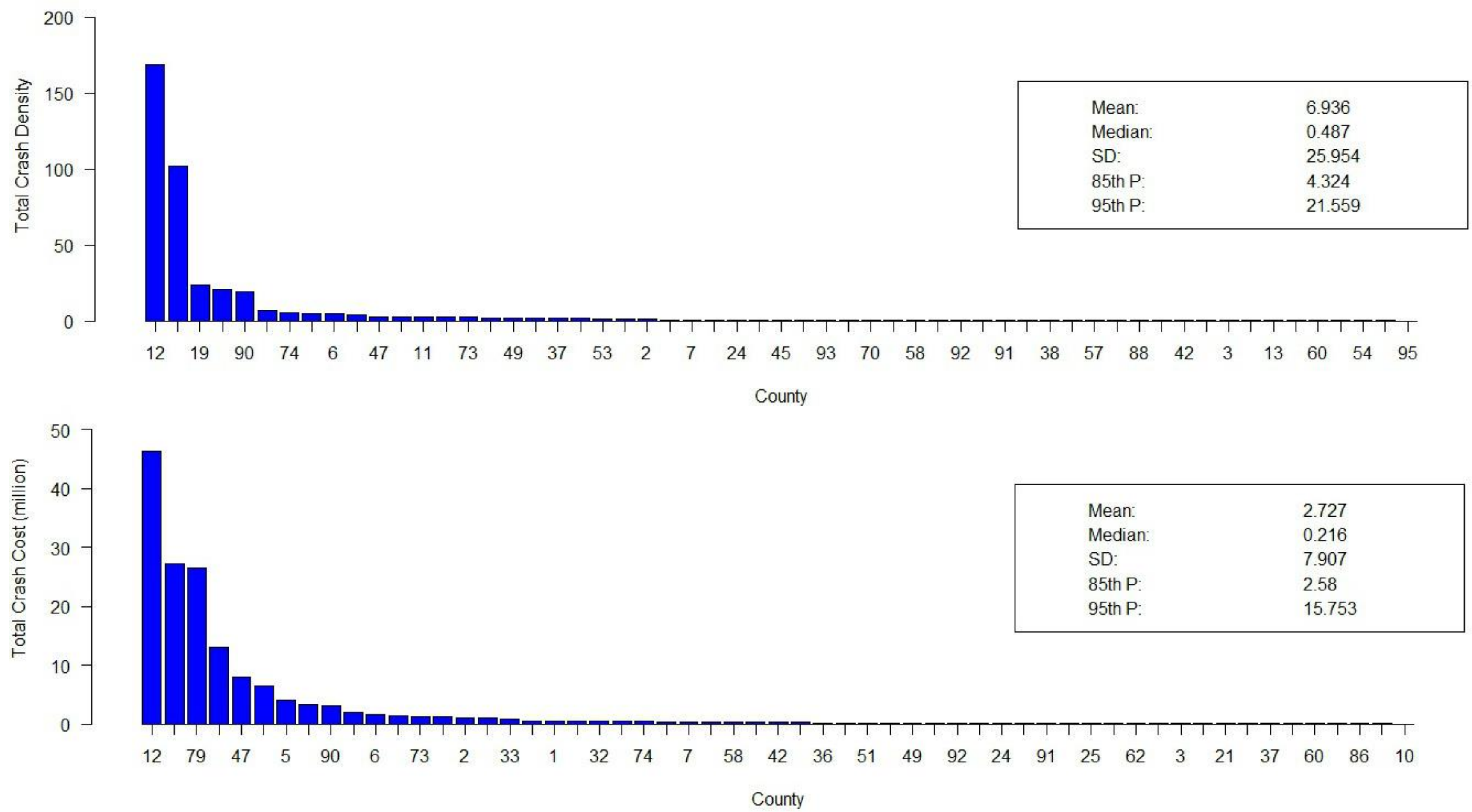


Figure 122 Crash Performance Measure: Year 2015

7.2 Conclusion

This section presented the calculation of performance measures using the predicted crash density and crash cost and explained the results for Shelby County. The first figure consisted of four graphs and the second figure contained 2 graphs. The first graph in figure 10 showed the trend of work zone crashes with number of work zones. The second graph showed the trend of work zone crashes with total number of work zone lane miles for each functional class of roadway. The third and fourth graph showed the bar plot of work zone crash cost with years and severity respectively. Figure 11 showed the calculated performance measures for the Shelby County. The five different performance measures are shown in five different color and line types. Figure 12 showed the calculated performance measures for the all the Counties for the year 2015 which also depicts the five performance measure values. Similarly, figures for other Counties, regions and for years are also created and shown in Appendix C, D, E and F that can be explained in a similar fashion.

8 DISCUSSION AND CONCLUSION

Work zone safety is identified as a major concern for all the transportation decision makers, agencies and the public. They have significant impacts on traffic conditions as well as safety of humans like workers and drivers. The growth of travel in the U.S. has increased significantly over the total lane mile of roadways and in order to preserve and maintain old roads or construct new roads, work zones are encountered on a regular basis which demands ample safety measures. Approximately four people get injured every hour due to crashes at work zones. TDOT has targeted the reduction of work zone crashes, at the administrative level, by incorporating it in the Individual Performance Plans of all operations staff. The objective of this research was to utilize past crash data, work zone data and roadway data maintained by TDOT, to identify and analyze crash trends and patterns in work zones, while taking into account, environmental and several other characteristics and develop performance metrics for Tennessee work zones. Identifying the measures will ease the process of setting goals and actionable targets for the TDOT operations staff and manage their performance reporting process.

A thorough literature review was conducted on various work zone safety-related subjects that primarily focused on work zone crashes, work zone safety and work zone performance measures studies. From the available literature it was concluded that various types of performance measures are widely used to evaluate work zones of various States and regions. The most commonly used types of work zone performance measures are exposure, safety, mobility, queuing, delay and reliability. The literature also revealed that the neural network (NN) technique was hardly used for crash prediction. Work zone crash data for year 2002- 2016 and roadway characteristics data for all the 95 Counties were collected from TRIMS database managed by TDOT. Work zone data was also collected from PPRM database. Some of the data sets like the active duration of WZ is not known from the PPRM database of TRIMS which limited the research to certain extent. The methodology implemented for the determination of significant factors affecting work zone crashes and the prediction of work zone crashes involved the use of ANN model to establish the empirical relationship between work zone crashes and risk factors. A broad range of variables were explored that included highway geometry, traffic and environmental characteristics. The neural network (NN) method was favored upon conventional statistical models due to its efficiency and accuracy. The methodology was also implemented to predict crash density and crash cost. The data set was divided into model training, cross-validation and prediction data. The MLP feed-forward NN was developed to analyze the predominant causal factors contributing to traffic crashes at work zones. Also, the correlations between explanatory variables and response variables were determined. The prediction results for both the work zone crash density and crash cost suggested that there are significant differences in prediction values between counties and the overall prediction of crash density is higher than observed crash density.

Performance measures were calculated for all the 95 Counties and four regions using the predicted crash density and crash cost and figures were made which are available in appendices C, D and E. The graphs showed the trend of work zone crashes with number of work zones. It also showed the trend of work zone crashes with total number of work zone lane miles for each functional class of roadway. Finally, it displayed the bar plot of work zone crash cost with years and severity respectively. The final graph shows the calculated performance measures for the Counties and regions. The five different performance measures are shown in five different color and line types which can be found in Appendix.

One of the main obstacles in this work zone crash analysis was the lack of work zone duration data. This report demonstrated state of the art workzone crash performance measures across the country, present a rich data collection of workzone crashes of all counties, propose a sound methodology for the prediction of work zone crashes, analyze the work zone crash patterns across the State and develop suitable work zone crash performance measurements. The proposed methodology and the performance measures can be efficient in supporting TDOT in achieving the goals by avoiding the rolling horizon method to get more accurate and precise work zone crash thresholds. Outcomes of this research may be also be used in better scheduling of work zones across the state and counties as well as incorporate safety improvements.

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APPENDICES

APPENDIX A: TABLE SUMMARIZING WORK ZONE SAFETY AND PERFORMANCE MEASURES

AUTHORS	CRASH TYPE	WORK ZONE LOCATION	FACTORS AFFECTING CRASHES/CRASH SEVERITY	PERFORMANCE MEASURES (if any)	DATA USED
(Clark and Fontaine, 2015)	Rear-end, angle, sideswipe-same direction, fixed object-off road	State of Virginia	Stopping or slowing due to congestion, Changing lanes because of work zone, Involved work zone vehicle, Involved a flagman	N/A (higher level of granularity in capturing causal relationships could prove valuable for DOT work zone safety performance measurement programs)	Crash data from VDOT including 64 workzone projects
(Bai et al., 2015)	Truck related crashes	Highway US-36, Kansas	Change in speed difference between cars and trucks	N/A PCMs were developed (Passenger car model)	Traffic volume, vehicle speed, classification and gap data
(Debnath et al., 2014)	N/A	Queensland, Australia	N/A	N/A developed Tobit regression technique for modeling the probability and the magnitude of non-compliance with speed limits at work zones locations	Speed data
(Debnath et al., 2015)	N/A	Queensland, Australia	Various Hazards in workzone	N/A Safety Measures reported	Workzone workers interview data
(Drum, 2015)	N/A			Reported the warnings signs used by various DOTs	Survey data
(Liljegren, 2014)	Road work crashes (head on, side, rear end, road departure,	Sweden	drunk driving, driving without a license, extreme speed and	N/A	Crash data from STRADA (Swedish Traffic Accident Data Acquisition)

	overtaking, pedestrian, other)		absence of seatbelt usage		
(Cordahi et al., 2015a)	Impact Assessment and secondary crashes	I-495, Maryland	N/A	<u>Network wide:</u> 1. Reduction in average delay 2. Increase in average speed <u>Incident Zone level:</u> 1. Reduction in maximum deceleration 2. Reduction in average sub-link speed <u>User level:</u> 1. Increase in average speed 2. Reduction in travel time 3. Increase in average following distance 4. Reduction in number of stops	Incident data, RITIS data (date, time location, speed, volume)
(Long et al., 2014)	Run-off road, horizontal curves, intersection, tree collisions, head-on	7 MoDOT districts (NE, NW, Kansas city, Central, St. Louis, Southwest, Springfield,	traffic queues, lane drops or distracted driving, human factors like cell phone usage, daylight and dark	N/A possible countermeasures and suggestions recommended	MoDOT's Transportation Management System (TMS) database, Missouri work zone crash data (2009 – 2011)
(Morris et al., 2016)	Work zone crashes (fatal, injury, PDO)	N/A	reduced lane widths, poor visibility (e.g. night or poorly marked barriers and objects), slow or stopped traffic (e.g. advanced warning and transition zone), and merging vehicles	N/A Examines four types of speed enforcements: i) control (no enforcement), ii) police car present, iii) dynamic "your speed" signs, and iv) automated speed enforcement (ASE)	Survey data of 60 participants of different age groups acquired for simulation

(Roberts and Smaglik, 2014)	Work zone crashes (fatal, injury, PDO)	Prescott, Arizona (SR 89)	inattentive driving, following too close for conditions, failure to yield right of way, driving too fast for conditions, and exceeding posted speed limits within work zones	N/A	Speed data collected using CMSR (Changeable message signs with radar)
(Shaw et al., 2016)	Bike-Ped Crashes in Work Zones	Wisconsin	Alcohol use, darkness, night time,	N/A Recommended advances toward work zone safety and mobility for pedestrians and bicyclists	219 bicycle and pedestrian crashes (2004 - 2013)
(Sun et al., 2014)	Work zone crashes (fatal, disabling injury, evident injury, possible injury, PDO)	Missouri	AADT, segment length, duration of observation, urban location, work zone presence, injury	<u>Crash modification factor (CMF):</u> $CMF(duration) = 1 + \frac{\%\ incre.in\ duration \times 1.11}{100}$ $CMF(length) = 1 + \frac{\%\ incre.in\ duration \times 0.67}{100}$	Work zone crash data, AADT and segment characteristics (length and duration of 162 freeway work zones)
(Ullman and Iragavarapu, 2014)	Work zone crashes (fatal, disabling injury, evident injury, possible injury, PDO)	Idaho	N/A	Equivalent Fatal Crash Cost Ratio, EFCCR = $\frac{EFCCR \times 65^3}{55^3}$	AADT, speed and duration of work zone project
(Cordahi et al., 2015b)	N/A	New Orleans	N/A	Vehicle Kilometers Traveled, Vehicle Hours Traveled, Vehicle Hours of Delay, Congested Vehicle Kilometers, Congested Vehicle Hours, Percentage of	Traffic data, network data, population data

				Time Congested, Travel Time Differences, Travel Time to Lodging Facilities, Unfulfilled Fueling Demand, Average wait time	
(“Work Zone Fatal Crashes Involving Large Trucks, 2012,” 2014)	Fatal crashes involving large trucks	USA	Work zone area, number of vehicles involved, rear-ended crash	N/A Descriptive statistics of large truck crashes in work zones throughout the country	Parked/Working large truck data from the Parkwork datafile in FARS
(Weng et al., 2014)	Work zone rear-end crashes of 4 different vehicle patterns (car-car, car-truck, truck-car, truck-truck)	Singapore	i) heavy work intensity; (ii) the lane adjacent to work zone; (iii) a higher proportion of heavy vehicles and (iv) greater traffic flow	N/A	12,978 sets of vehicle trajectory data:6548 sets from CTE workzone and 6430 sets from TPE workzone
(Akepati, 2010)	Work zone crashes. 70% of work zone crashes occur in the activity area. PDO and rear-end collisions are more predominant in terms of crash severity and collision type	Iowa, Kansas, Missouri, Nebraska and Wisconsin (Smart Work Zone Deployment Initiative (SWZDI) region)	most of the work zone crashes occurred under clear environmental conditions as during daylight, no adverse weather, Multiple-vehicle crashes more predominant than single-vehicle crashes in work zone crashes, inattentive driving, following too close, failure to yield right of way, driving too fast, exceeding posted speed limits within work zones	N/A Ordered probit model developed. Risk factors towards more severe crashes include work zone crashes involving trucks, light duty vehicles, vehicles following too close, sideswipe collisions of same-direction vehicles, non-deployment of airbags, and driver age	Iowa work zone crash database (2002-2006)
(Bai and Li, 2007)	<u>Injury crashes-</u> Overturned,	Kansas Highway work zones	Drivers aged 15 – 34, daytime non-peak hours	N/A	4443 injury crash dataset from

	collision with pedestrian, parked car, bicycle, animal, fixed object, collision with other vehicle(head on, rear end, angle-side, sideswipe-same, sideswipe-opposite, backed into)		(10 am – 4 pm), rural major multi-lane arterials, speed limit 51 – 60 mph, driver error,		KDOT database (1992 – 2004)
(Carrick and Washburn, 2007)	N/A Described methodology to improve collection system of work zone crash data	Florida	N/A	N/A	N/A
(Chu et al., 2005)	N/A Evaluated the effectiveness of Automated work zone information system (AWIS)	Southern California	N/A	N/A	Traffic count and speed data collected using counters and speed guns
(Duffy and McAvoy, 2009)	Used macro ergonomic approach to study work zone crashes and near crashes to validate driving simulator	Ohio	N/A	N/A	Driving data in work zones
(Garber and Woo, 1990)	Work zone crashes	Virginia	Number of vehicles involved, alcohol, work	N/A	Work zone sites data (1982-1985),

			zone length, project duration		accident data, traffic volumes, speeds, headways
(Garber and Zhao, 2002)	Angle, fixed object on road, fixed object off road, rear end, sideswipe-same	Virginia	Predominant in Activity area, mostly rear-end crashes, sideswipe-same crash in transition area, multi-vehicle	N/A	Work zone crash data (1996-1999)
(Hallmark et al., 2013)	Work zone crashes	Iowa, Kansas, Missouri, Nebraska, Wisconsin	N/A Created a toolbox: *Synthesis of work zone performance measure*	3 different types of performance measures: Exposure: • VMT through the work zone • Number of vehicles passing through the workzone • Hours of work zone activity • Hours of dedicated enforcement in work zone • Percent of time when work activity occurs • Average number of work activity hours per day • Percent of hours when one lane or more lanes are closed Safety: • $\Delta CR = MCR_{wk} - MCR_{bef}$ ΔCR= change in crash rate MCR_{wk} = Monthly crash rate for work zone	Exposure: Project characteristics, work activities, traffic volumes, capacity Safety: Traffic crashes (number, severity, type, contributing factors, direction of travel), Worker accident and injuries due to traffic crashes (time, location, type, severity), Number and results of work-zone inspection scores, Road user complaints Mobility: Queue characteristics

<table>
<tr>
<td></td>
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<td></td>
<td>MCR_{bef} = Monthly crash rate for roadway segment before work zone

Total crashes
Percent change in work zone crash cost
Number of highway worker injury or worker injury rate per hours worked
Average or 85th percentile speed
% exceeding speed limit
Speed citation frequency
Work zone score based on inspection (5 – excellent to 1-very poor)
Frequency of work zone intrusions

<u>Mobility:</u>

Queuing measures
Travel speed
Delay
Travel time reliability
Queue length
Queue duration
Average speed
Volume to capacity
Level of service
Volume
User measures

</td>
<td>(beginning and end time, location, direction of travel), Travel time and delay (time, location, direction of travel), Agency rating scores</td>
</tr>
</table>

(Ullman and Schroeder, 2015)	Work zone crashes (typically fatalities)	N/A	N/A	<u>Mobility performance measure (PM):</u> • Average delay per vehicle during peak hour • Change in 95th percentile travel time • Percent of time when queues • % of projects experiencing more than 5 events that exceed maximum queue length • Change in number of hour-miles along the facility with operating speeds less than 40 mph <u>Safety PM:</u> • Change in crash rate per-vehicle-mile traveled during peak and off-peak periods throughout construction • Percent of vehicles exceeding the posted work zone speed limit by more than 10 mph • Frequency of forced merges per 1000 lane closure vehicle passages	Exposure data, indicator/stratification data, performance data

				• Worker injury rates per 200,000 worker-hours Customer satisfaction PM: • Average rating scores for each survey question	
(Ullman et al., 2011a, 2011b, 2009)	Work zone crash data (injury and fatality)	• I-95, Lumberton, NC • I-95, Philadelphia, PA • I-405, Seattle, WA • I-15/US95 Design-Build Project, Las Vegas, NV • I-15 Express Lane Project, Las Vegas, NV	N/A	Exposure PM: • % calendar days with work activity • % available working days with activity • Average hours of work per day • % work activity hours (no. of lanes closed) • Average lane closure length • Lane mile hours of closure • Vehicles passing through the work zone in evaluation period during work activities, lane closures and inactive times • Vehicle miles of travel in evaluation period during work activities, lane closures and inactive times Queuing PM:	Project data, work Activities data, crash data, and traffic operations data

				• % of work activity periods when queuing occurred • Average duration when a queue was present • Average length when a queue was present • Maximum length of queue during evaluation period • % of work activity when queue >1 mile • Amount(or %) of traffic that encounters a queue Delay PM: • Total delay during entire evaluation period • Total delay per work period • Total delay per work period when queues are present • Average delay during work activities per entering vehicle • Average delay during work activities per queued vehicle	

				• Maximum individual delay during evaluation period • % of vehicles experiencing delays greater than 10 minutes <u>Travel time reliability PM:</u> $buffer\ index = \frac{95th\ percentile\ TT - Ave.TT}{Average\ TT}$ <u>Safety PM:</u> • % change in crash rate in work zone (total, severe=injury+fatal) • Change in crash costs from expected no-work zone crash costs	
(Haseman et al., 2010)	Freeway crashes	I-65, Northwestern Indiana	N/A Suggested acquisition of work zone travel time data to assess relationship between crashes and workzone queuing	N/A	Crash dataset and travel time data
(Kang et al., 2004)	N/A	N/A	N/A	N/A Developed algorithm for speed limit control at highway workzones for crash minimization	Speed, network and traffic flow data

(Khattak et al., 2002)	Injury and non-injury crashes	California freeway work zones	work zone injury and non-injury crash frequency increases with longer workzone duration and length, ADT, urban location	Safety performance of pre-work and during-work zone: Total crash rate (CR) = $\frac{\sum T}{\sum (A \times L \times D)/10^6}$ T = total no. of crashes in a work-zone/segment A = ADT L = workzone/segment length D = Duration of observation in days	Crash data (crash frequency and injury severity), road inventory data (average daily traffic (ADT) and urban/rural character), and work zone related data (duration, length, and location)
(Khattak and Targa, 2004)	Truck involved workzone crashes	North Carolina	Workzone crashes involving large trucks are more injurious than non–work zone crashes, multivehicle on 2-way divided/un-divided roadways, higher speed limit, adjacent to activity area	N/A	data from the Highway Safety Information System (HSIS)
(Li and Bai, 2008a)	Work zone fatal and injury crashes	Kansas highway work zones	poor light condition, truck involvement, having only two travel lanes, and high speed limit	N/A Crash severity index (CSI) models were developed	85 fatal crashes (1998-2004), 604 injury crashes (2003-2004)
(Li and Bai, 2009)	Severe work zone crashes	Kansas	Effectiveness of Temporary Traffic control (TTC) measures determined (stop sign/signal, flagger/officer control, flasher device, no passing zone, pavement center/ridgeline)	N/A Binary logistic regression model developed	Crash data from KDOT accident database (2003-2004)

(Li and Bai, 2008b)	Fatal and injury crashes in highway workzones	Kansas highway work zones	Inattentive driving, daylight, rear-end, principal arterial, speed limit 51-60 mph	N/A	Crash data from KDOT database (1992-2004)
(Meng et al., 2010)	Crashes in long term work zone	Southeast Michigan work zone	62% decrease of individual fatality risk and 44% reduction of individual injury risk if mean travel speed is reduced by 20%	N/A Quantitative Risk Assessment (QRA) model developed	Southeast Michigan Traffic Crash Records Database (1998-2008)
(Morgan et al., 2010)	N/A	N/A	N/A	N/A simulator-based results of assessment of driver response to two different urban highway work zone configurations	Recorded data used (driver speed, braking, travel path and collision frequency)
(Muttart et al., 2007)	Rear-end and sideswipe crashes	N/A	N/A cell phone use reduces driver awareness and may increase the likelihood of a crash in work zone activity areas	N/A Simulation based study	N/A
(Bourne et al., 2010)	Work zone crashes	N/A	N/A	<u>Currently in use:</u> <u>Safety PM:</u> • Crash frequency • Crash rates • Crash costs • Service petrol dispatch frequency	<u>safety data:</u> police crash reports, DOT supplemental crash data collection, inspection reports, service petrol/fire department calls, TMC incident

				• Fire department dispatch frequency • Speeds • Speeding citation frequency • Inspection scores • Worker fatalities and injuries • Work zone intrusion frequency Mobility & Operational PM: • Delay per vehicle • Queue length • Duration of queue • Volume/ capacity ratio • Level of service • Volume (throughout) • % of time at free flow speed • % work zones meeting expectations for traffic flow • User complaints	reports, customer complaints Mobility data: Manual or electronic (i.e., camera) visual inspection of acceptable travel conditions, Manual sampling of travel times, speeds, and queue lengths, Electronic monitoring of speeds, volumes, and lane occupancies, Electronic monitoring of elapsed travel times via Bluetooth or other technology, User complaints

APPENDIX B: WORK ZONE CRASH FREQUENCY BY WORK ZONE TYPE

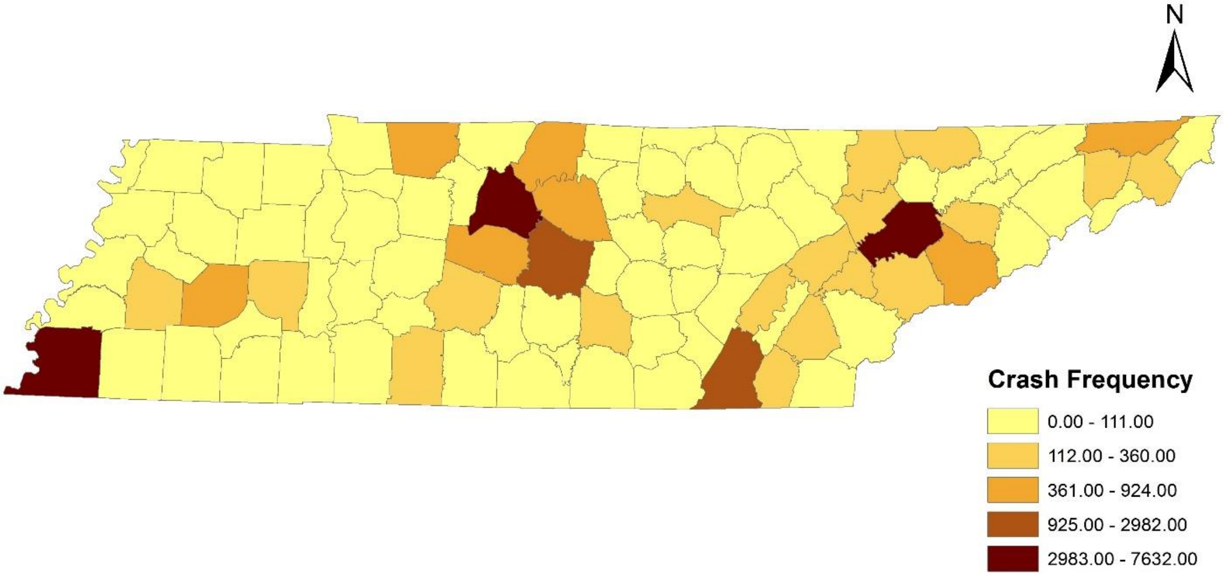


Figure 133 Construction work zone crash frequency by county

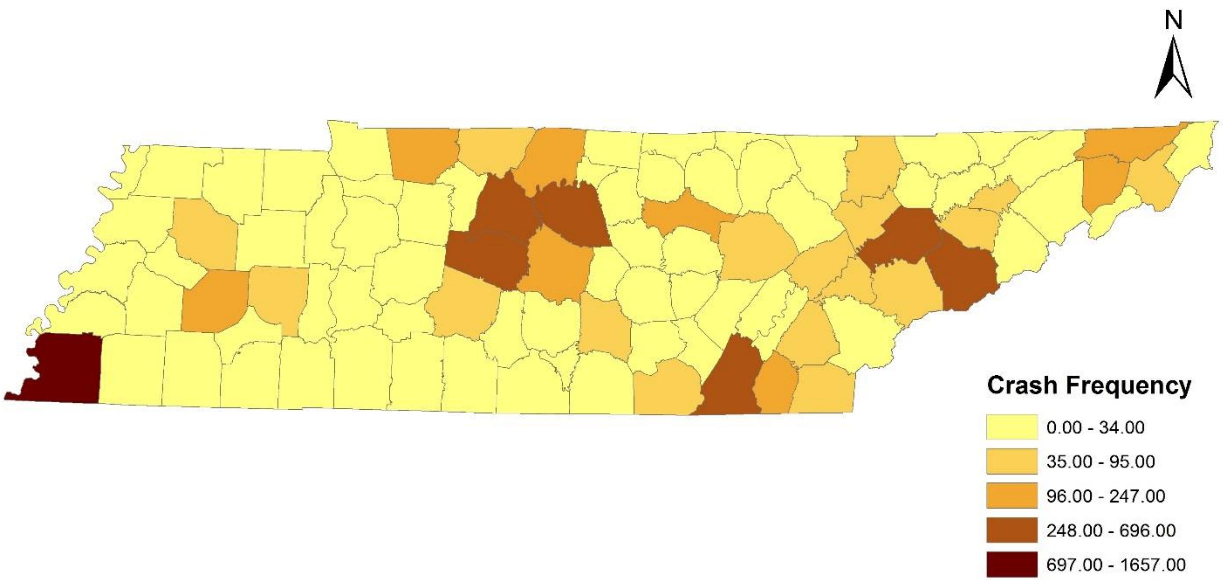


Figure 144 Maintenance work zone crash frequency by county

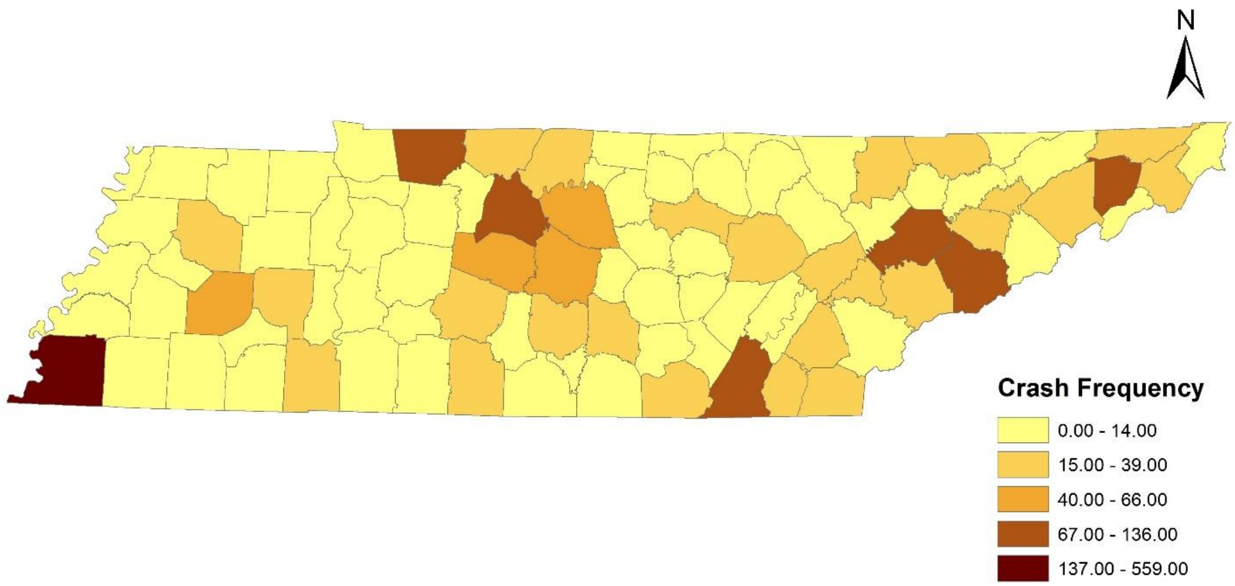


Figure 155 Utility work zone crash frequency by county

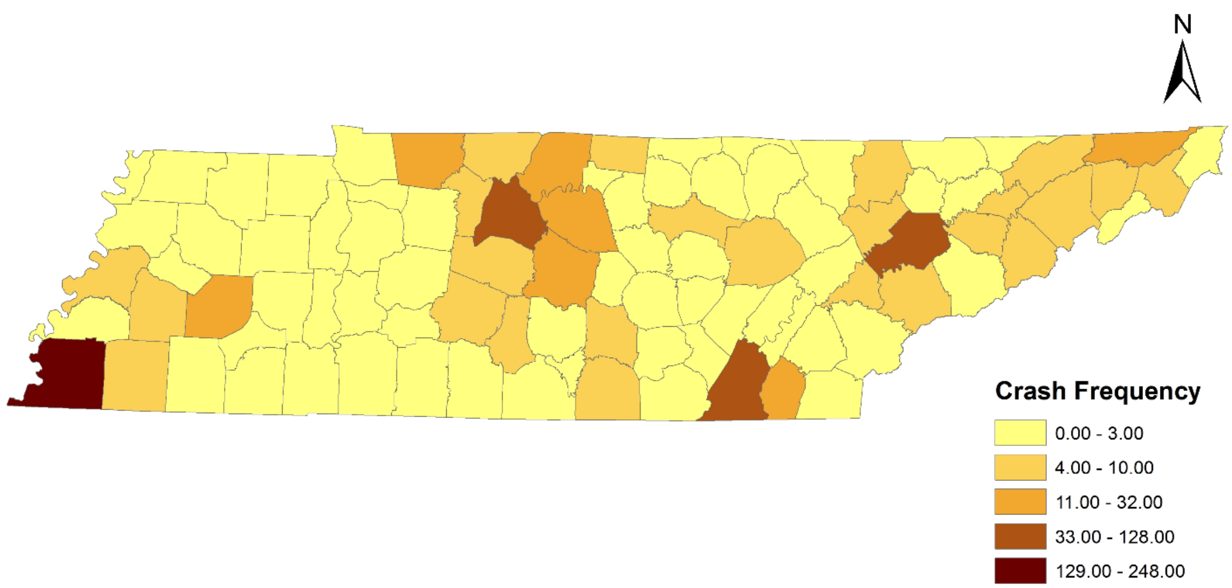


Figure 166 Other work zone crash frequency by county

APPENDIX C: WORK ZONE CRASH ANALYSIS BY COUNTY

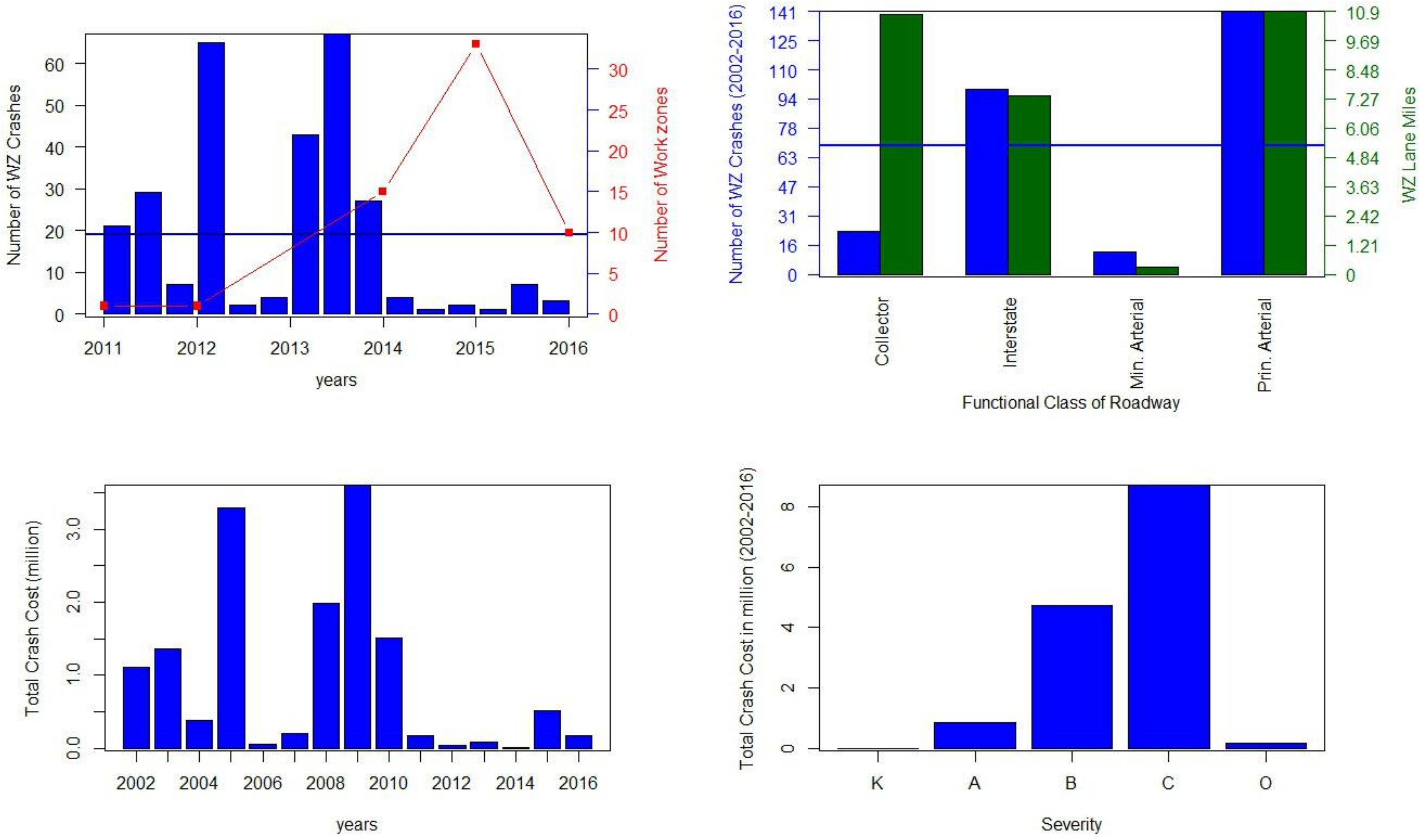


Figure 177 Workzone Crash Analysis - Anderson County

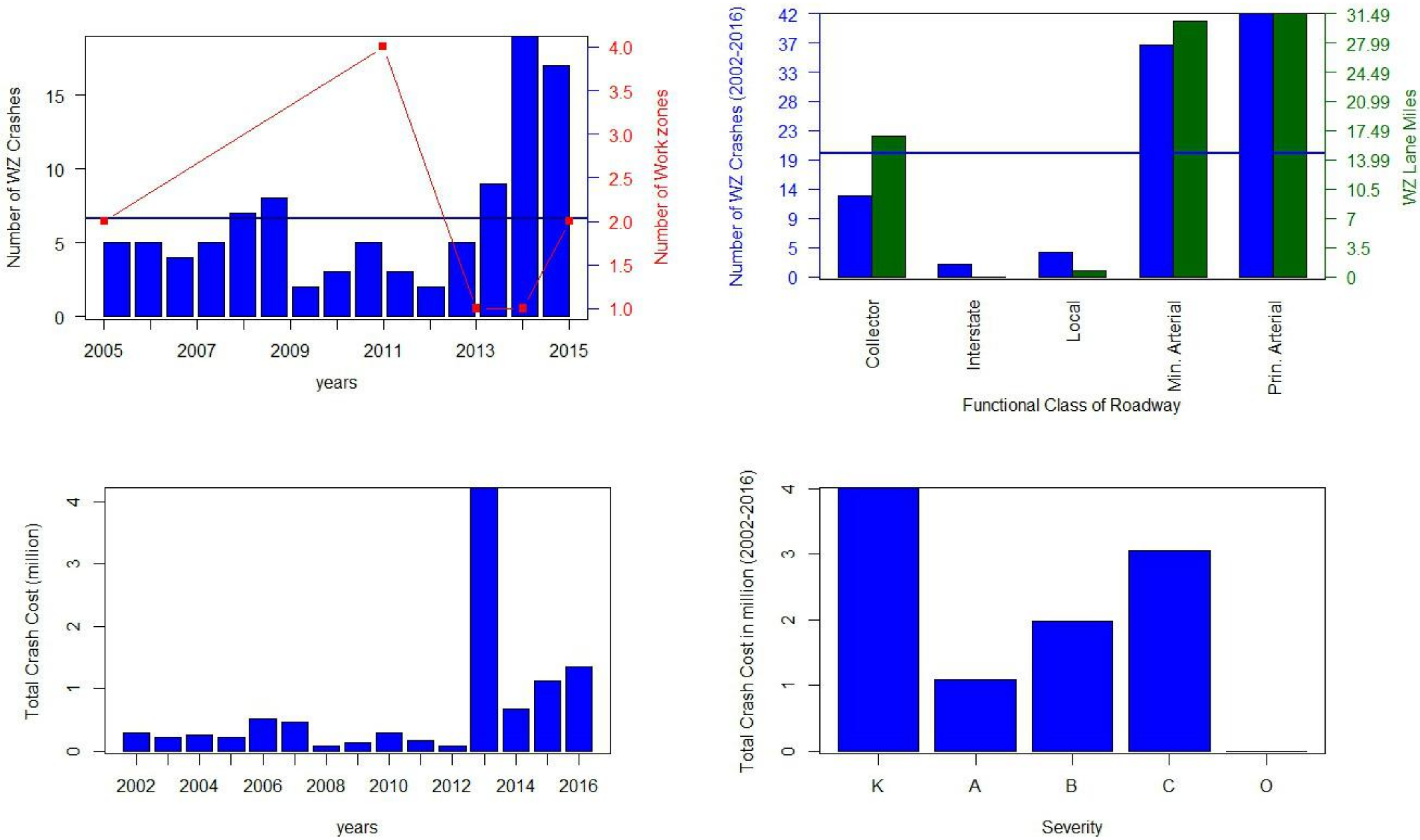


Figure 18 Workzone Crash Analysis - Bedford County

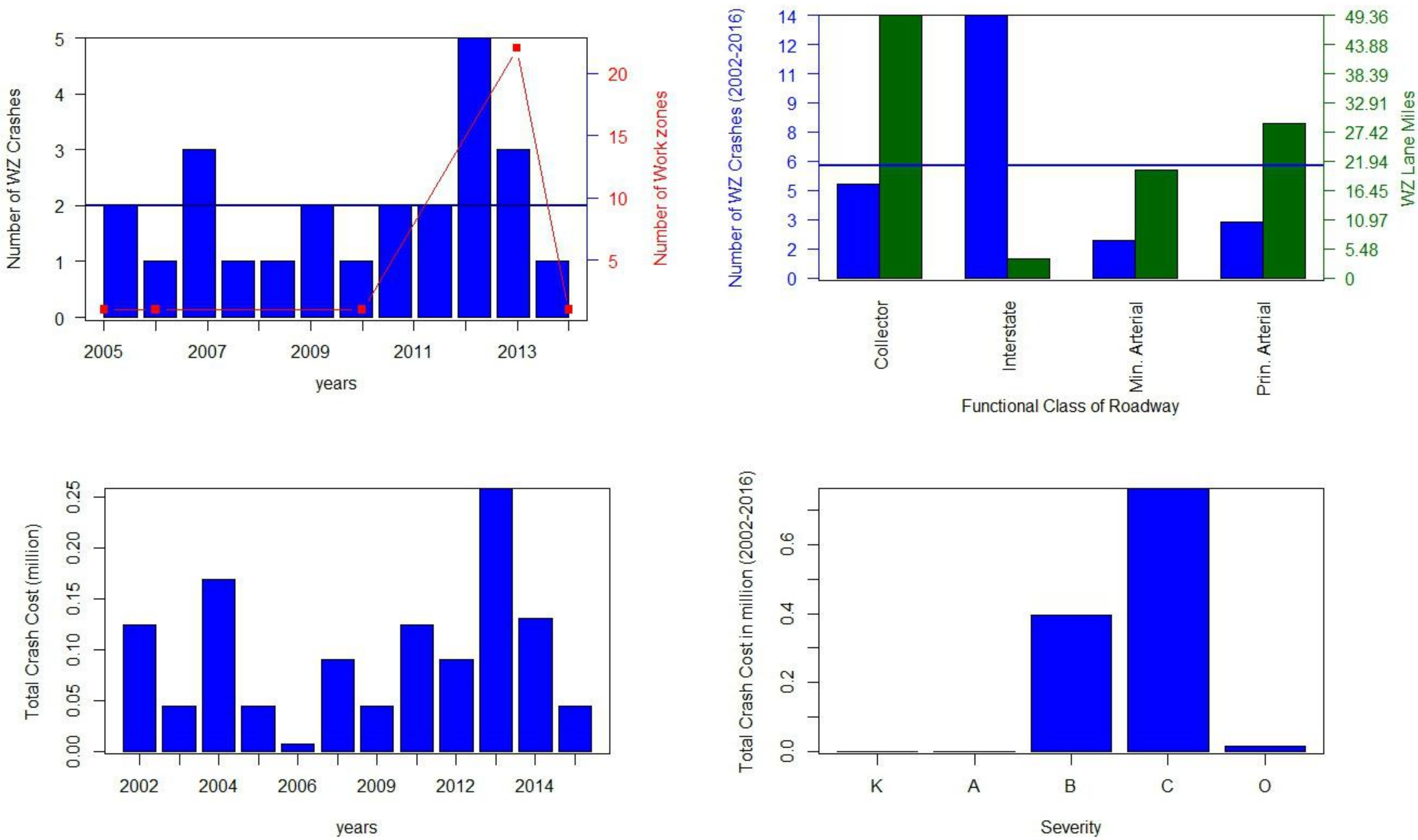


Figure 19 Workzone Crash Analysis - Benton County

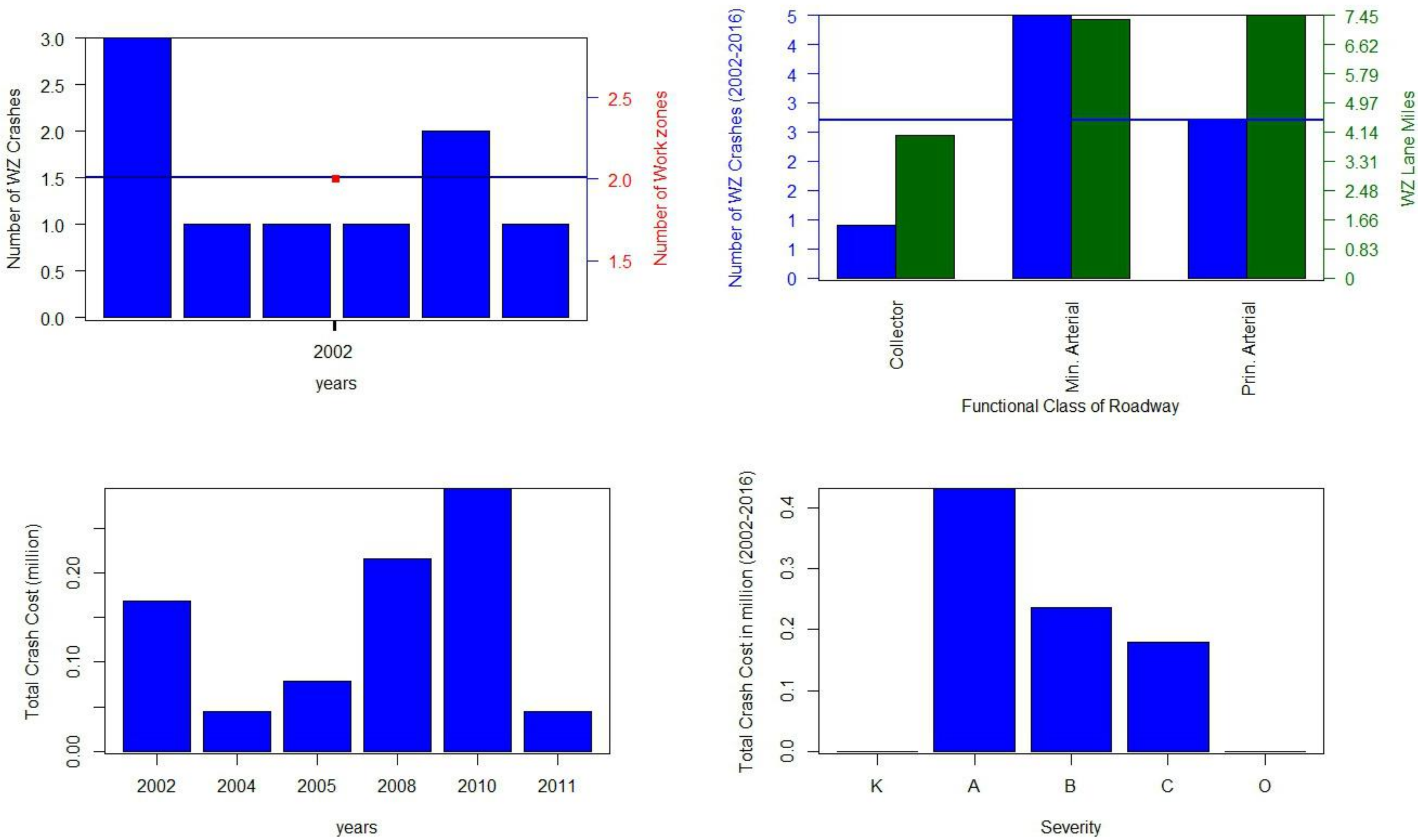


Figure 180 Workzone Crash Analysis - Bledsoe County

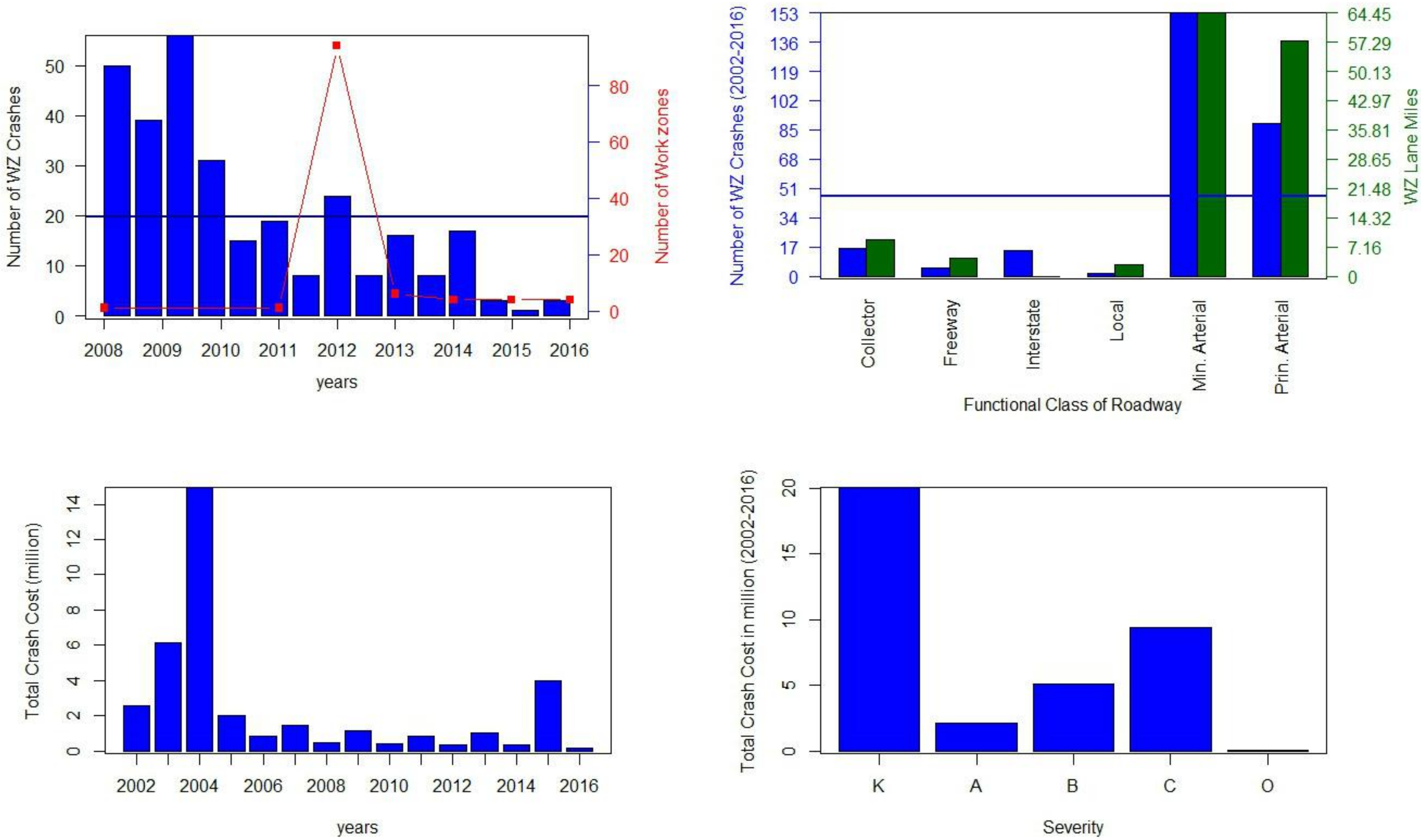


Figure 191 Workzone Crash Analysis - Blount County

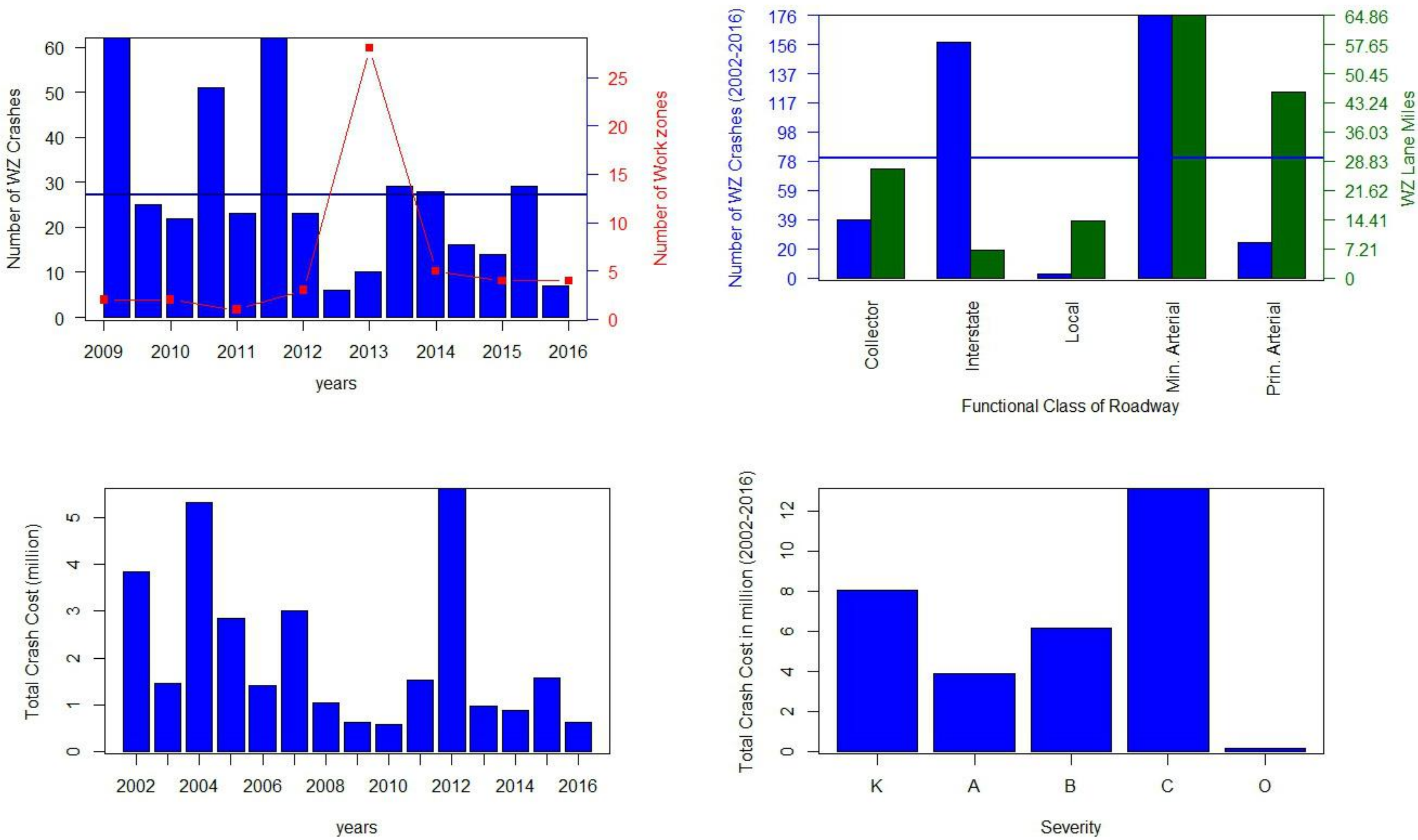


Figure 202 Workzone Crash Analysis - Bradley County

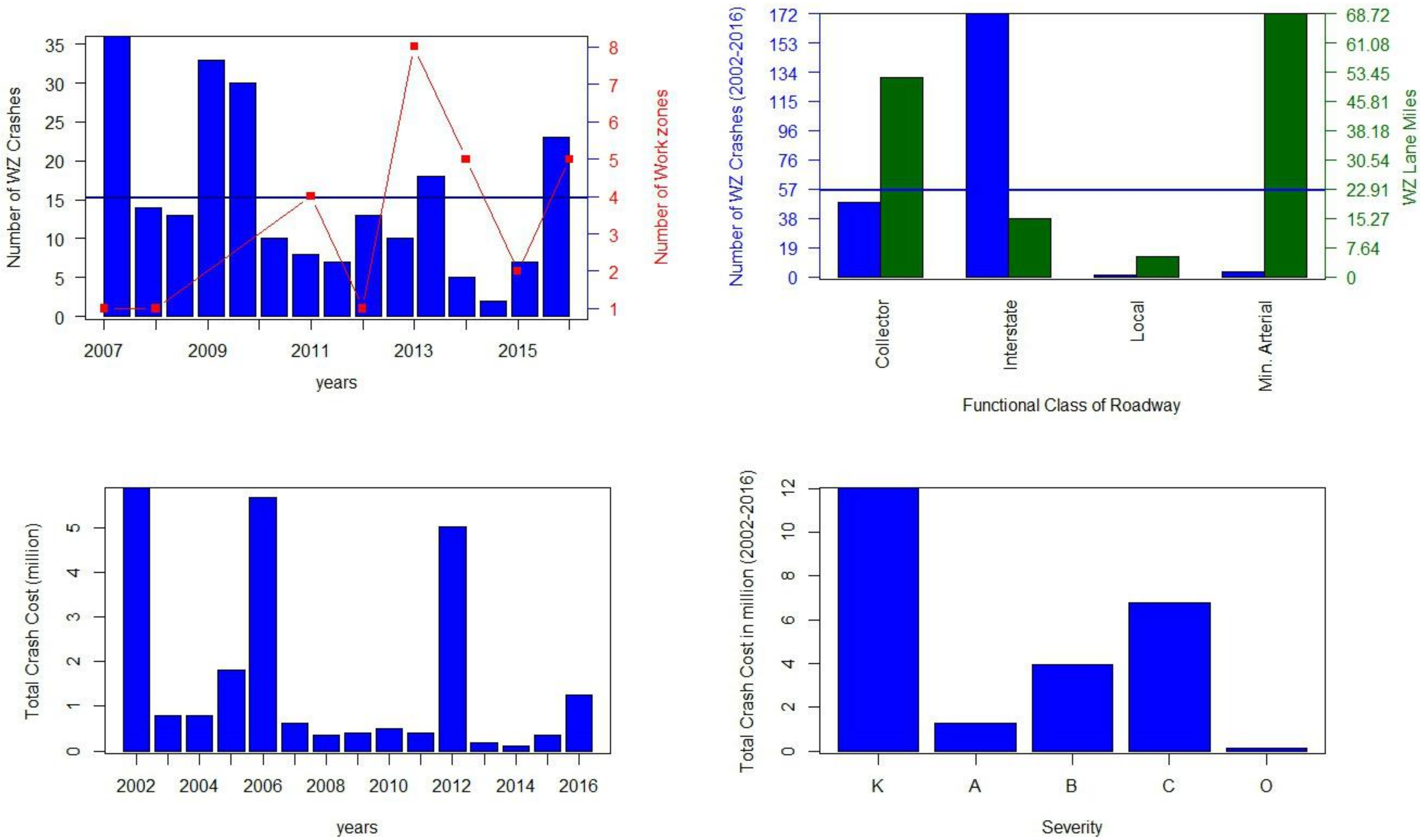


Figure 213 Workzone Crash Analysis - Campbell County

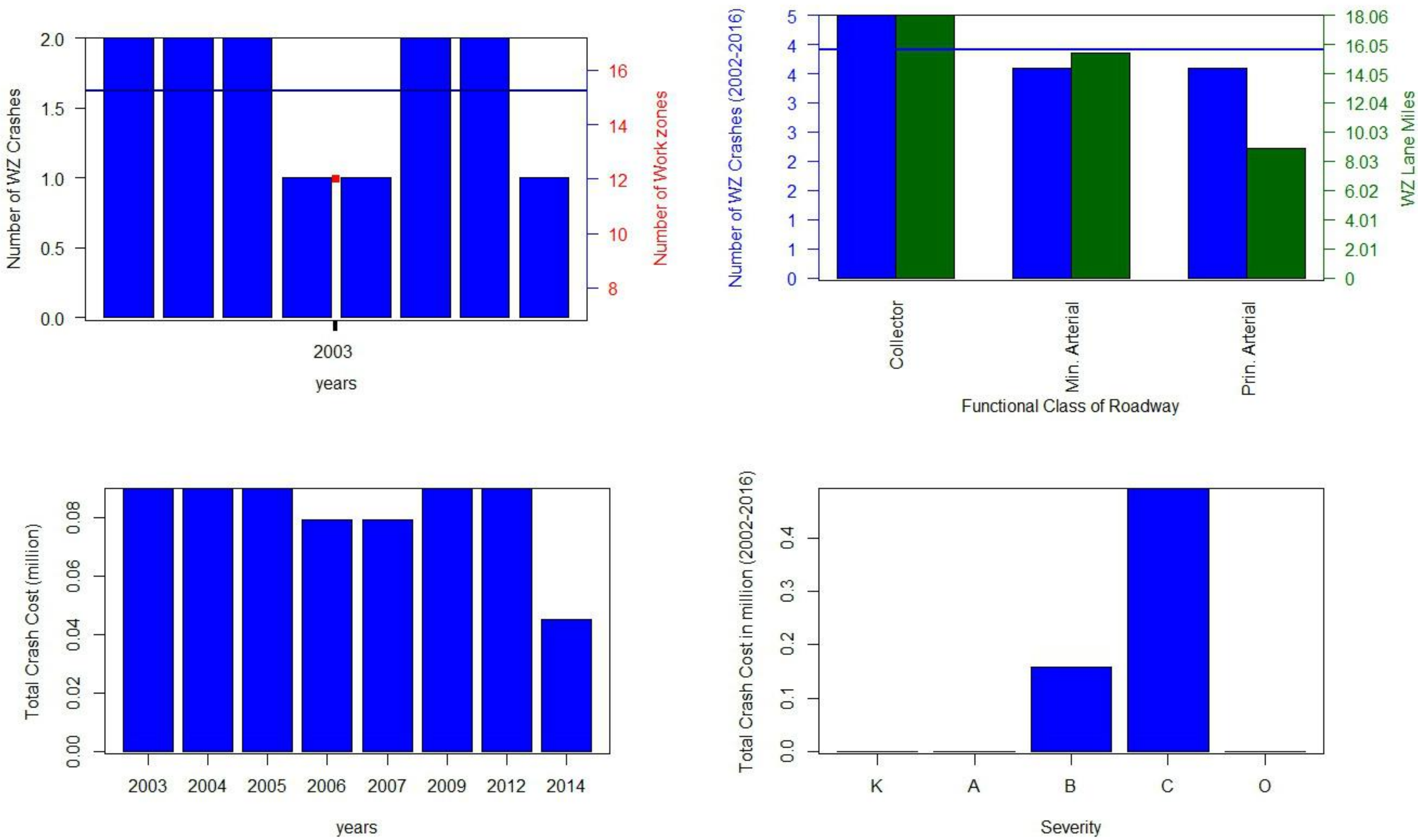


Figure 224 Workzone Crash Analysis - Cannon County

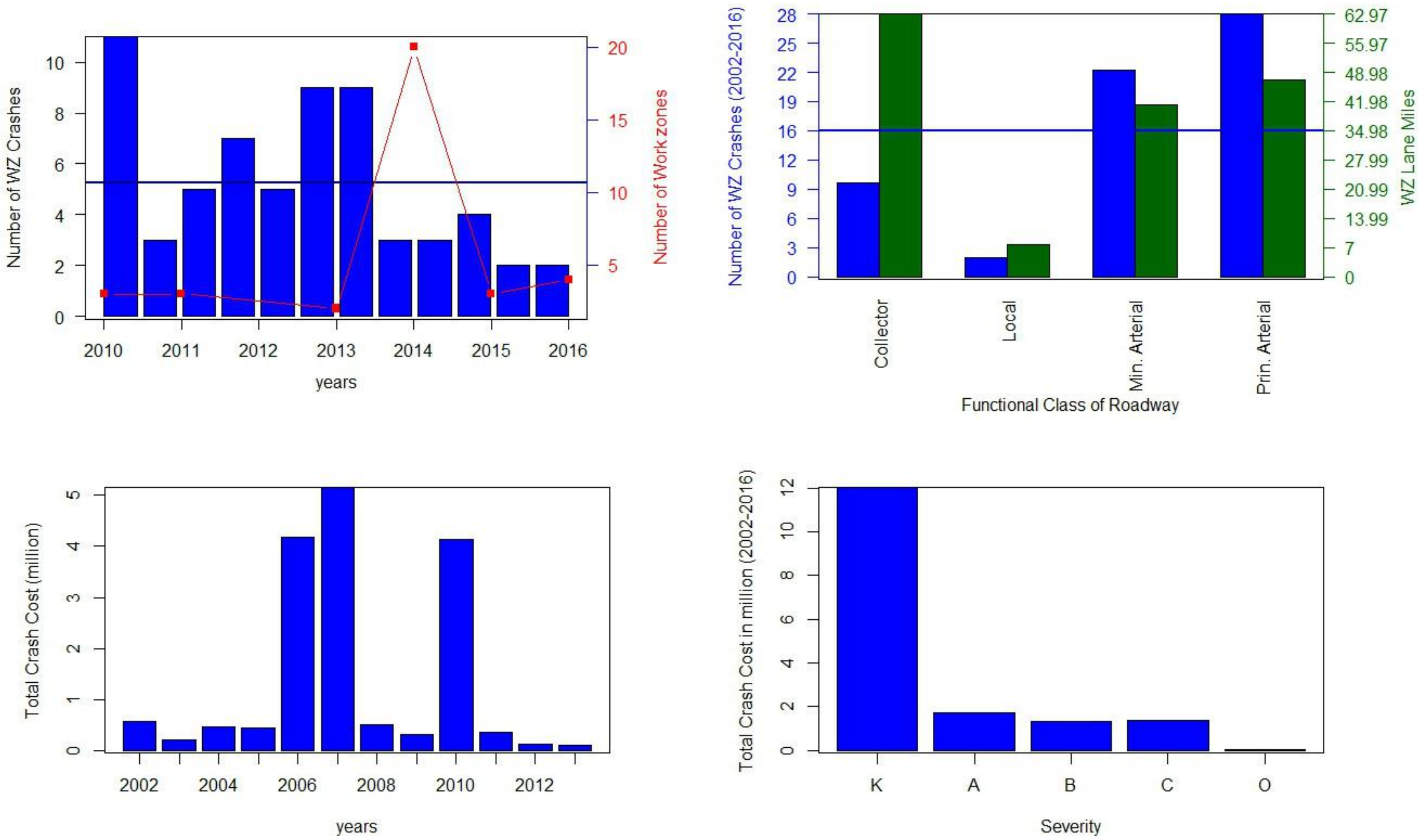


Figure 235 Workzone Crash Analysis - Carroll County

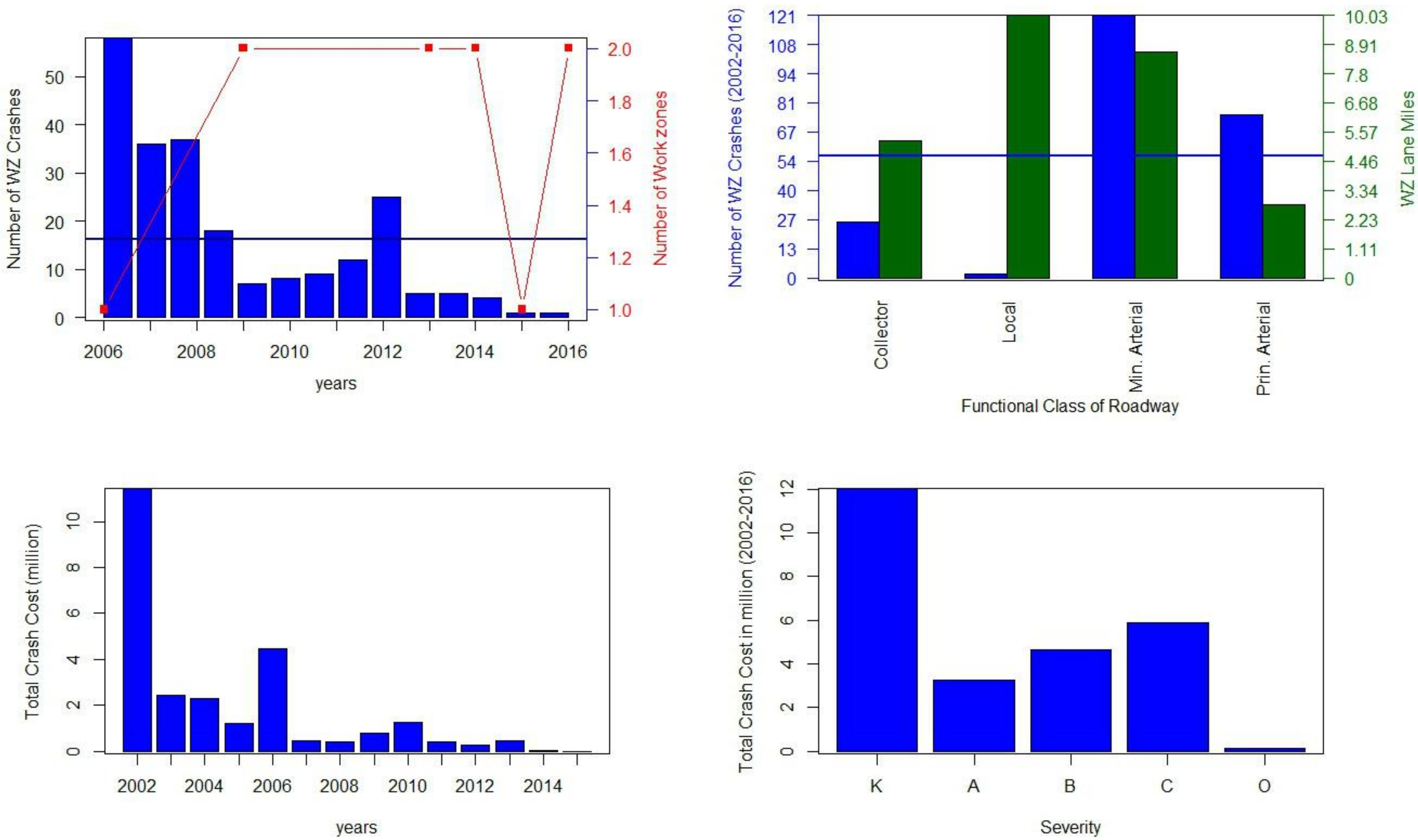


Figure 246 Workzone Crash Analysis - Carter County

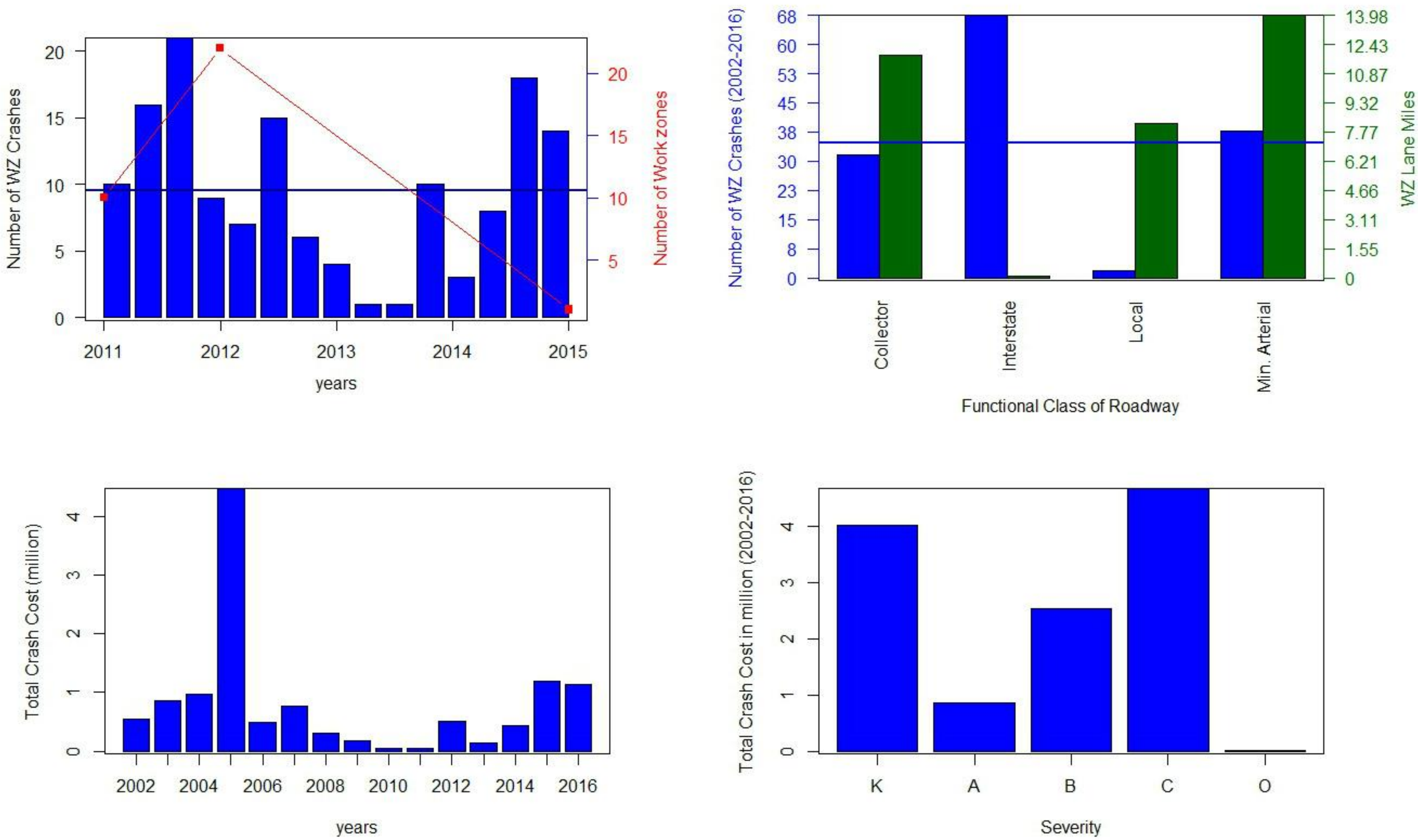


Figure 257 Workzone Crash Analysis - Cheatham County

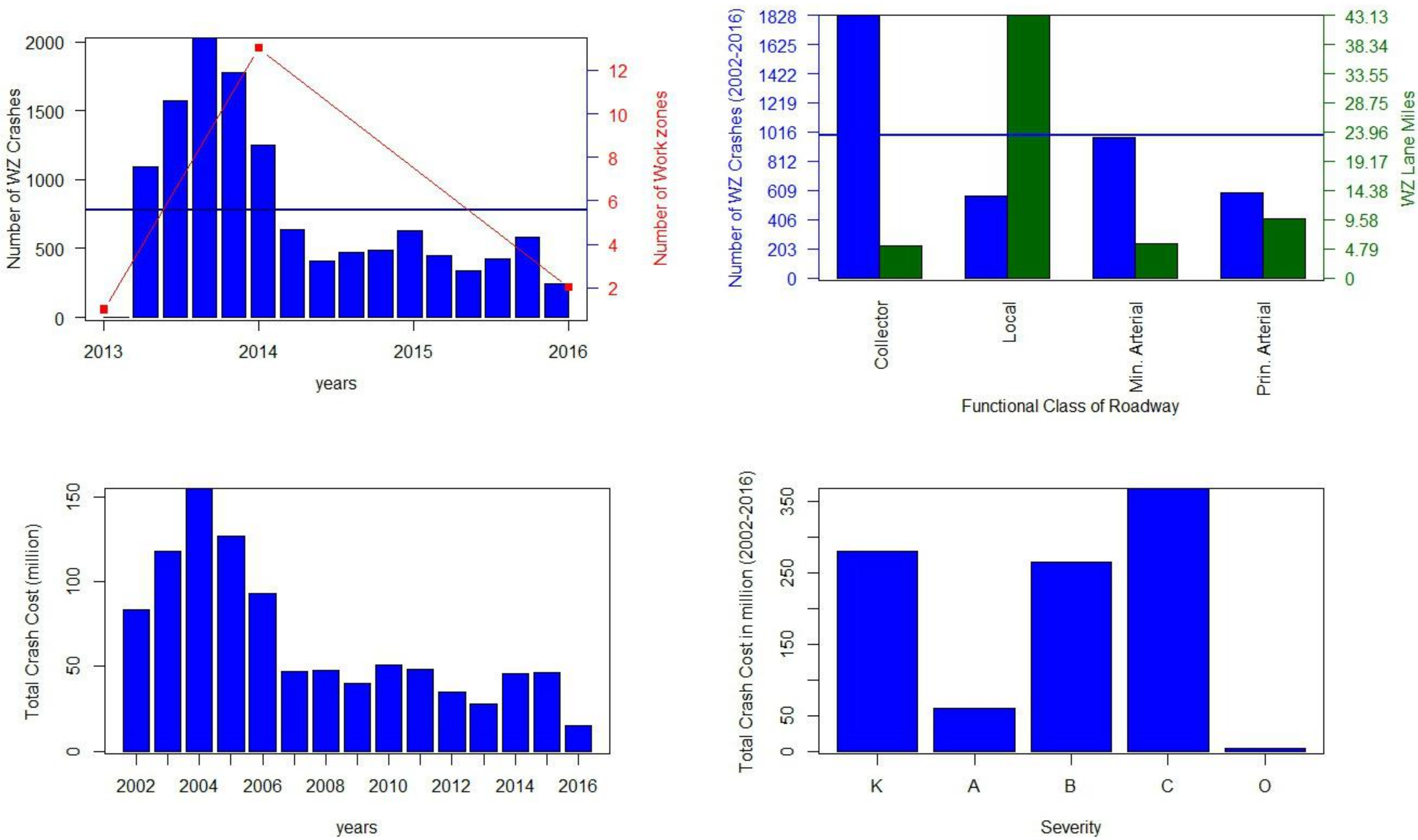


Figure 28 Workzone Crash Analysis - Chester County

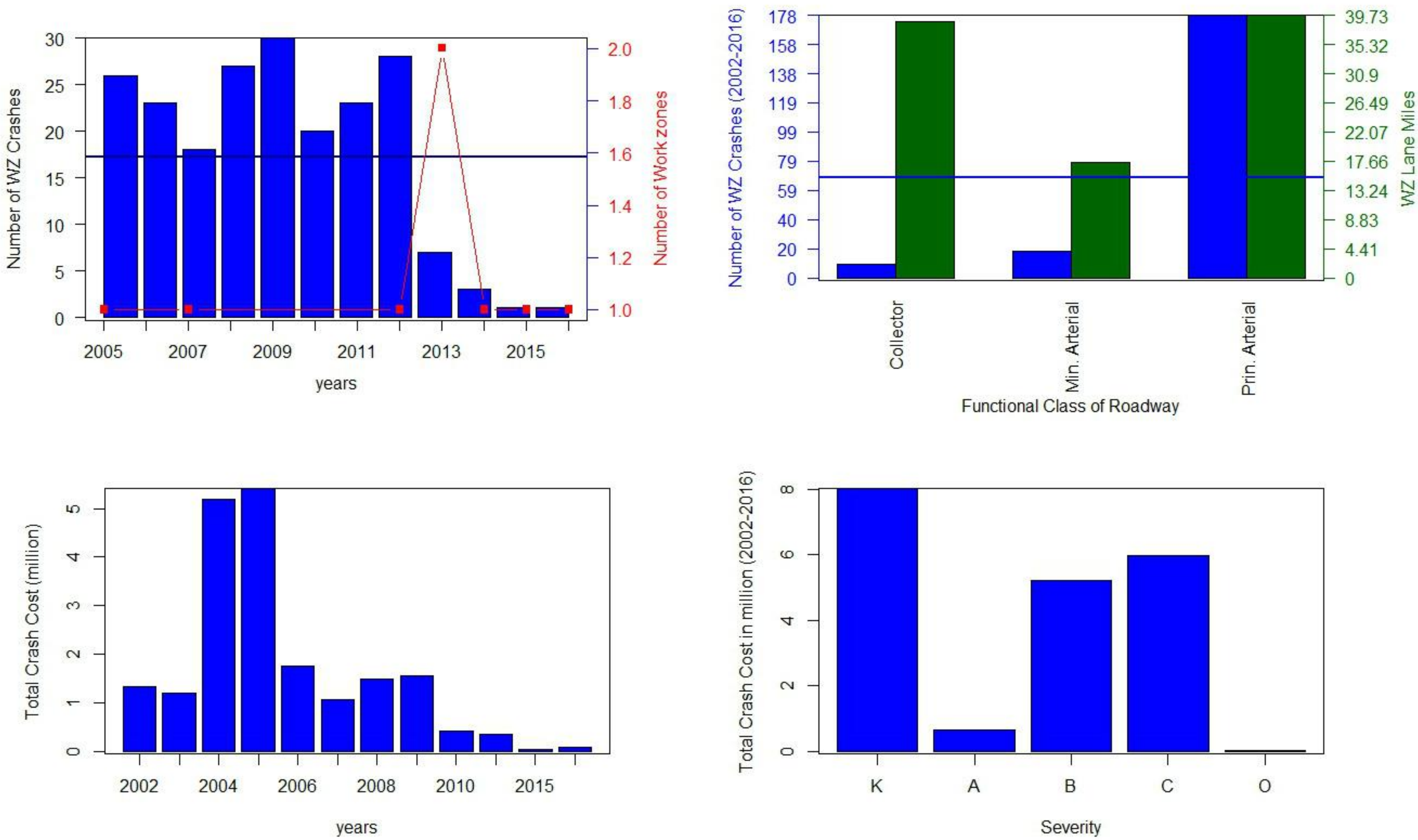


Figure 29 Workzone Crash Analysis - Claiborne County

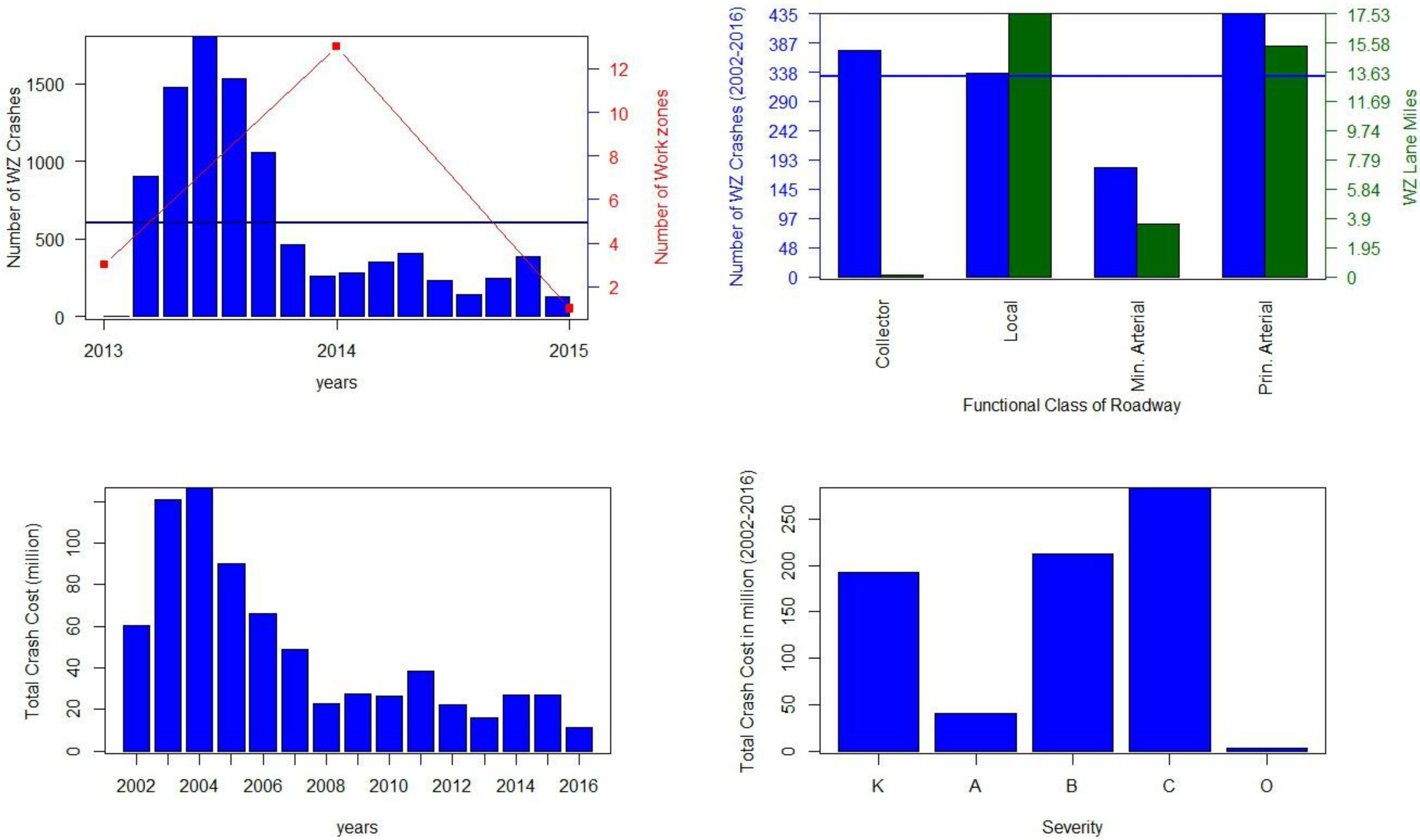


Figure 260 Workzone Crash Analysis - Clay County

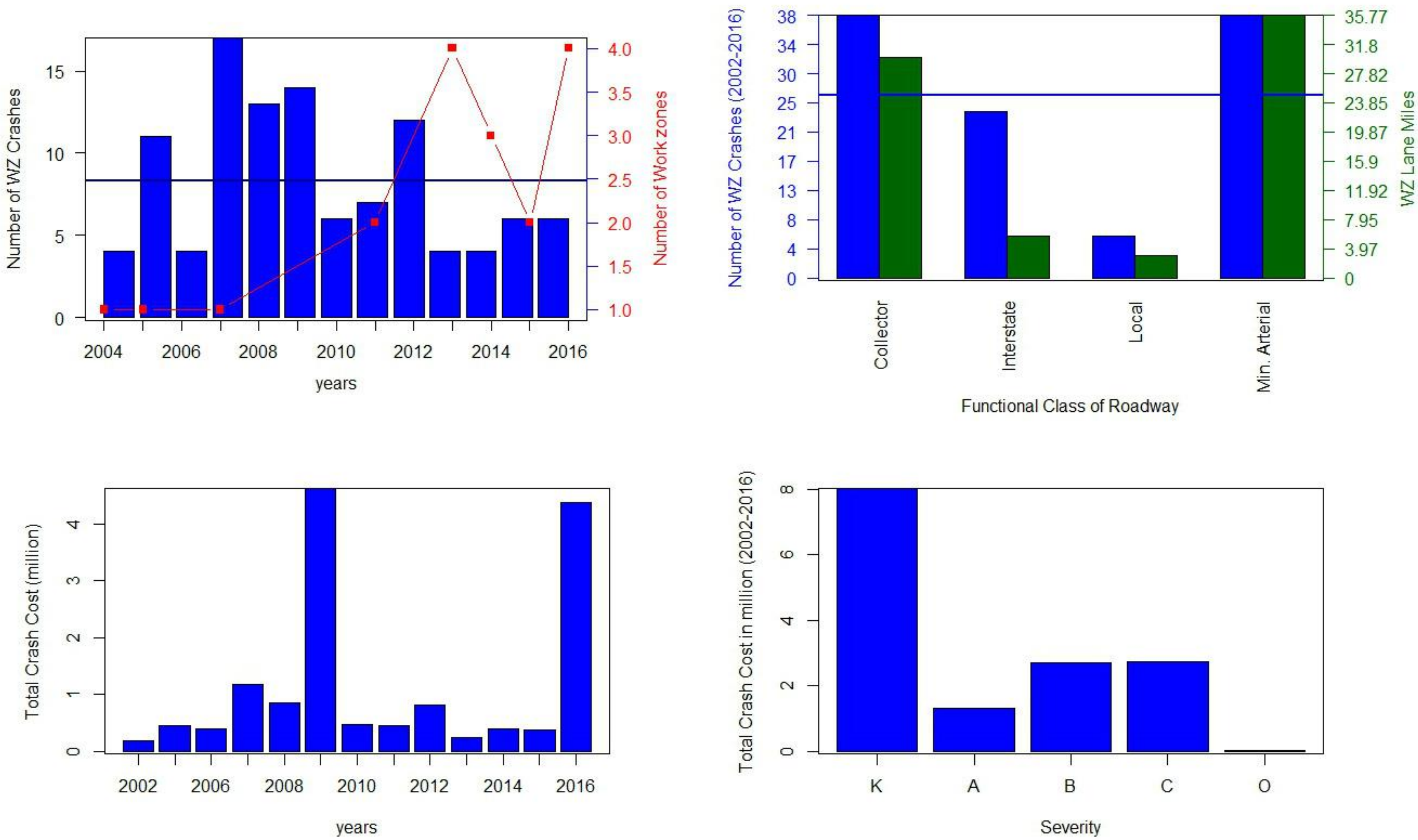


Figure 271 Workzone Crash Analysis - Cocke County

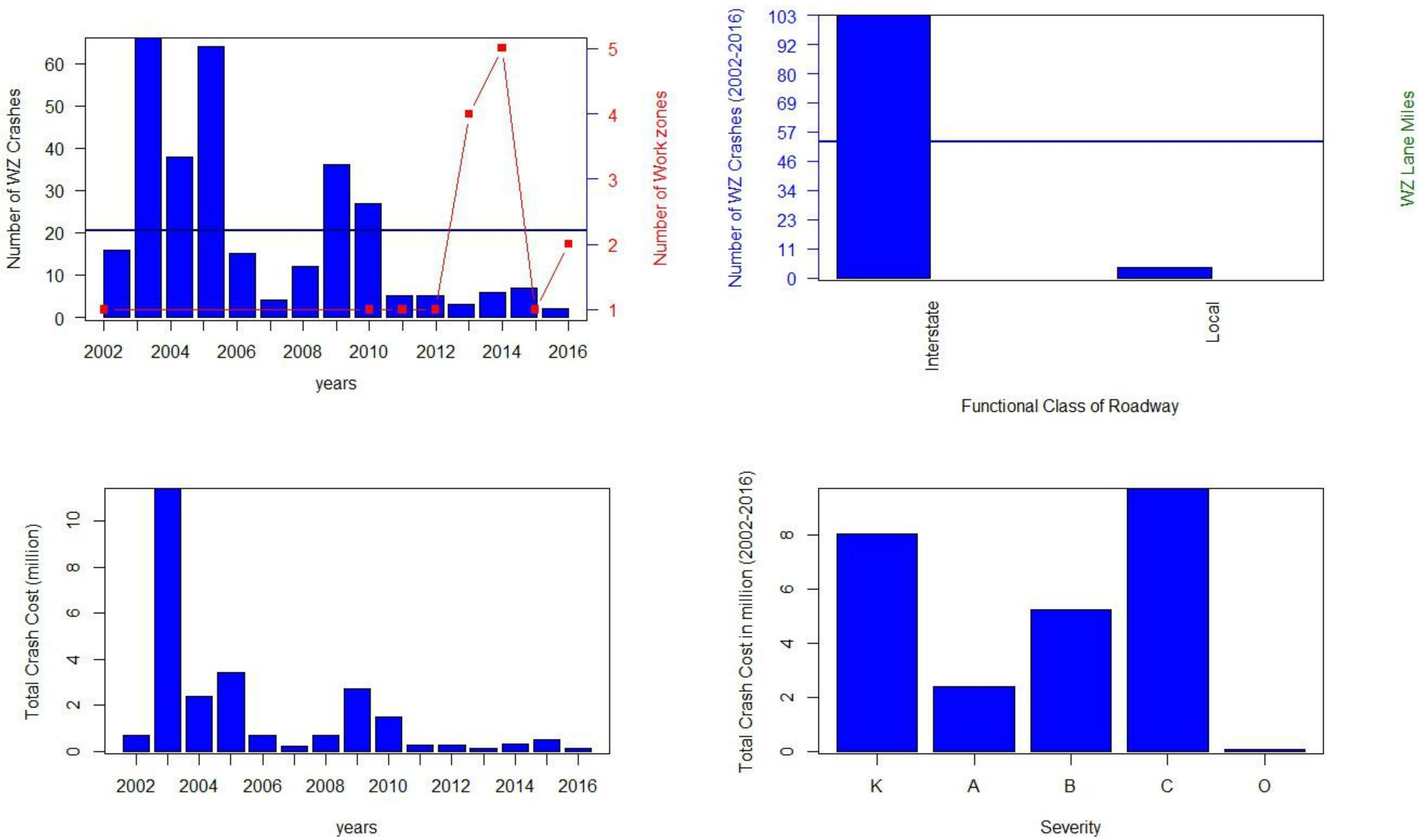


Figure 282 Workzone Crash Analysis - Coffee County

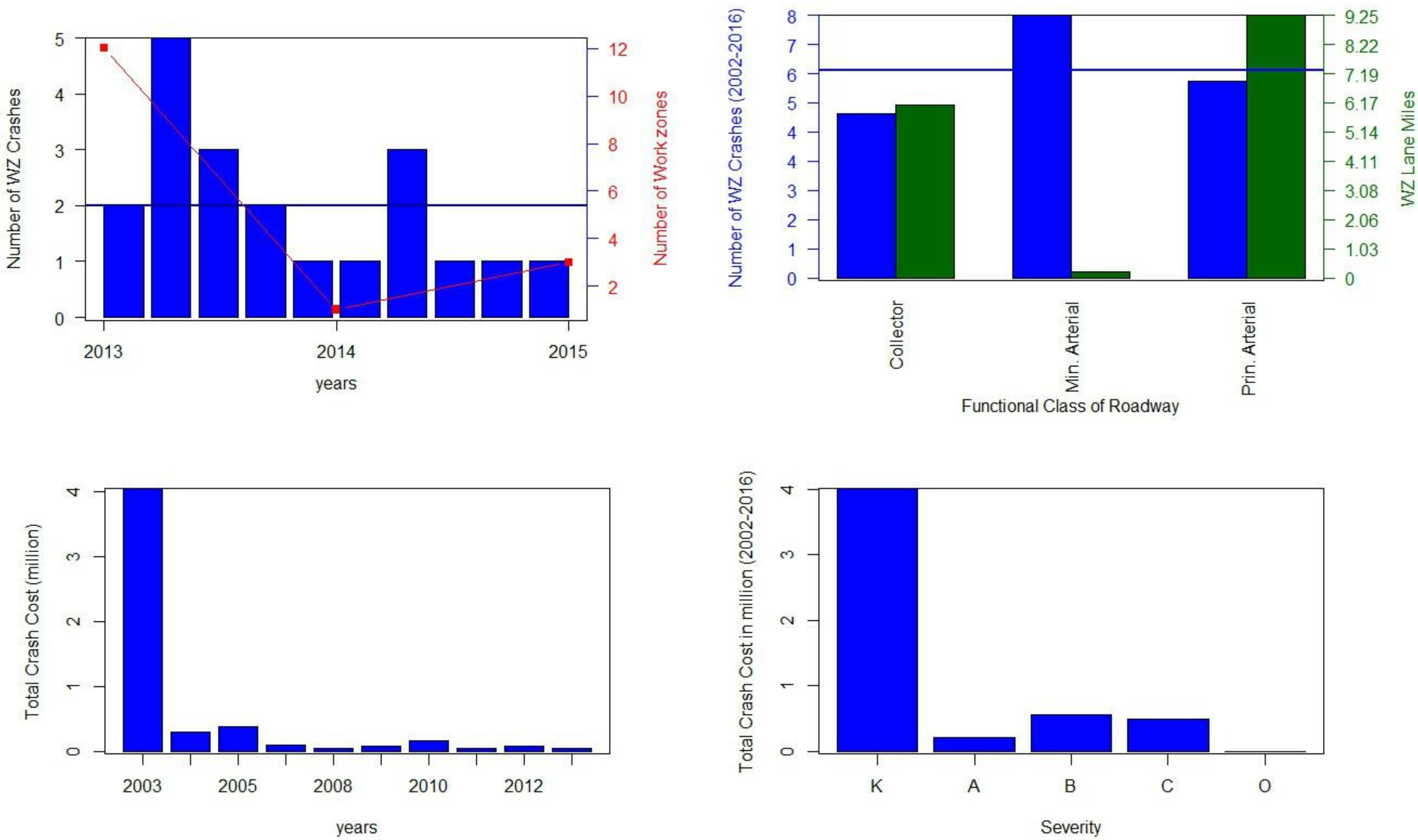


Figure 293 Workzone Crash Analysis - Crockett County

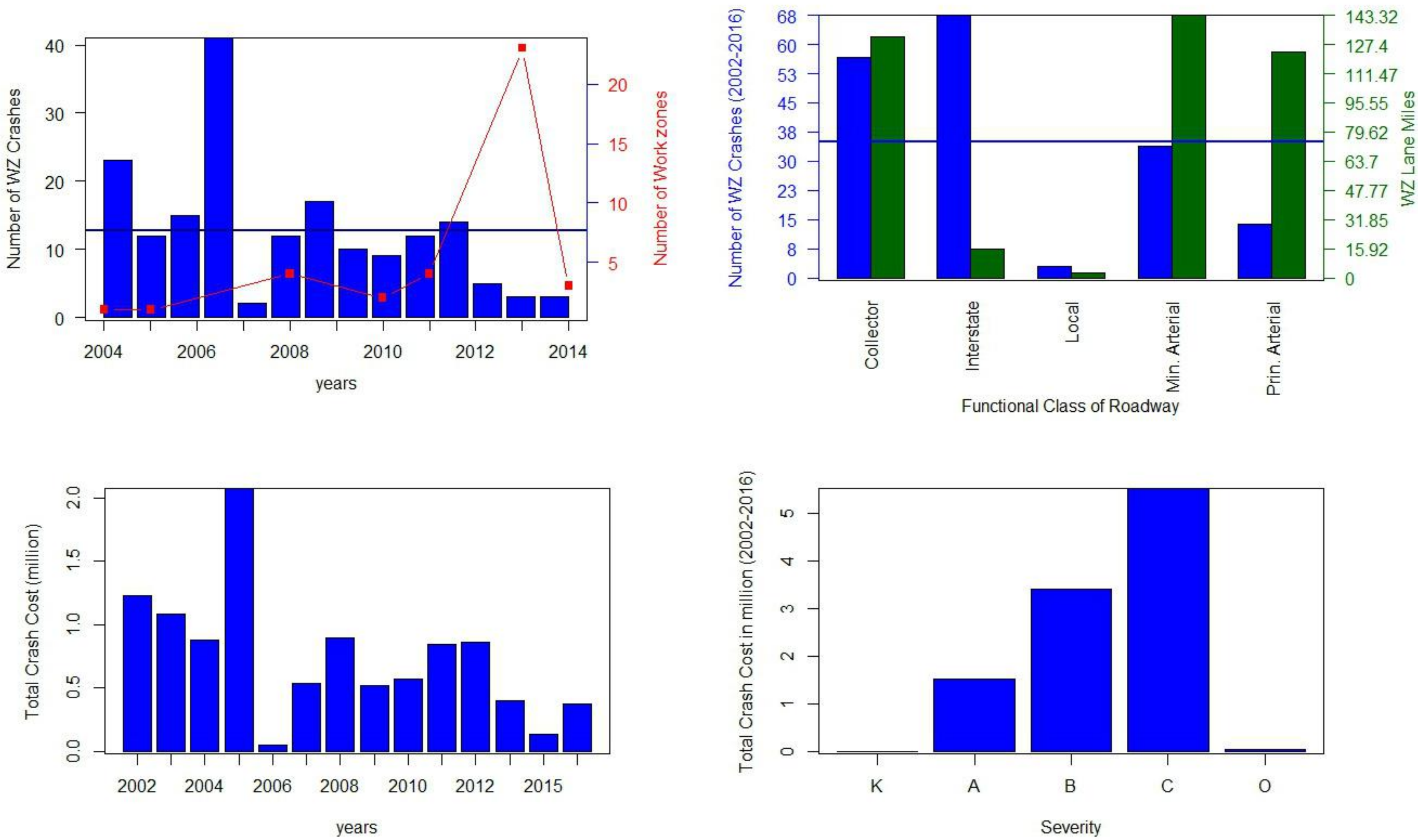


Figure 304 Workzone Crash Analysis - Cumberland County

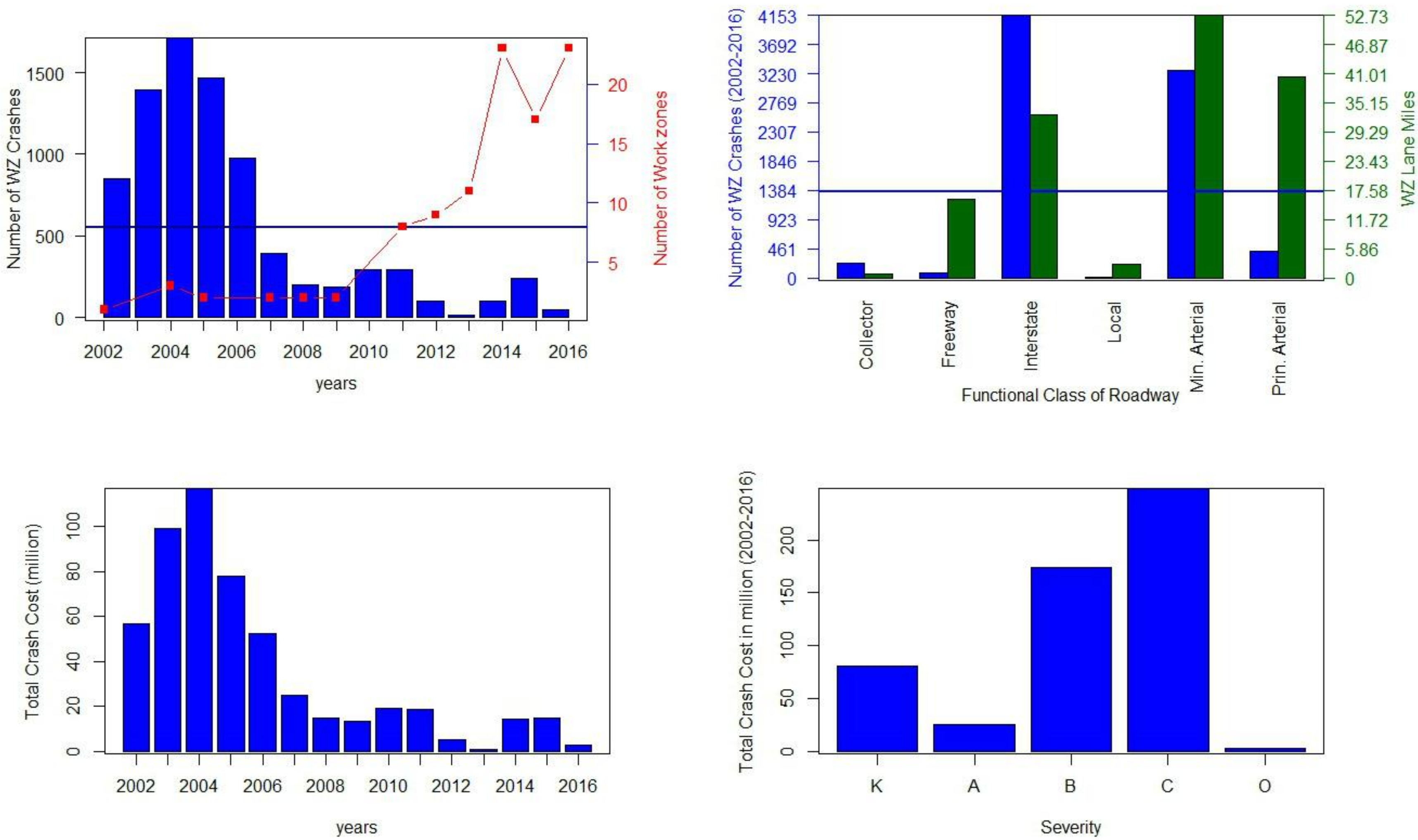


Figure 315 Workzone Crash Analysis - Davidson County

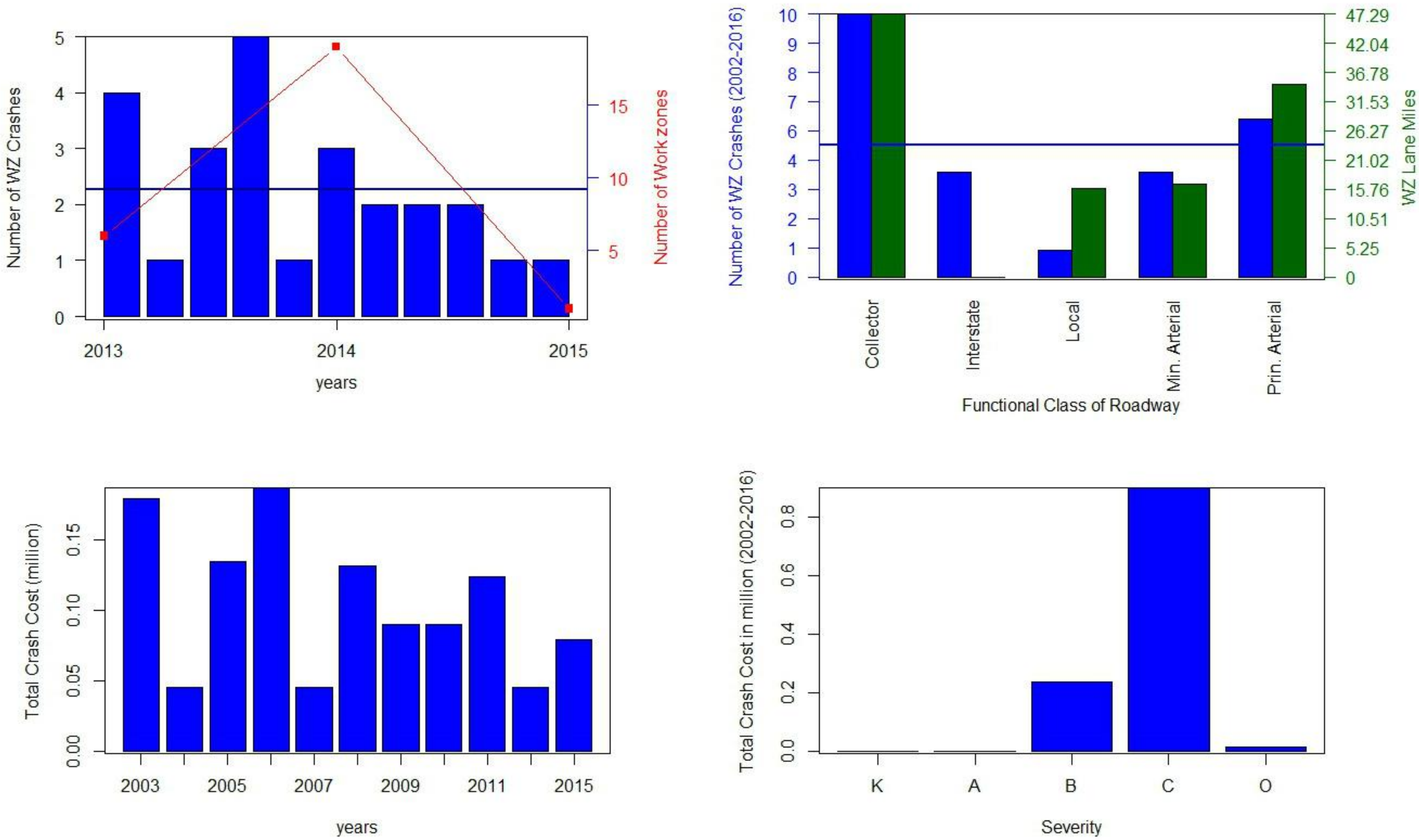


Figure 326 Workzone Crash Analysis - Decatur County

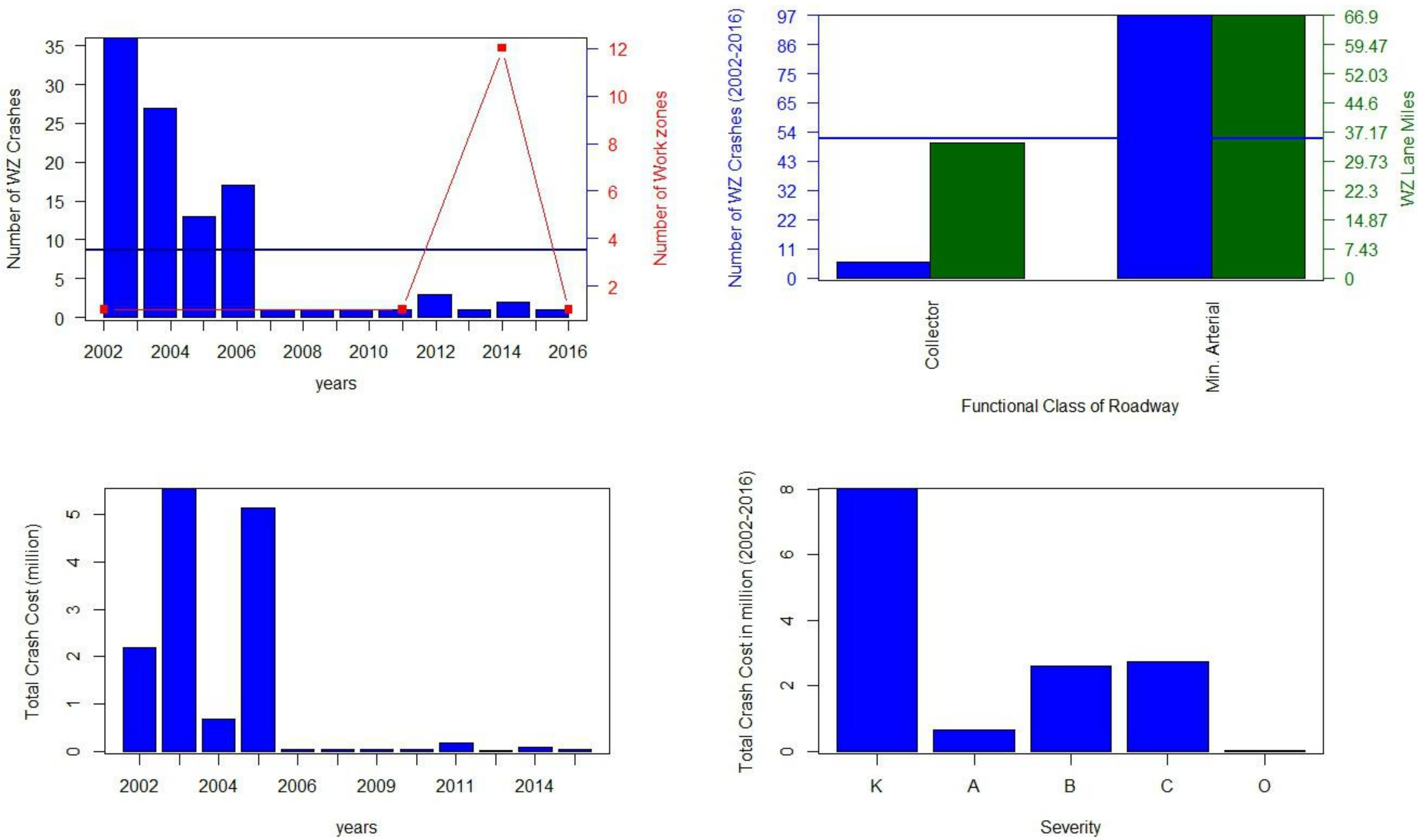


Figure 337 Workzone Crash Analysis - DeKalb County

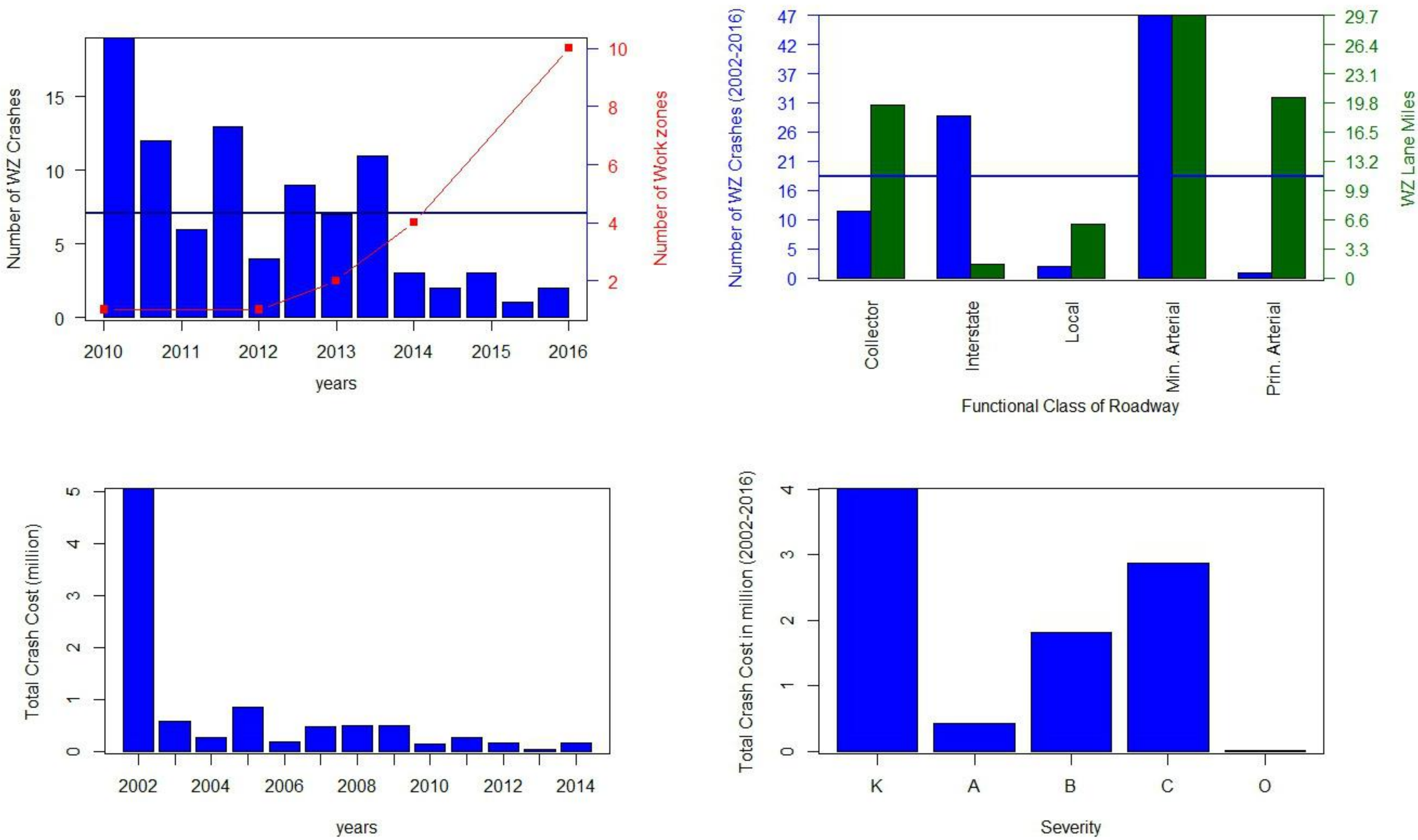


Figure 38 Workzone Crash Analysis - Dickson County

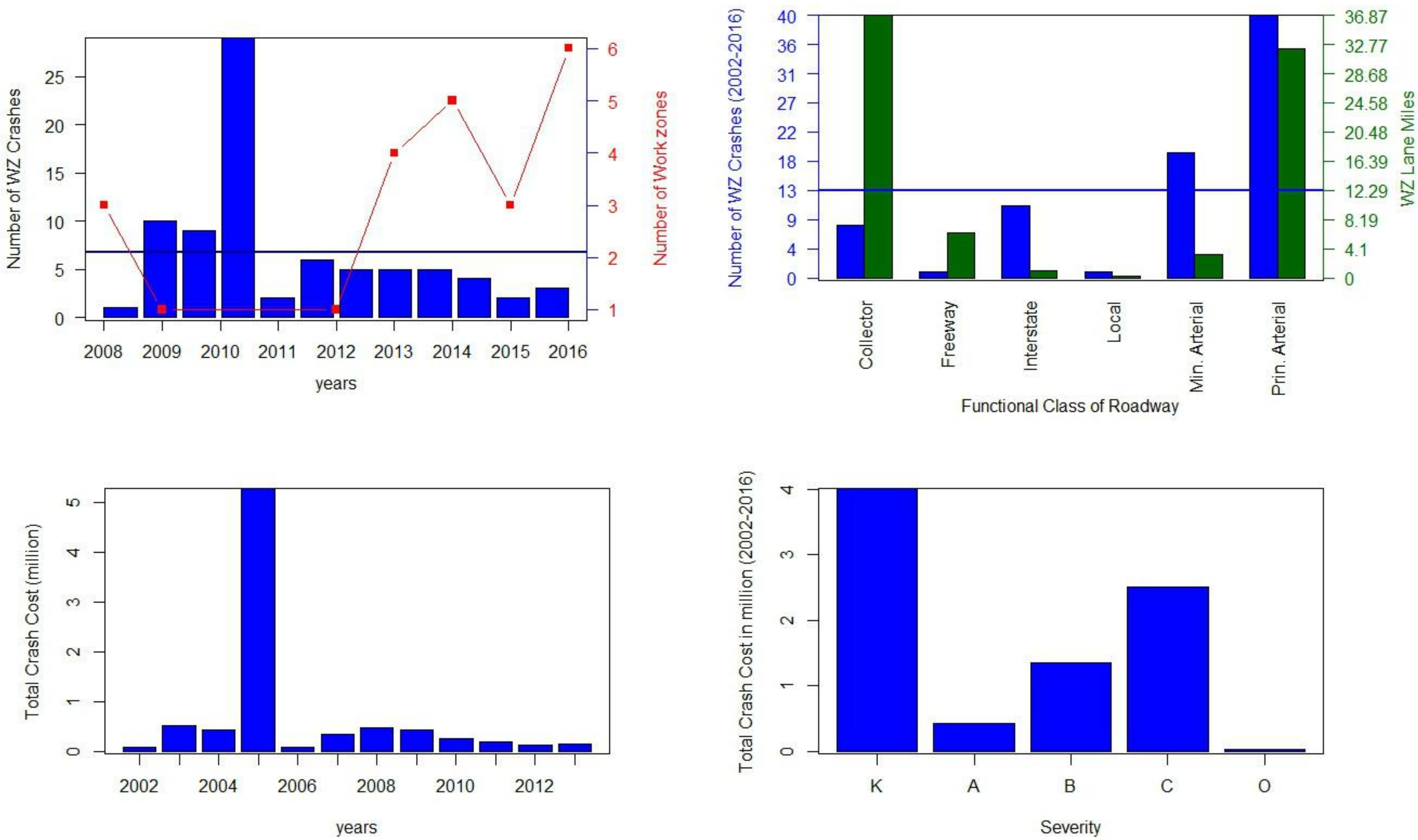


Figure 39 Workzone Crash Analysis - Dyer County

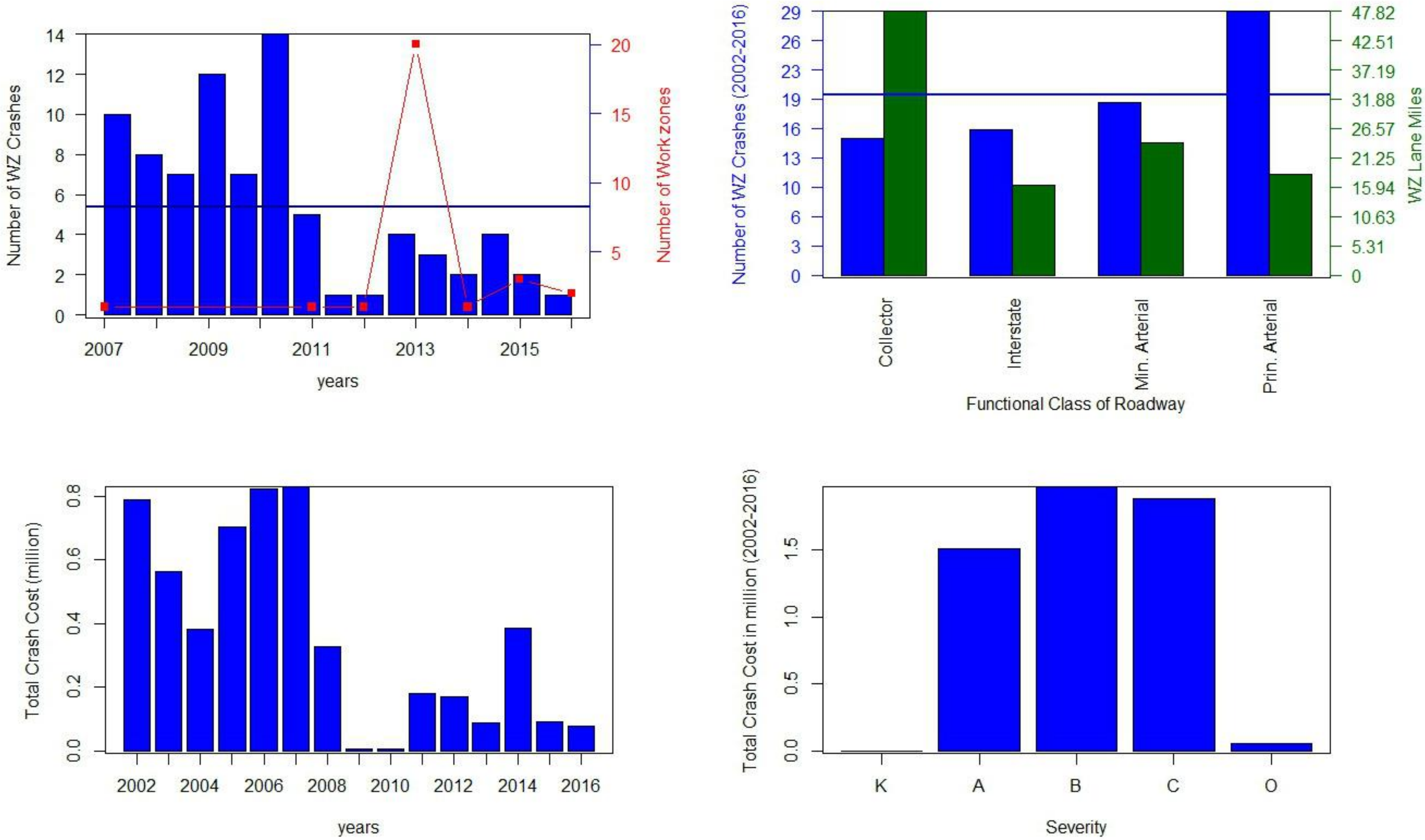


Figure 340 Workzone Crash Analysis - Fayette County

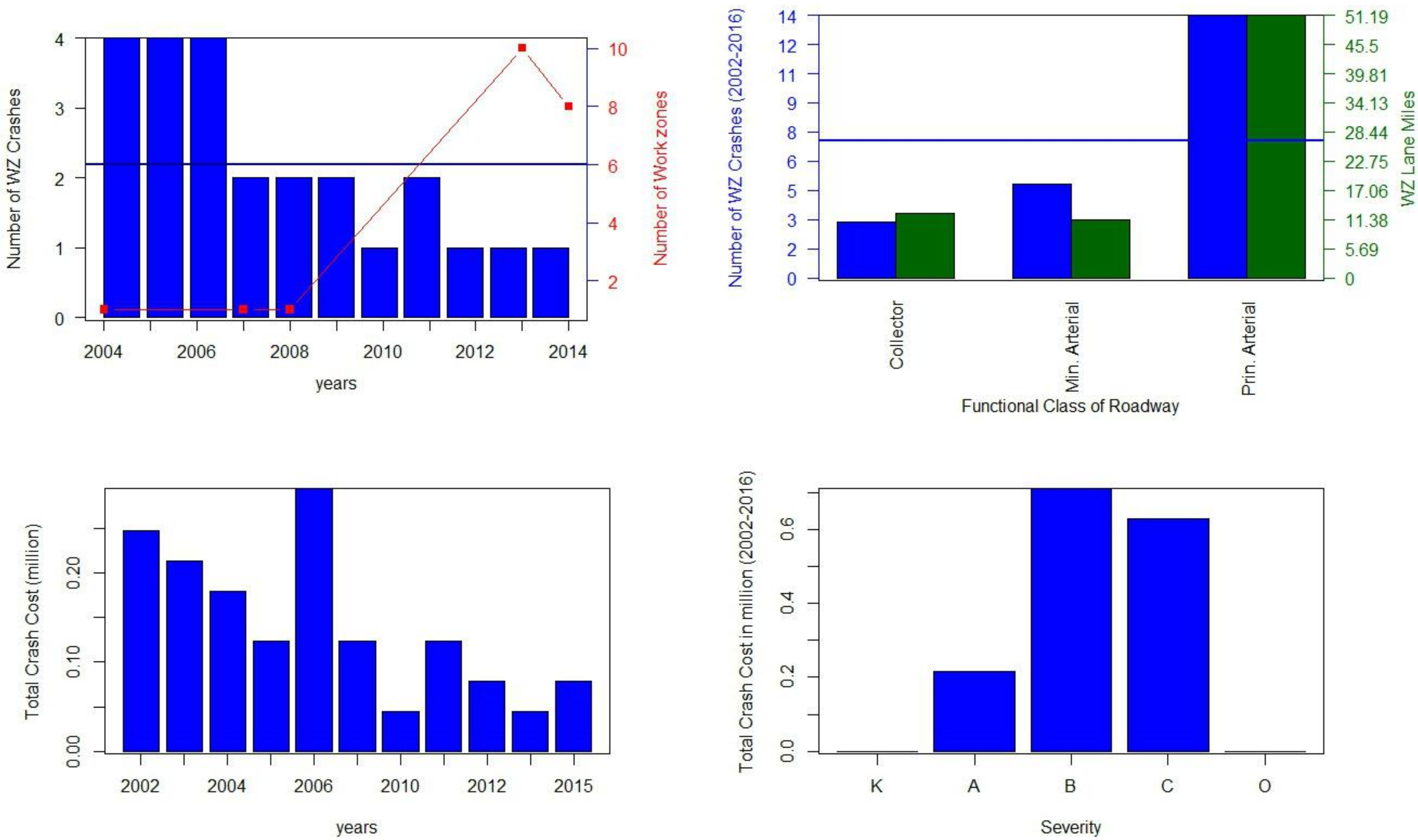


Figure 351 Workzone Crash Analysis - Fentress County

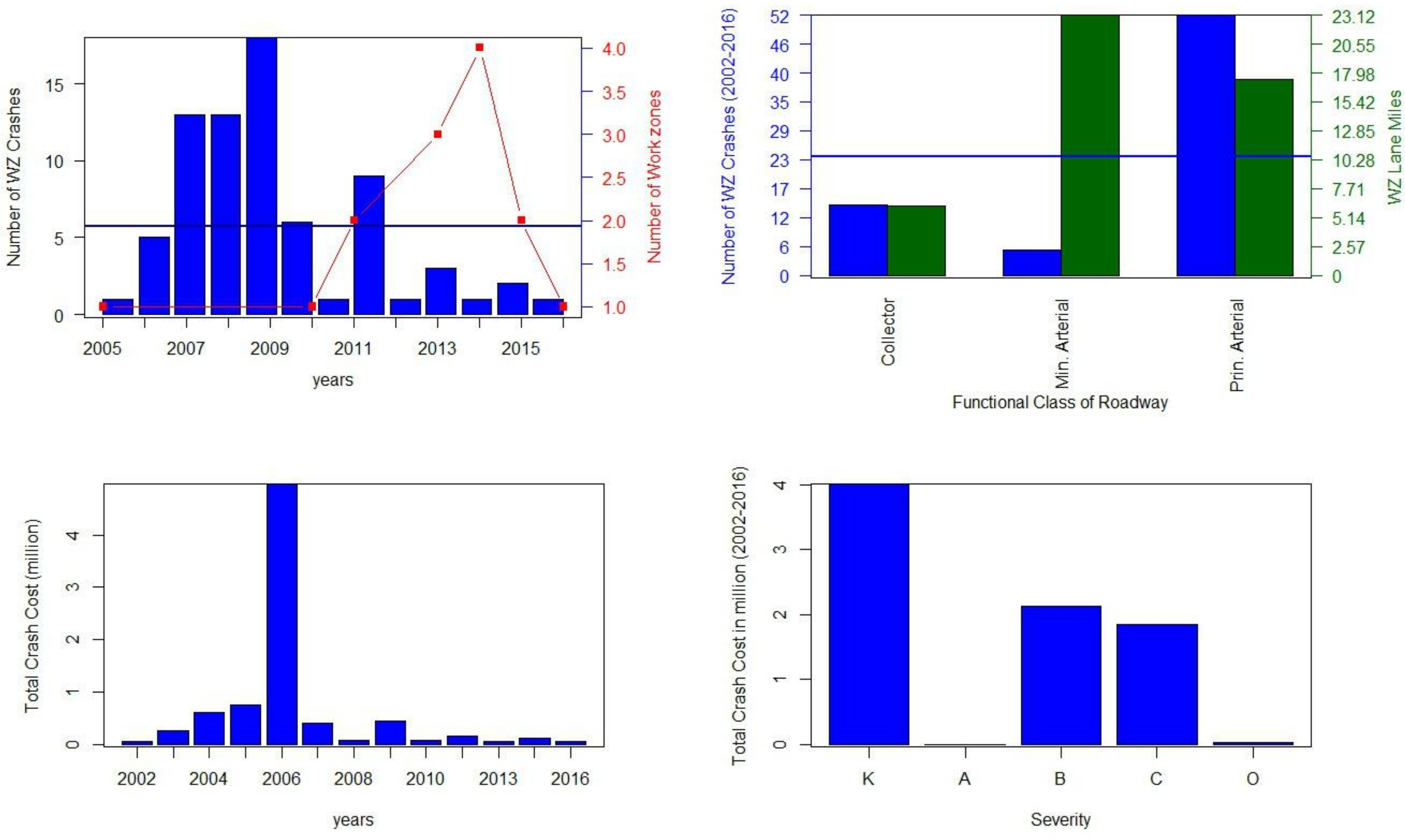


Figure 362 Workzone Crash Analysis - Franklin County

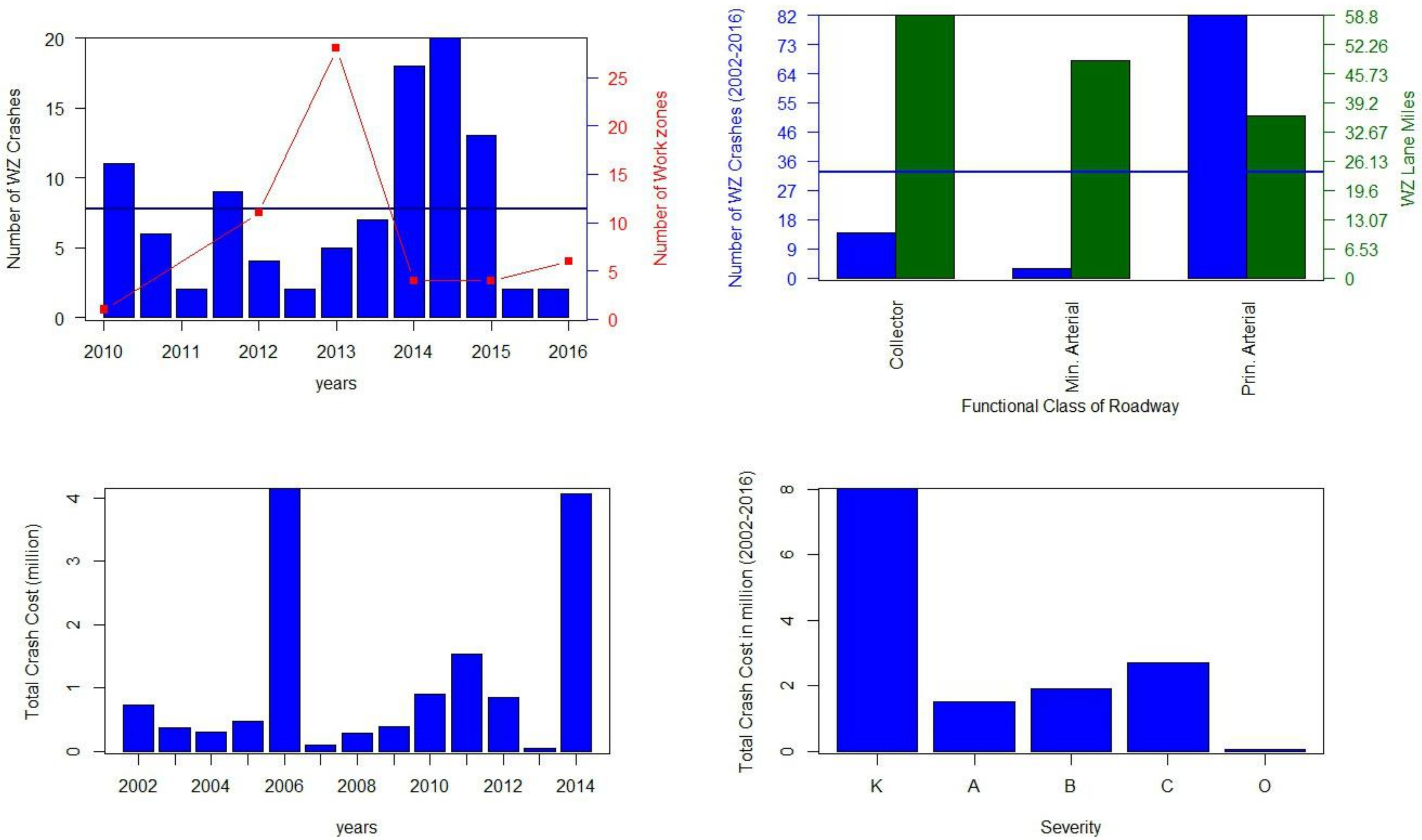


Figure 373 Workzone Crash Analysis - Gibson County

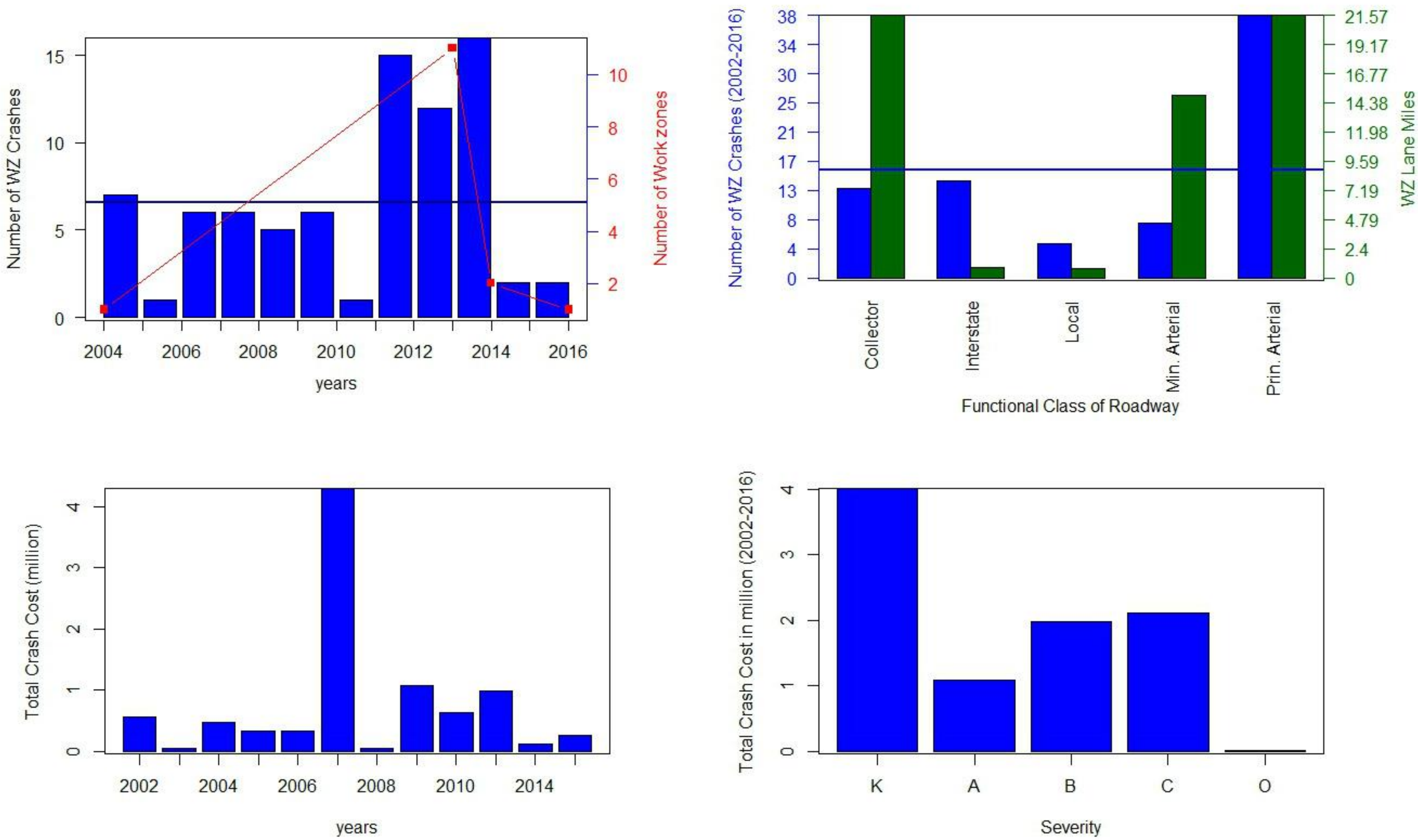


Figure 384 Workzone Crash Analysis - Giles County

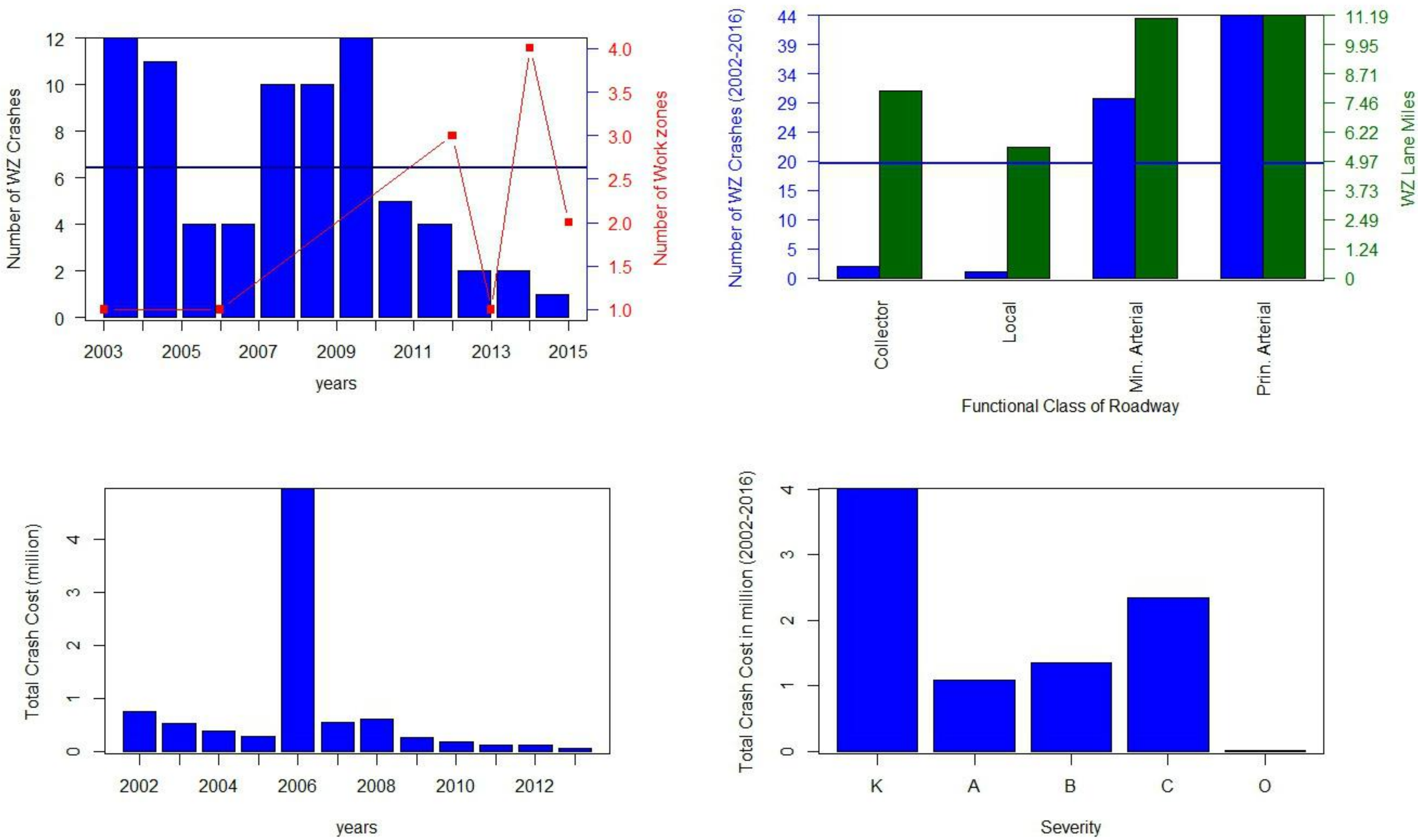


Figure 395 Workzone Crash Analysis - Grainger County

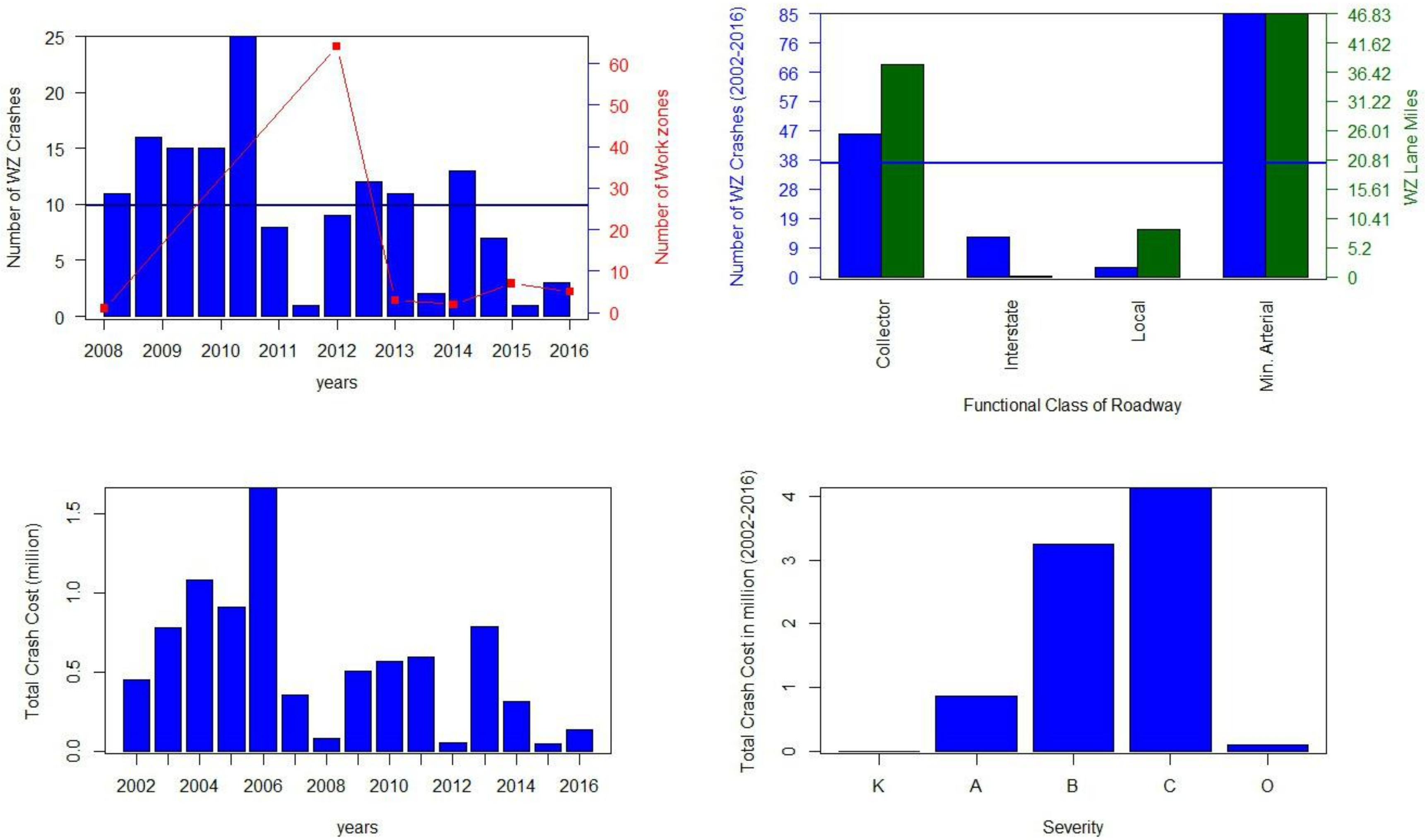


Figure 406 Workzone Crash Analysis - Greene County

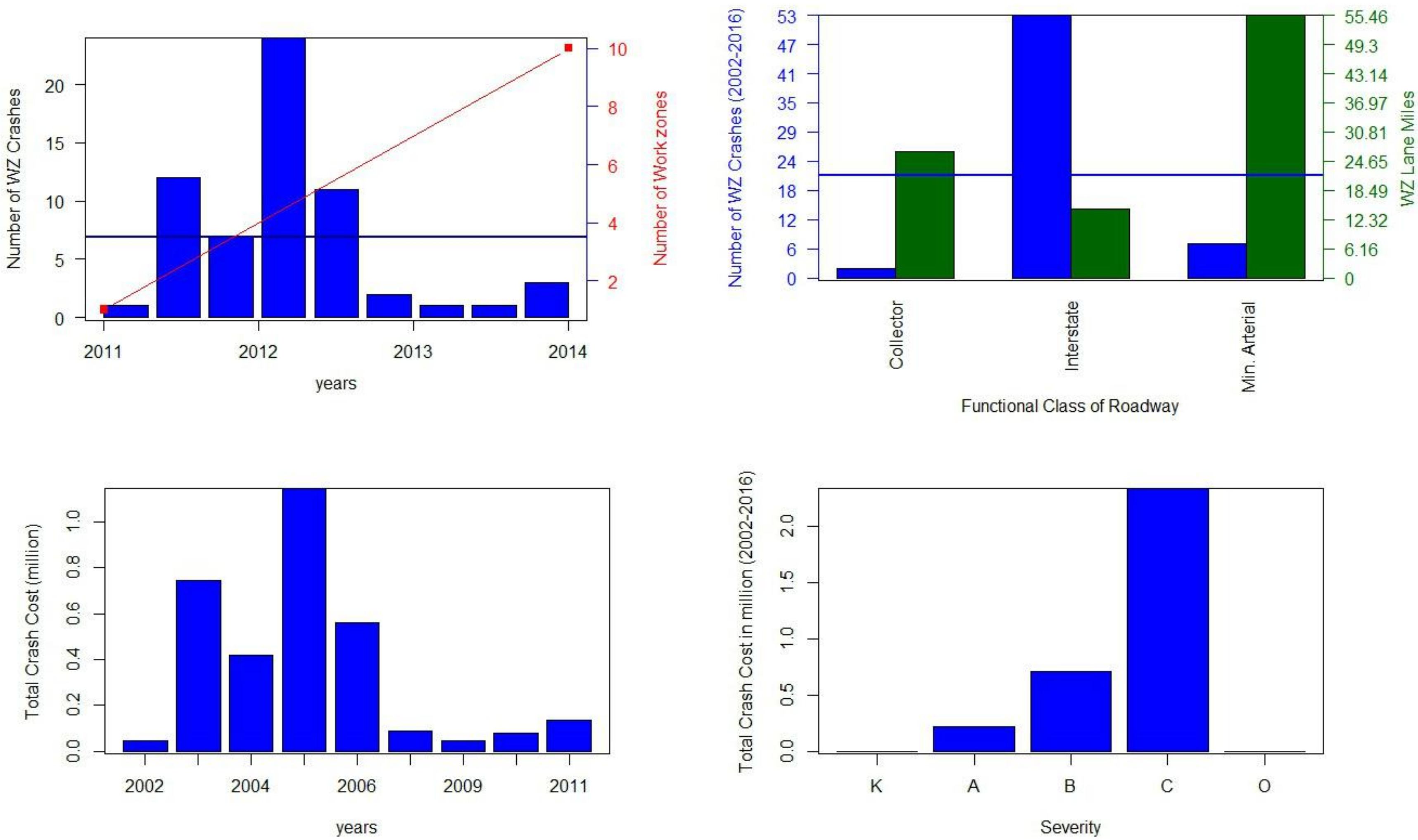


Figure 417 Workzone Crash Analysis - Grundy County

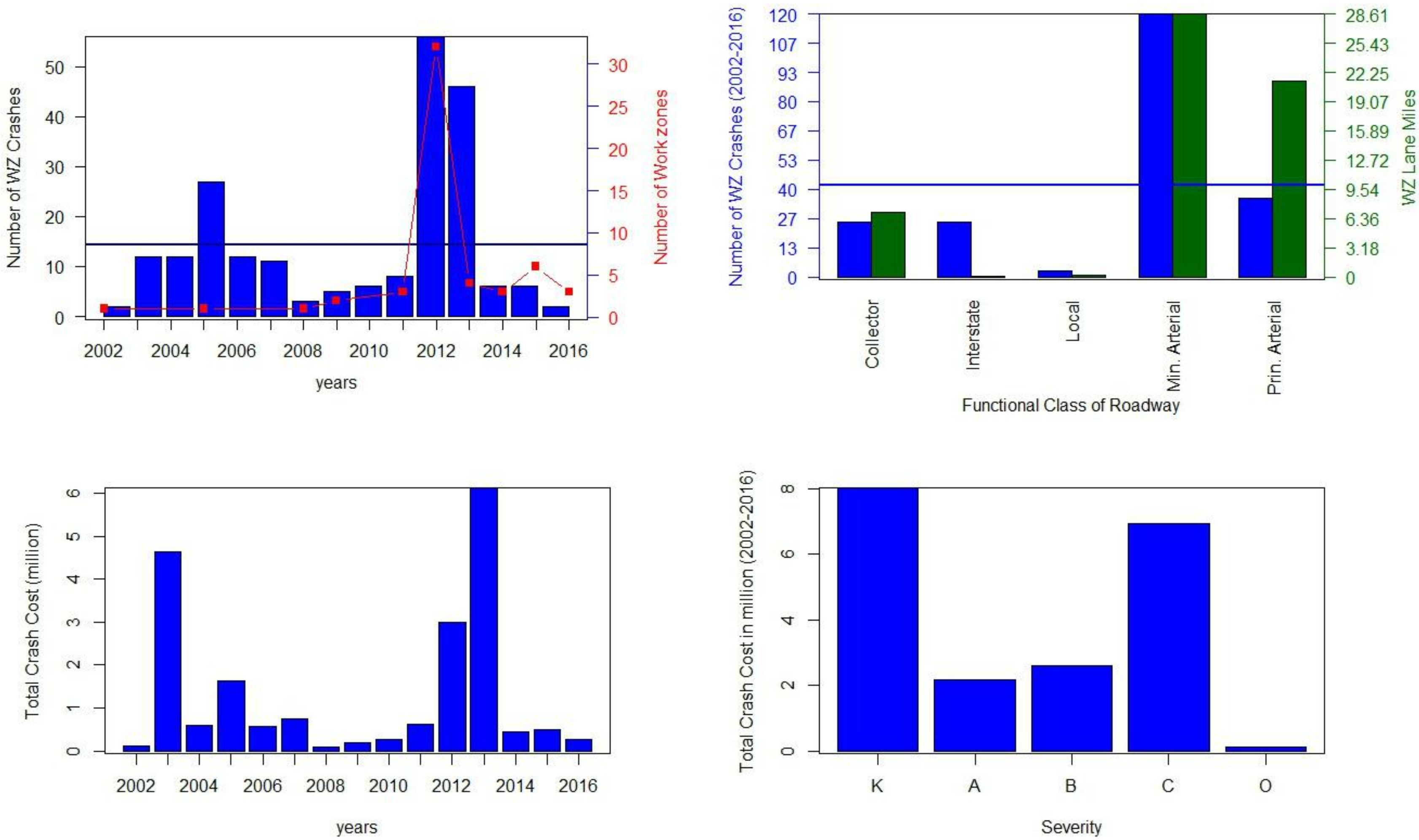


Figure 48 Workzone Crash Analysis - Hamblen County

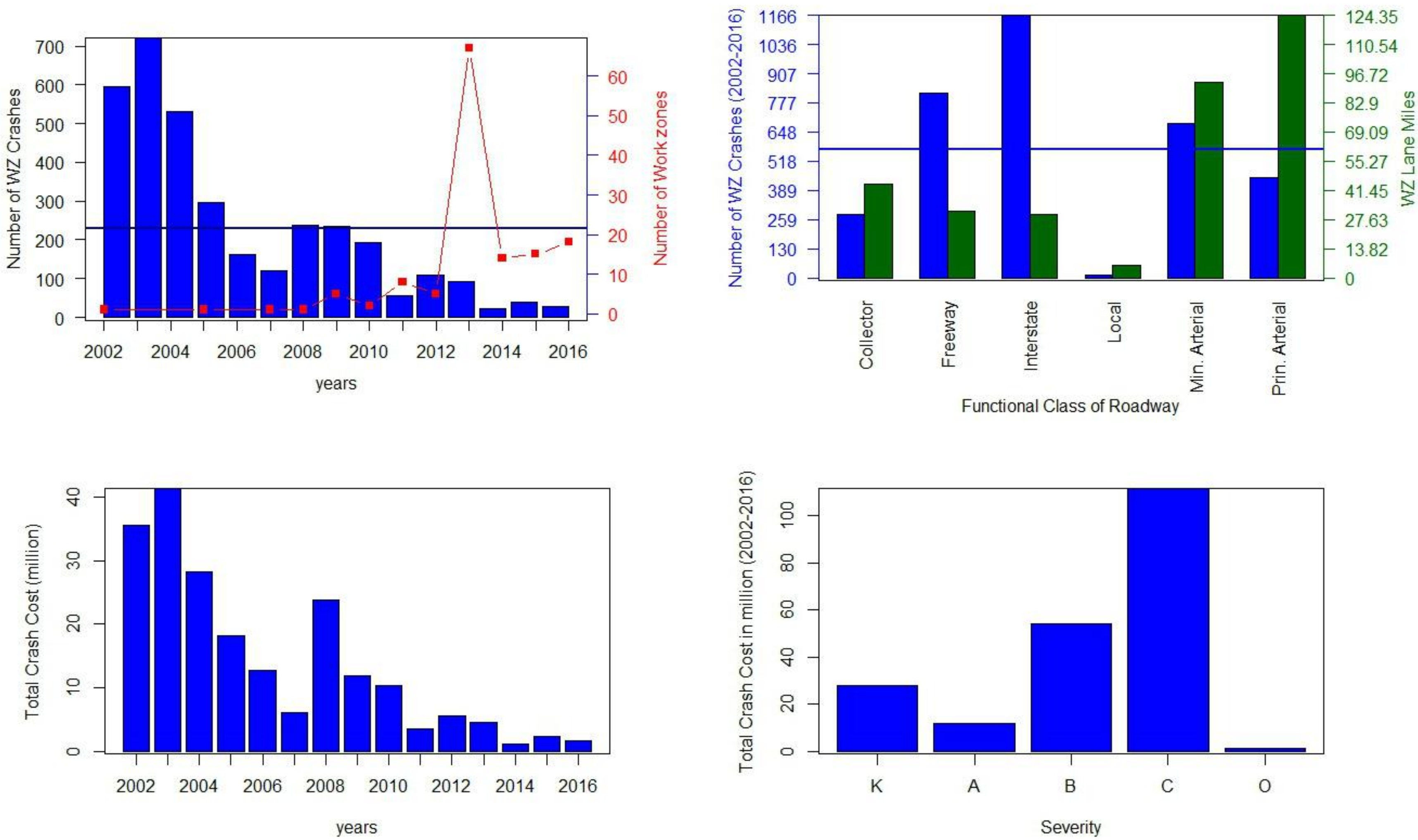


Figure 49 Workzone Crash Analysis - Hamilton County

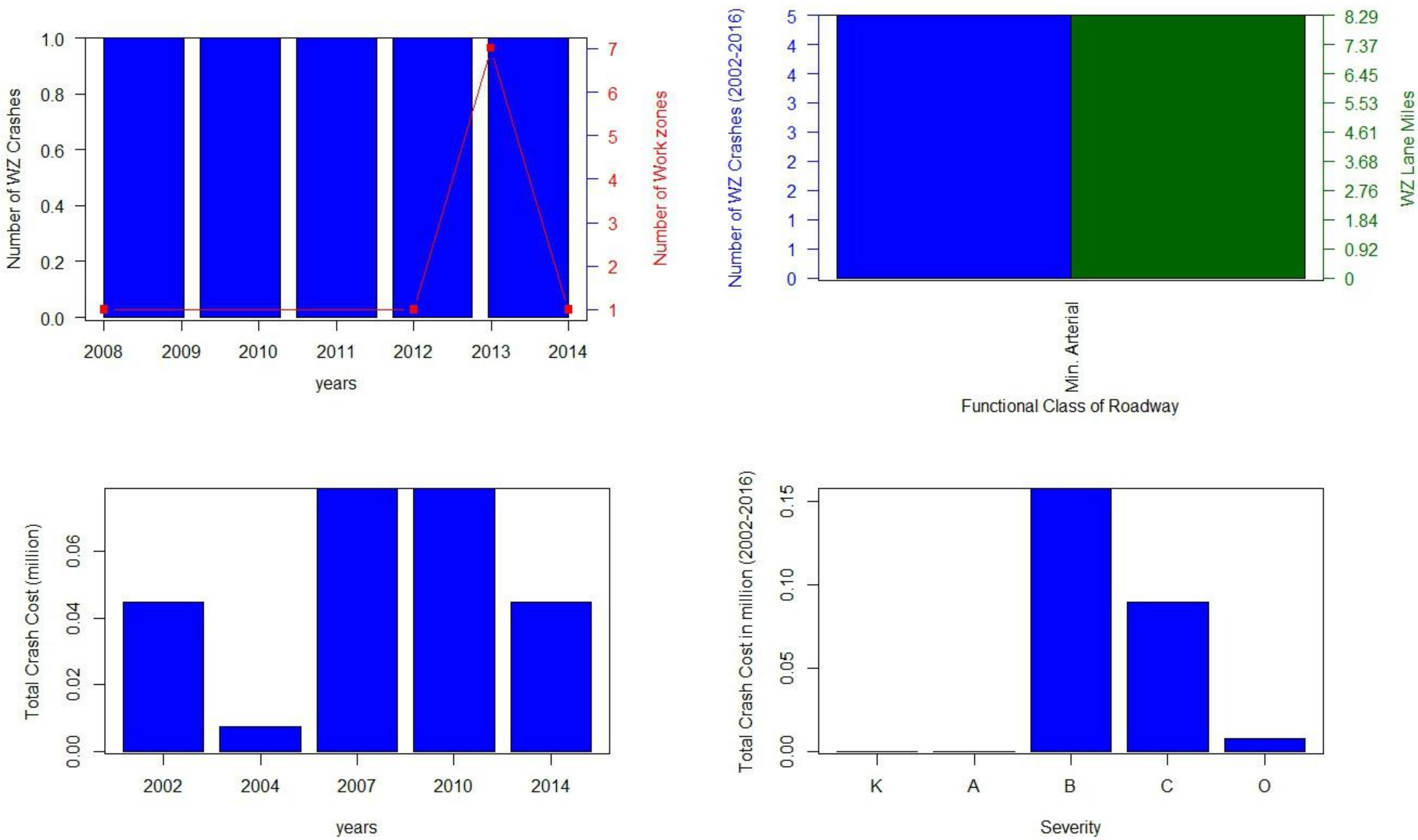


Figure 420 Workzone Crash Analysis - Hancock County

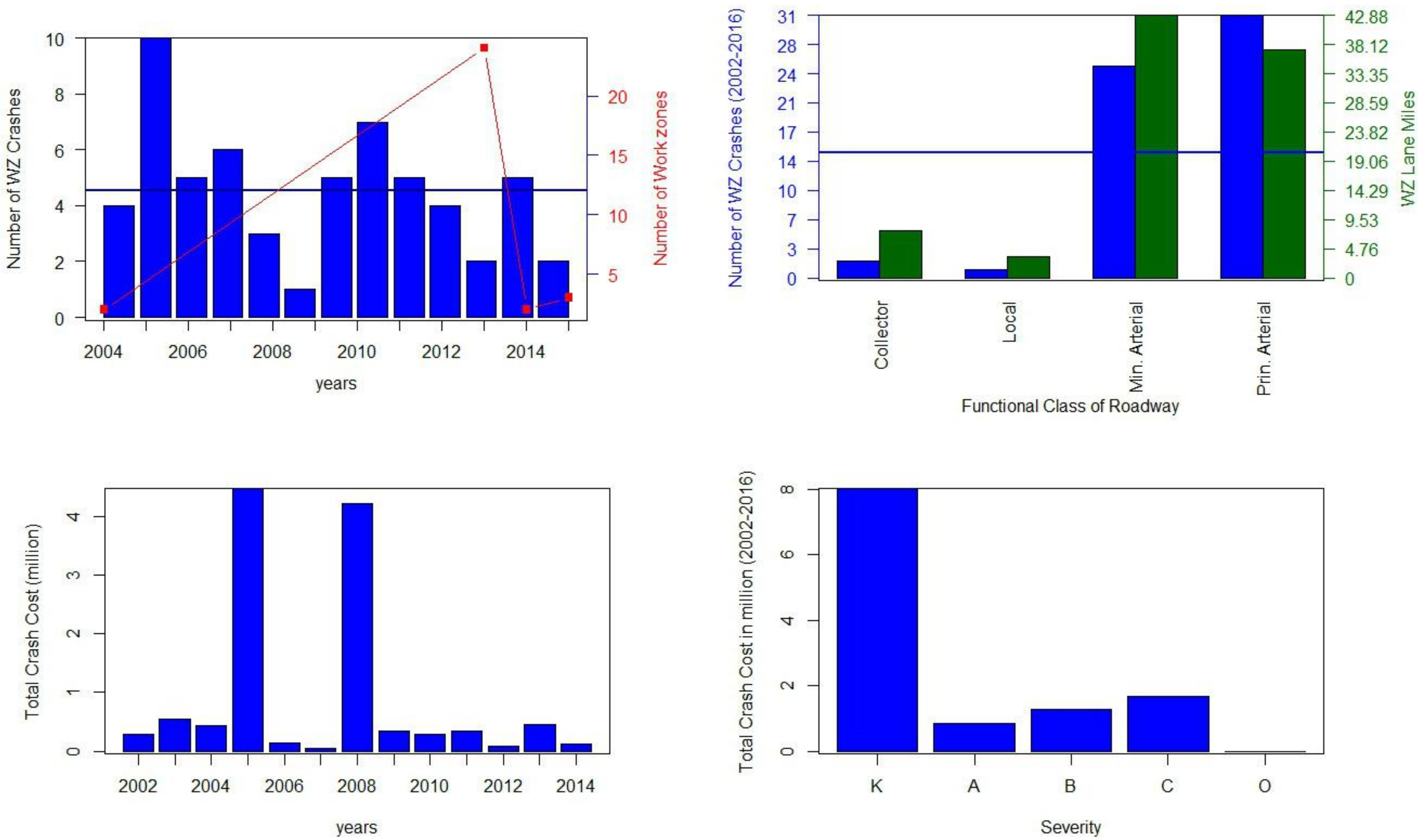


Figure 431 Workzone Crash Analysis - Hardeman County

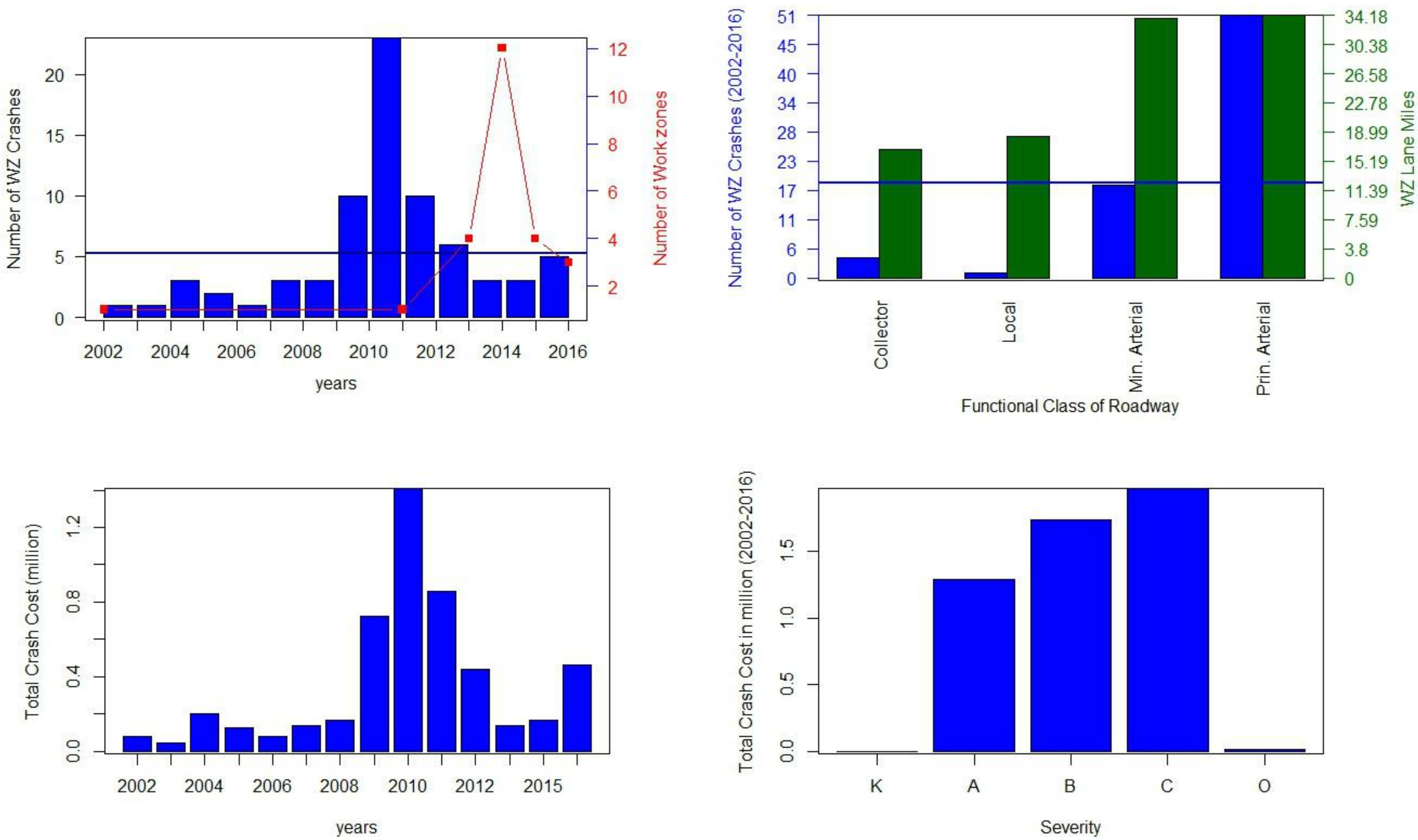


Figure 442 Workzone Crash Analysis - Hardin County

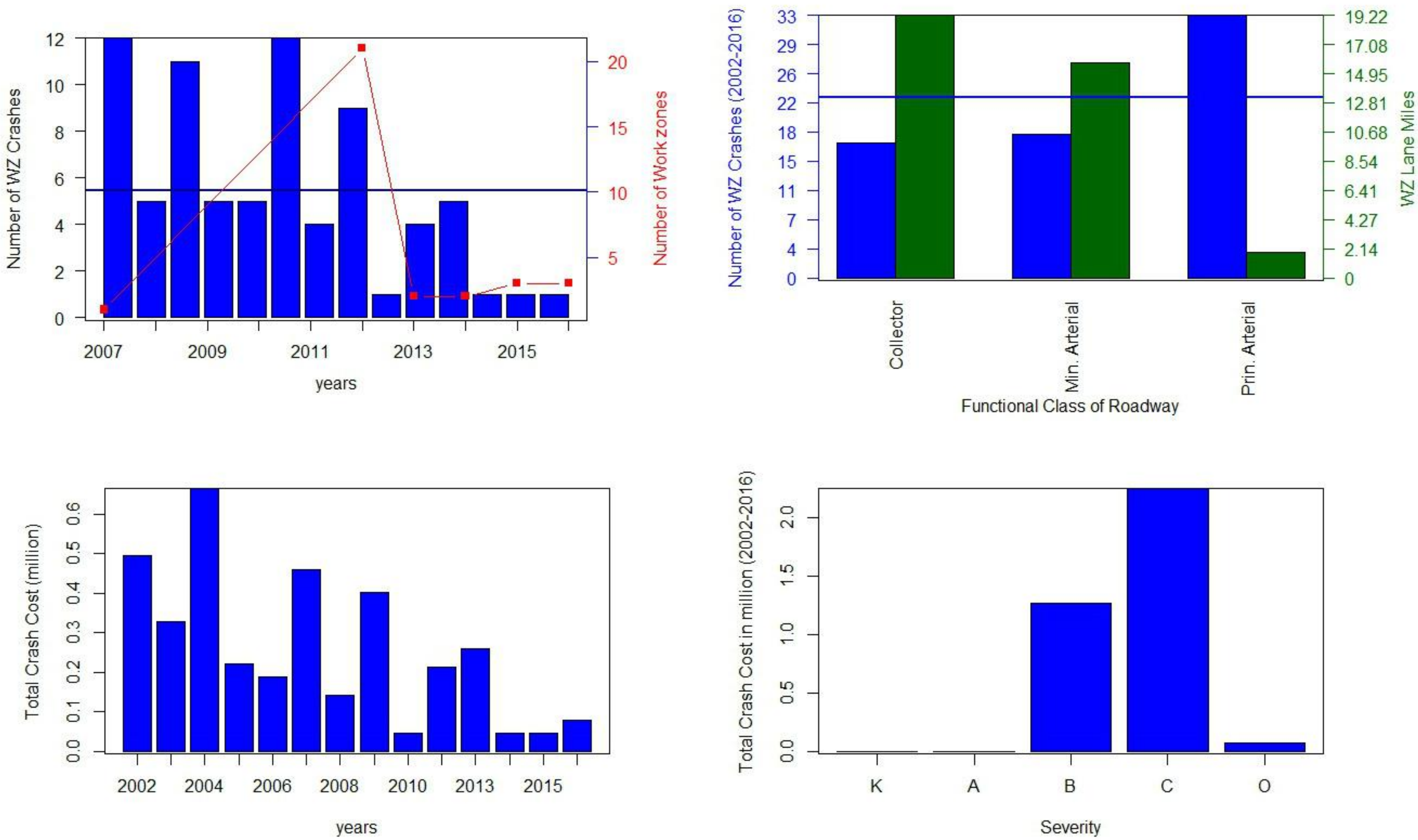


Figure 453 Workzone Crash Analysis - Hawkins County

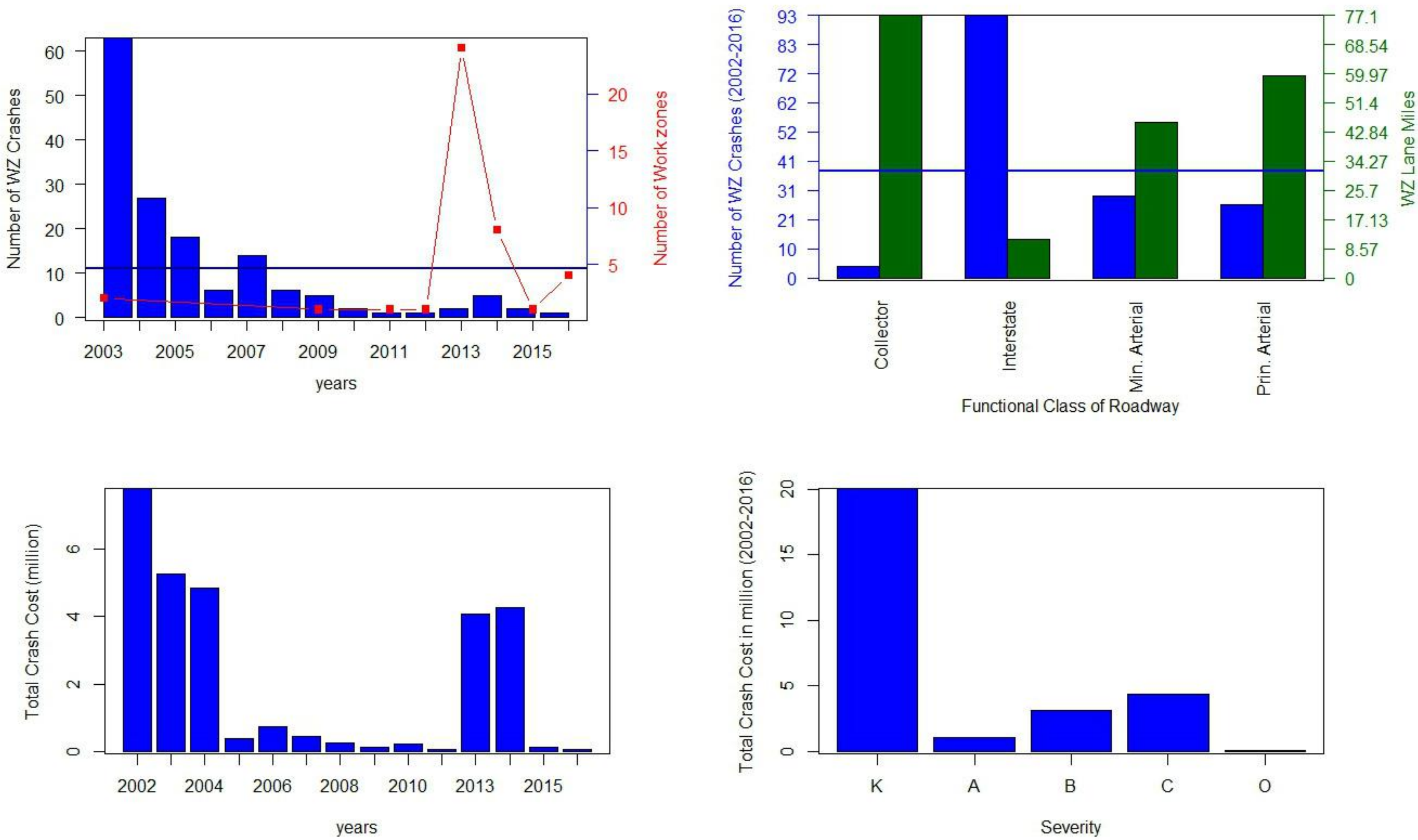


Figure 464 Workzone Crash Analysis - Haywood County

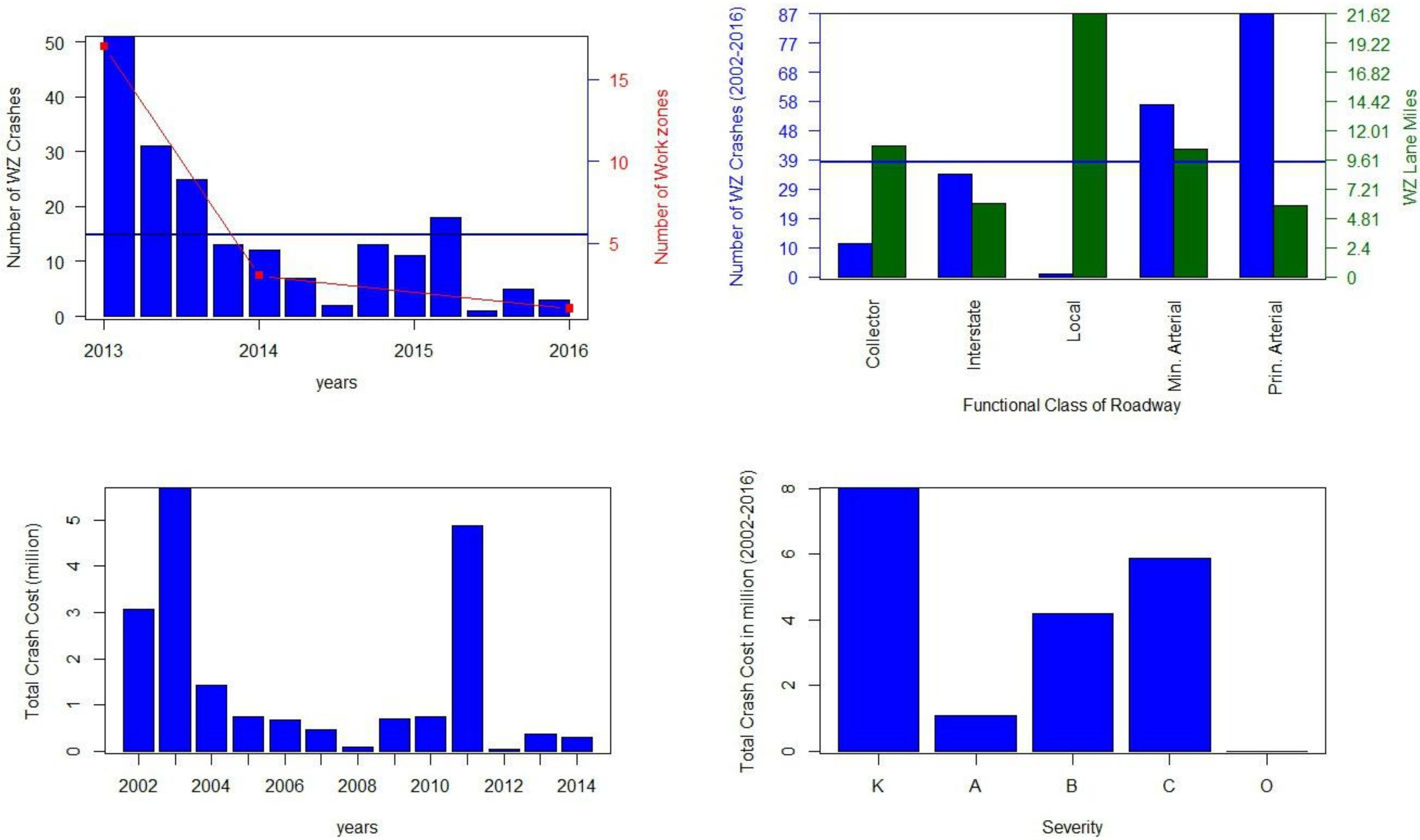


Figure 475 Workzone Crash Analysis - Henderson County

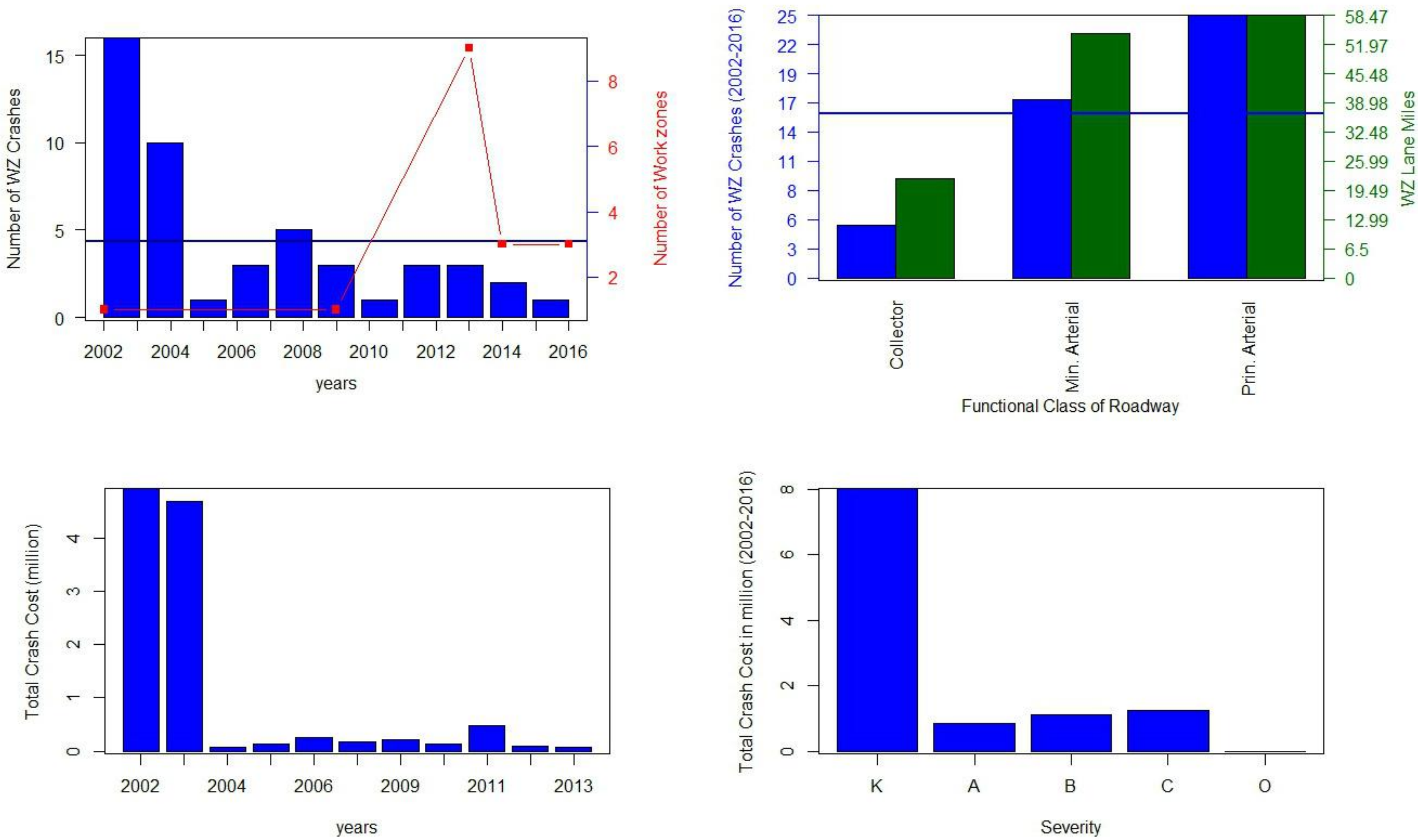


Figure 486 Workzone Crash Analysis - Henry County

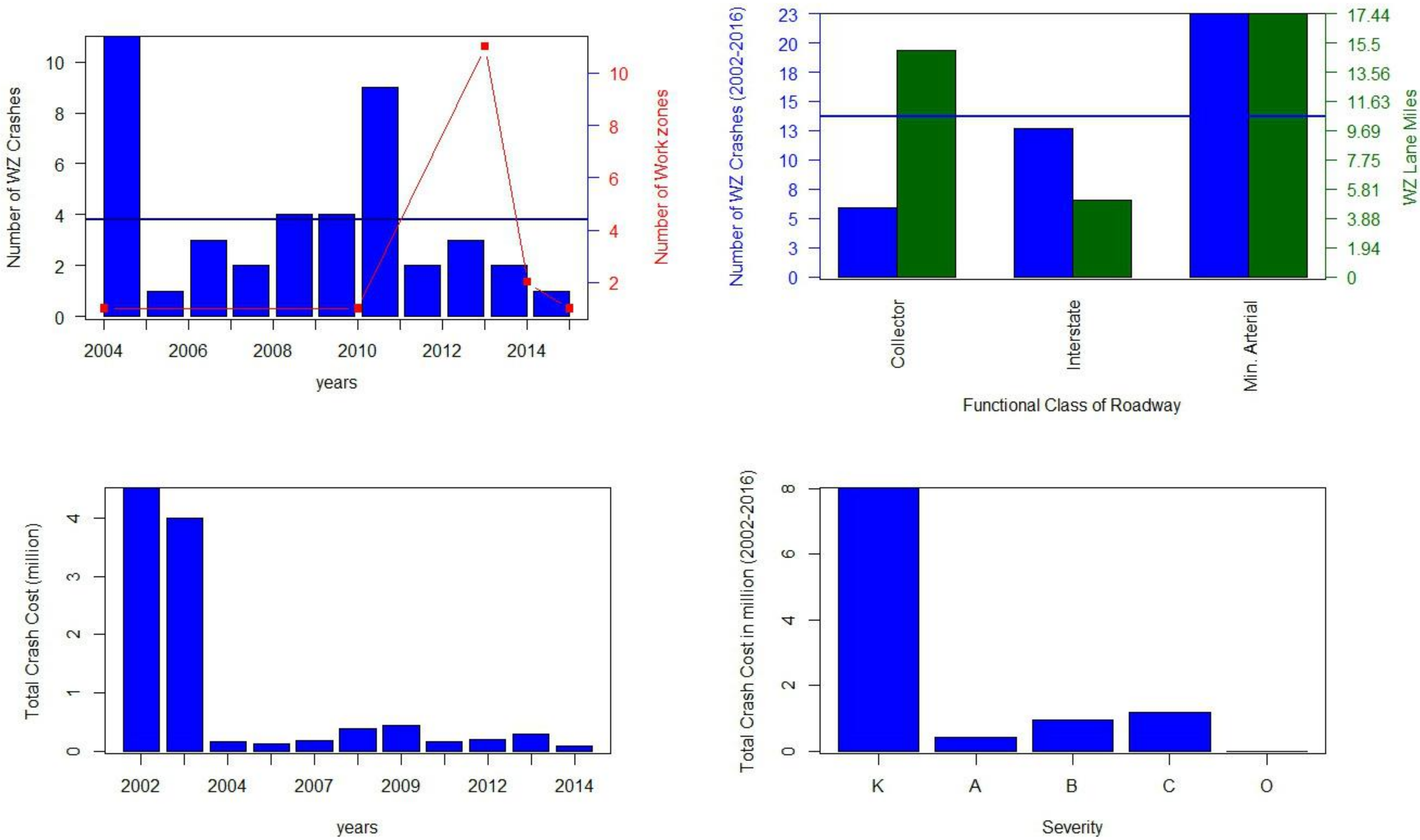


Figure 497 Workzone Crash Analysis - Hickman County

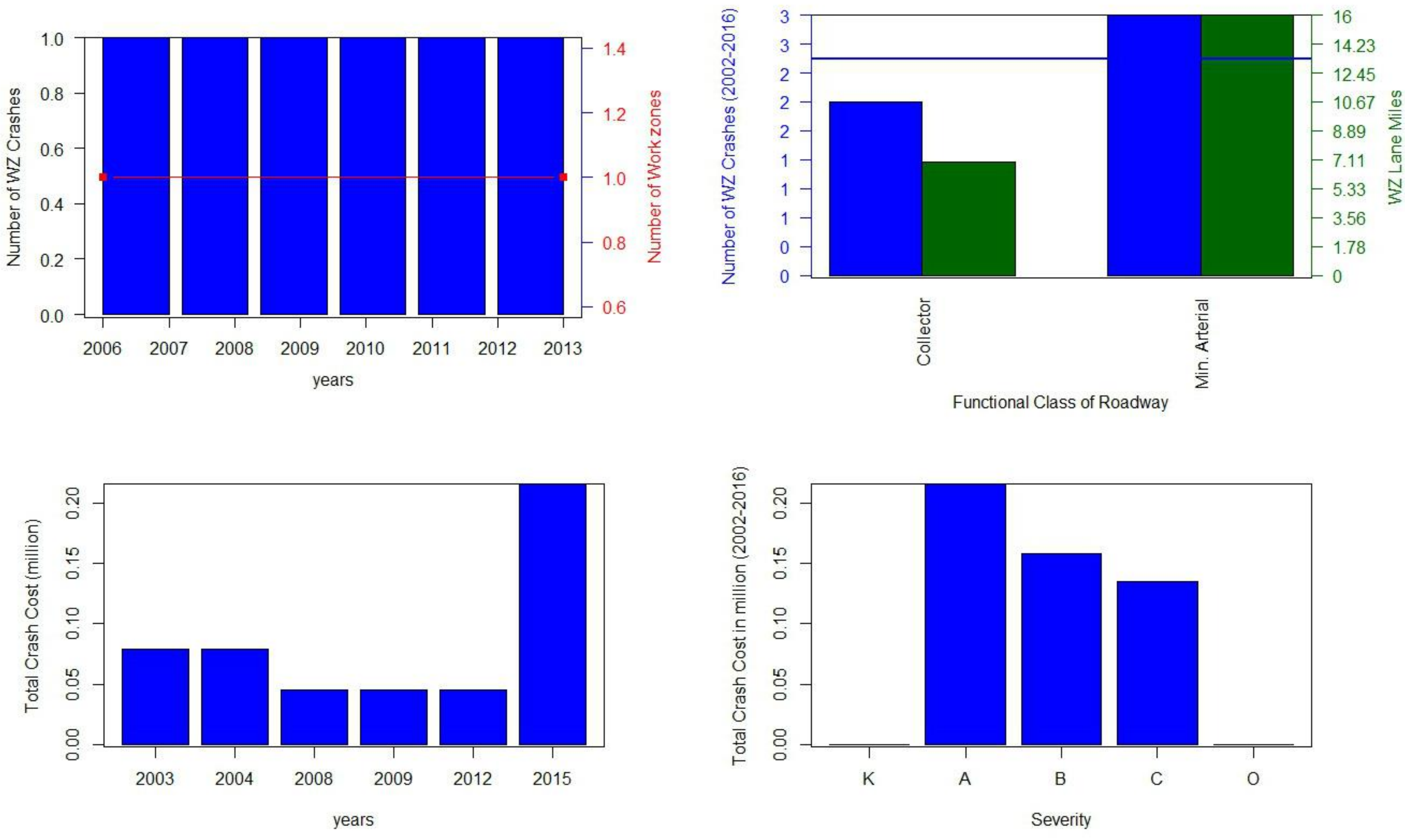


Figure 58 Workzone Crash Analysis - Houston County

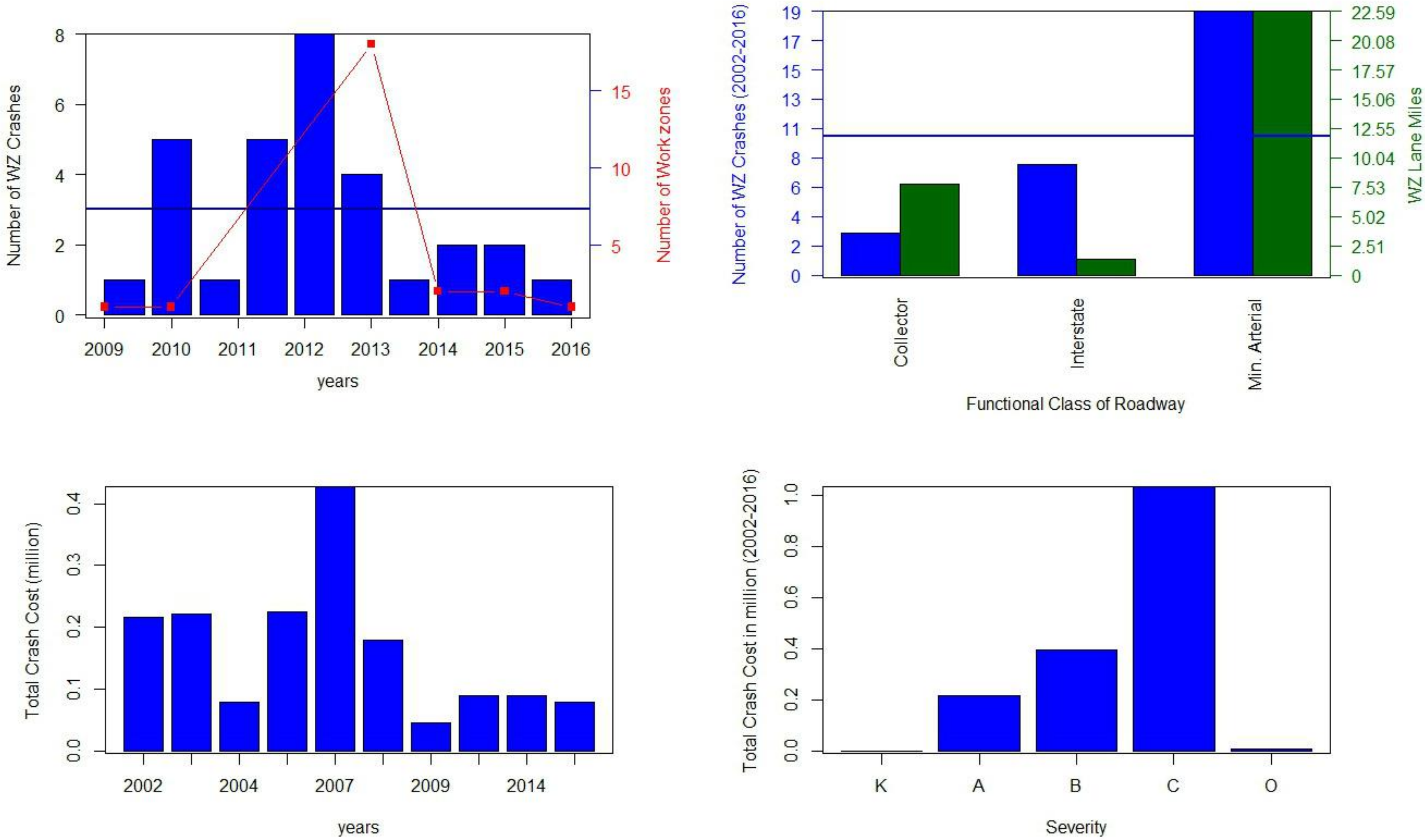


Figure 59 Workzone Crash Analysis - Humphreys County

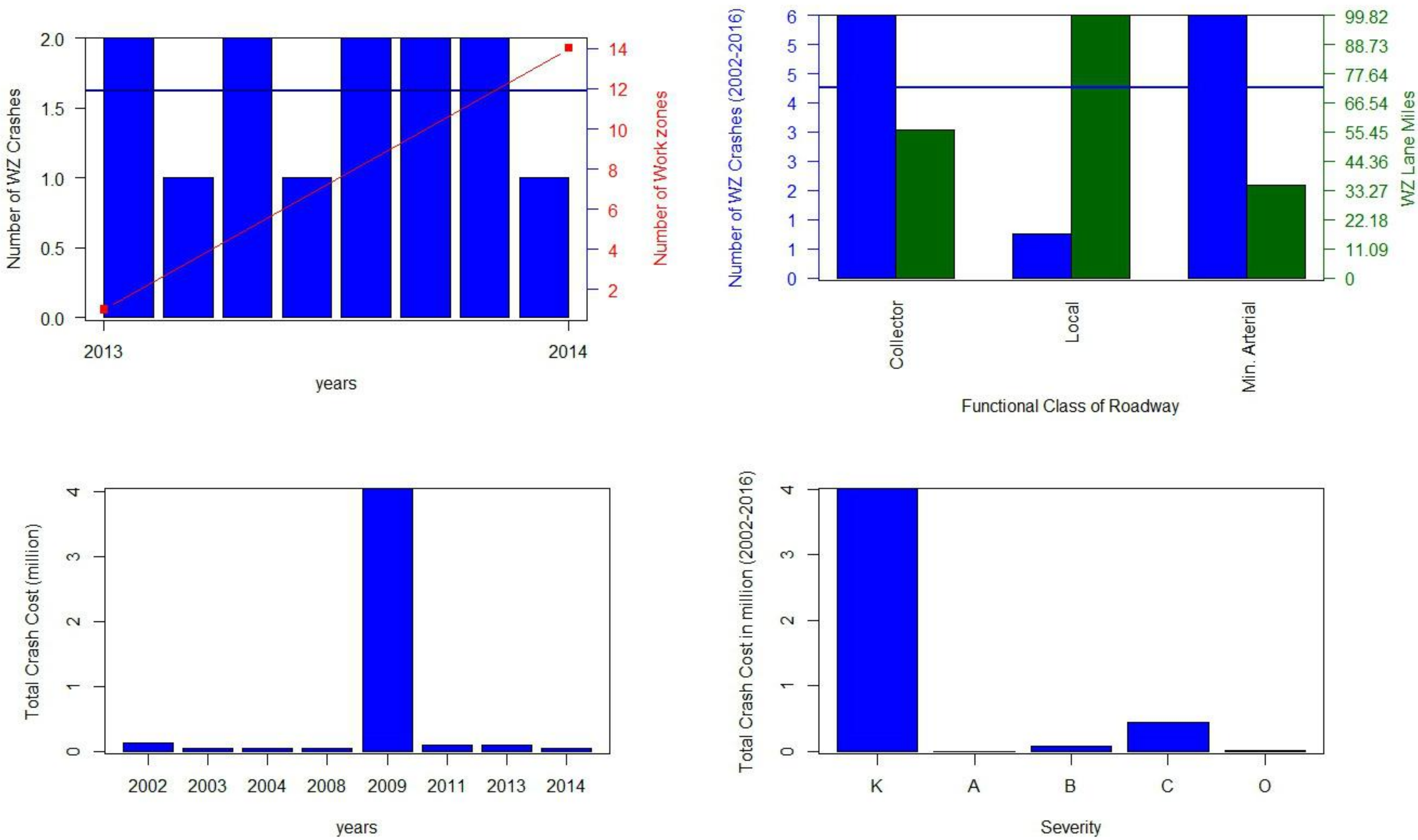


Figure 500 Workzone Crash Analysis - Jackson County

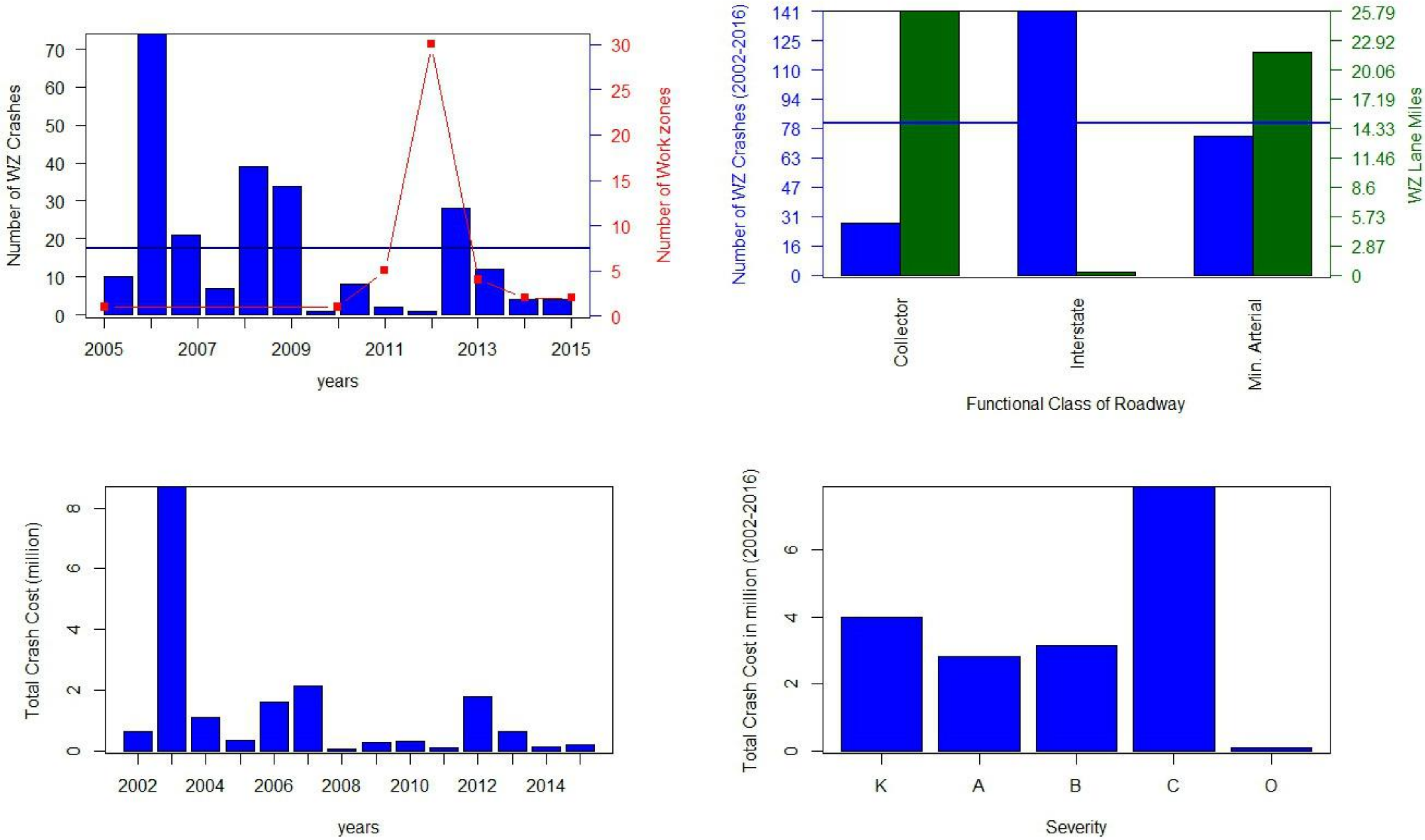


Figure 511 Workzone Crash Analysis - Jefferson County

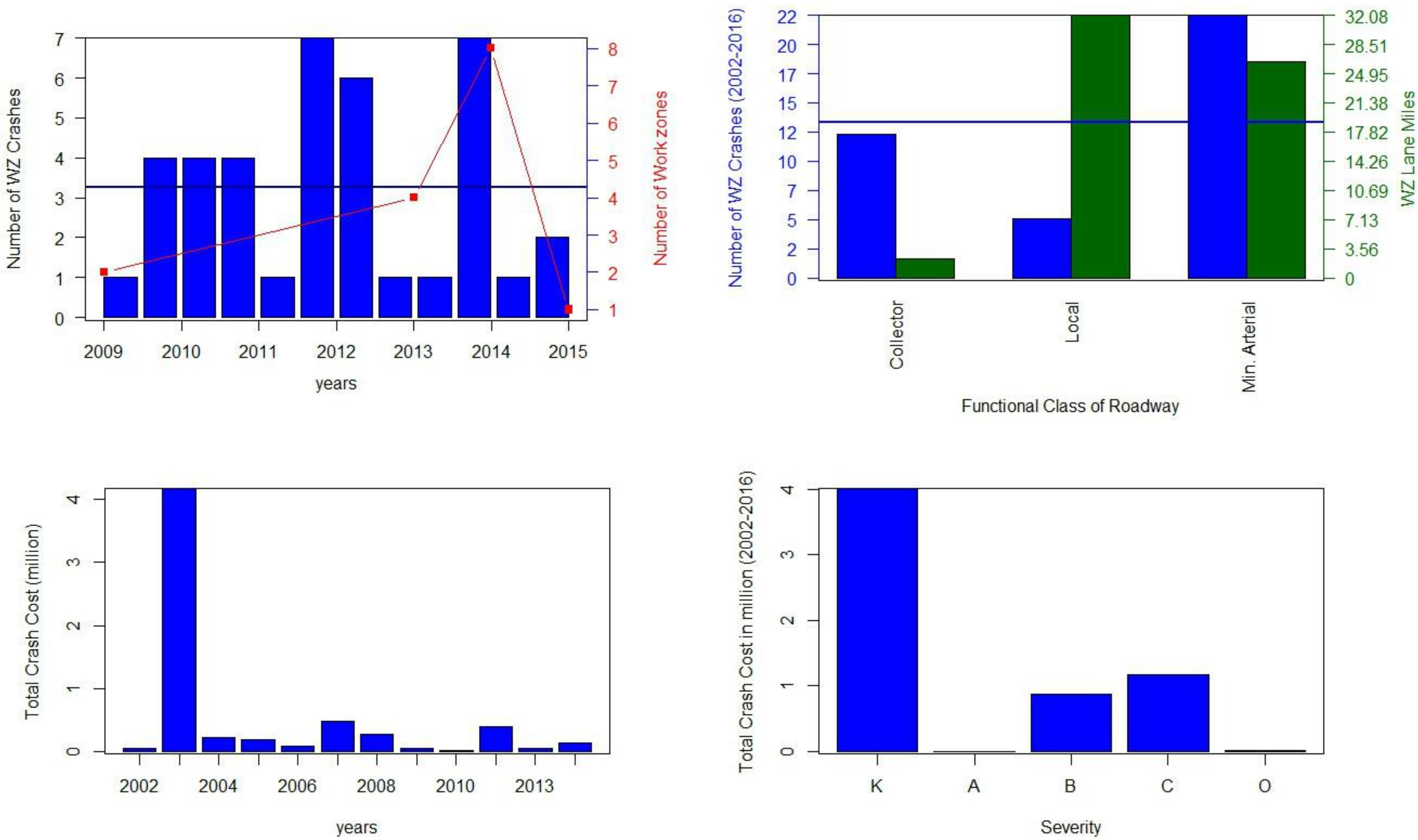


Figure 522 Workzone Crash Analysis - Johnson County

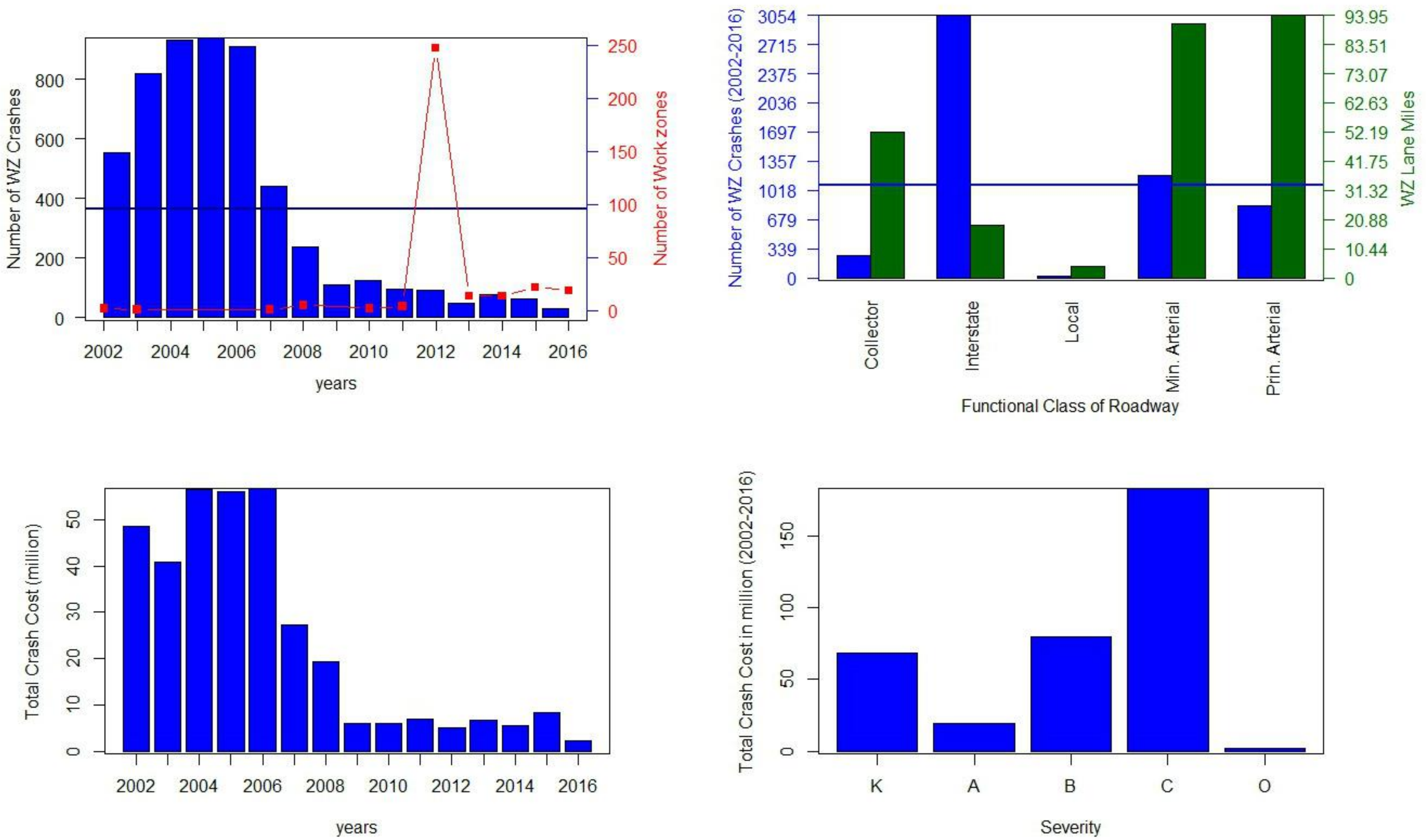


Figure 533 Workzone Crash Analysis - Knox County

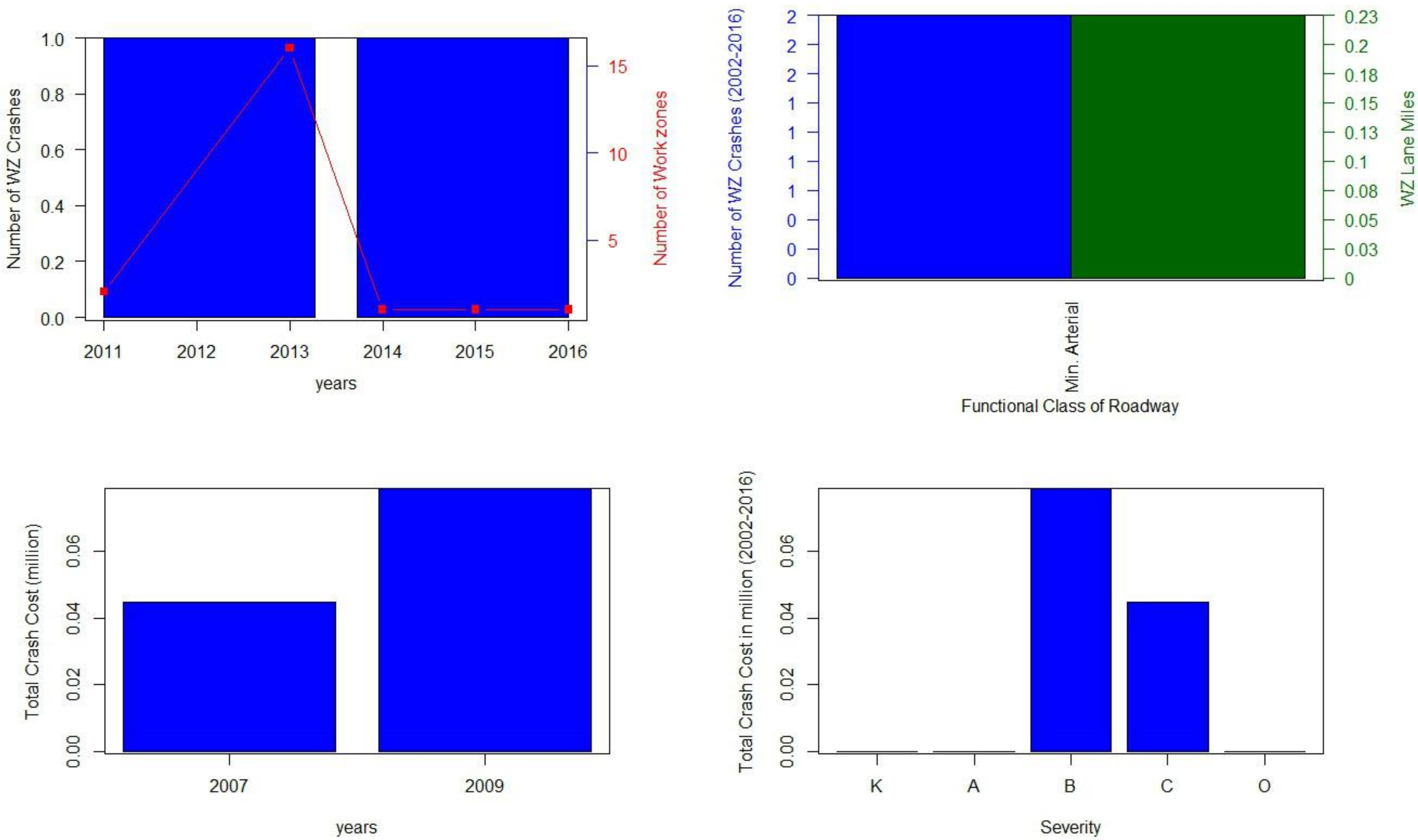


Figure 544 Workzone Crash Analysis - Lake County

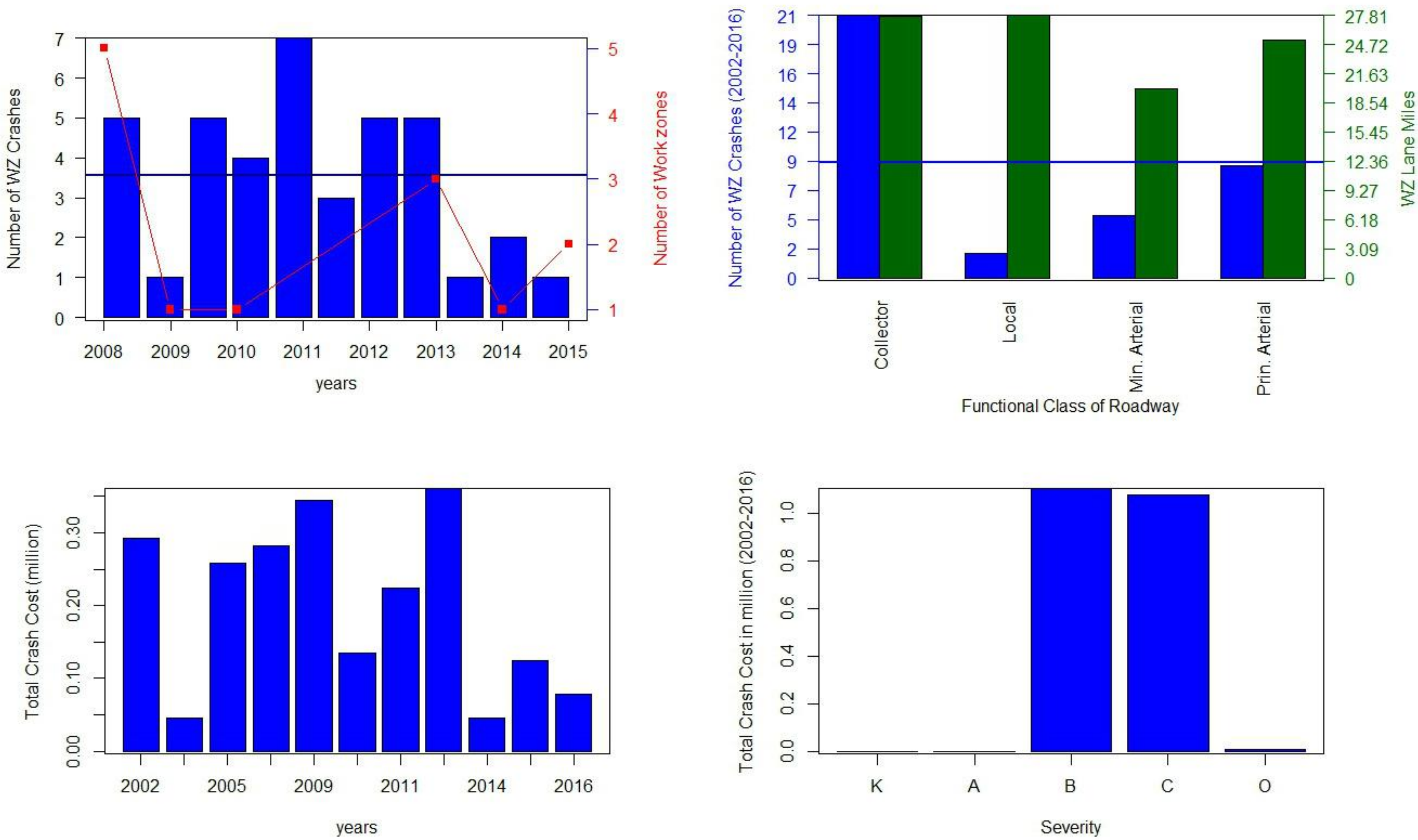


Figure 555 Workzone Crash Analysis - Lauderdale County

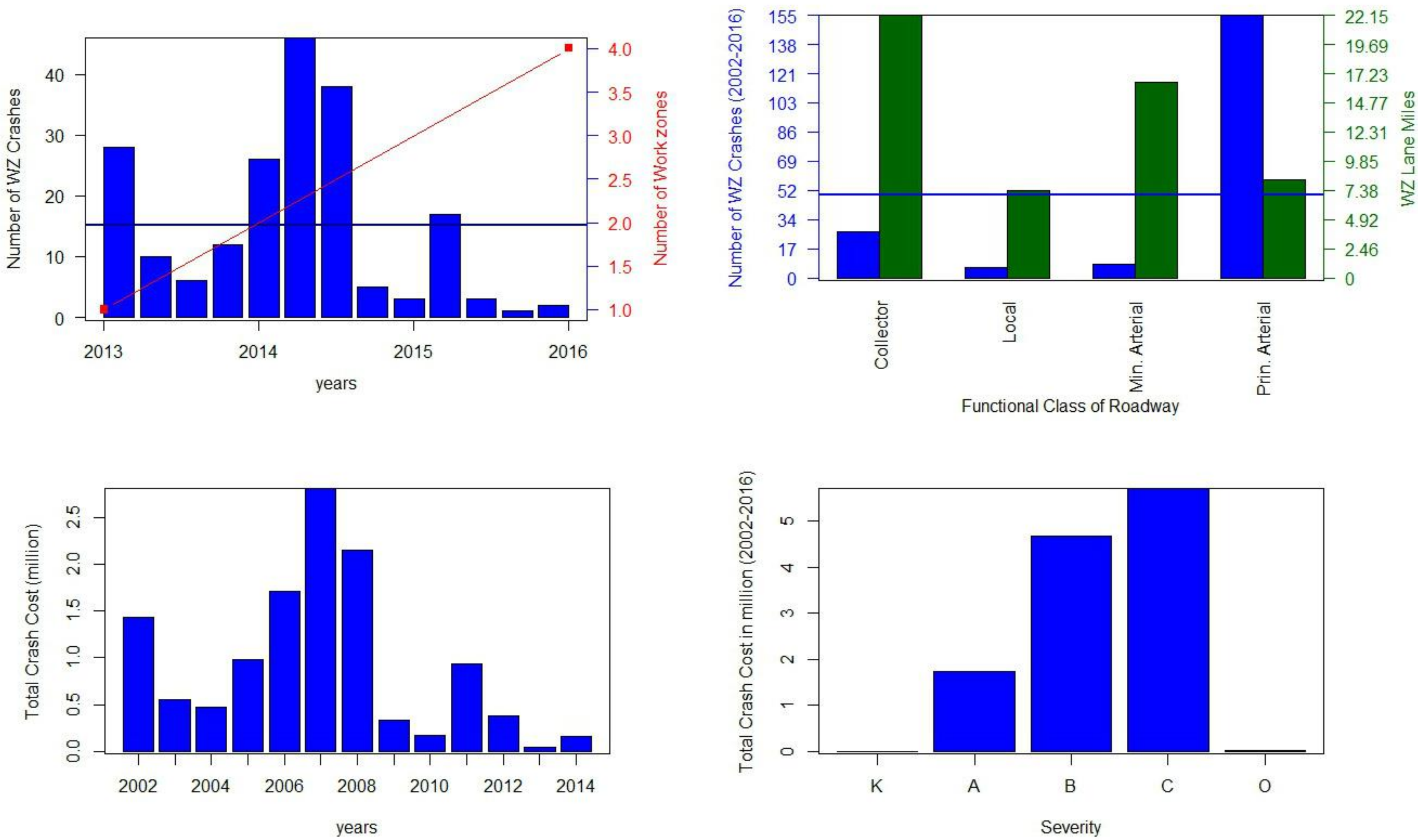


Figure 566 Workzone Crash Analysis - Lawrence County

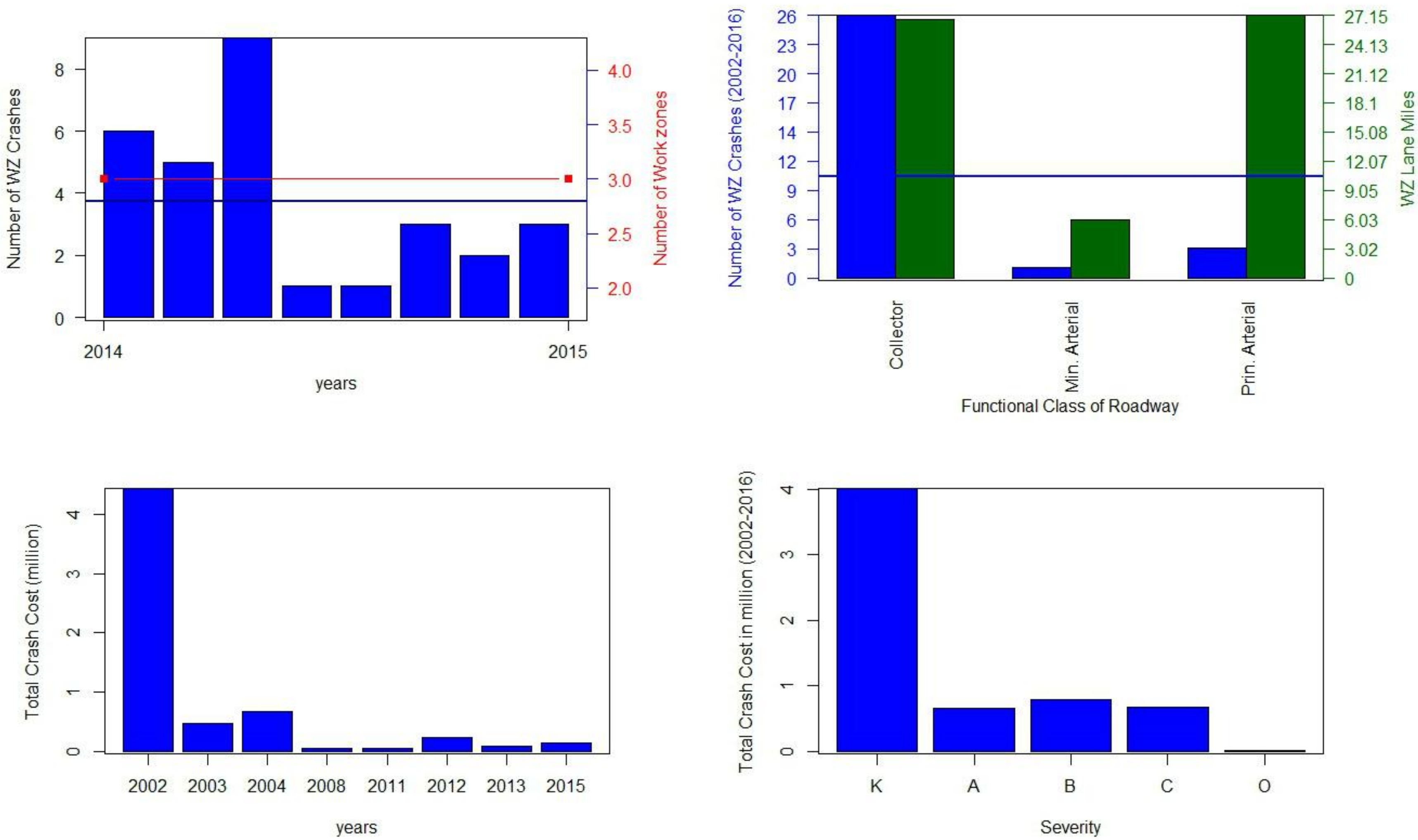


Figure 577 Workzone Crash Analysis - Lewis County

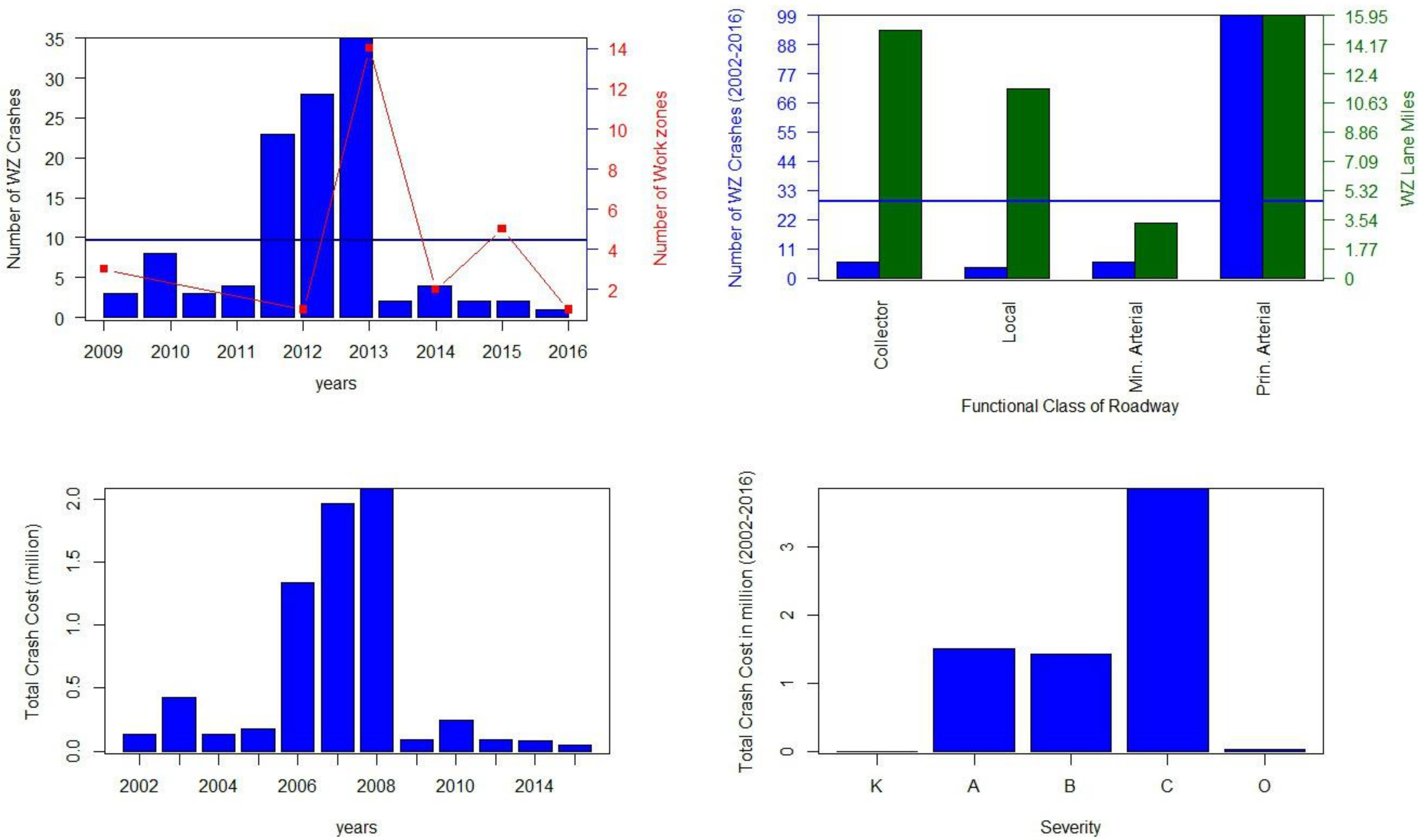


Figure 68 Workzone Crash Analysis - Lincoln County

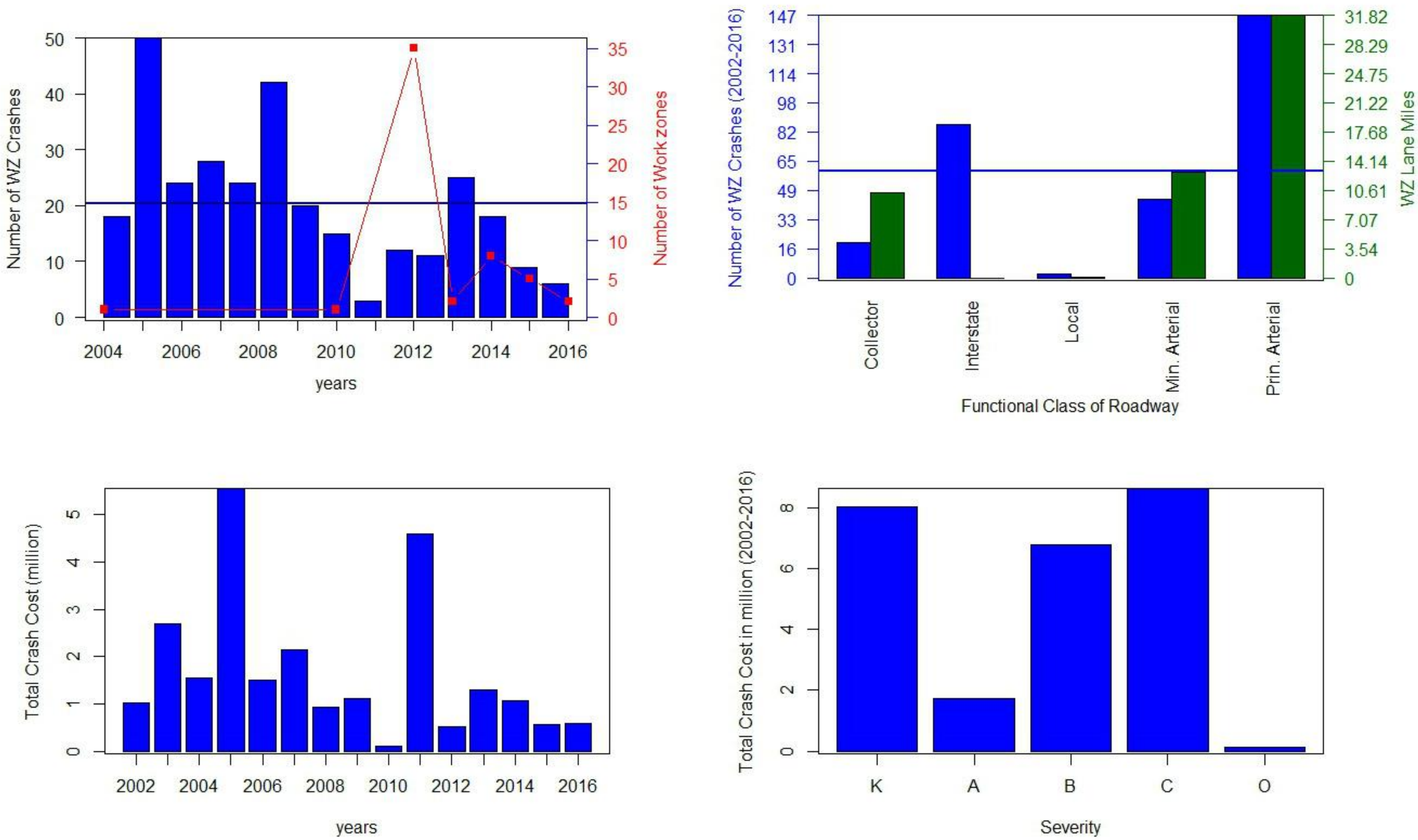


Figure 69 Workzone Crash Analysis - Loudon County

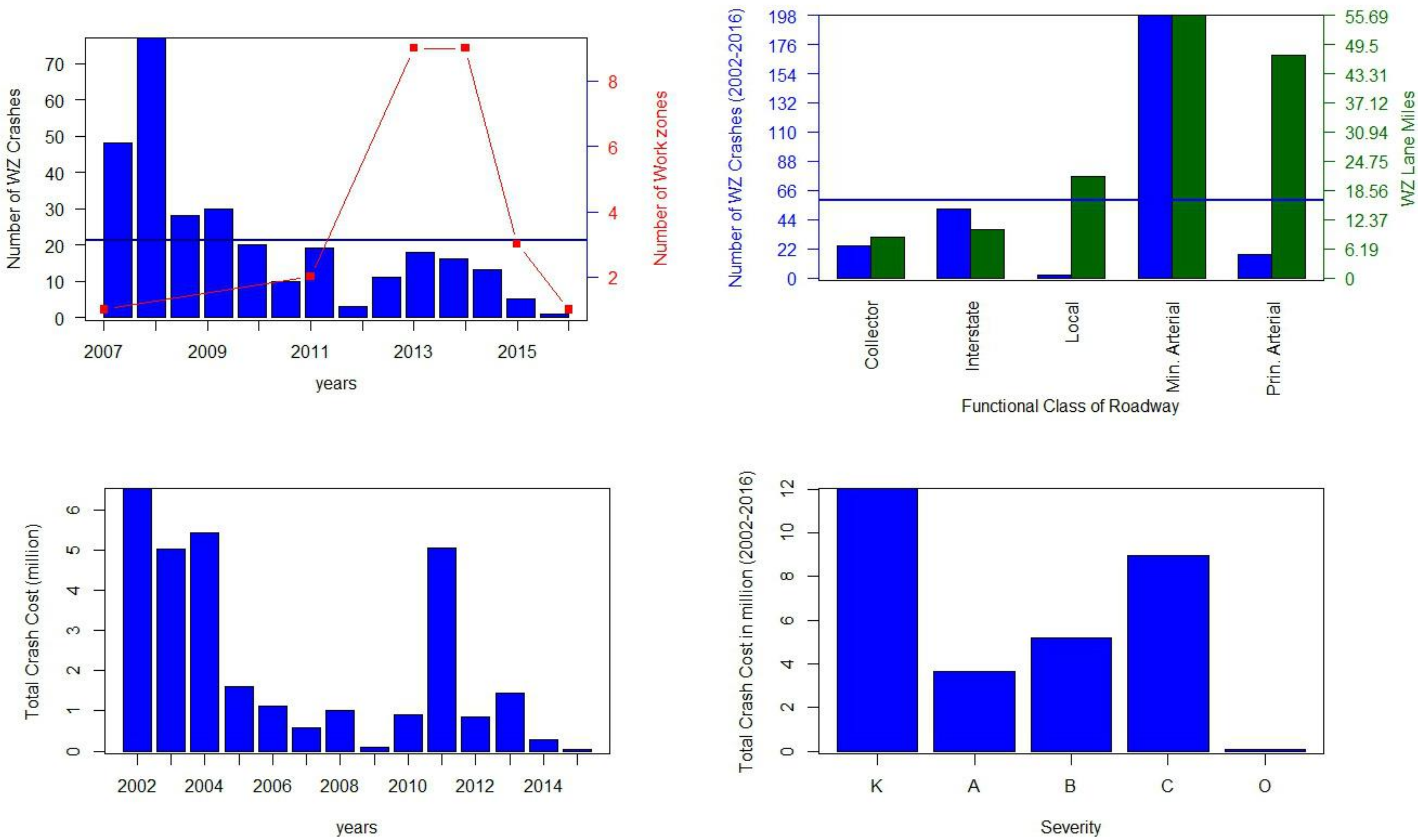


Figure 580 Workzone Crash Analysis - McMinn County

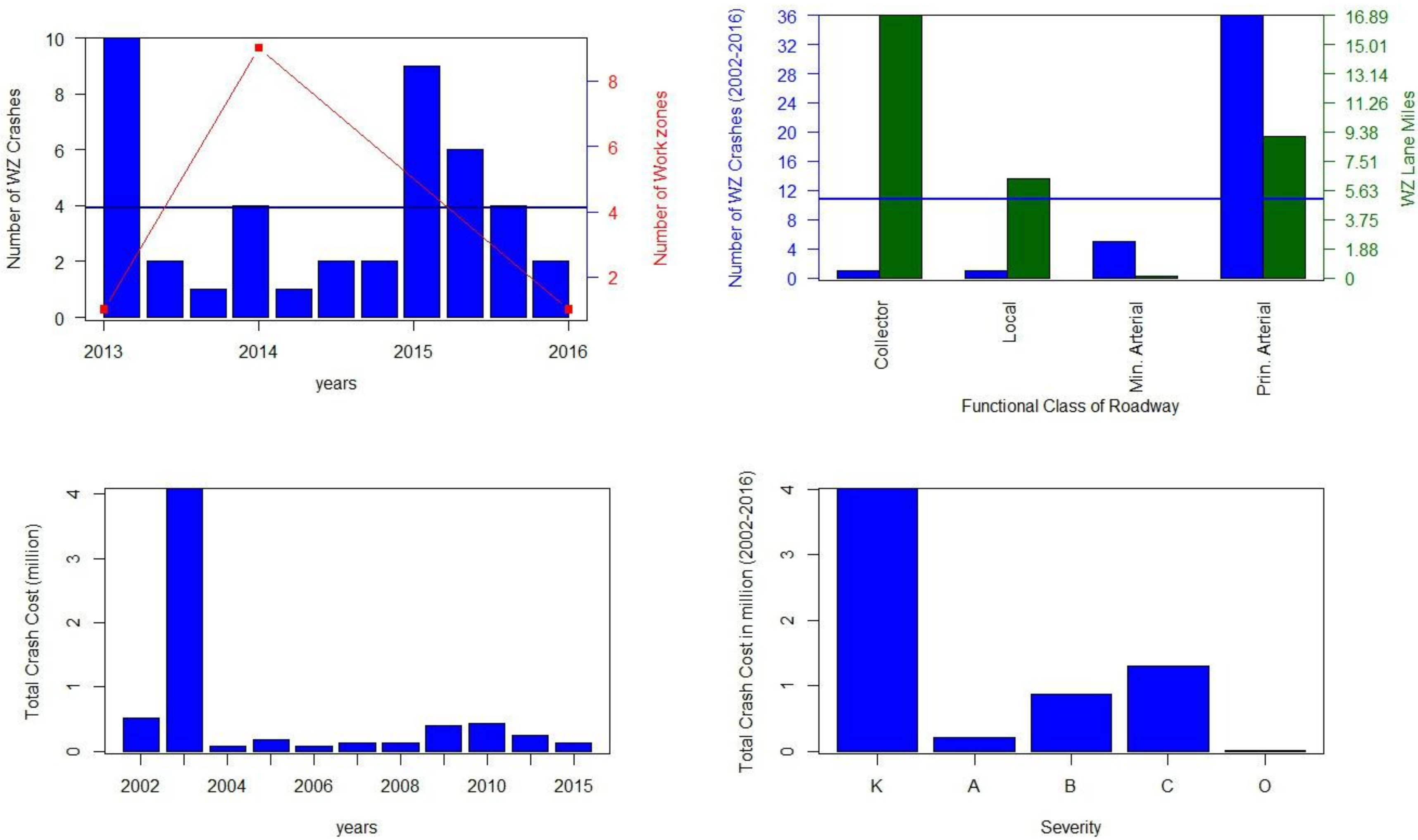


Figure 591 Workzone Crash Analysis - McNairy County

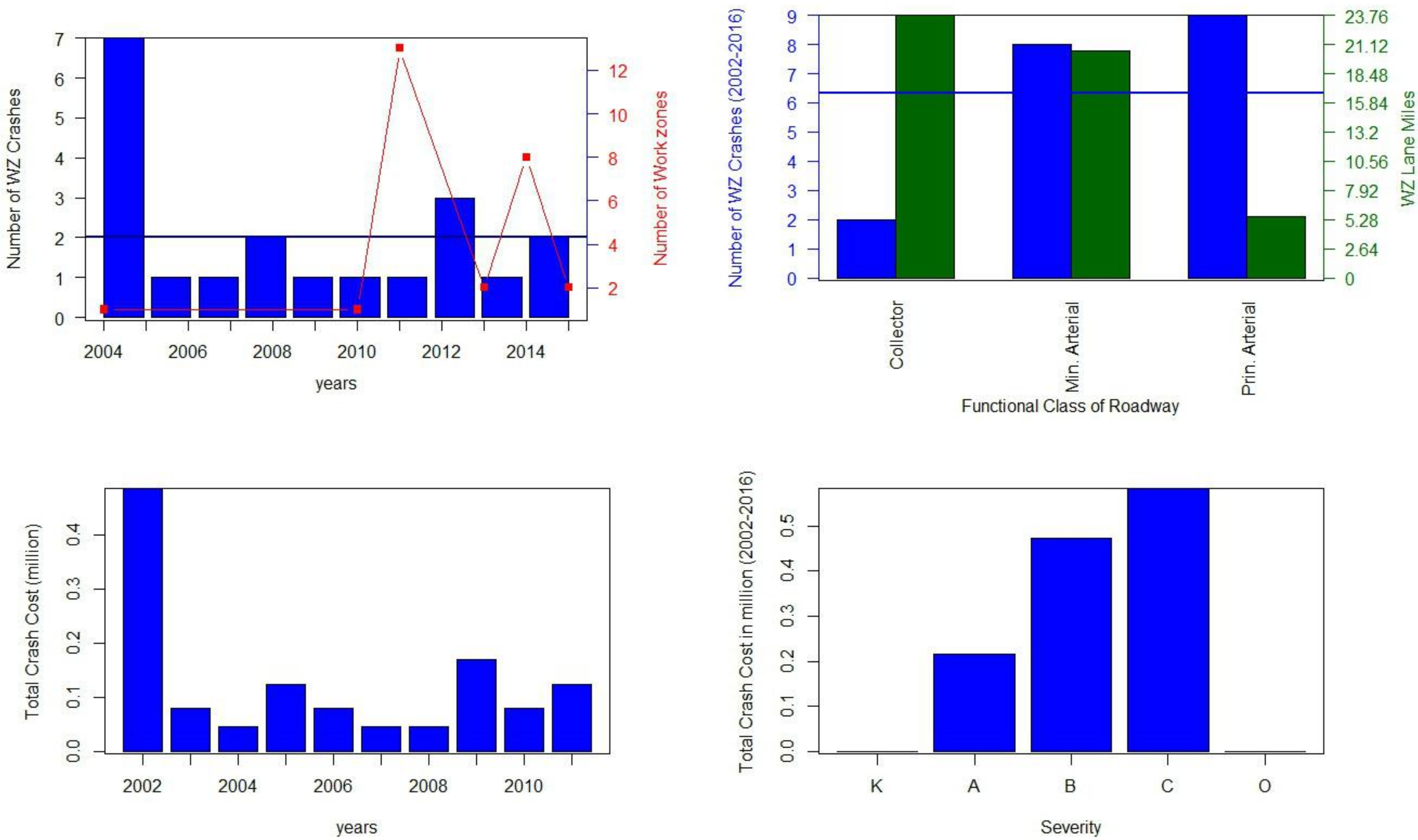


Figure 602 Workzone Crash Analysis - Macon County

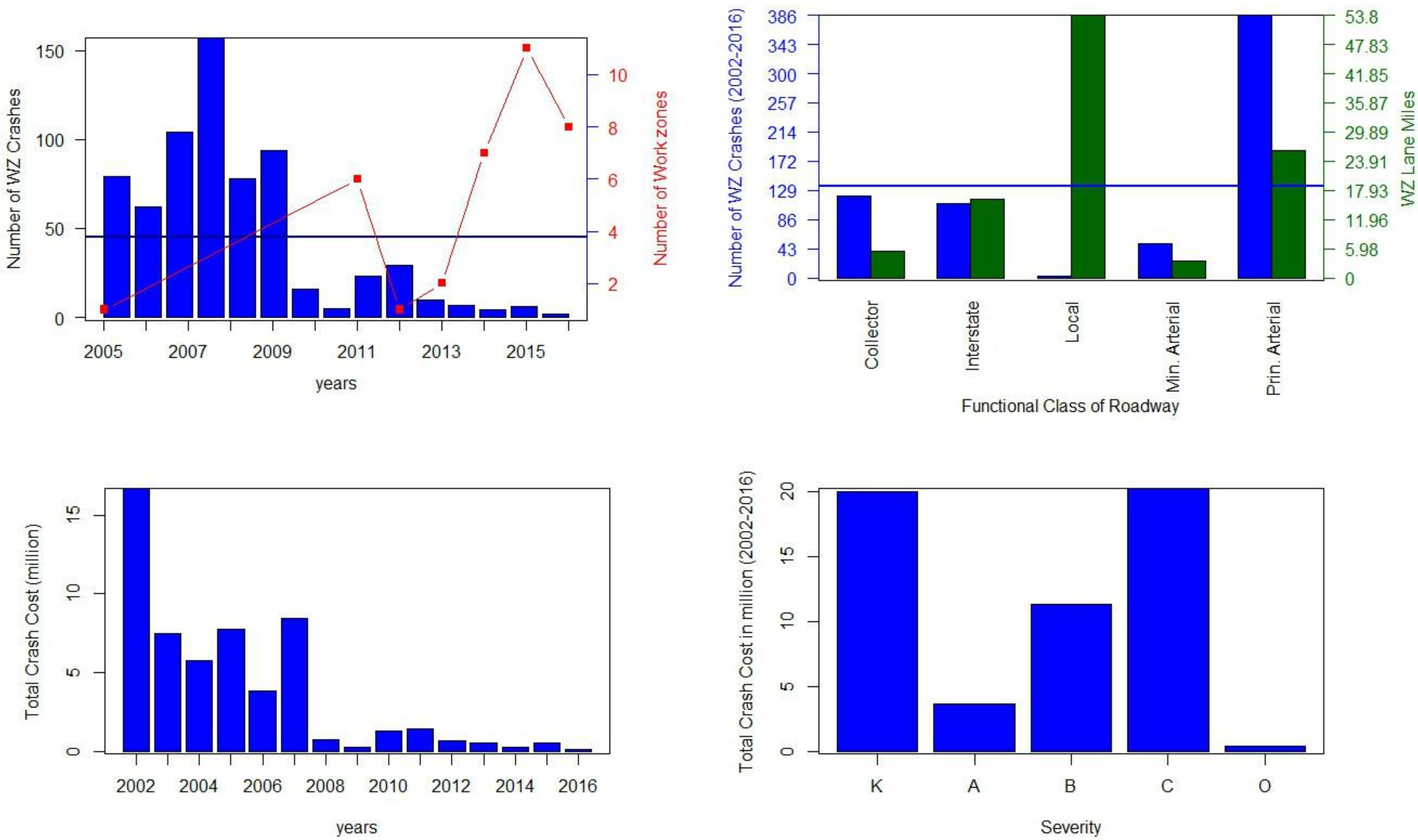


Figure 613 Workzone Crash Analysis - Madison County

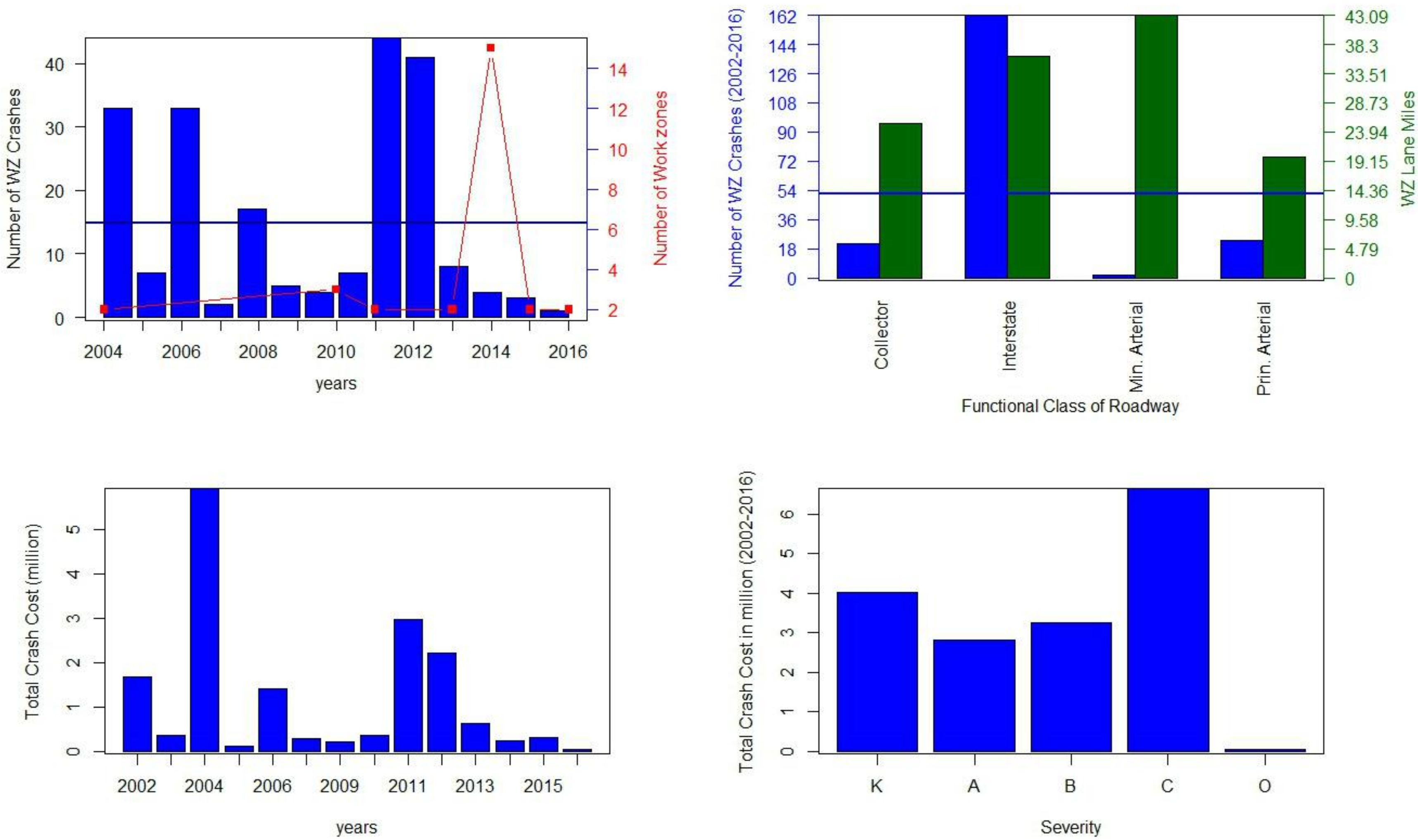


Figure 624 Workzone Crash Analysis - Marion County

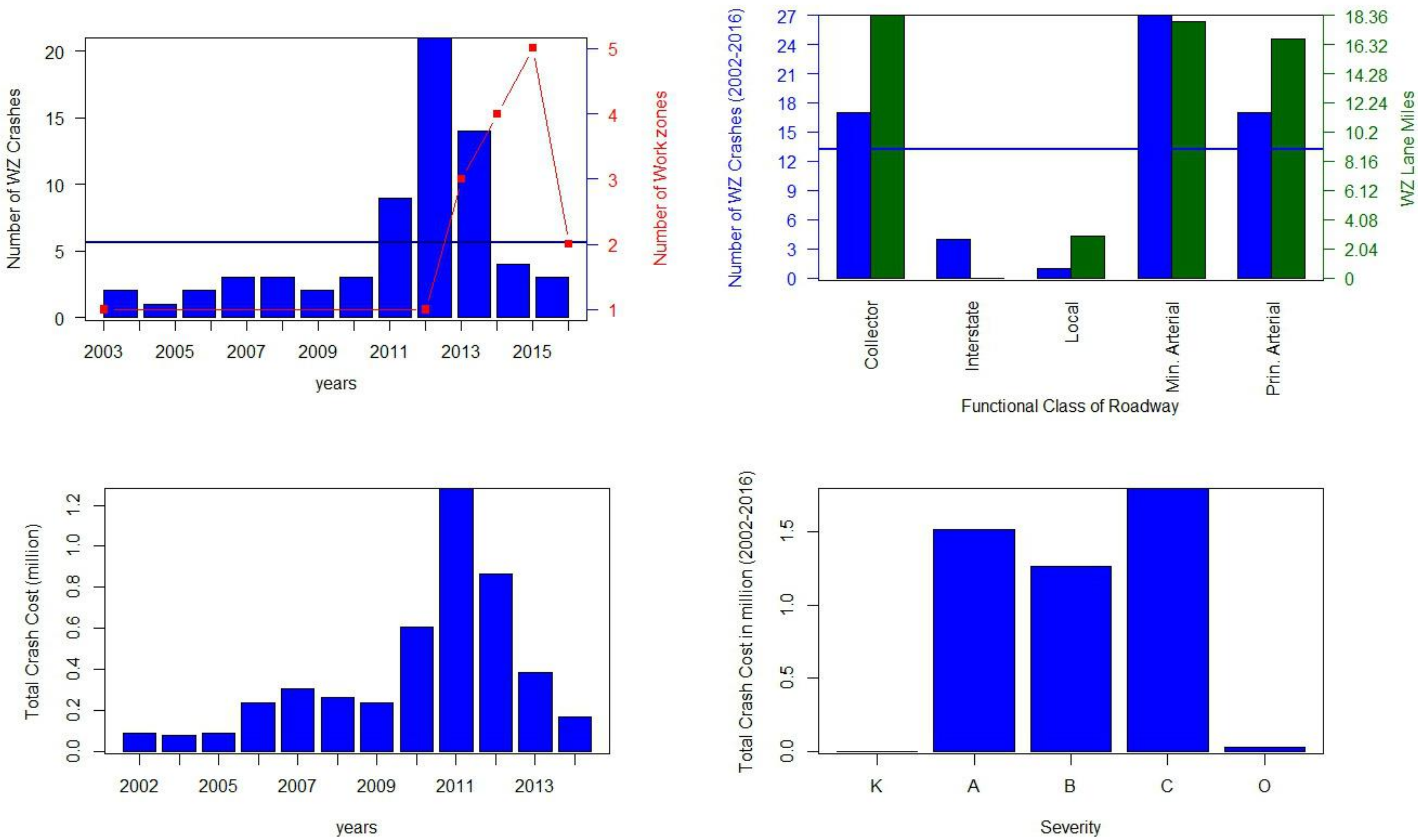


Figure 635 Workzone Crash Analysis - Marshall County

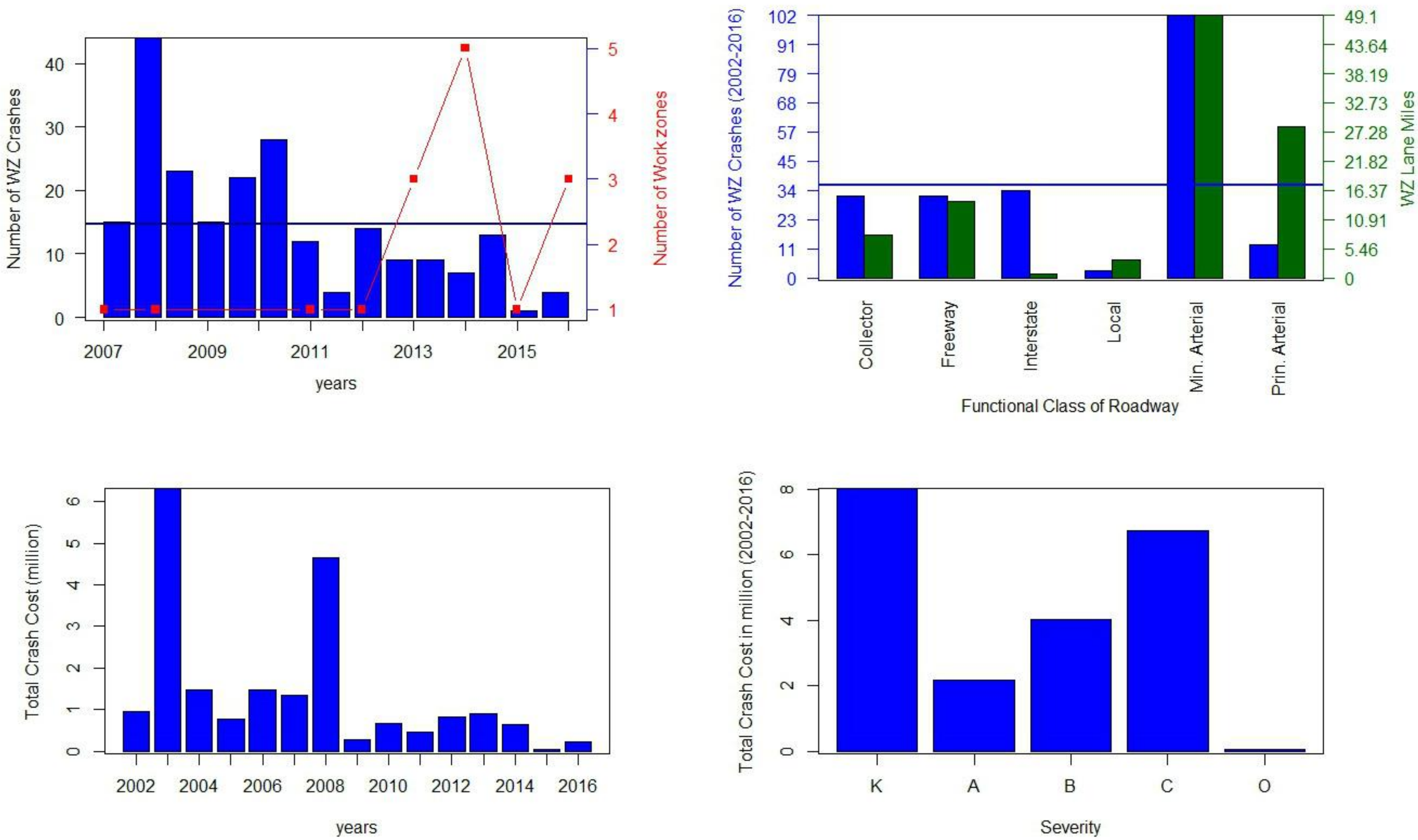


Figure 646 Workzone Crash Analysis - Maury County

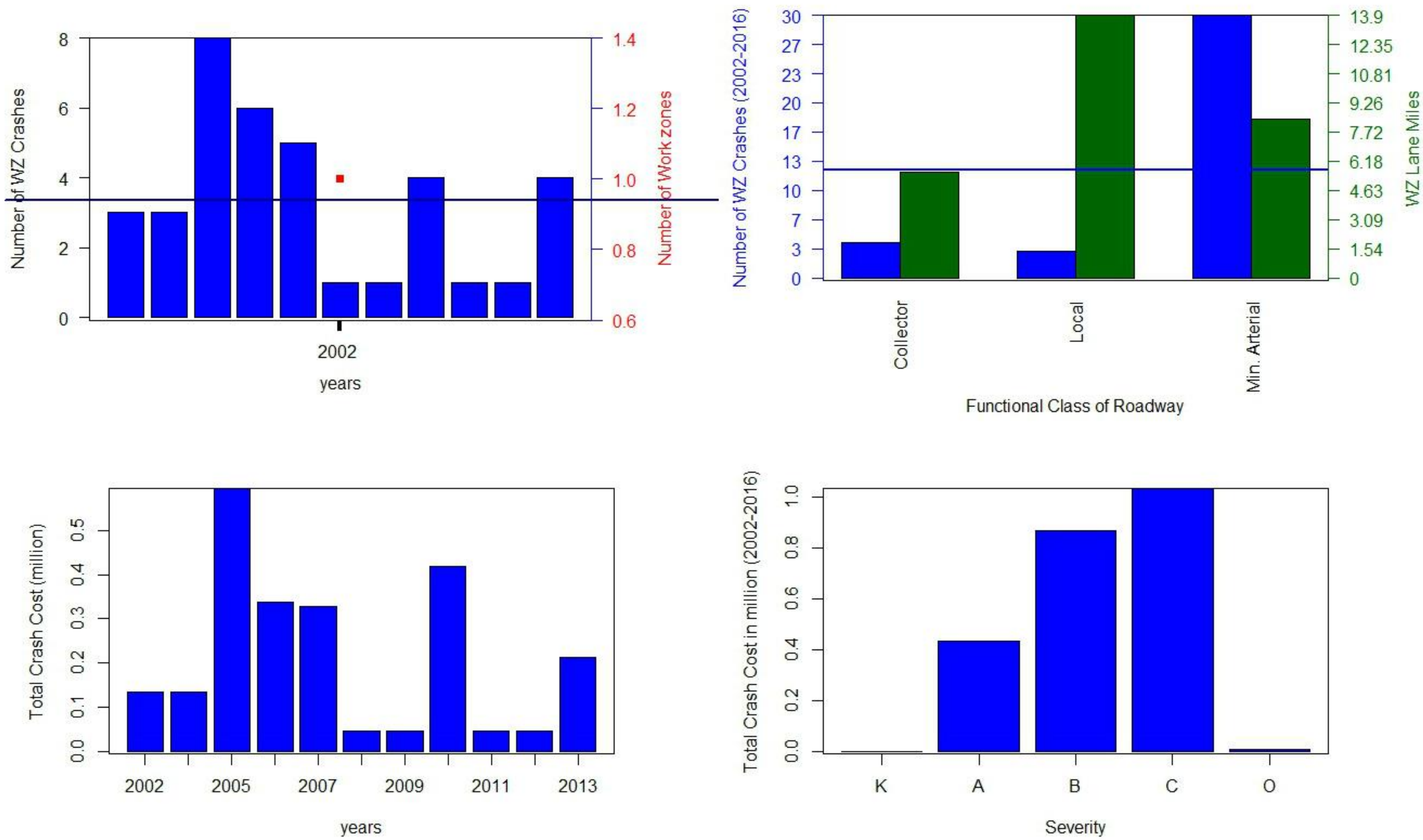


Figure 657 Workzone Crash Analysis - Meigs County

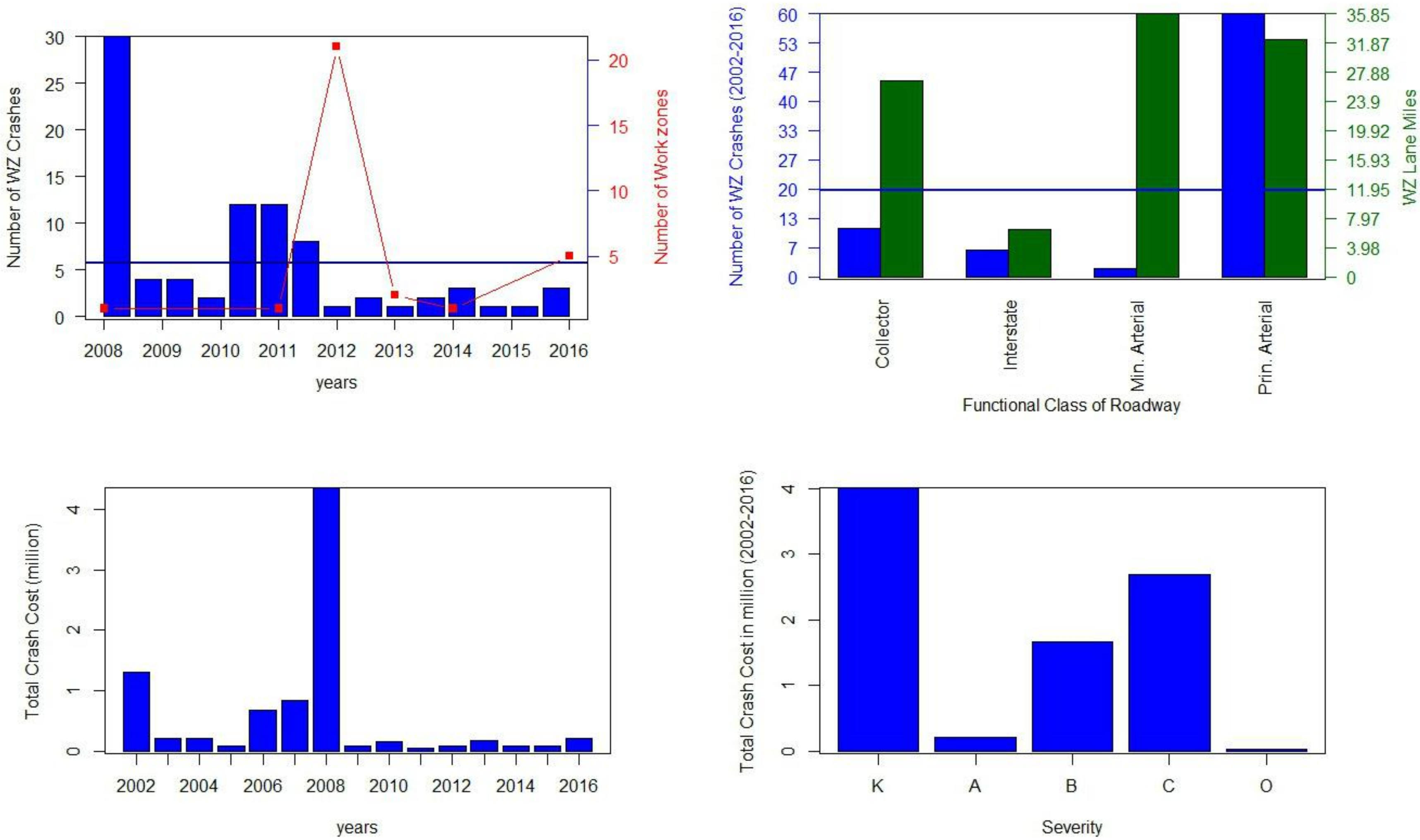


Figure 78 Workzone Crash Analysis - Monroe County

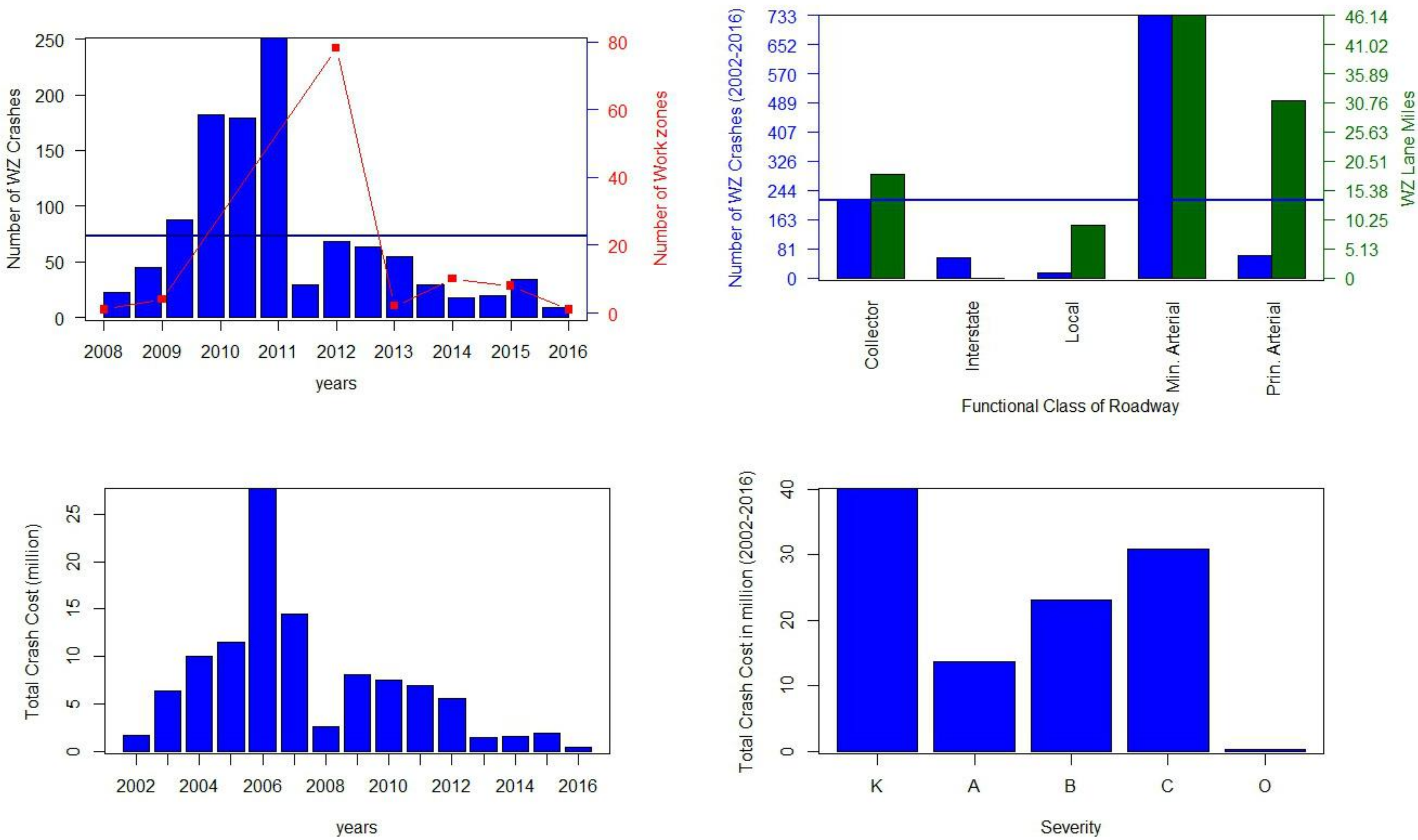


Figure 79 Workzone Crash Analysis - Montgomery County

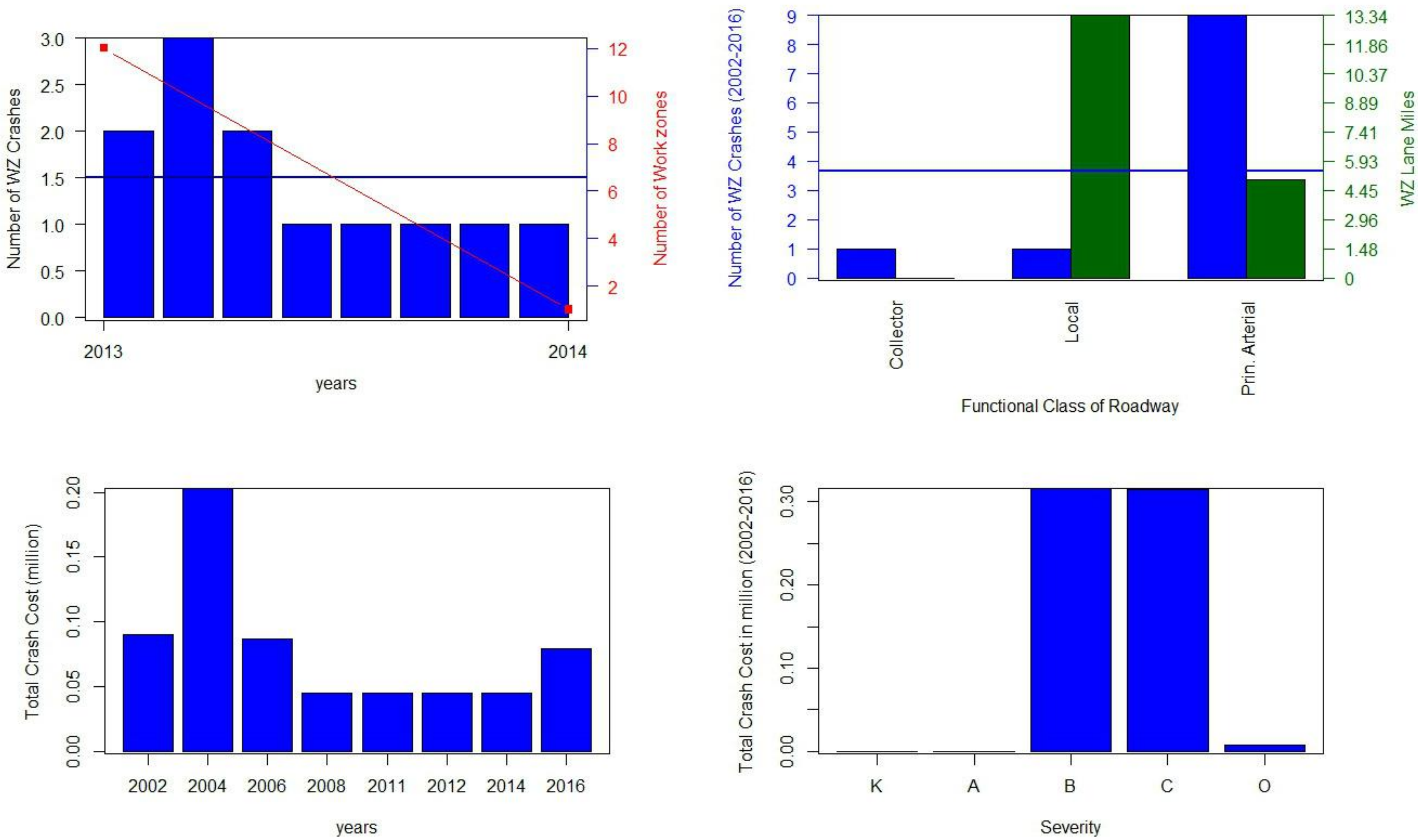


Figure 660 Workzone Crash Analysis - Moore County

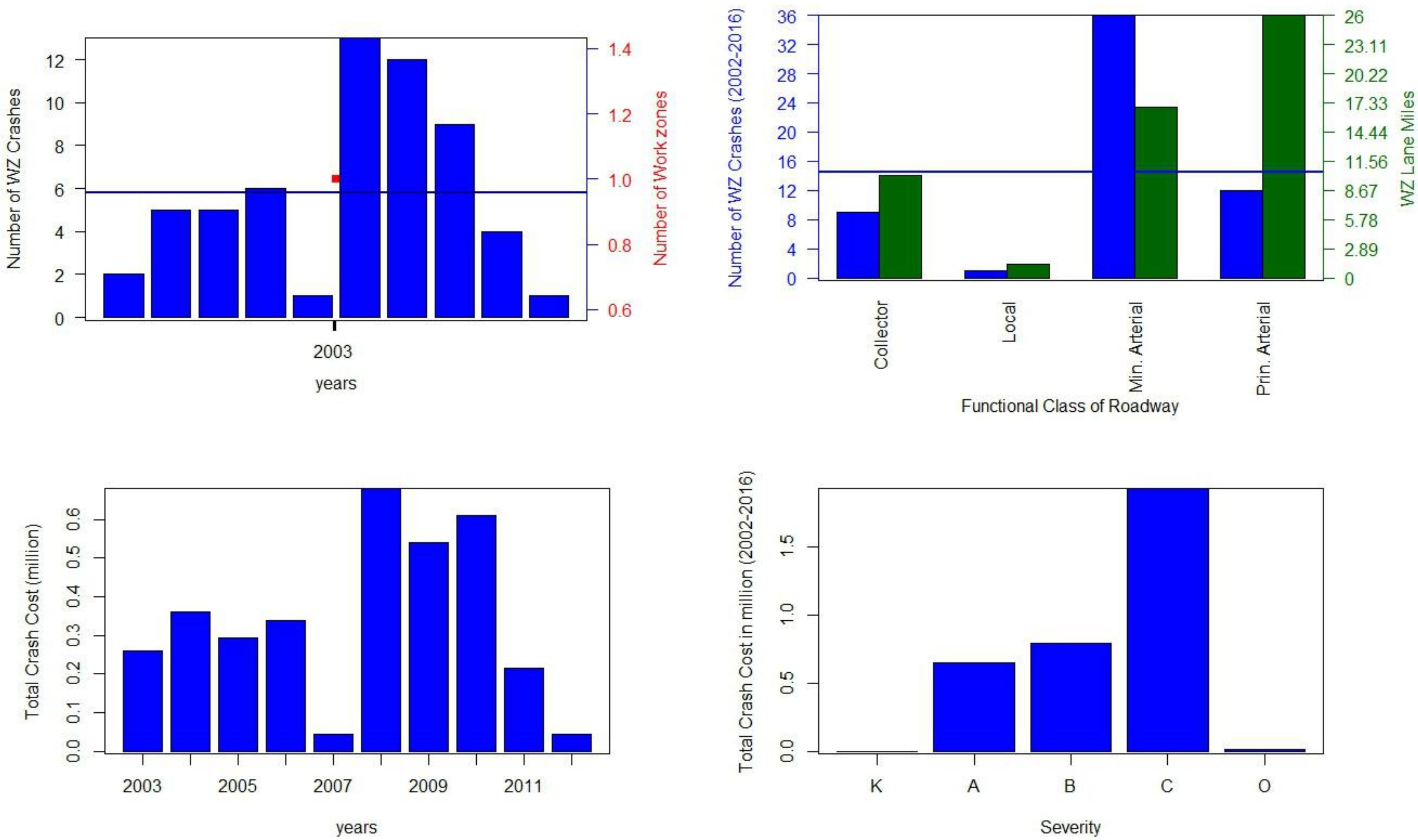


Figure 671 Workzone Crash Analysis - Morgan County

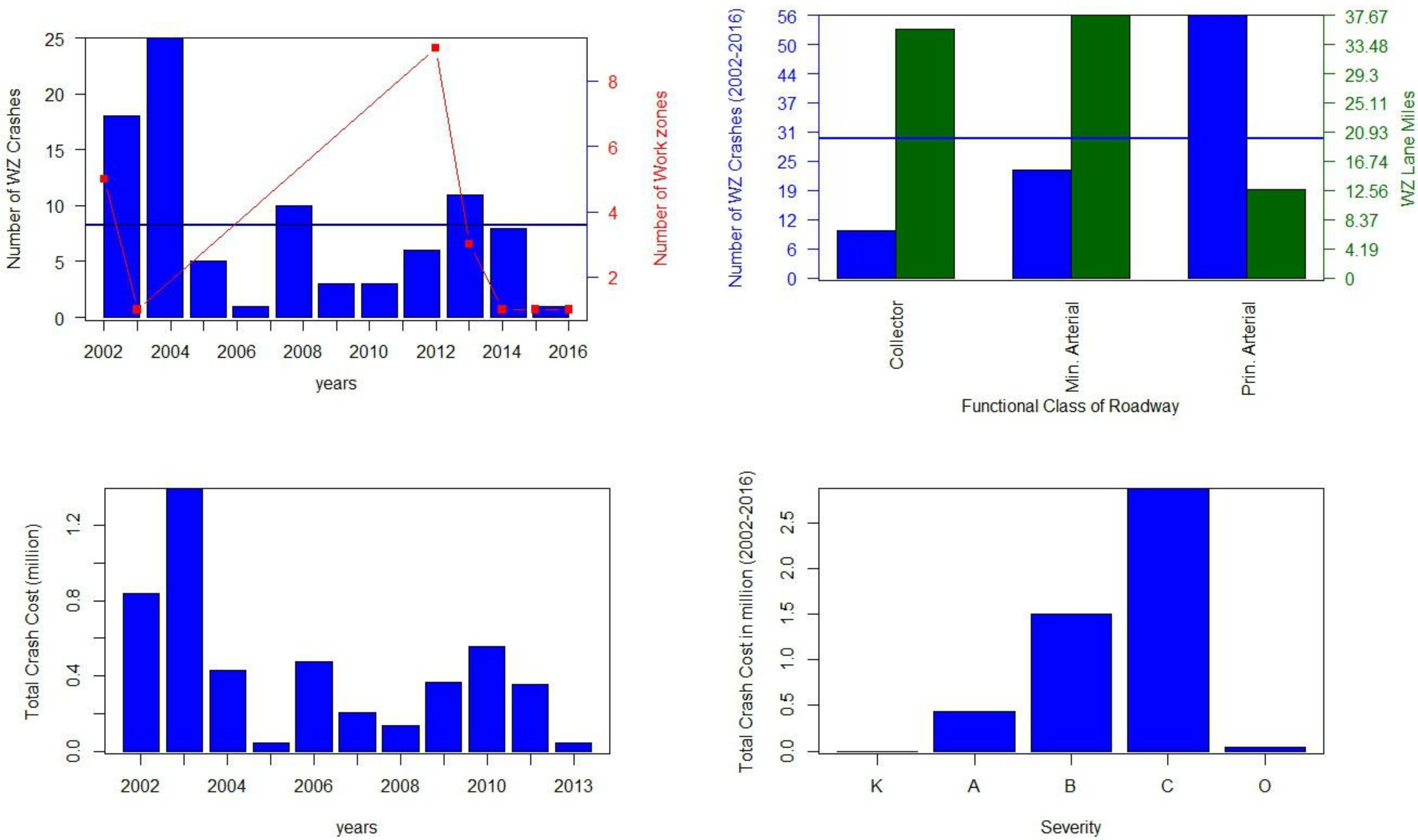


Figure 682 Workzone Crash Analysis - Obion County

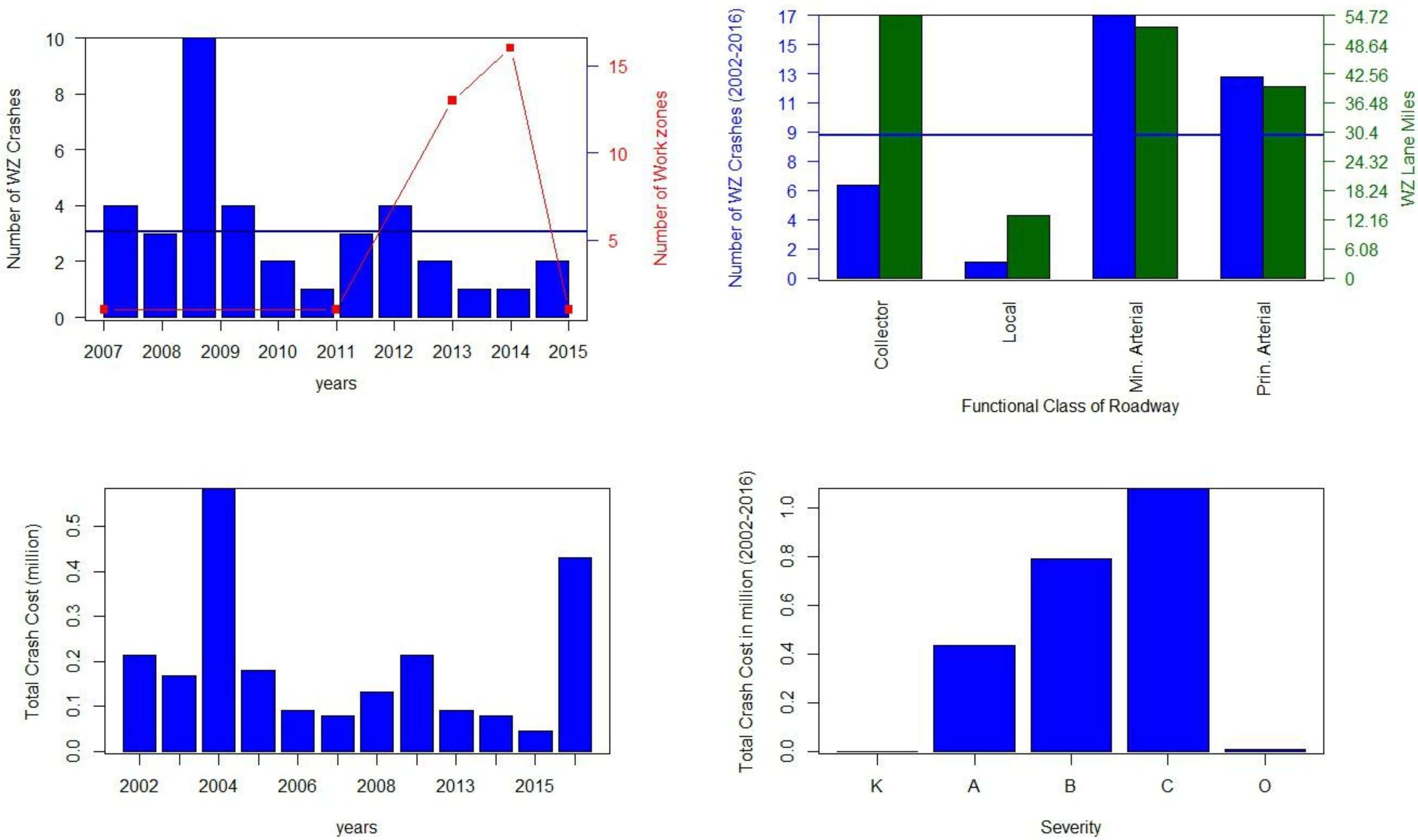


Figure 693 Workzone Crash Analysis - Overton County

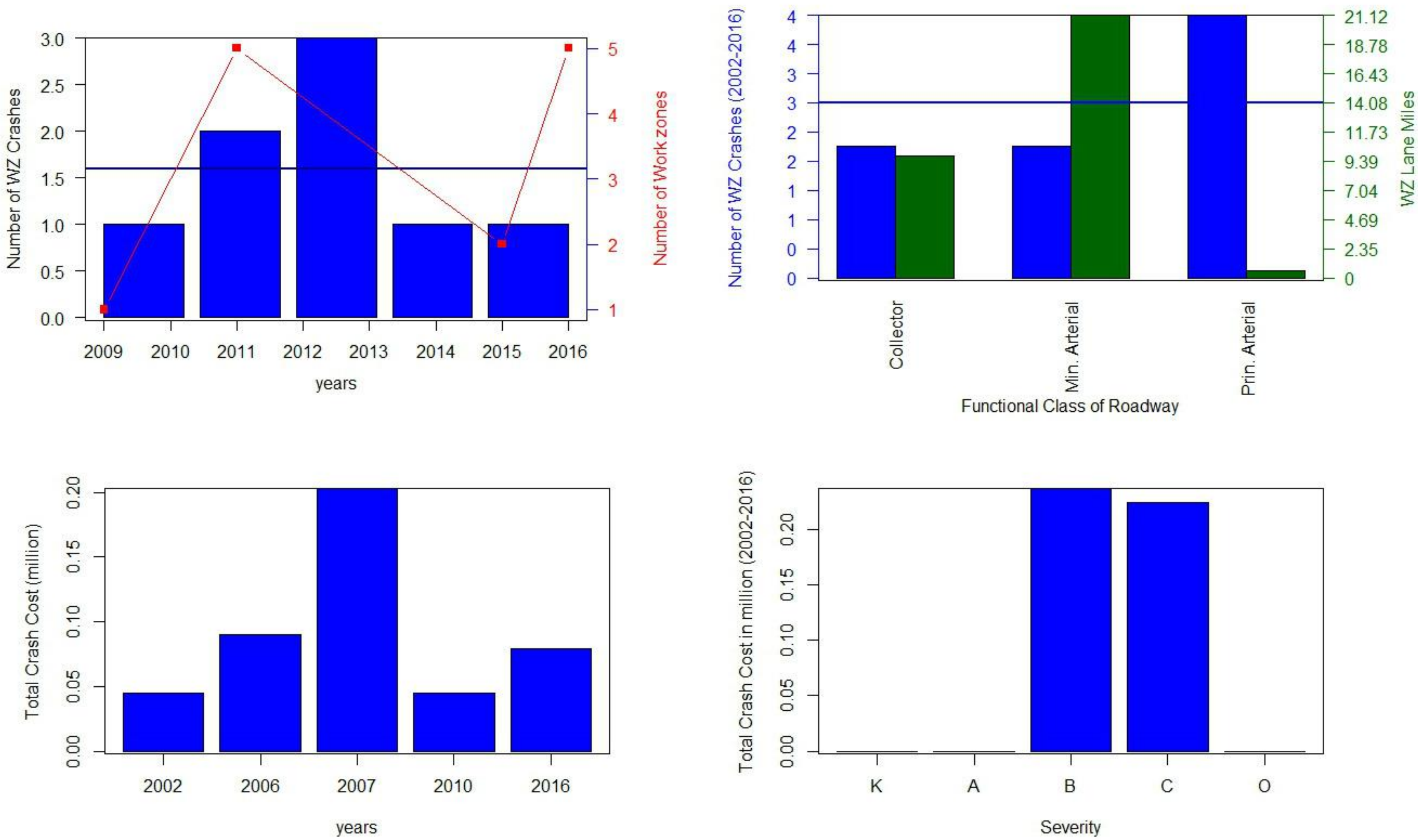


Figure 704 Workzone Crash Analysis - Perry County

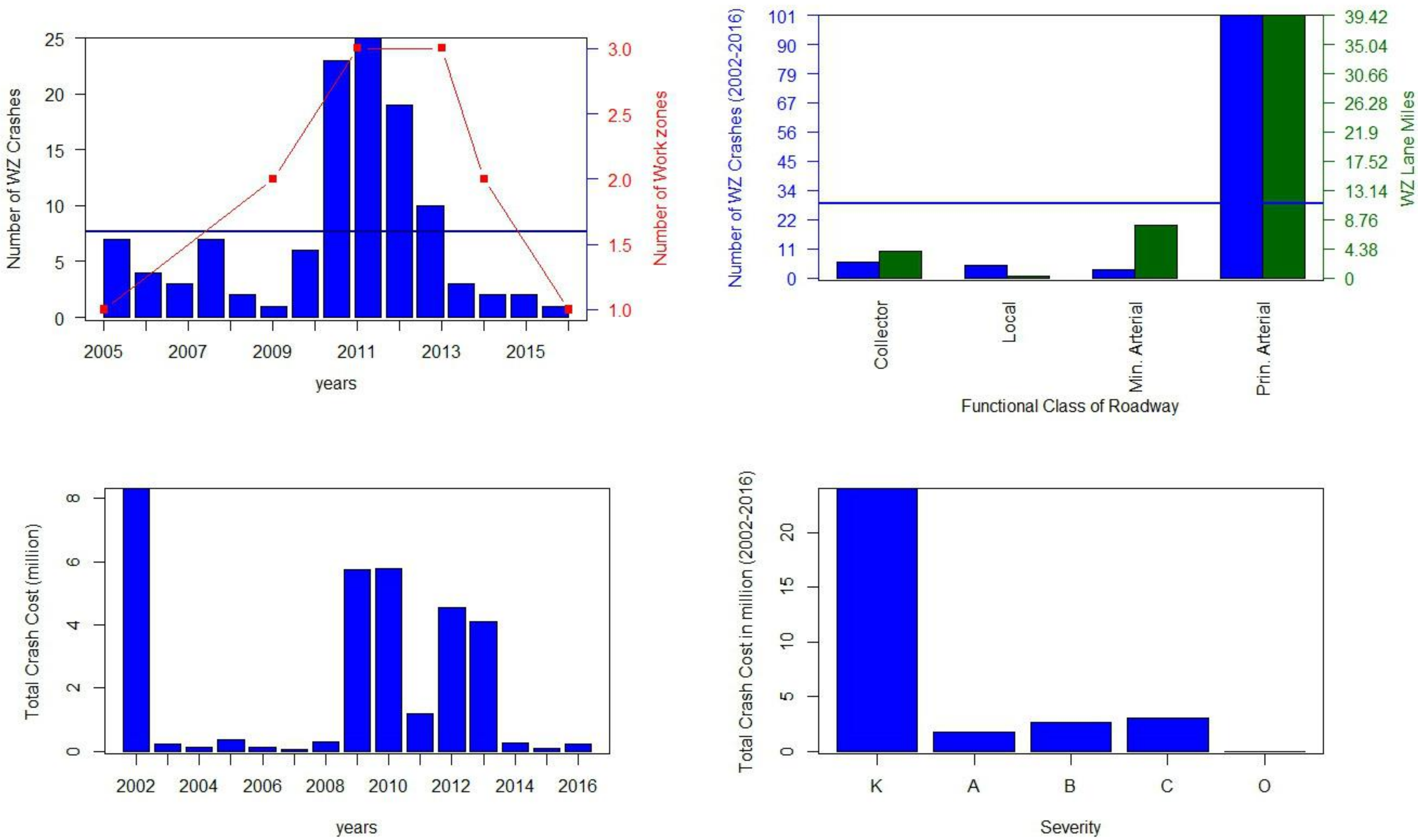


Figure 715 Workzone Crash Analysis - Polk County

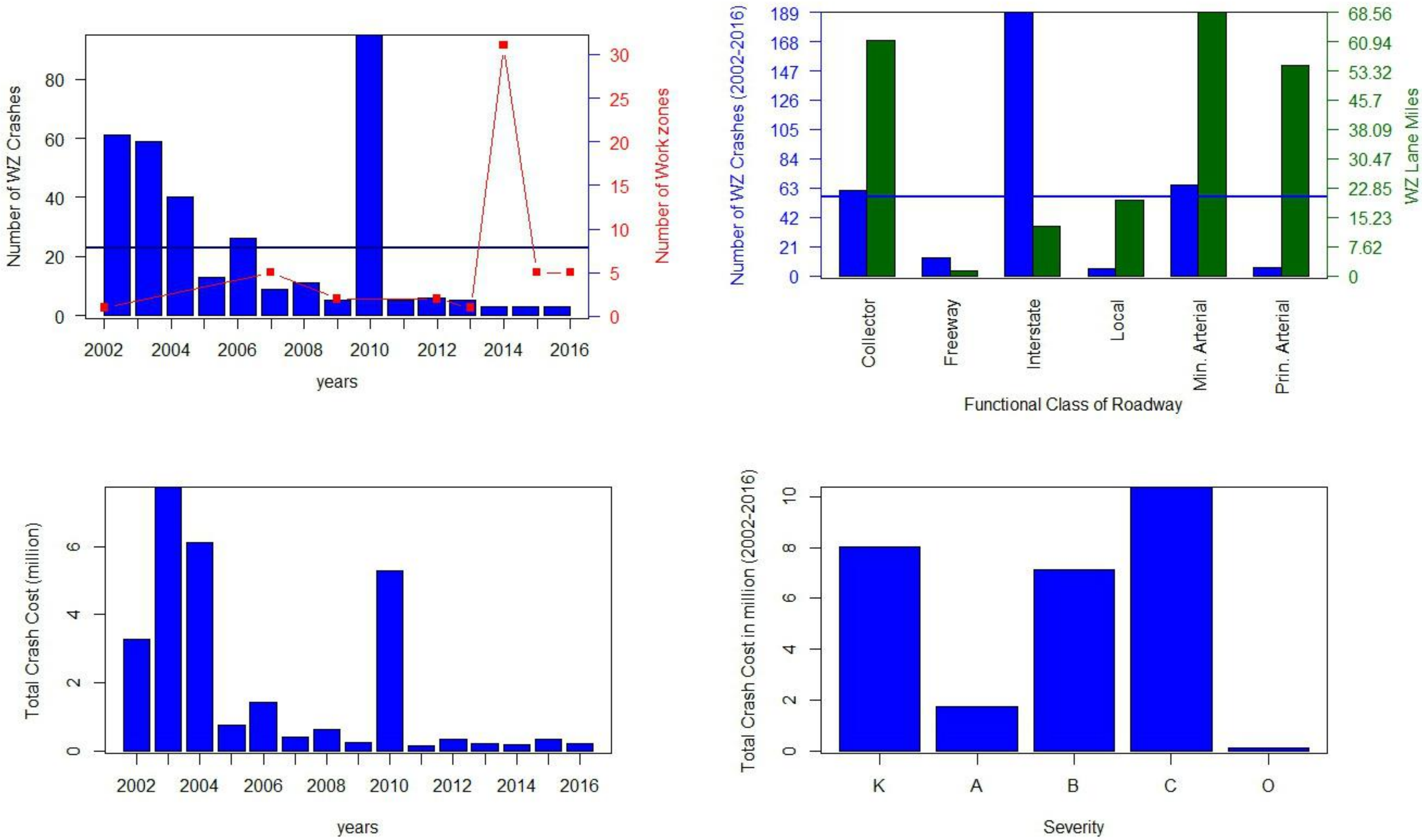


Figure 726 Workzone Crash Analysis - Putnam County

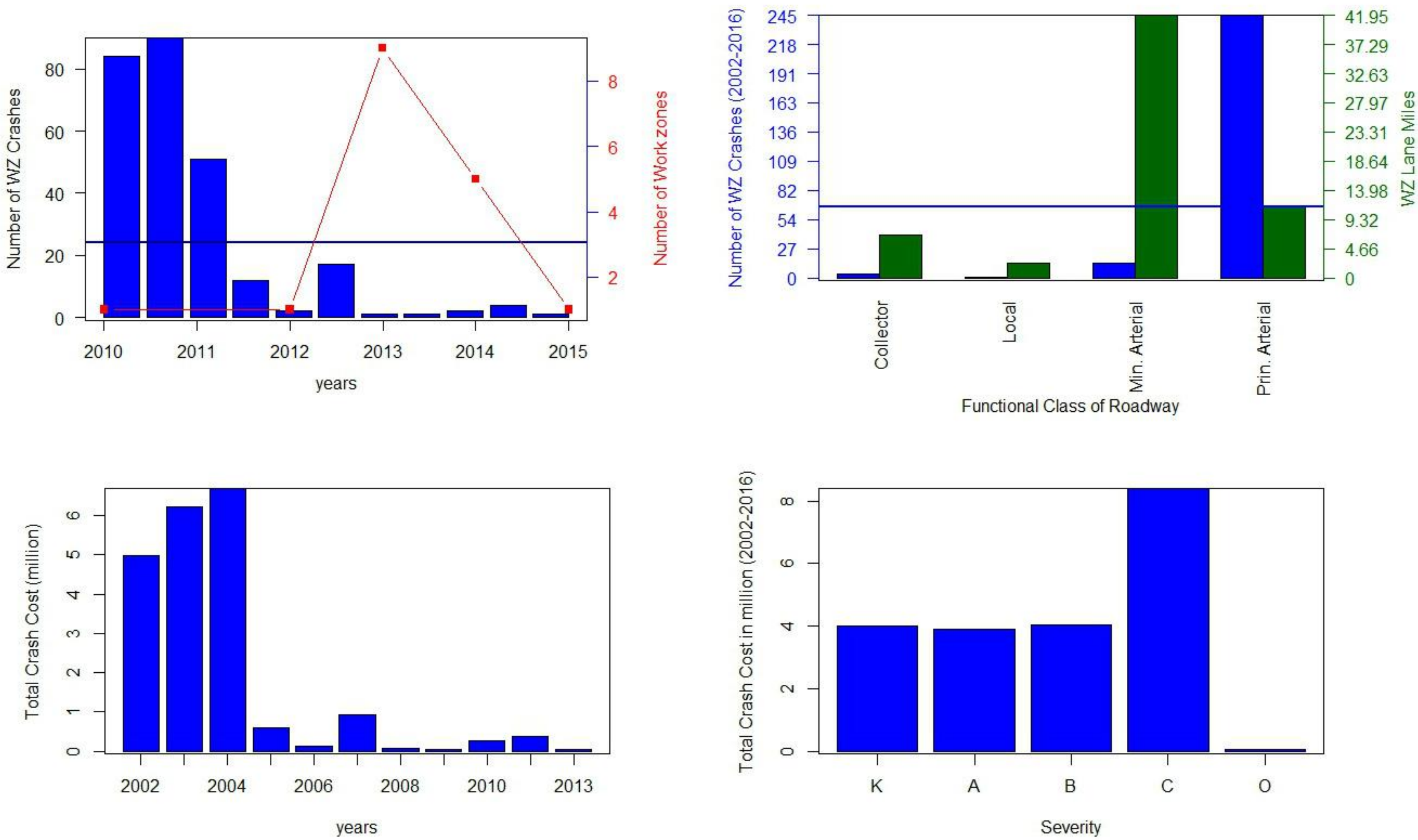


Figure 737 Workzone Crash Analysis - Rhea County

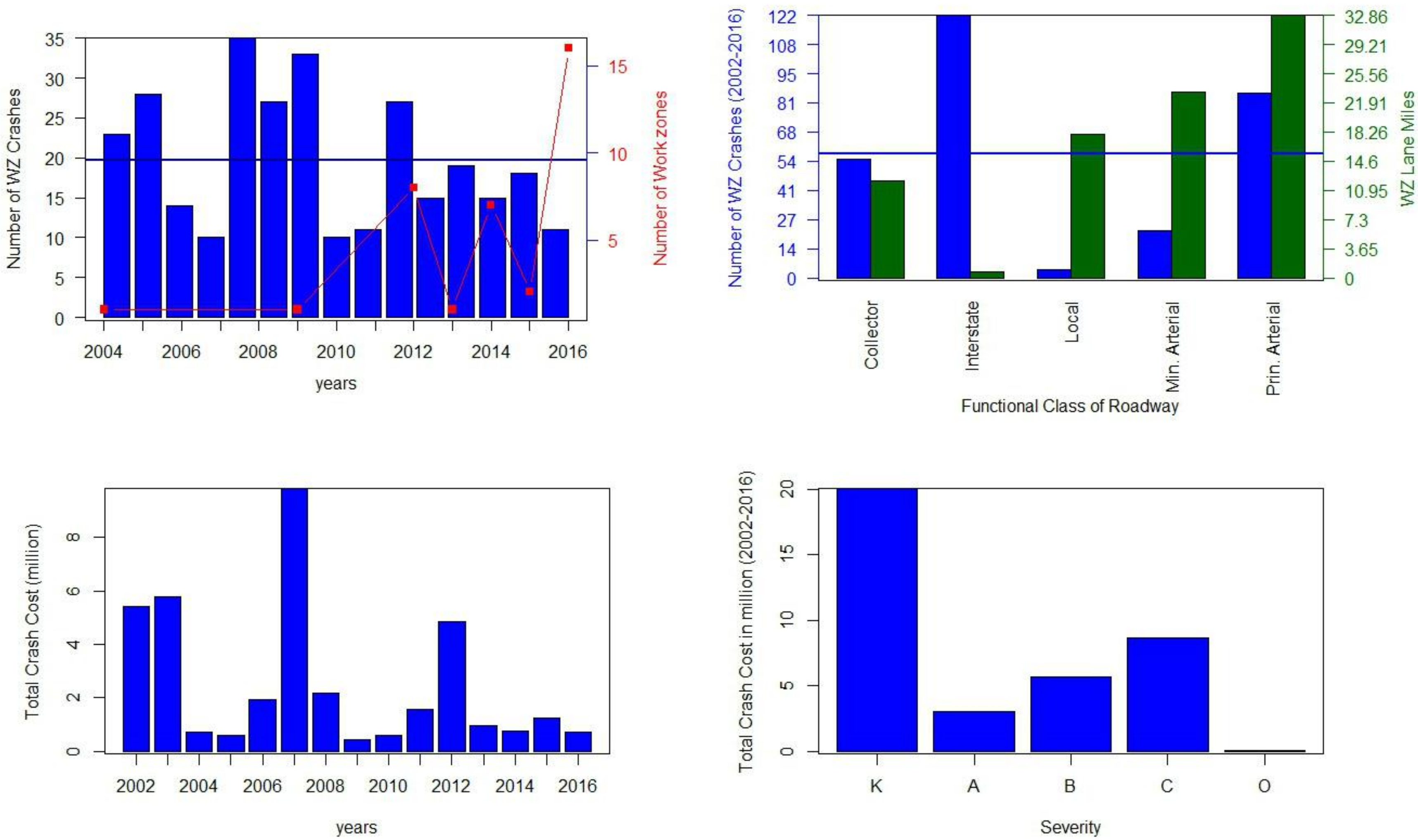


Figure 88 Workzone Crash Analysis - Roane County

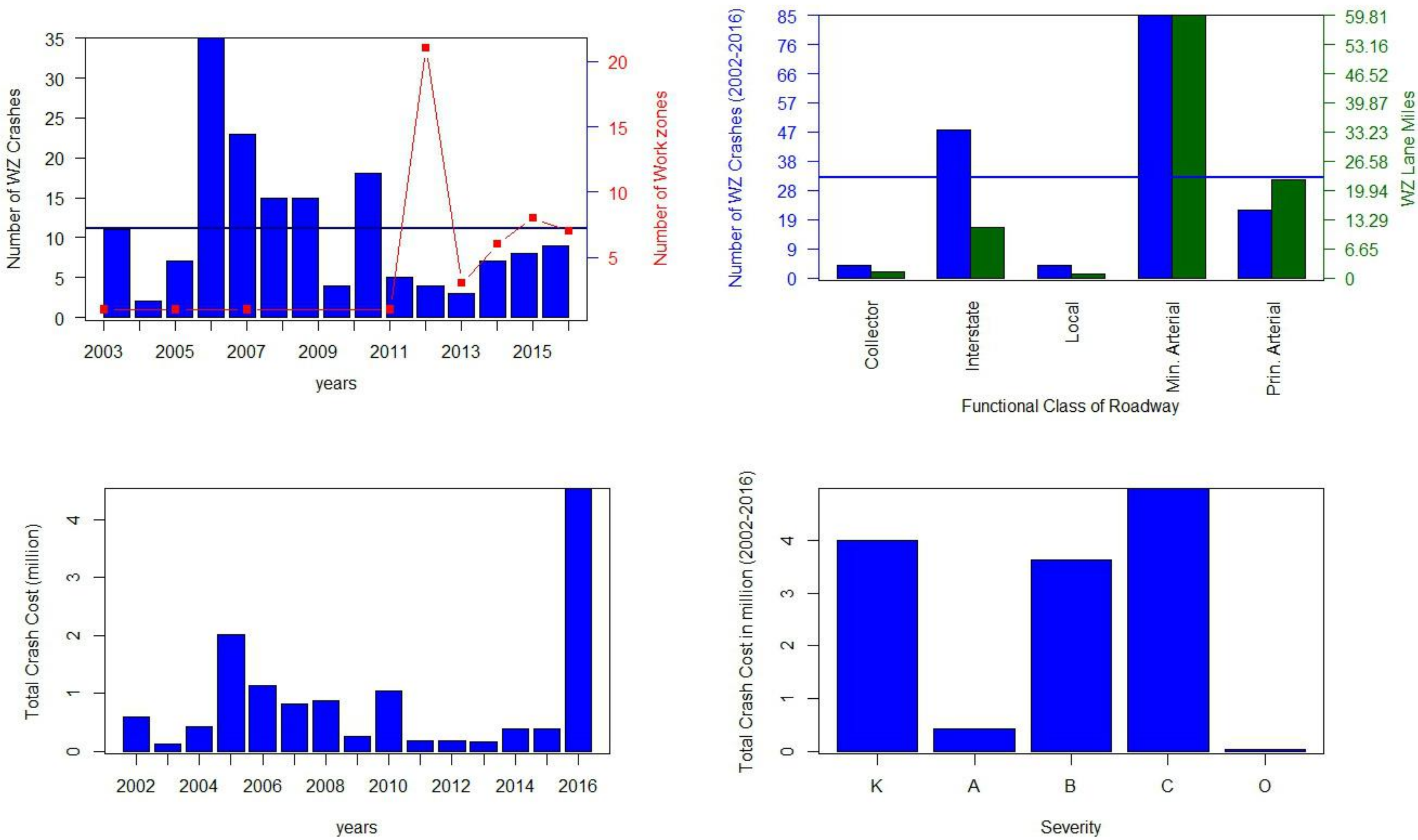


Figure 89 Workzone Crash Analysis - Robertson County

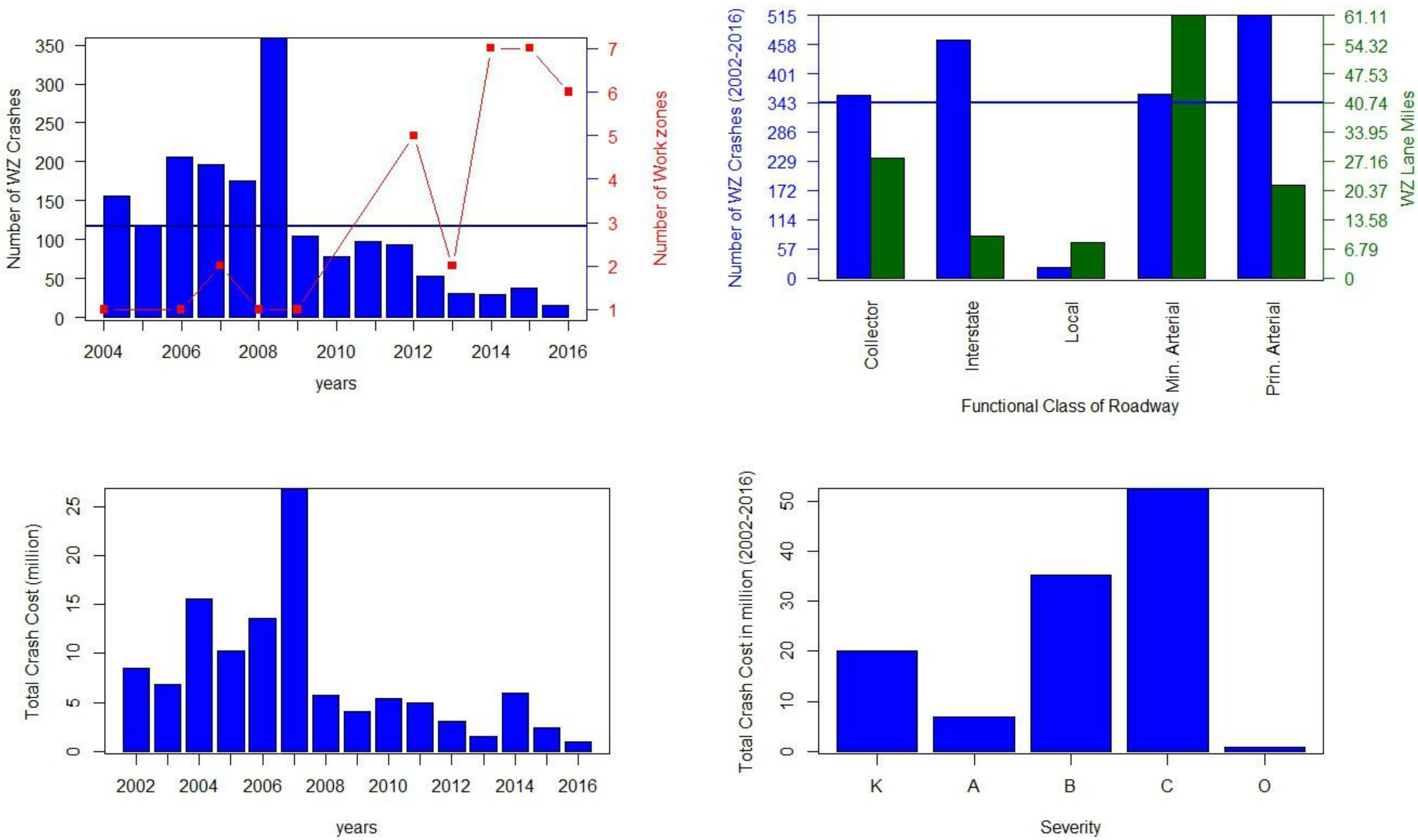


Figure 740 Workzone Crash Analysis - Rutherford County

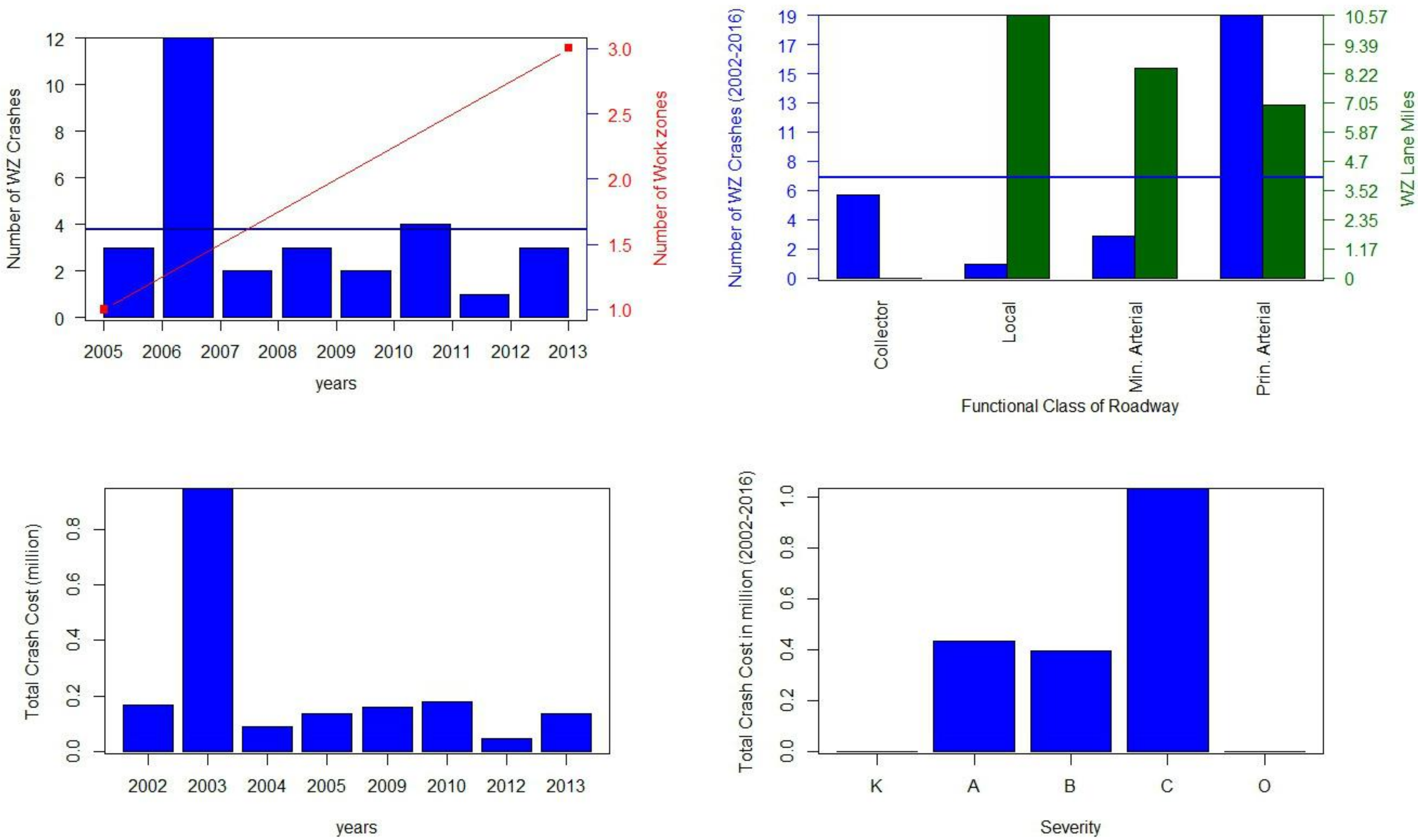


Figure 751 Workzone Crash Analysis - Scott County

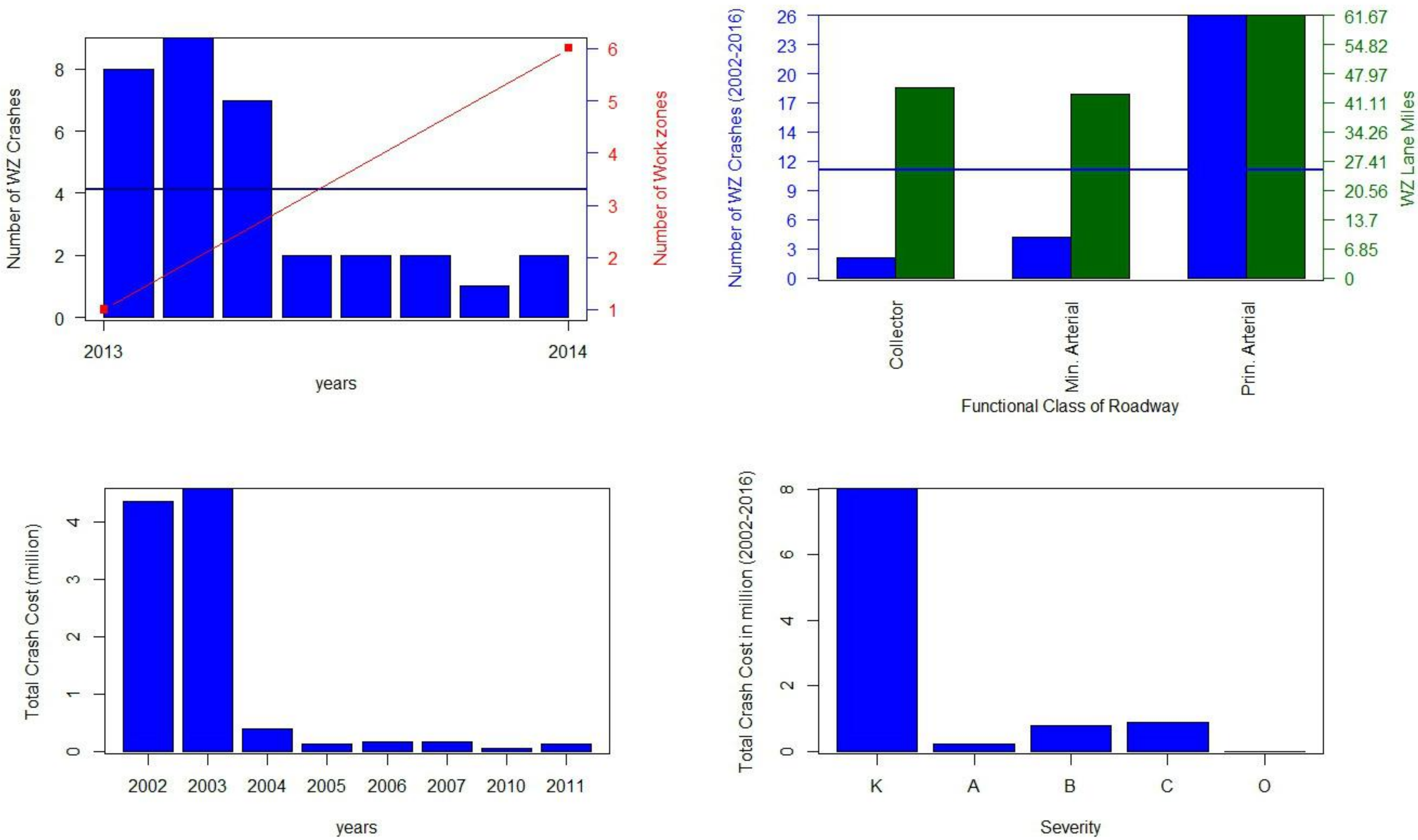


Figure 762 Workzone Crash Analysis - Sequatchie County

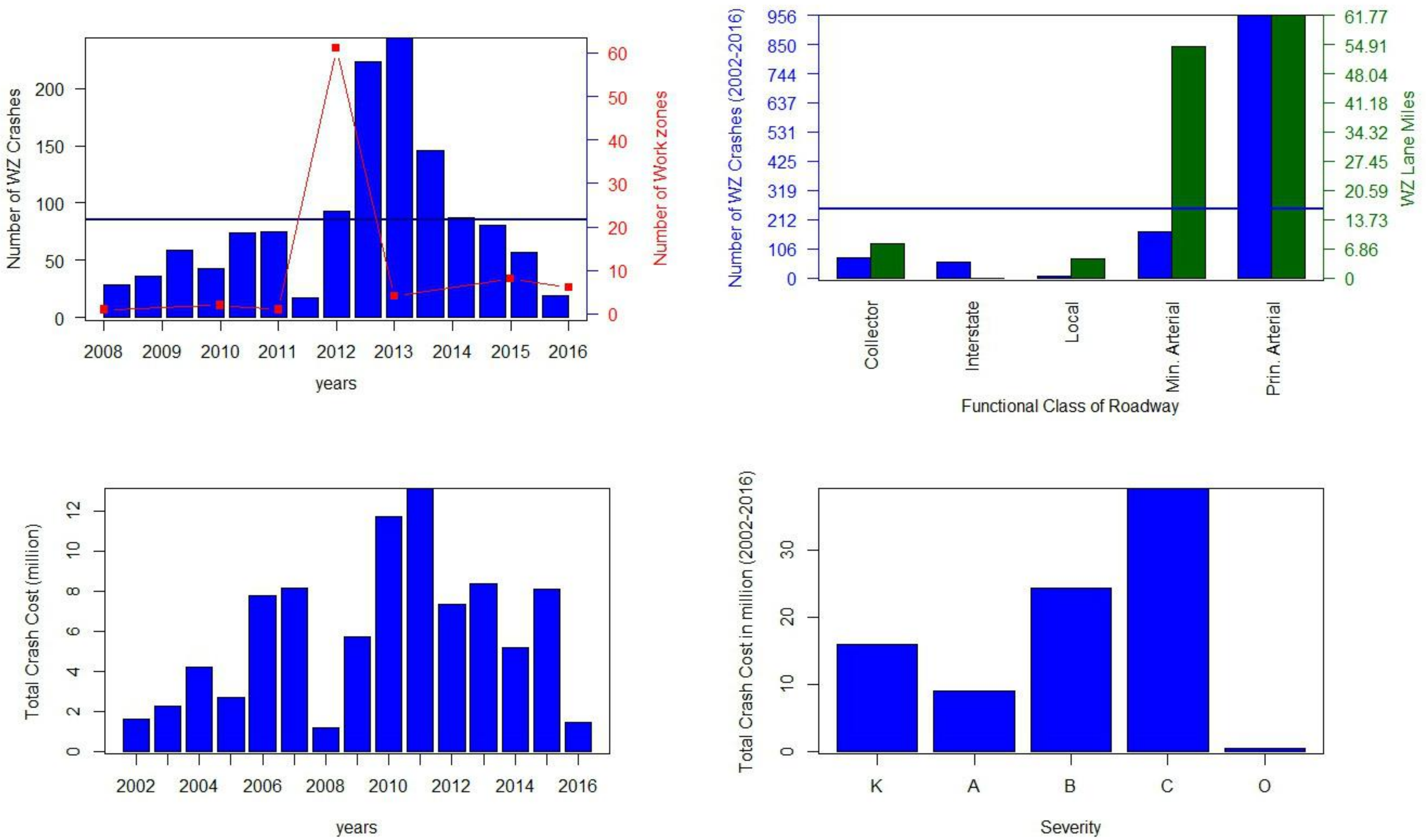


Figure 773 Workzone Crash Analysis - Sevier County

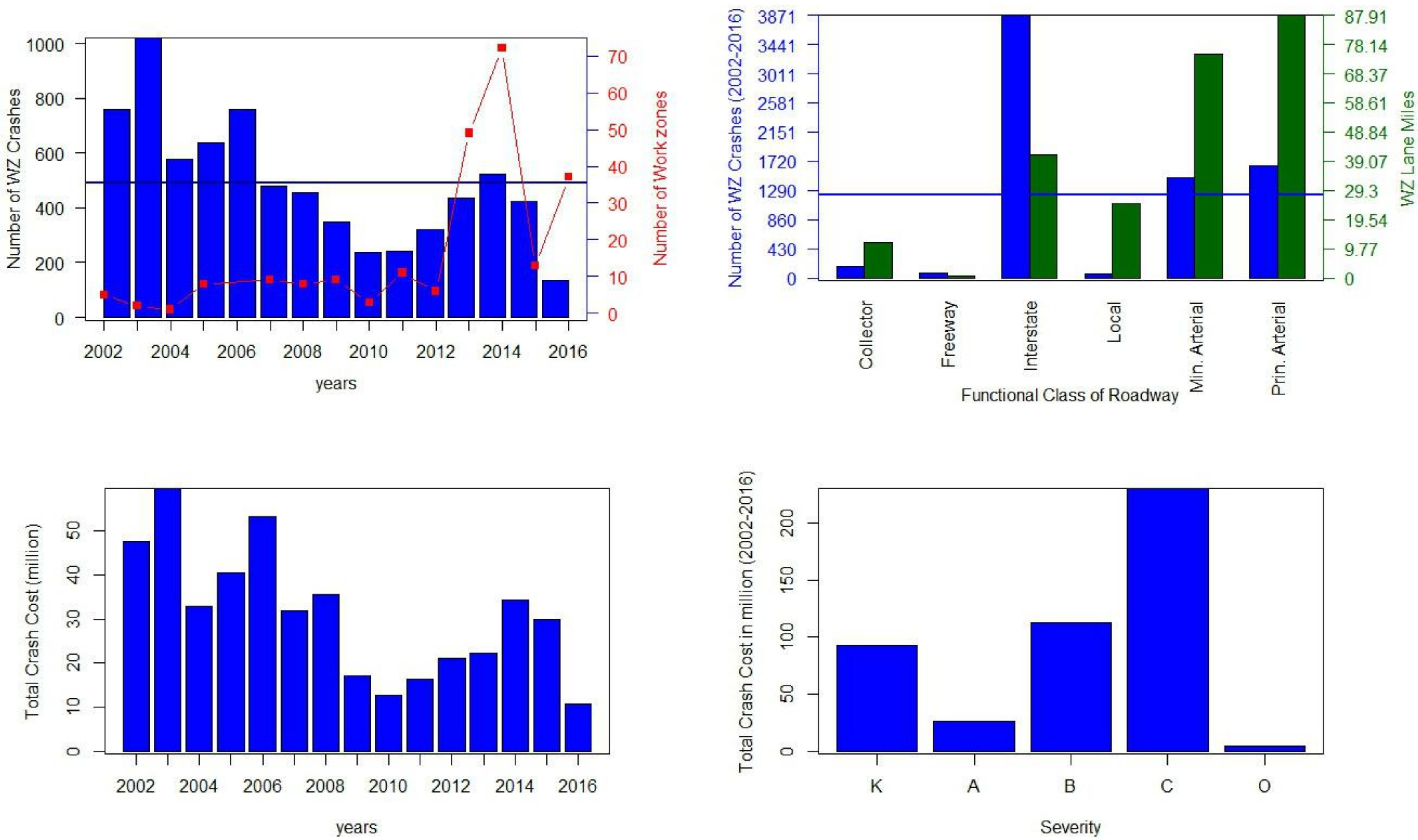


Figure 784 Workzone Crash Analysis - Shelby County

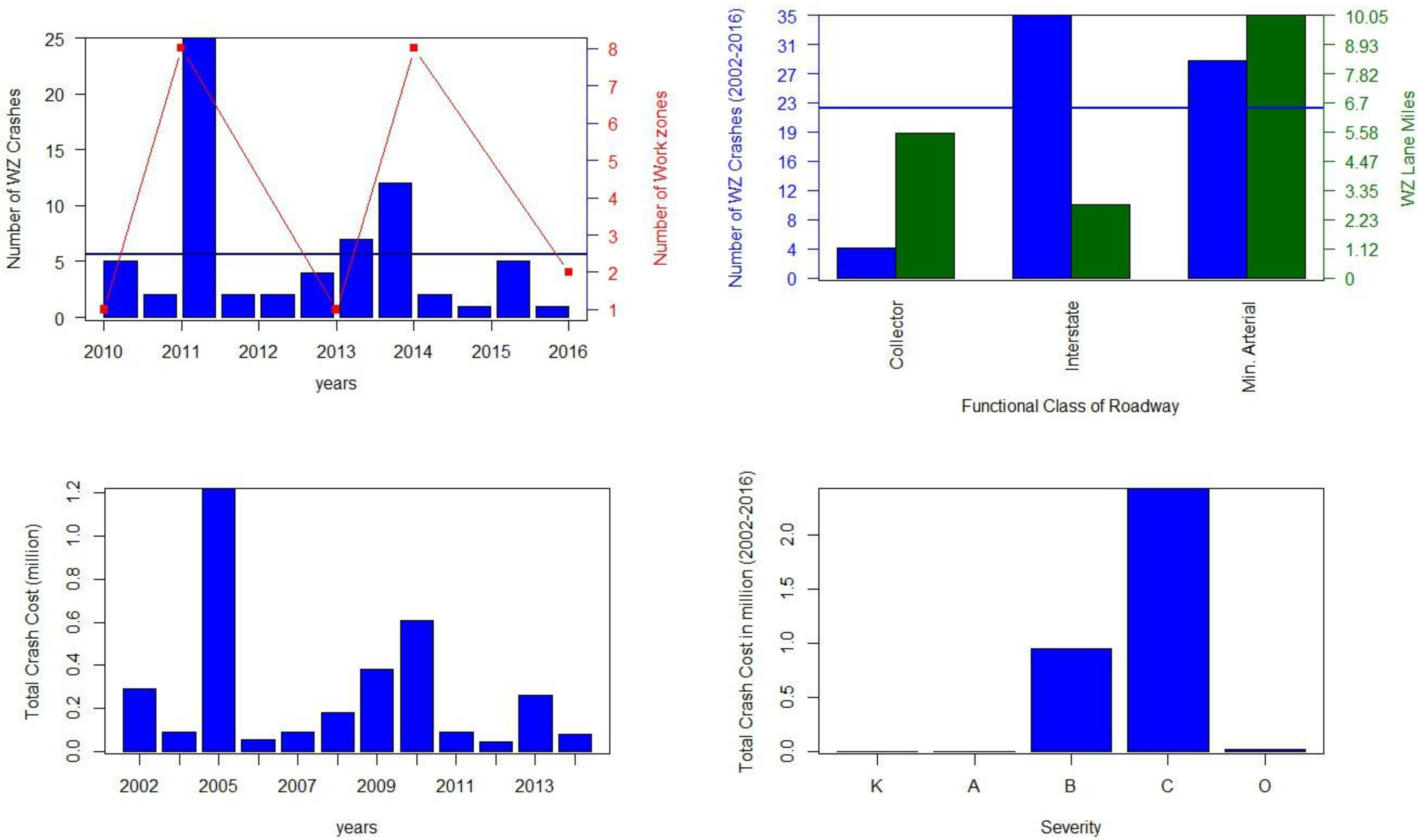


Figure 795 Workzone Crash Analysis - Smith County

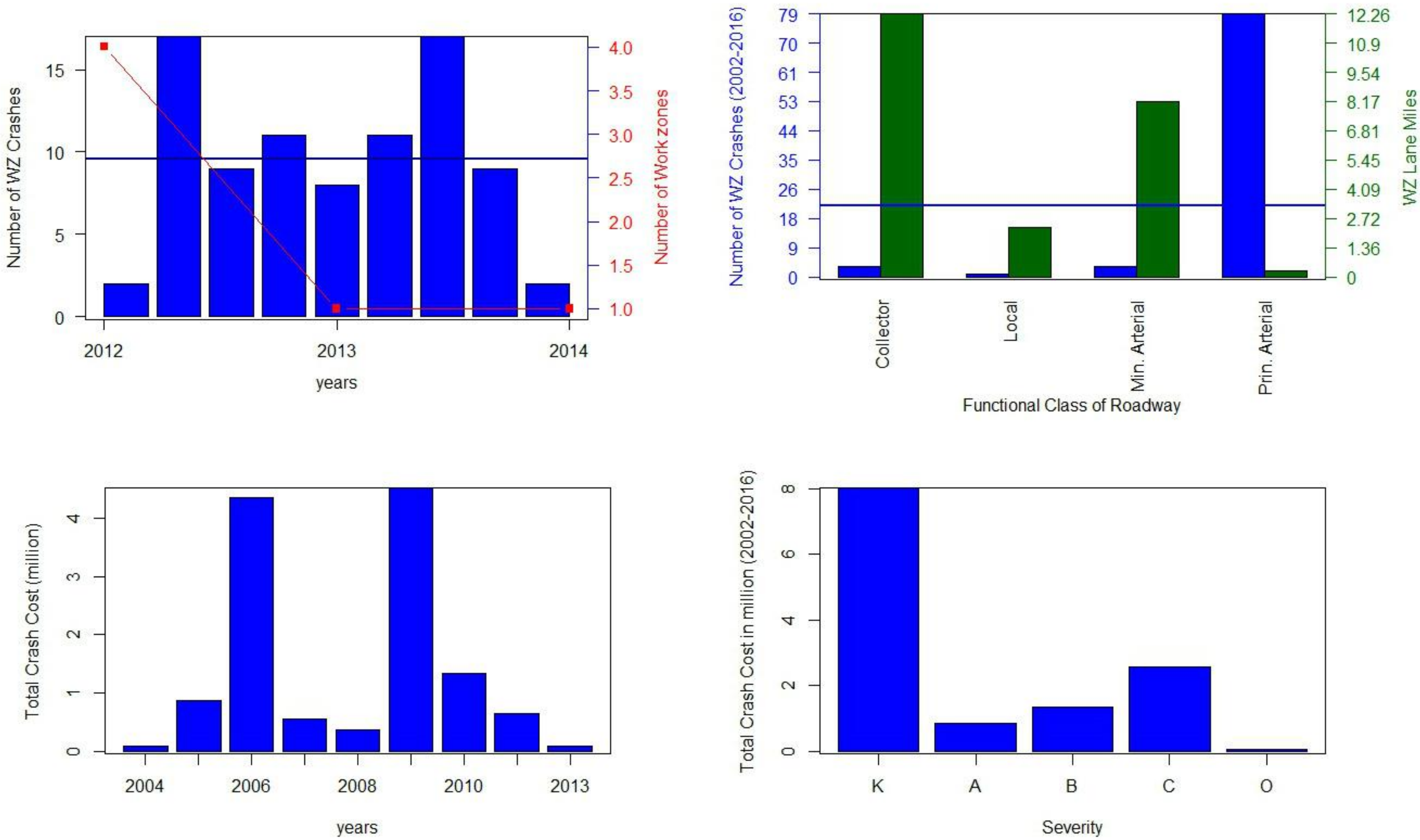


Figure 806 Workzone Crash Analysis - Stewart County

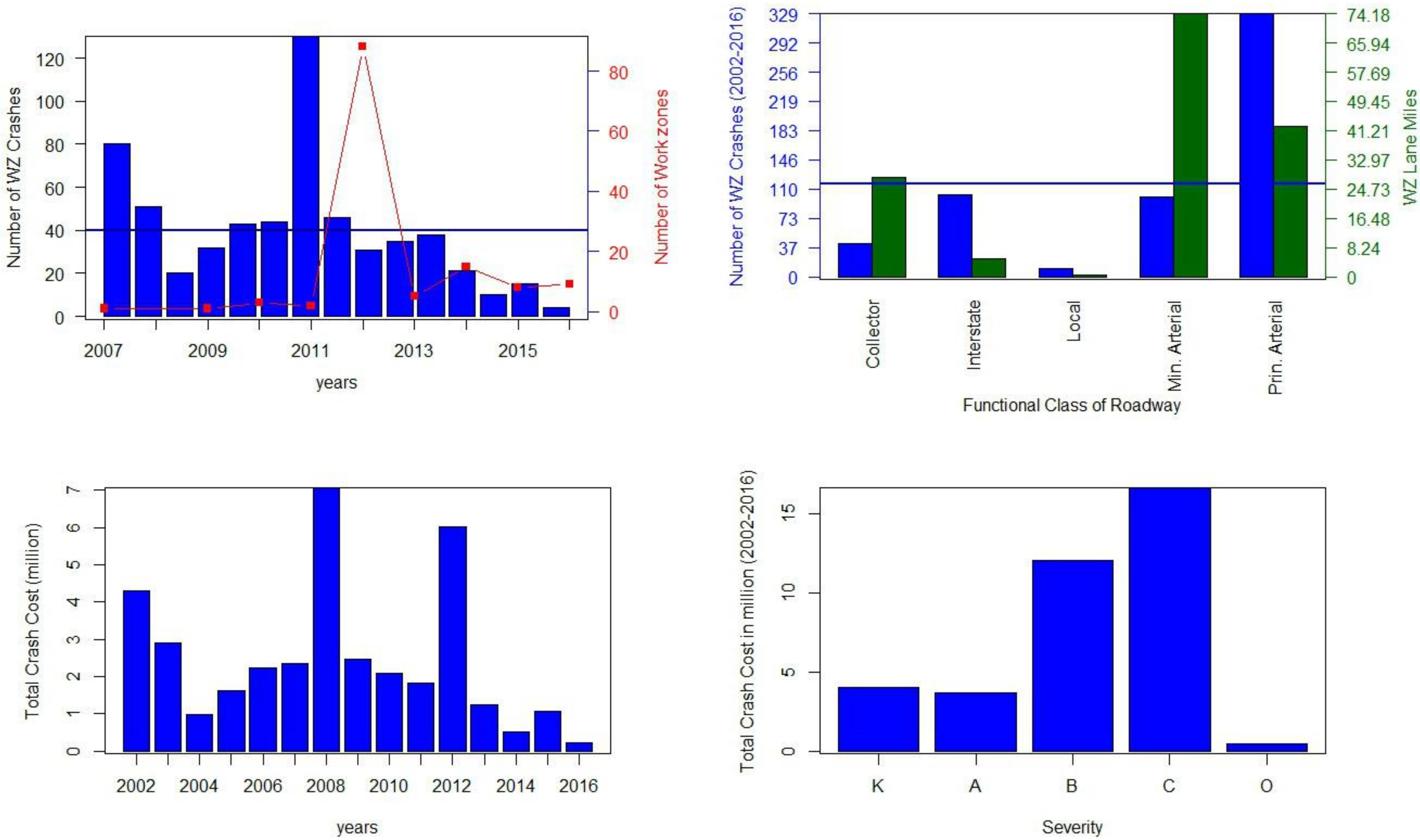


Figure 817 Workzone Crash Analysis - Sullivan County

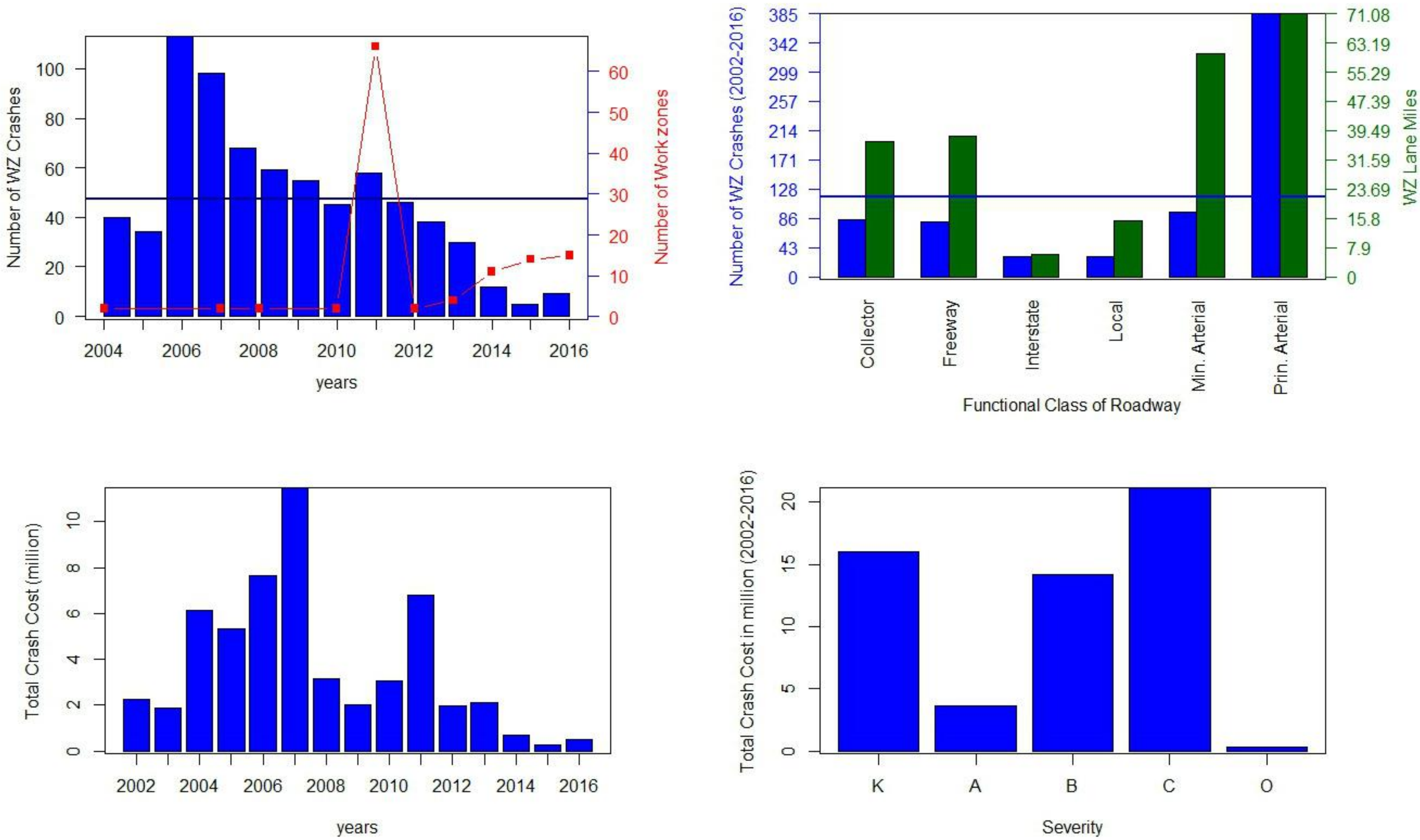


Figure 82 Workzone Crash Analysis - Sumner County

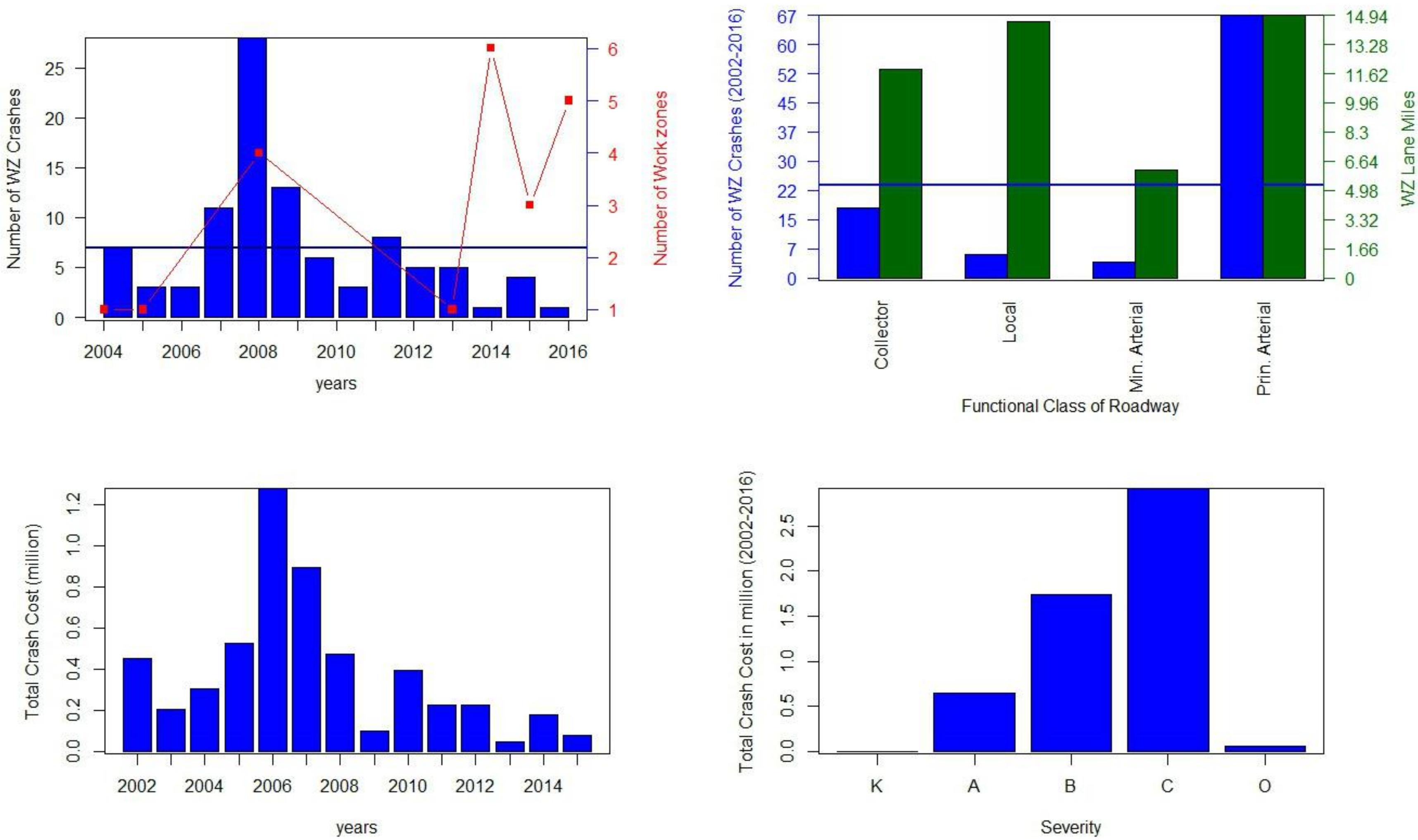


Figure 83 Workzone Crash Analysis - Tipton County

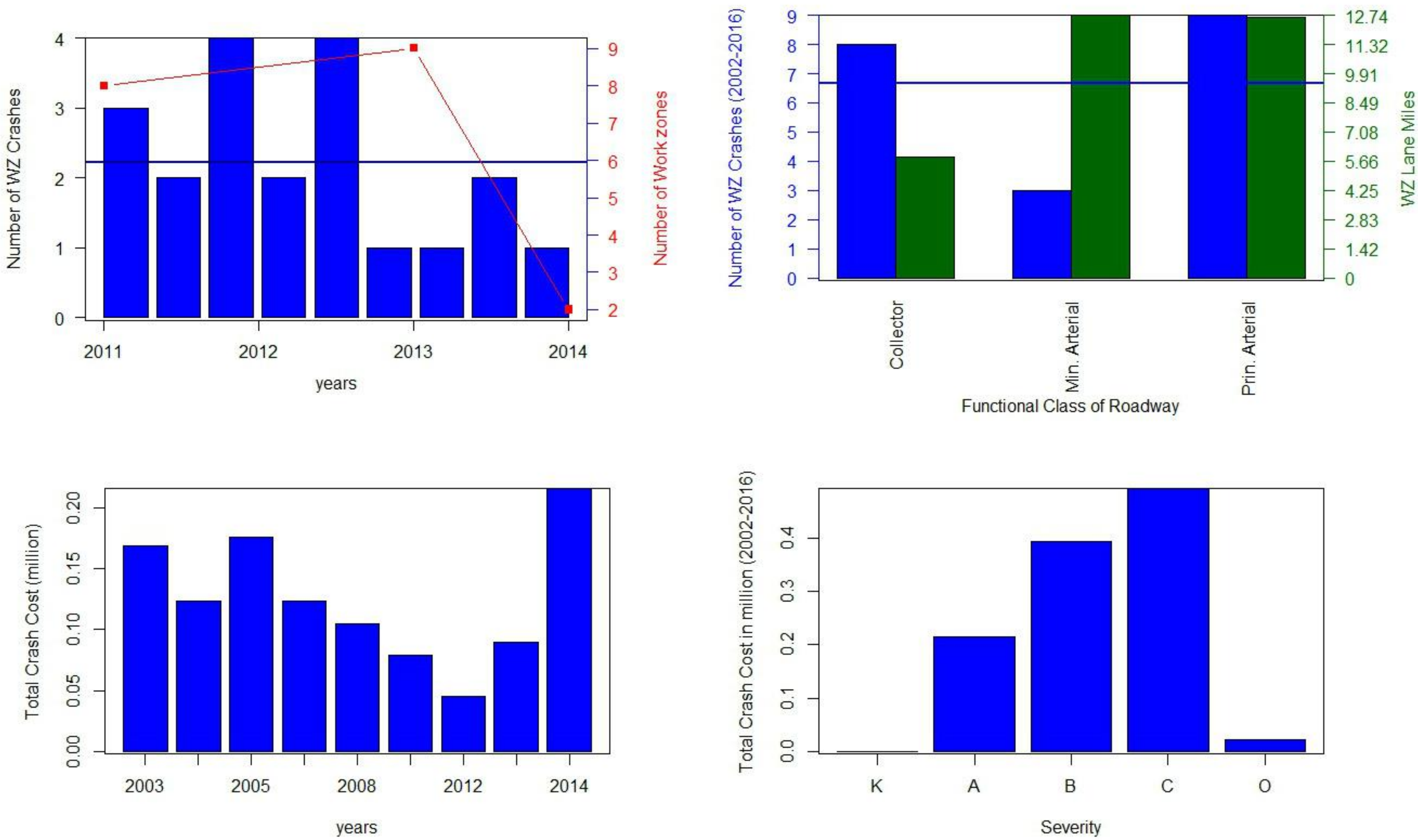


Figure 84 Workzone Crash Analysis - Trousdale County

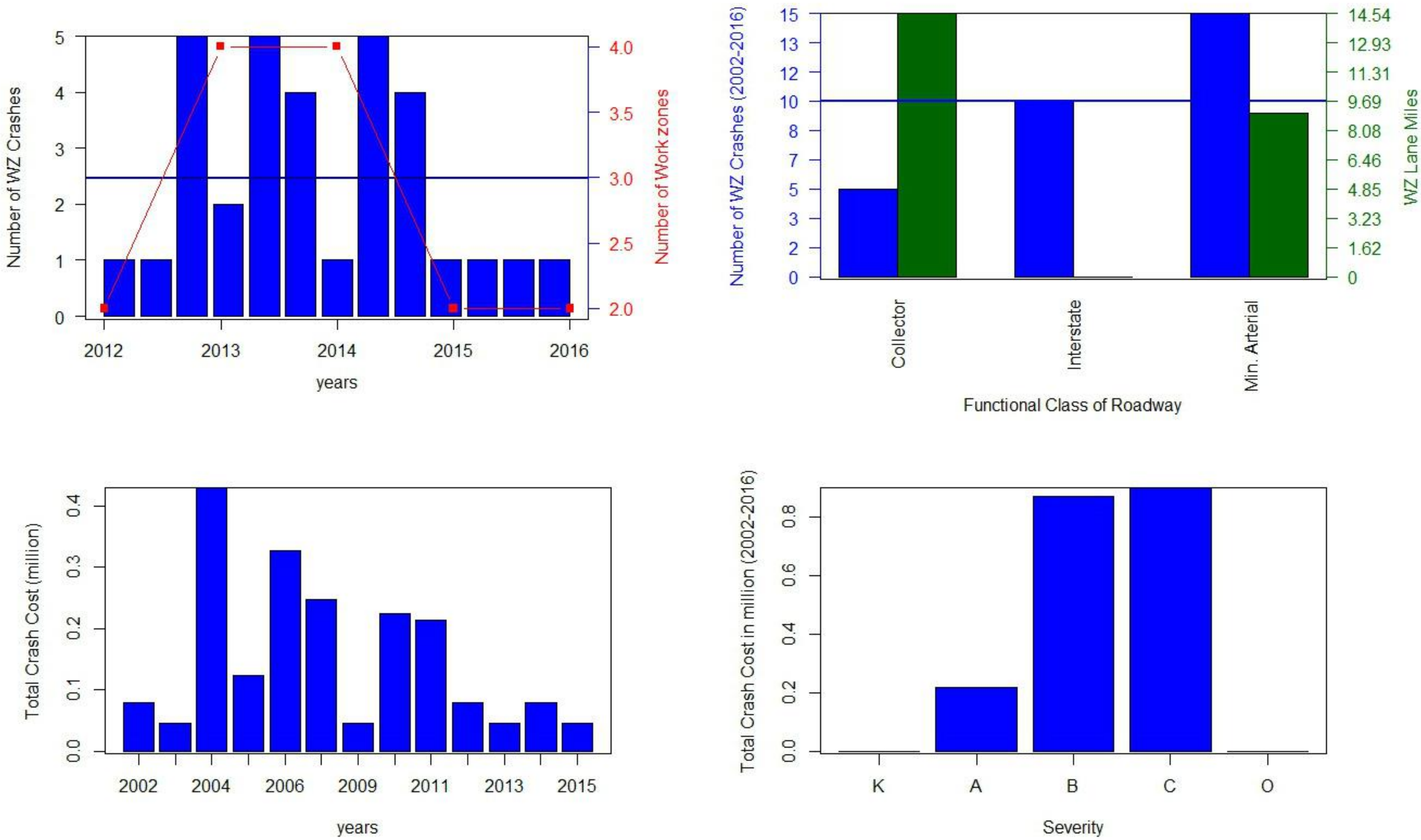


Figure 85 Workzone Crash Analysis - Unicoi County

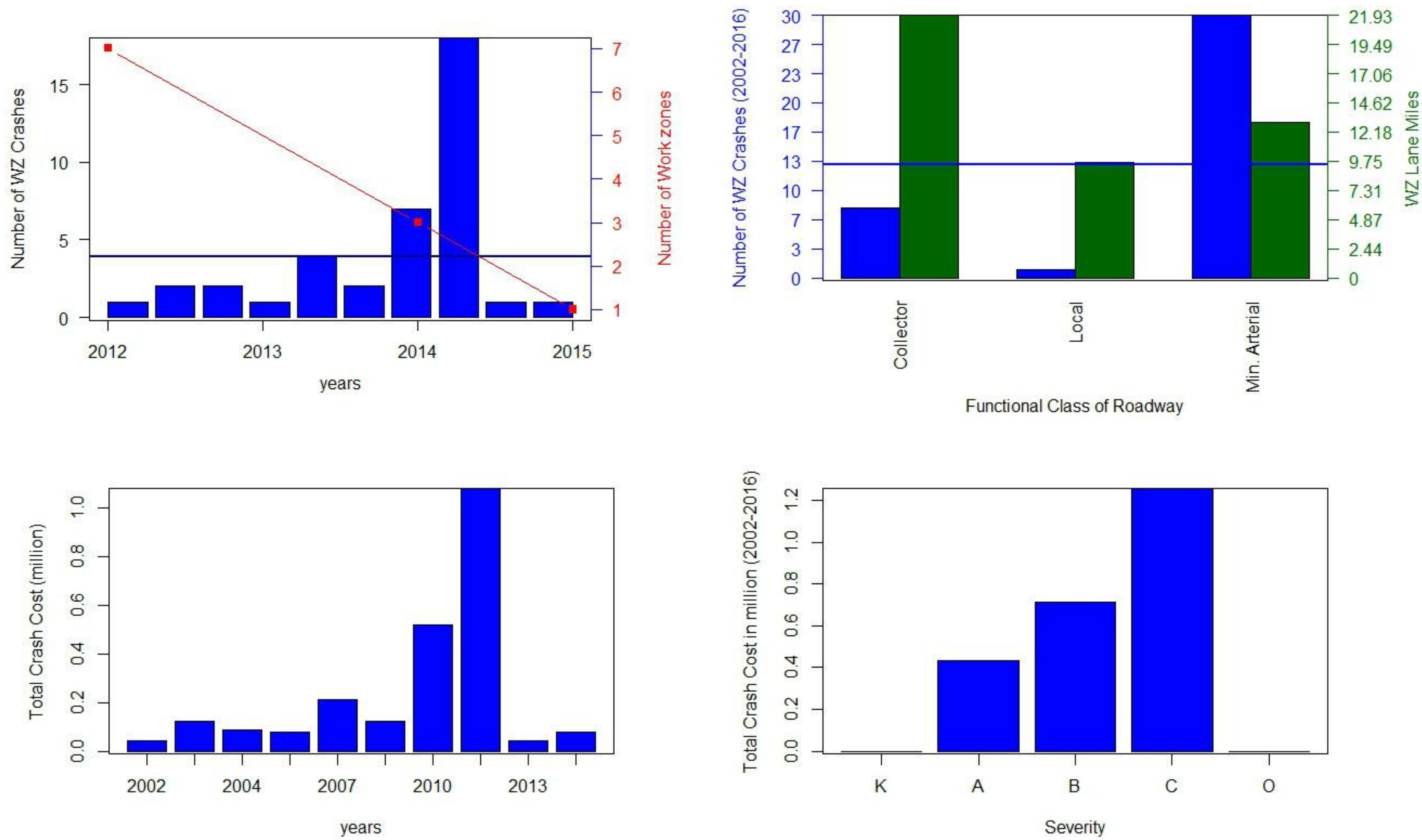


Figure 86 Workzone Crash Analysis - Union County

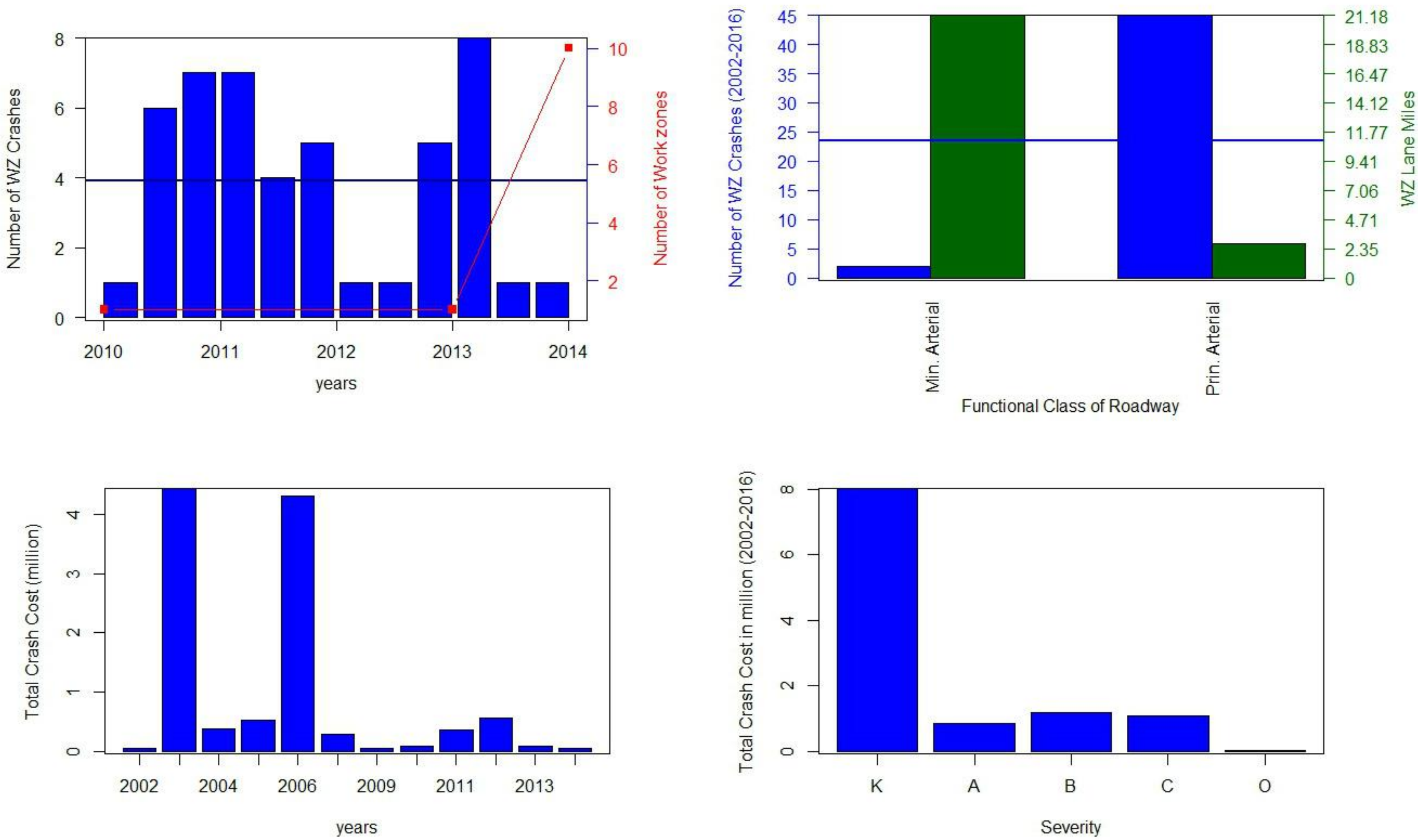


Figure 87 Workzone Crash Analysis - Van Buren County

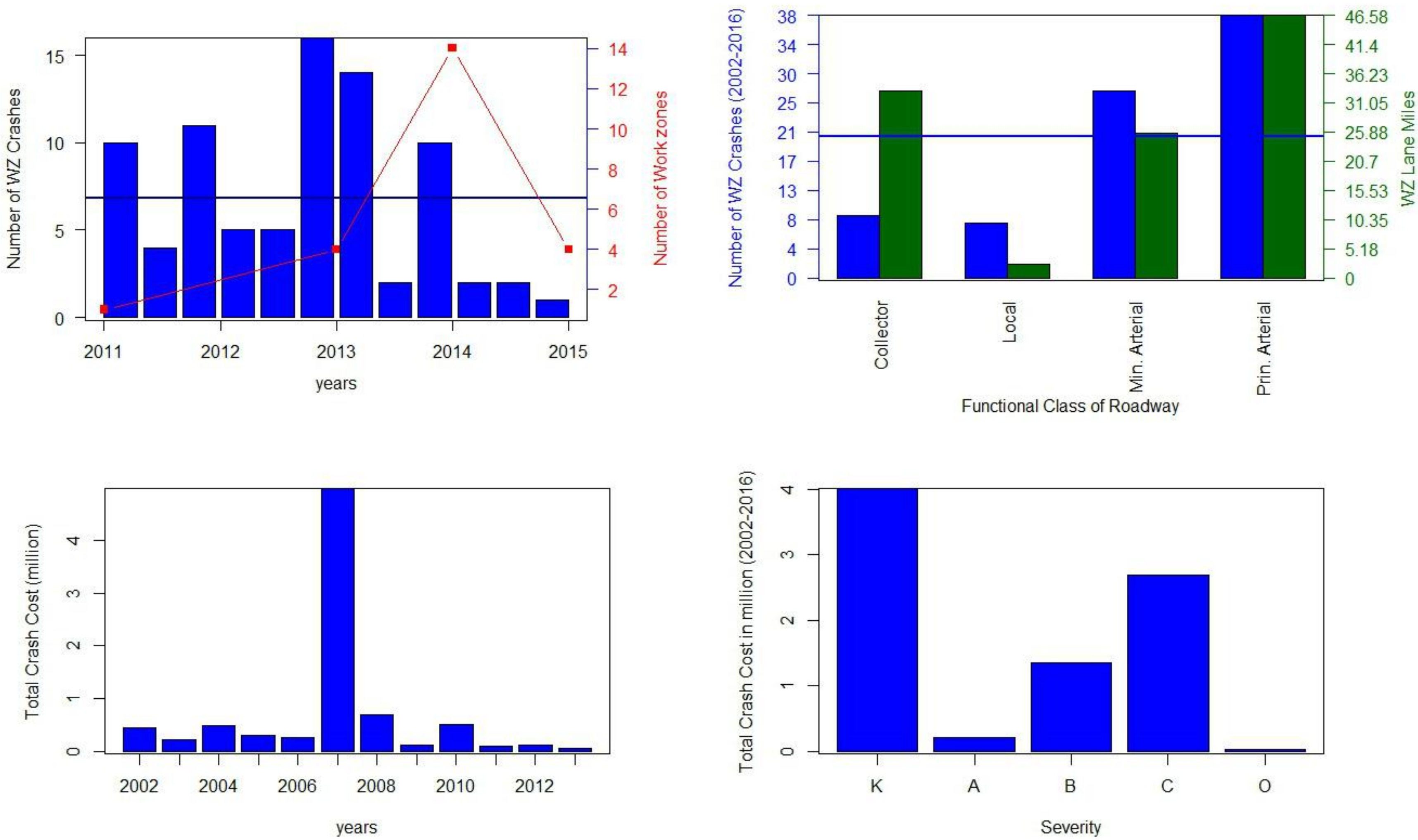


Figure 88 Workzone Crash Analysis - Warren County

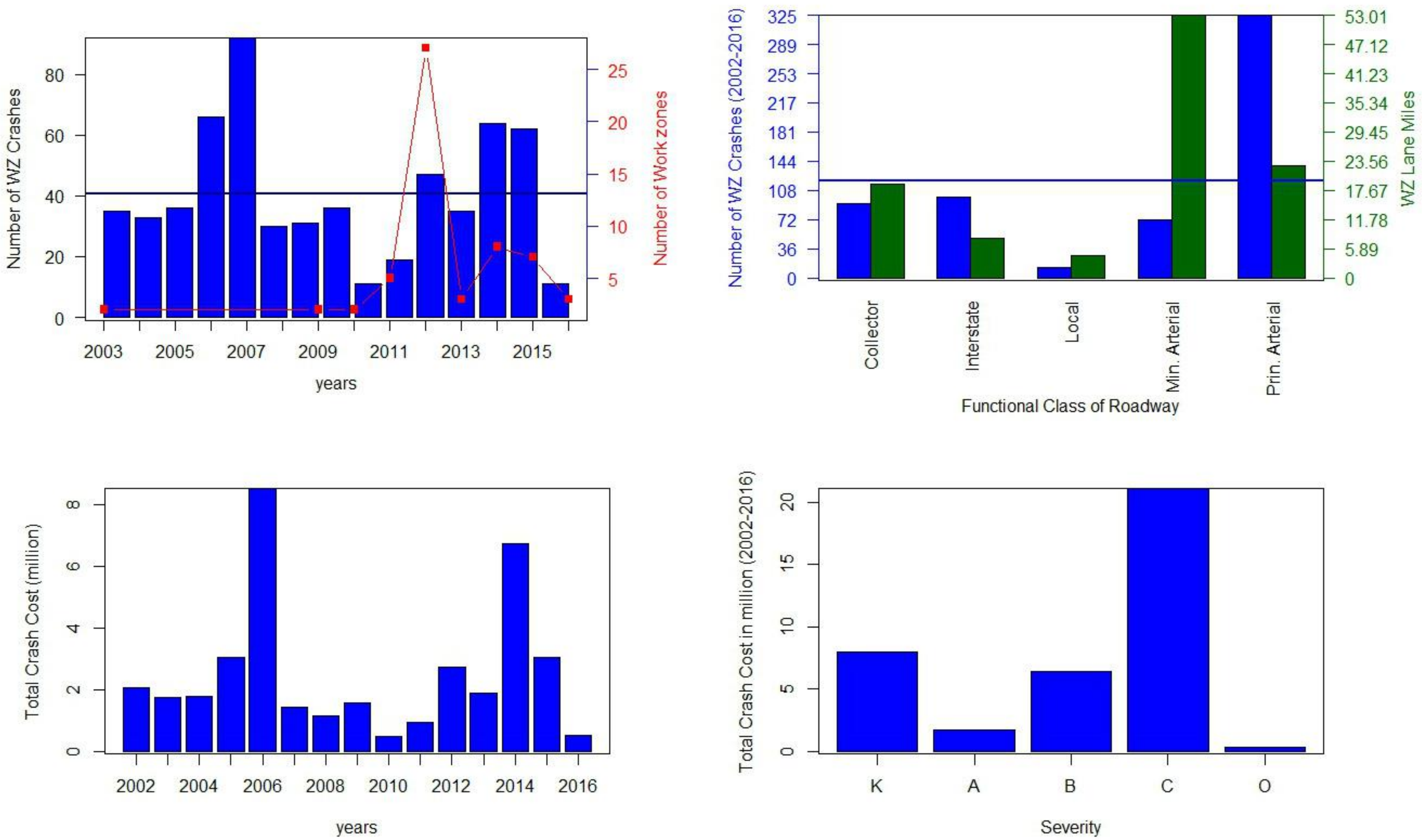


Figure 89 Workzone Crash Analysis - Washington County

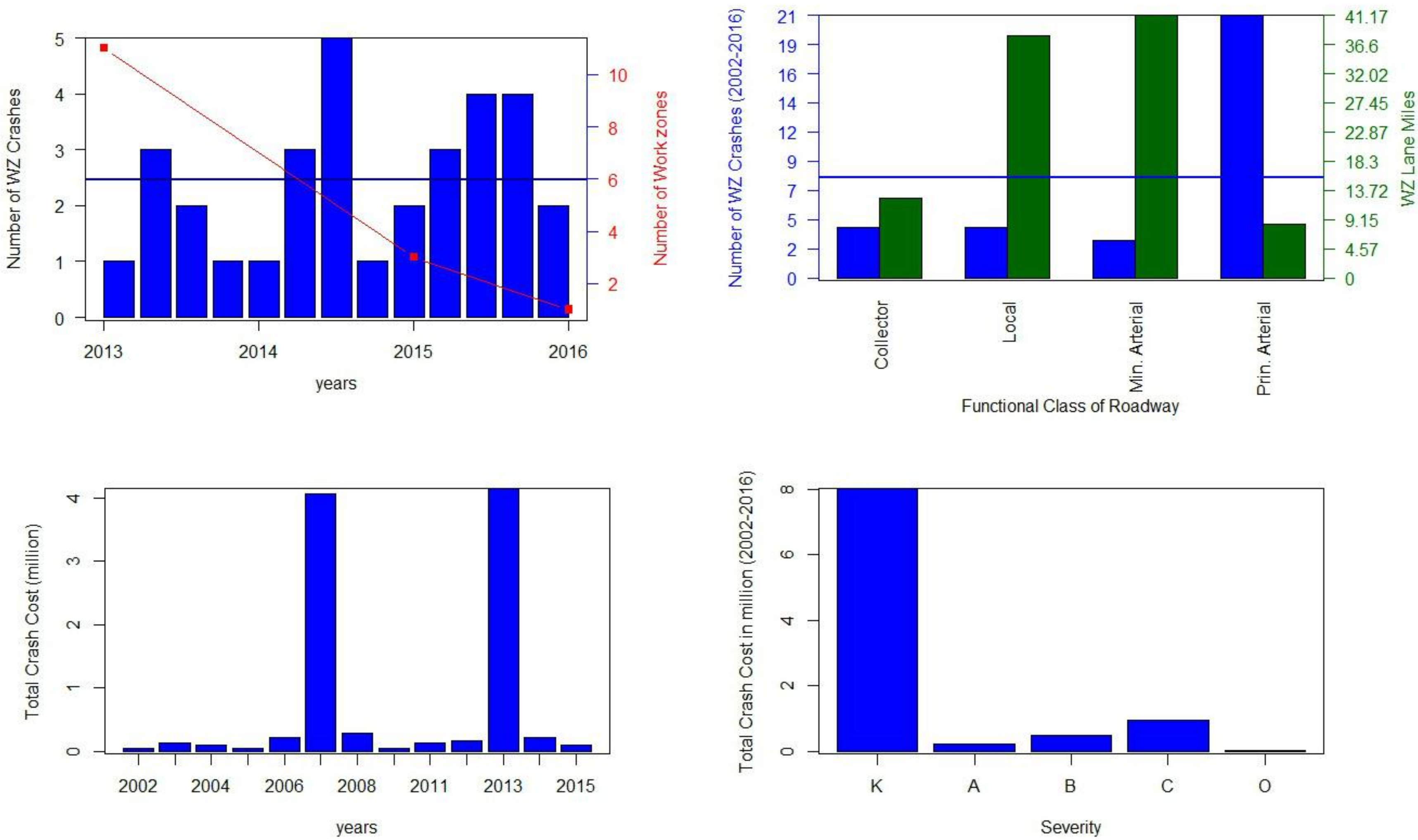


Figure 90 Workzone Crash Analysis - Wayne County

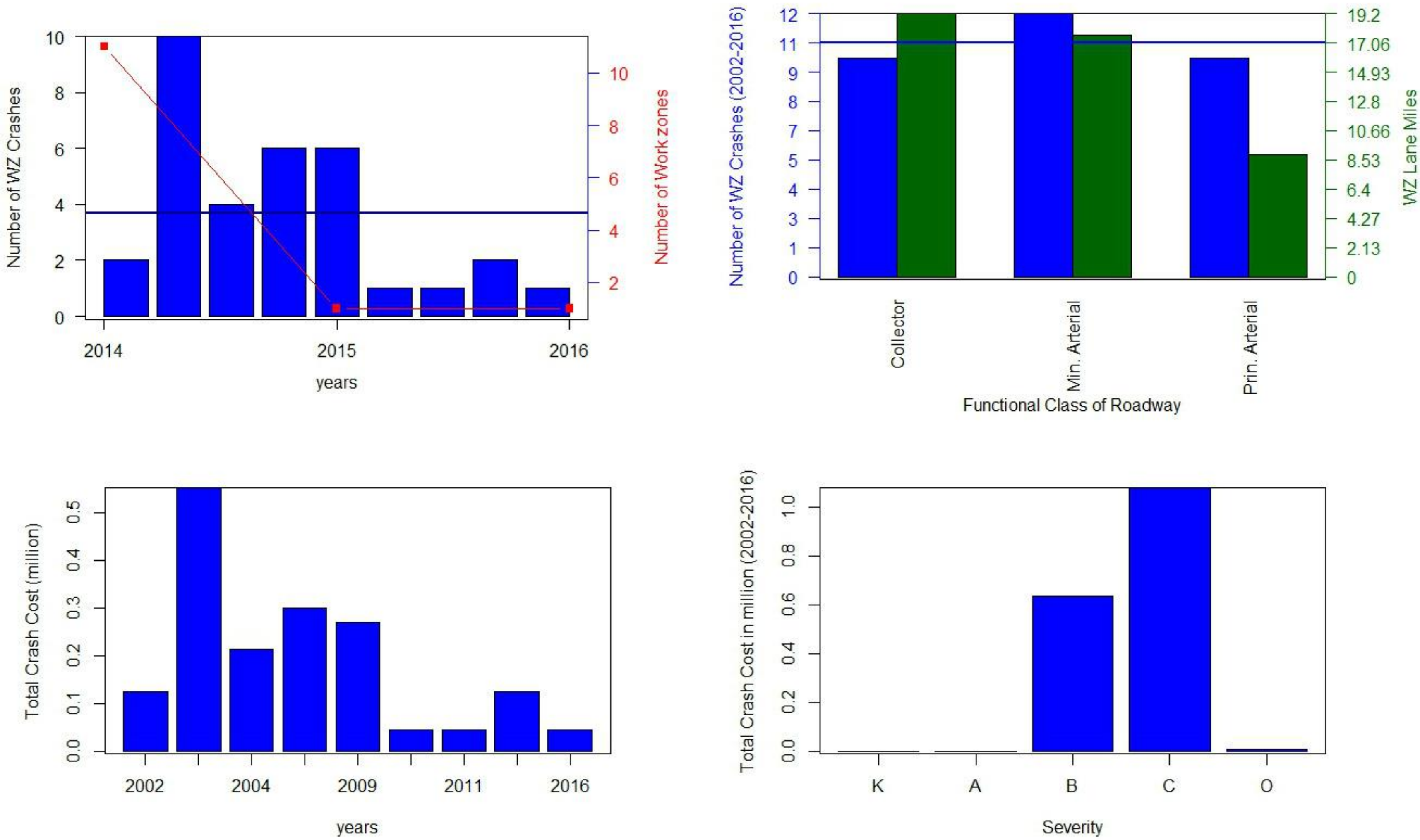


Figure 91 Workzone Crash Analysis - Weakley County

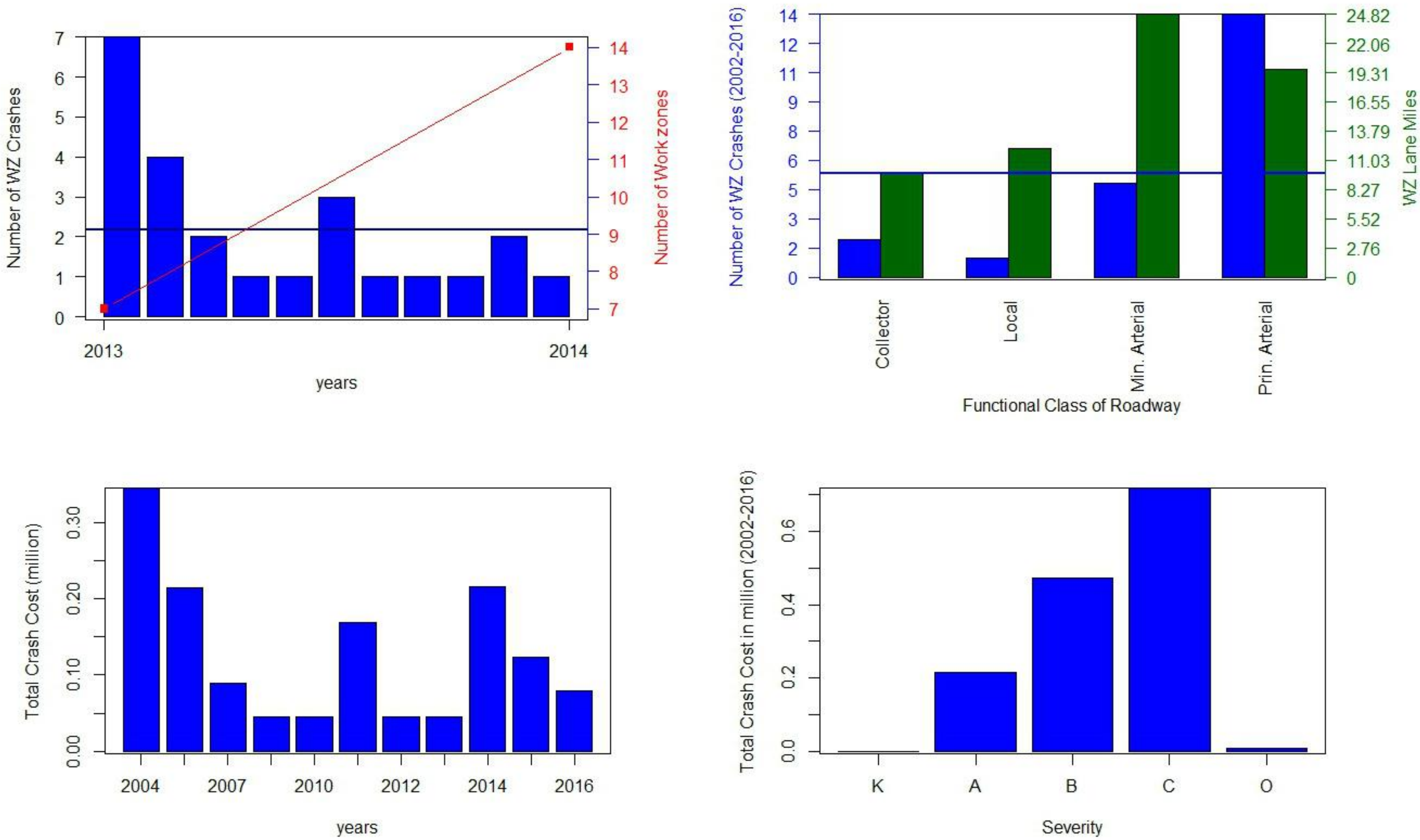


Figure 92 Workzone Crash Analysis - White County

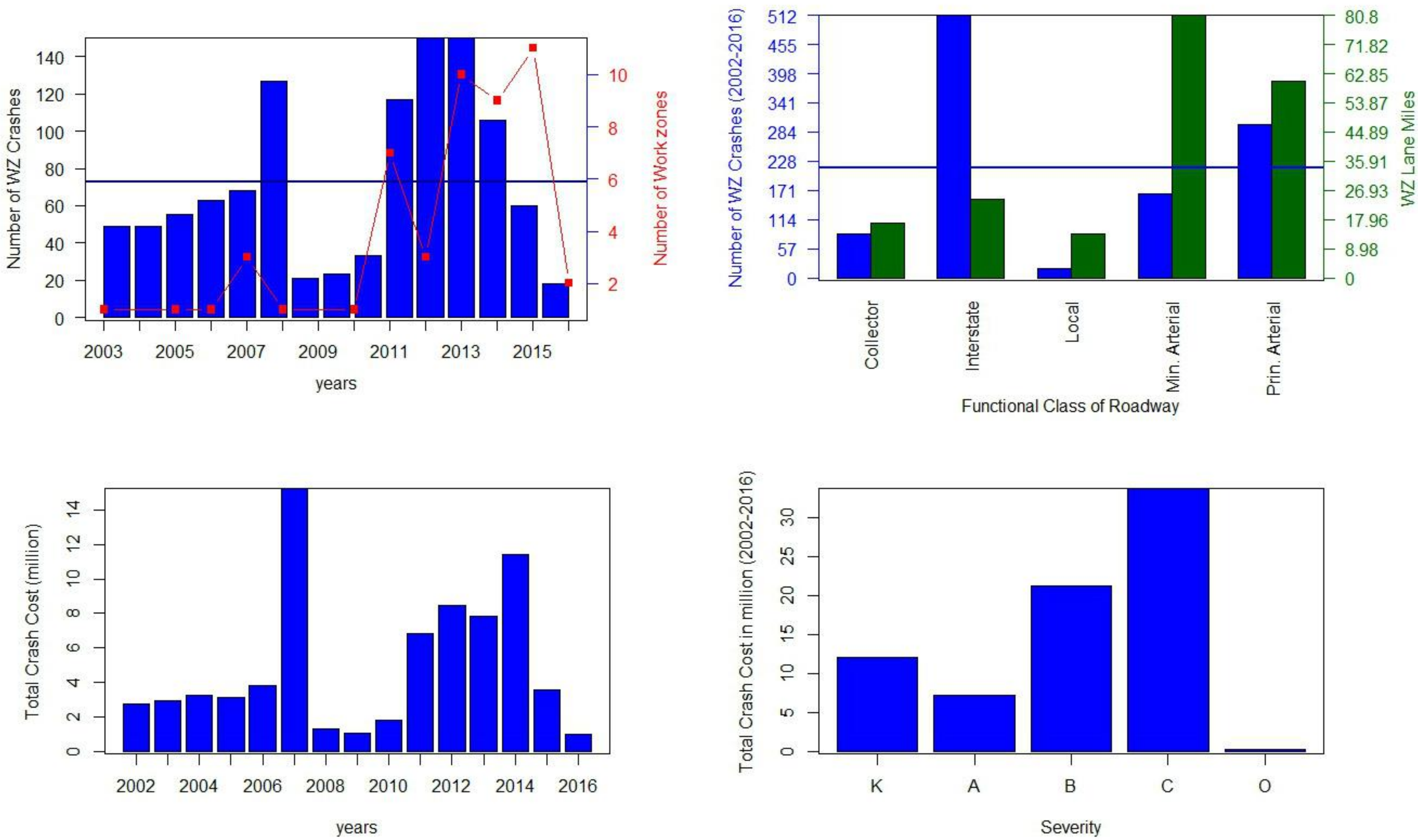


Figure 93 Workzone Crash Analysis - Williamson County

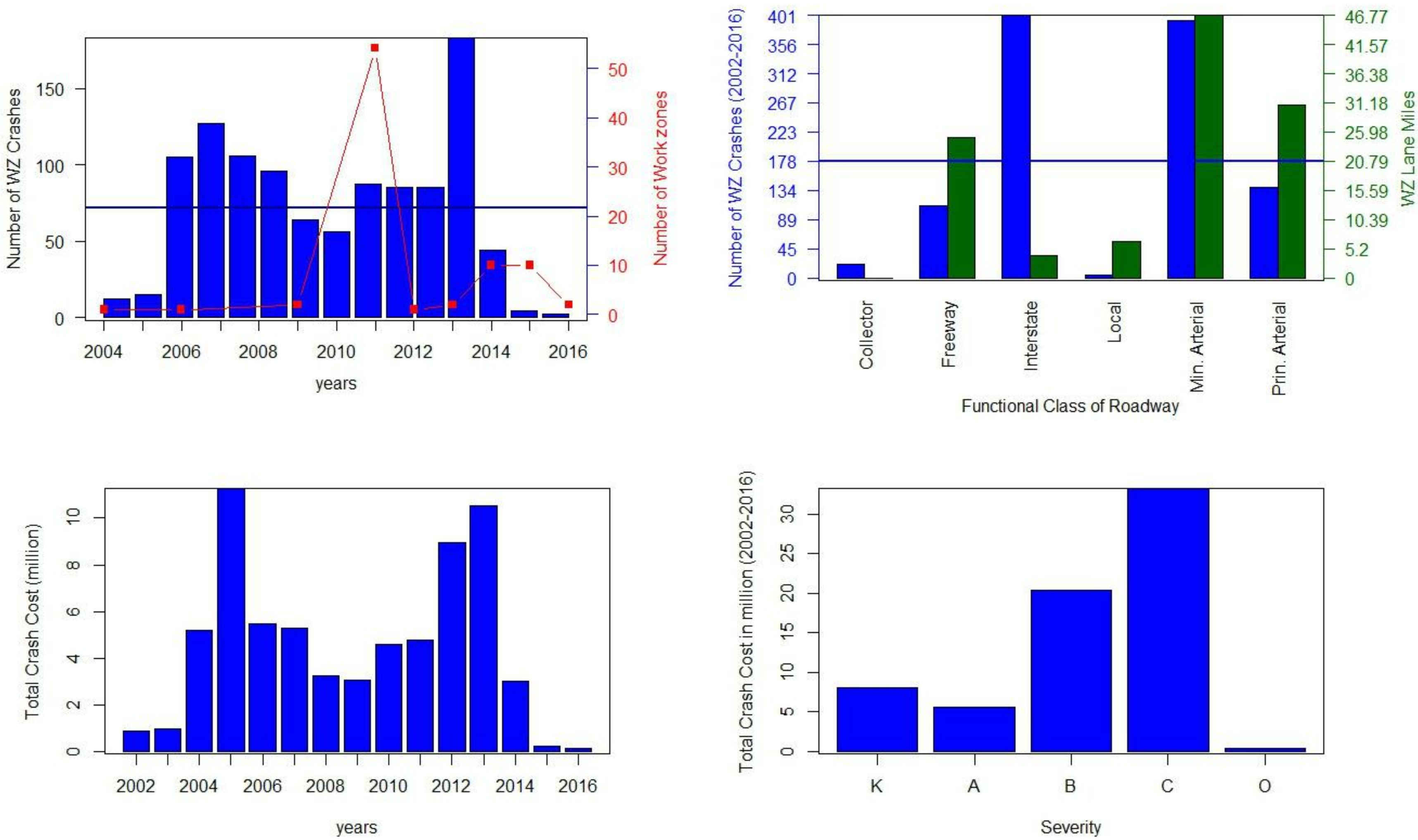


Figure 94 Workzone Crash Analysis - Wilson County

APPENDIX D: WORK ZONE CRASH ANALYSIS BY REGION

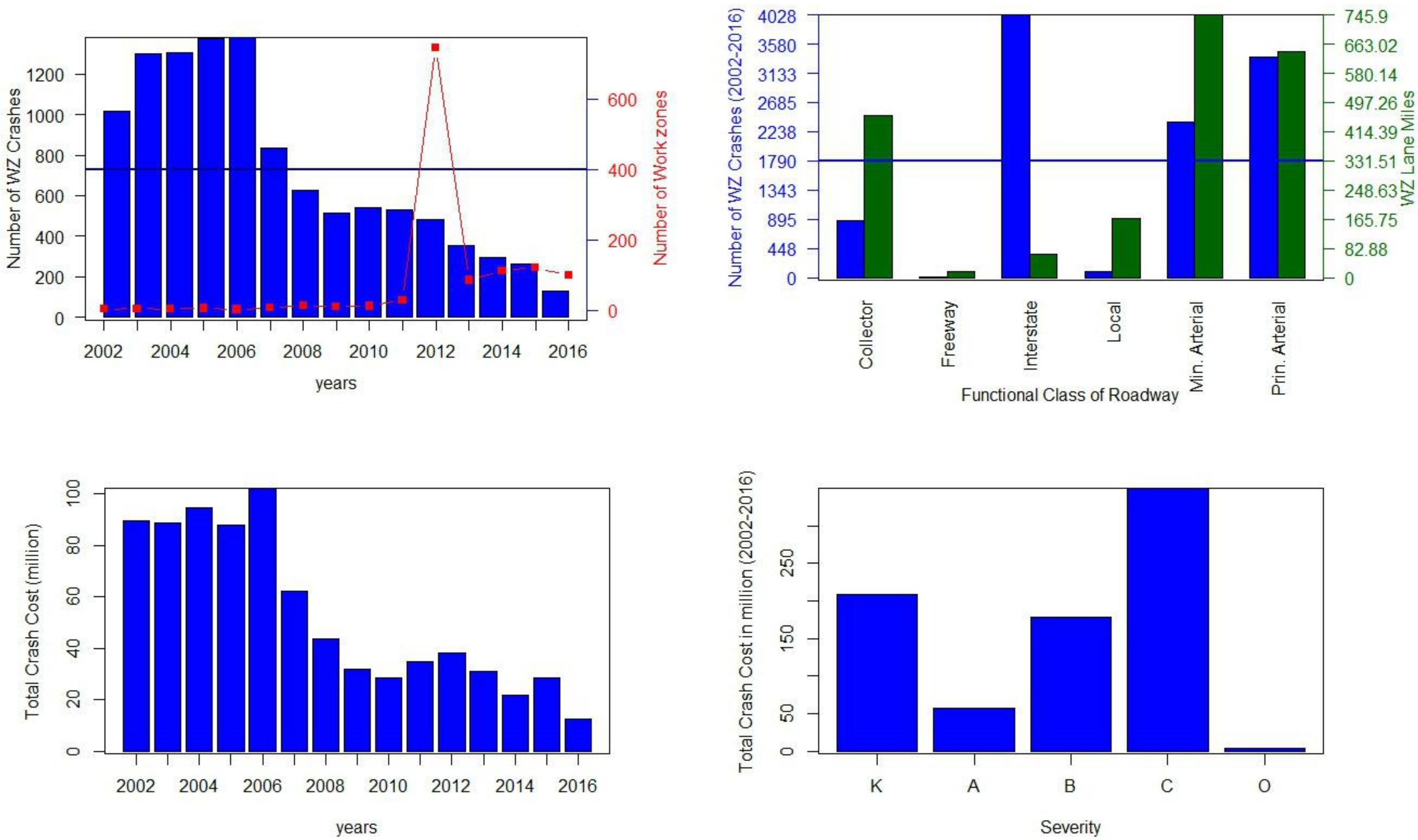


Figure 95 Workzone Crash Analysis - Region 1

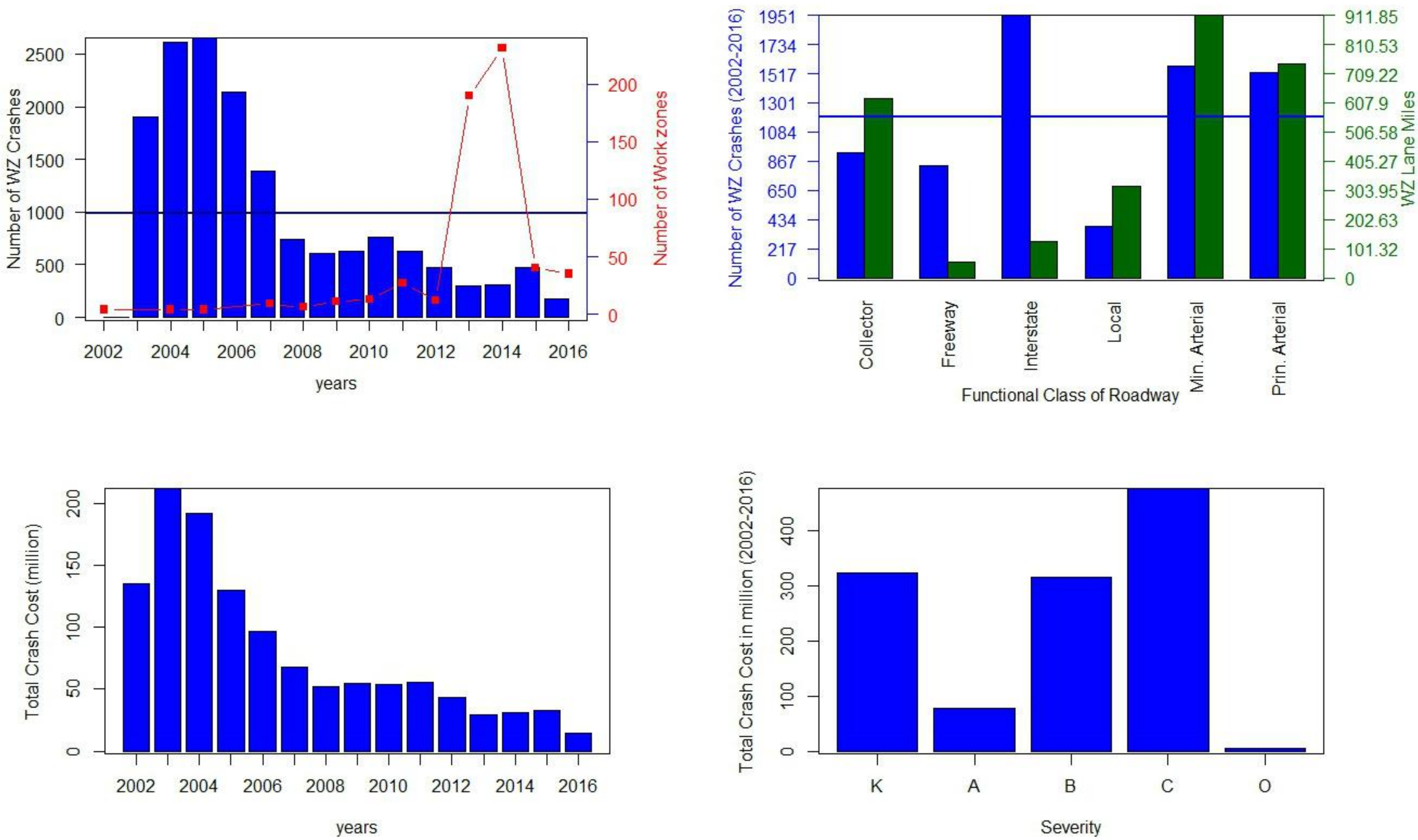


Figure 96 Workzone Crash Analysis - Region 2

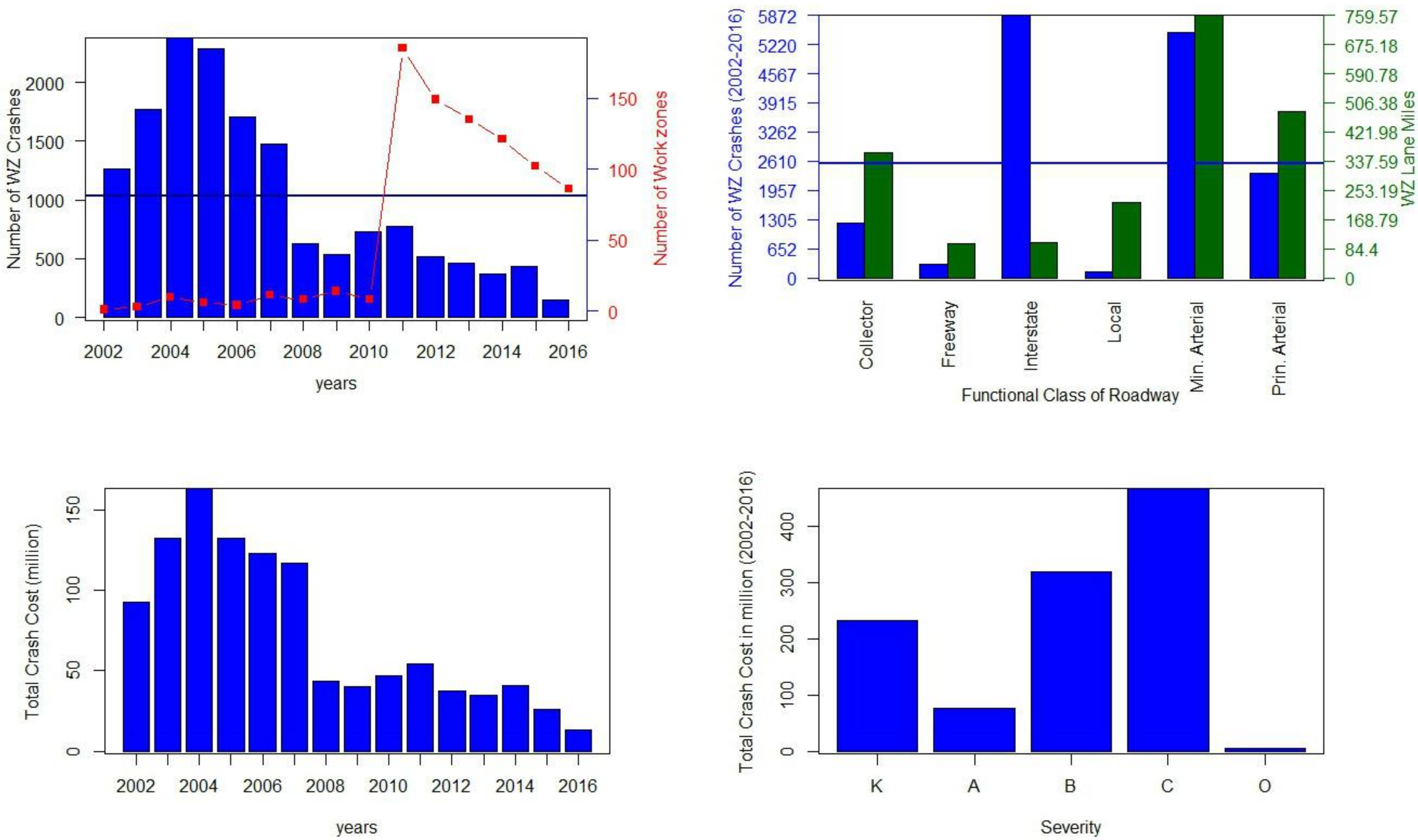


Figure 97 Workzone Crash Analysis - Region 3

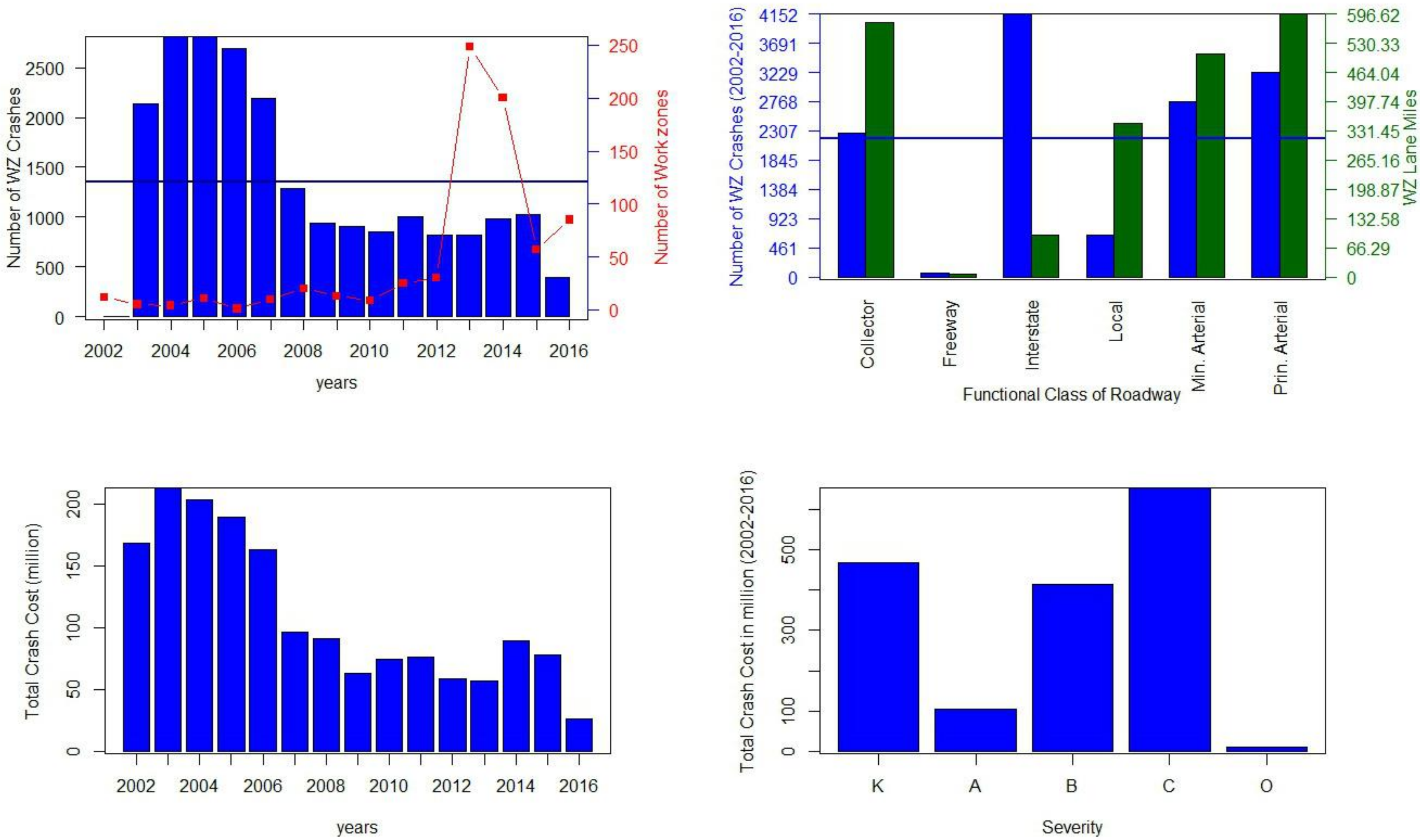
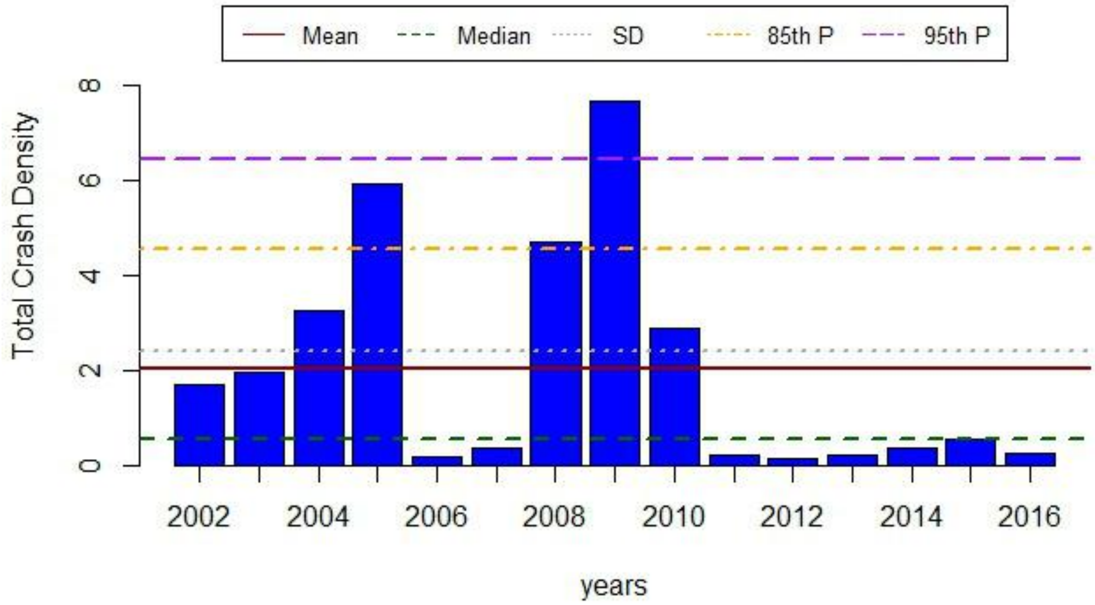


Figure 98 Workzone Crash Analysis - Region 4

APPENDIX E: WORK ZONE CRASH PERFORMANCE MEASURES BY COUNTY



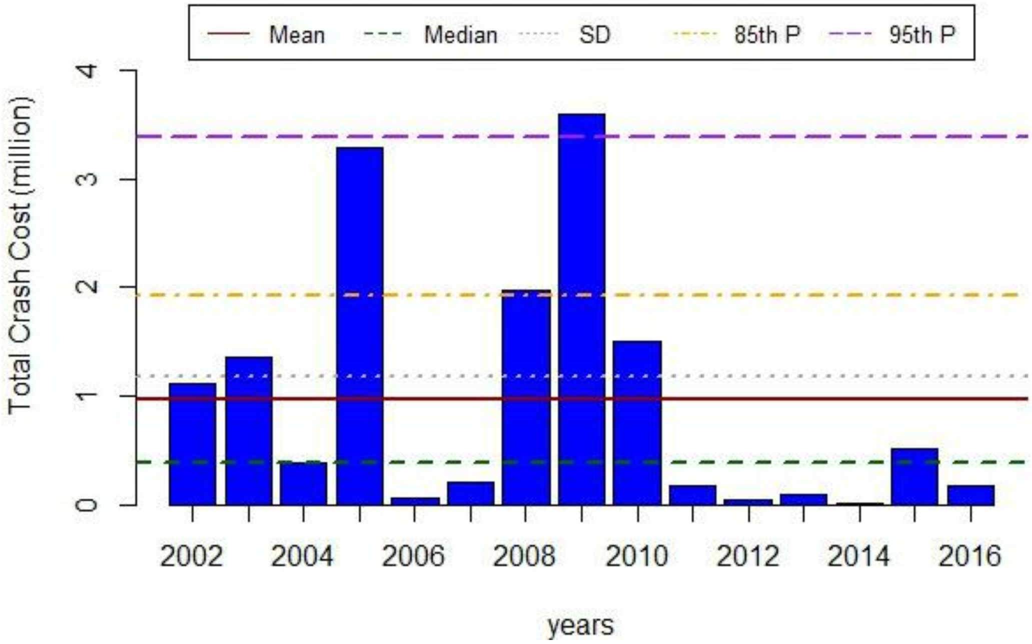


Figure 99 Crash Performance Measure: Anderson County

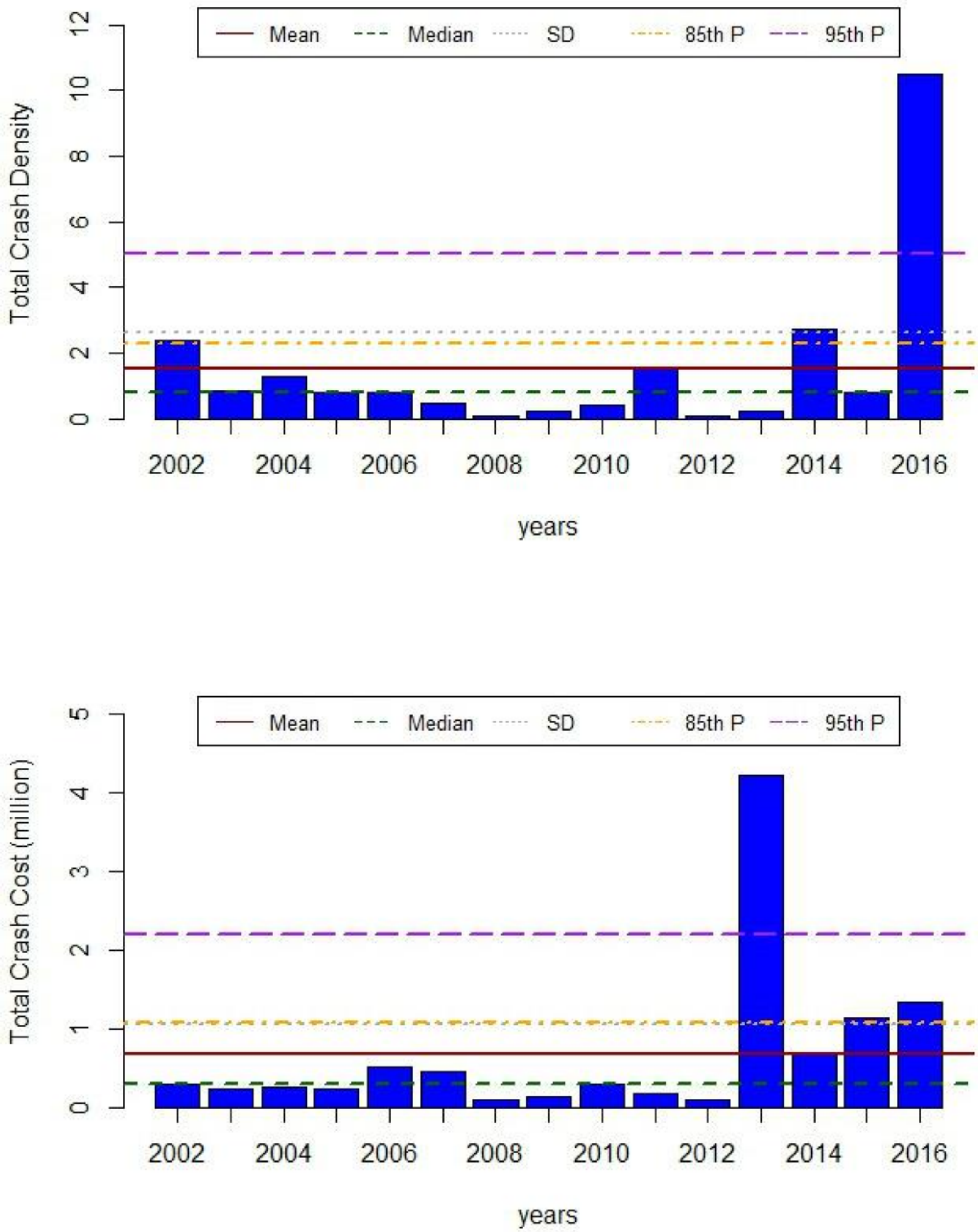


Figure 100 Crash Performance Measure: Bedford County

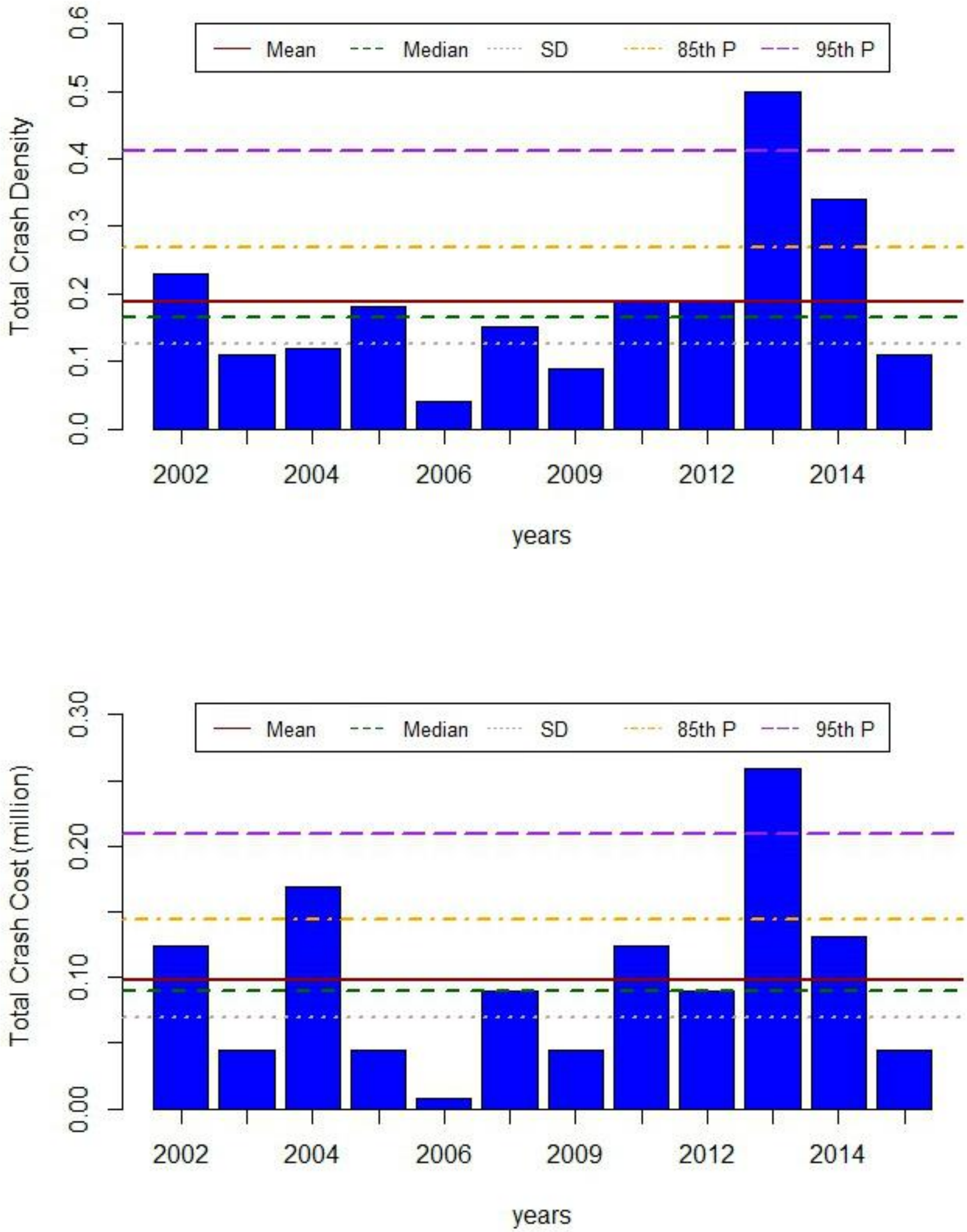
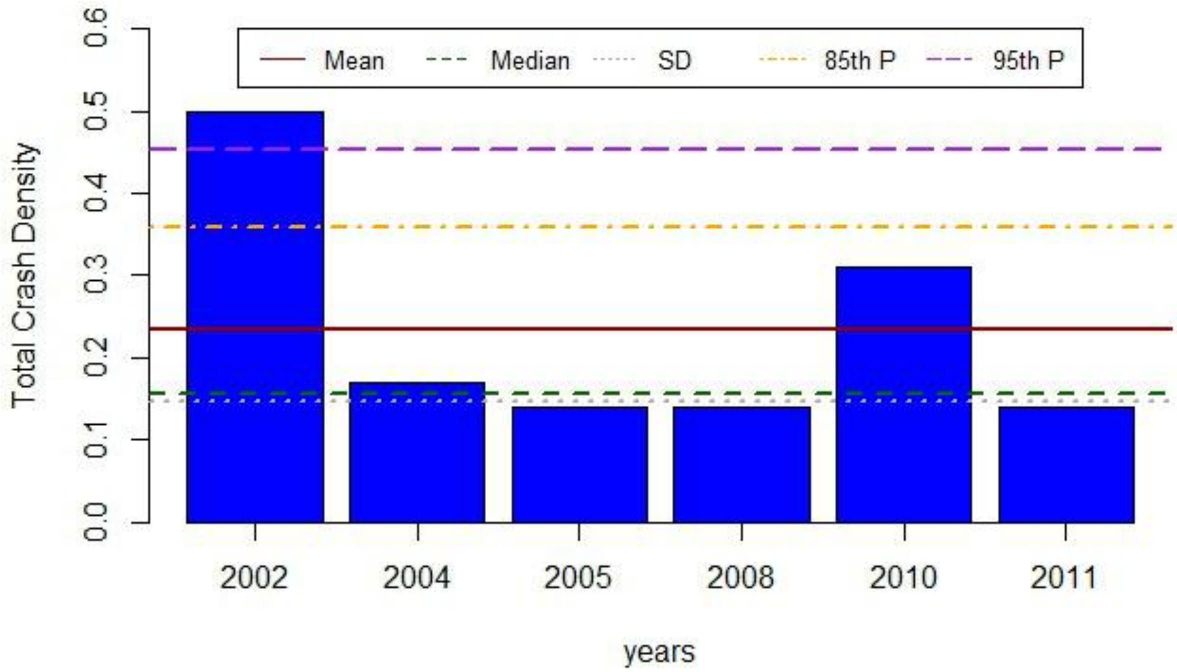


Figure 101 Crash Performance Measure: Benton County



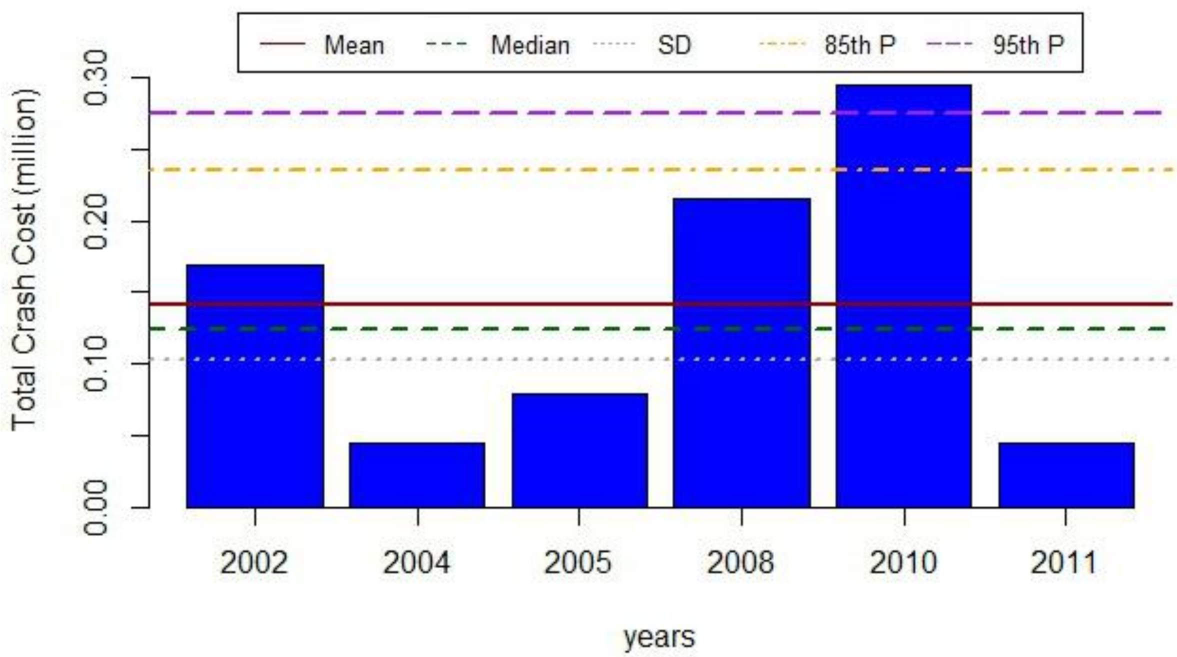


Figure 102 Crash Performance Measure: Bledsoe County

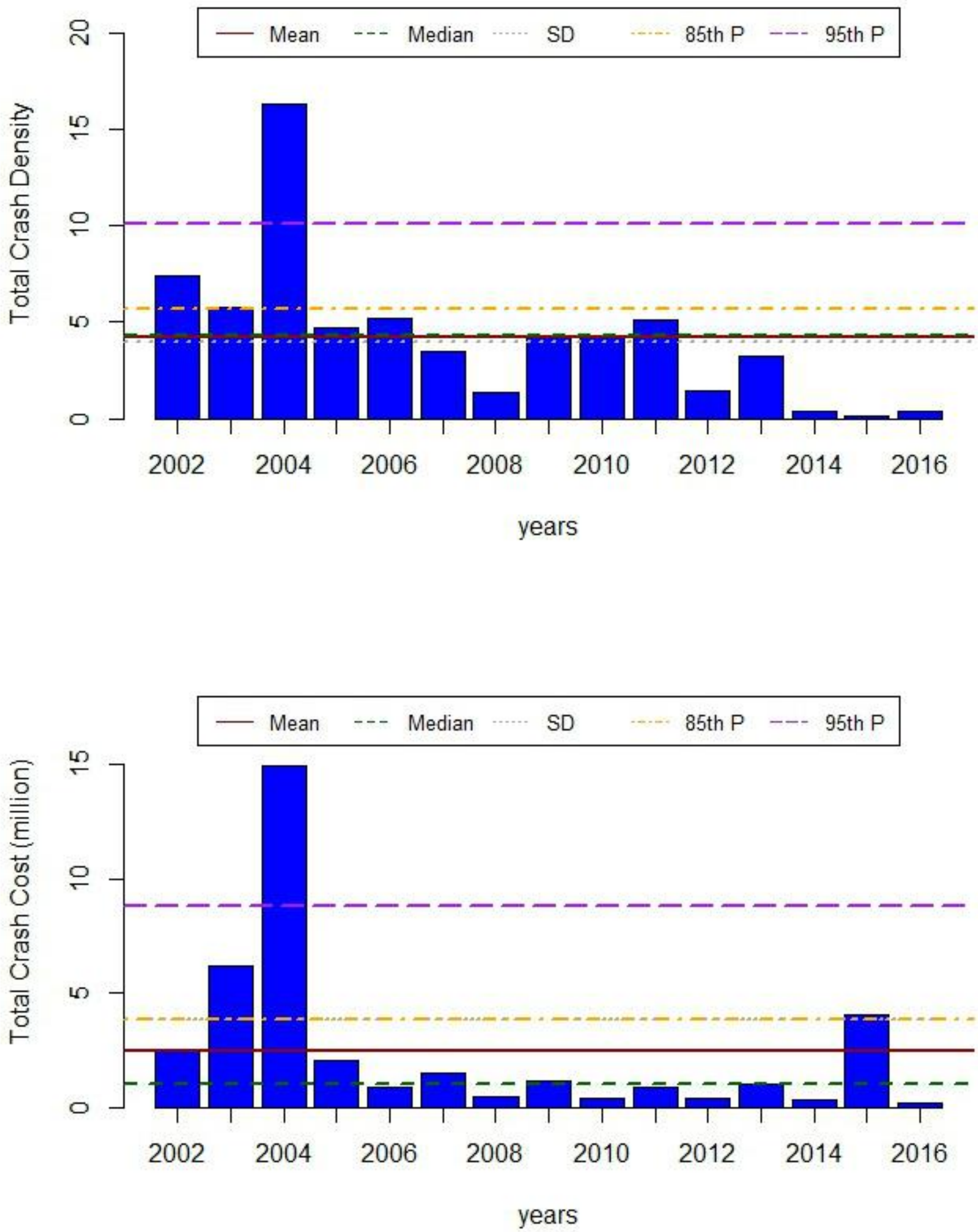
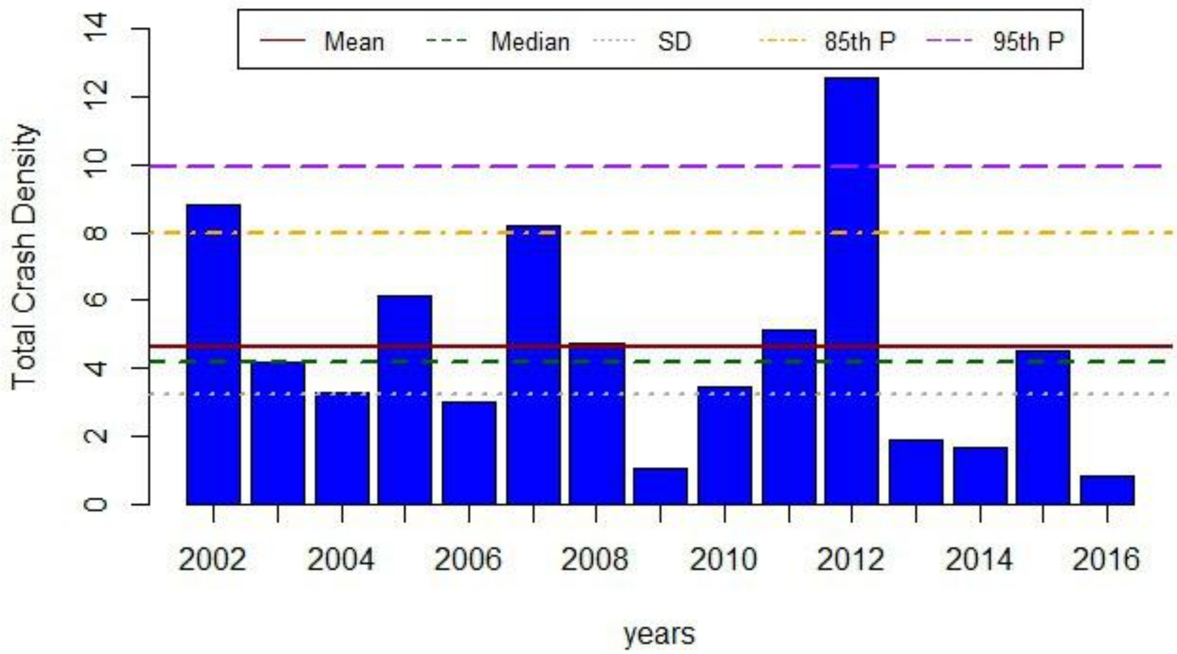


Figure 103 Crash Performance Measure: Blount County



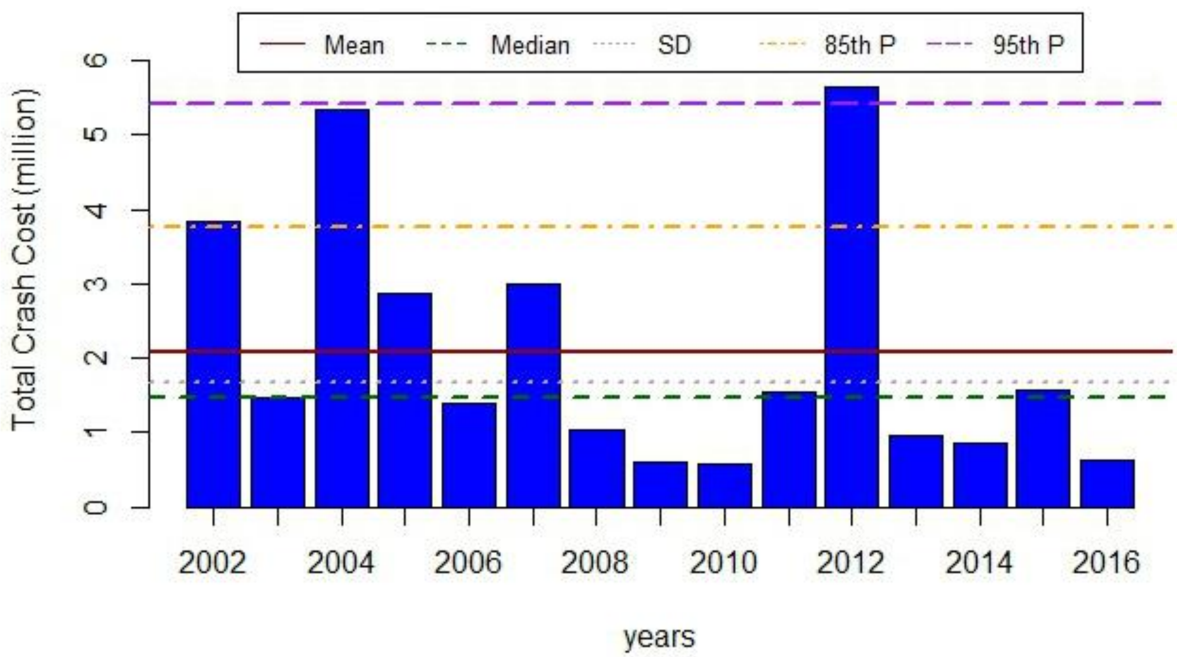
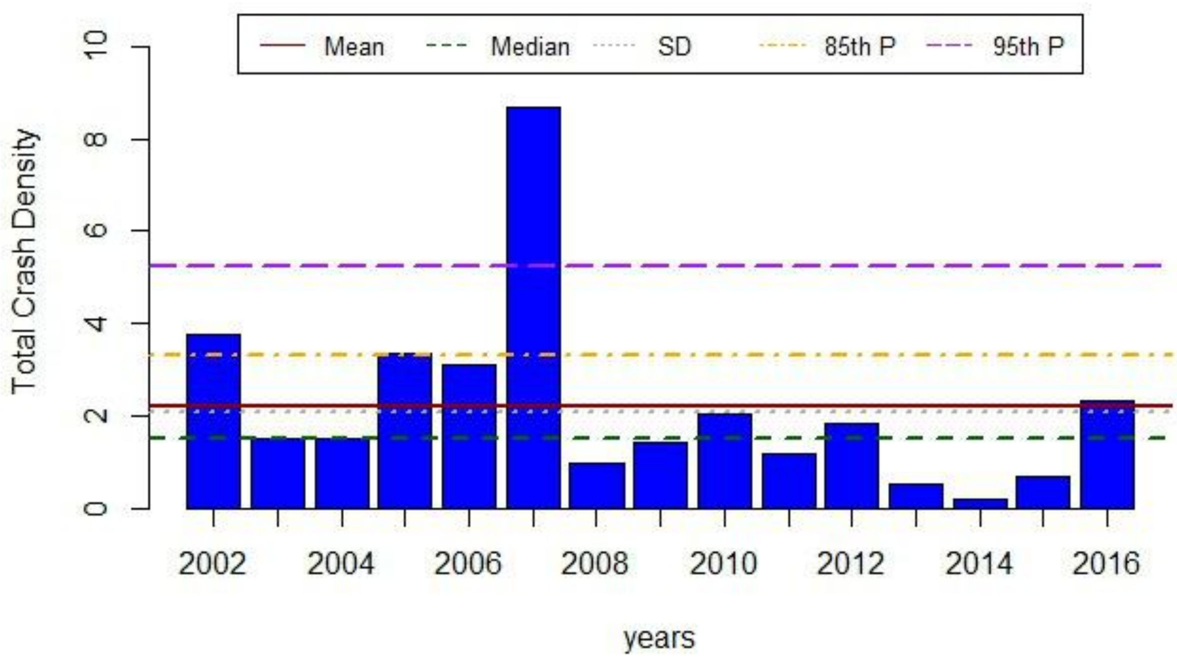


Figure 104 Crash Performance Measure: Bradley County



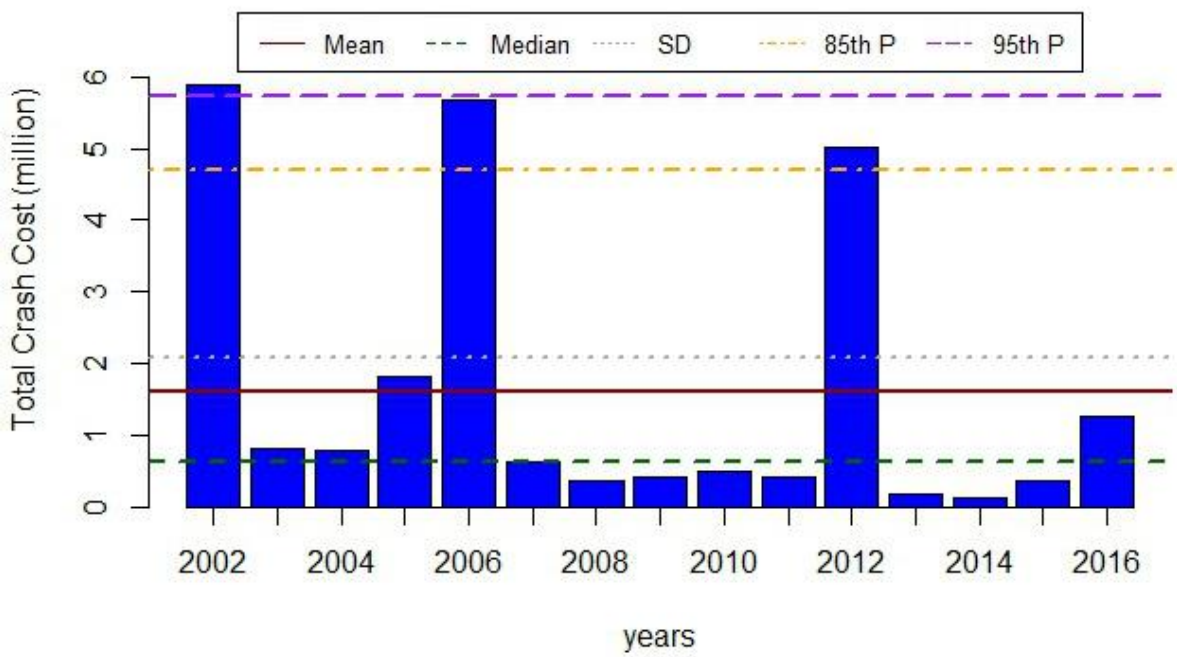


Figure 105 Crash Performance Measure: Campbell County

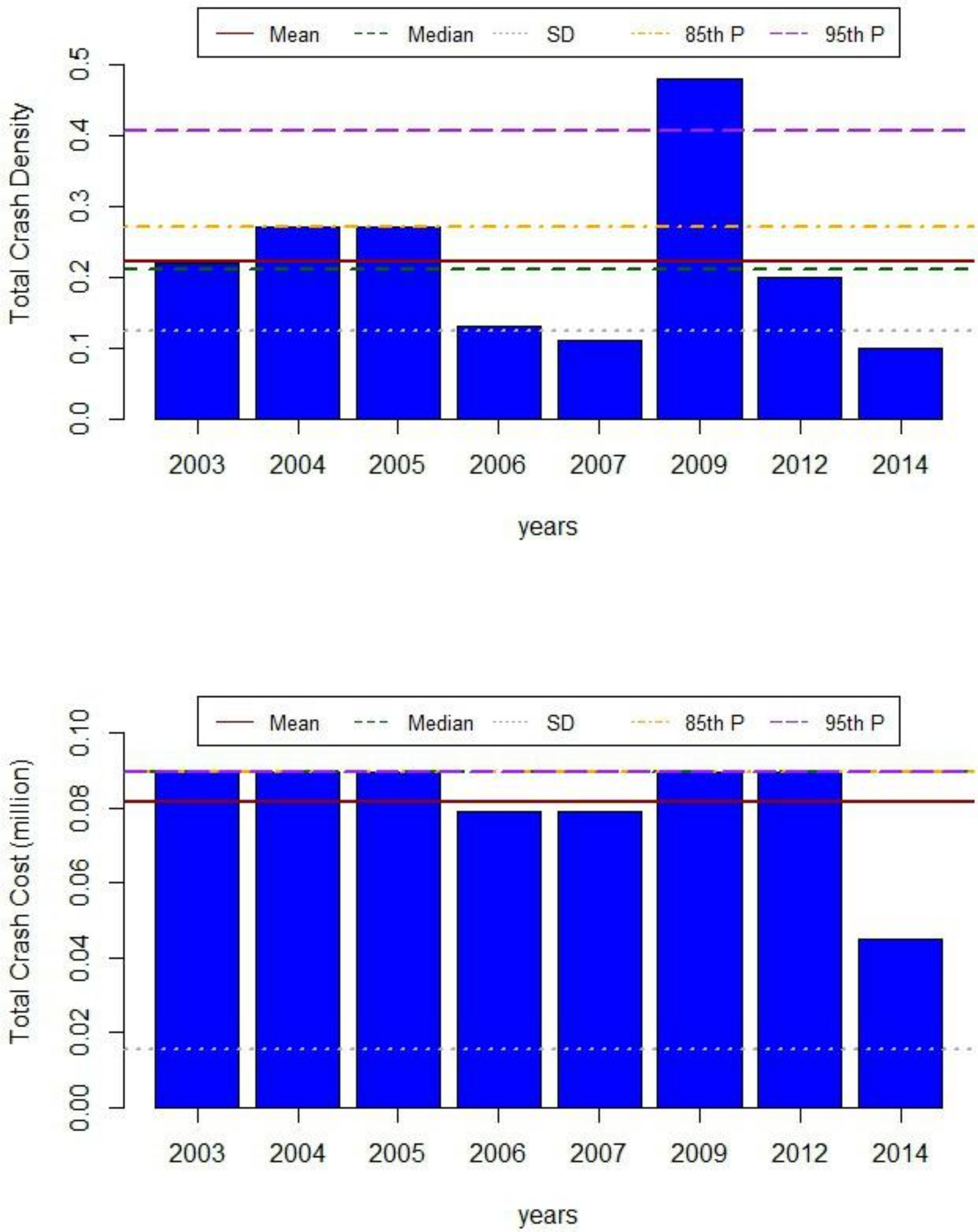


Figure 106 Crash Performance Measure: Cannon County

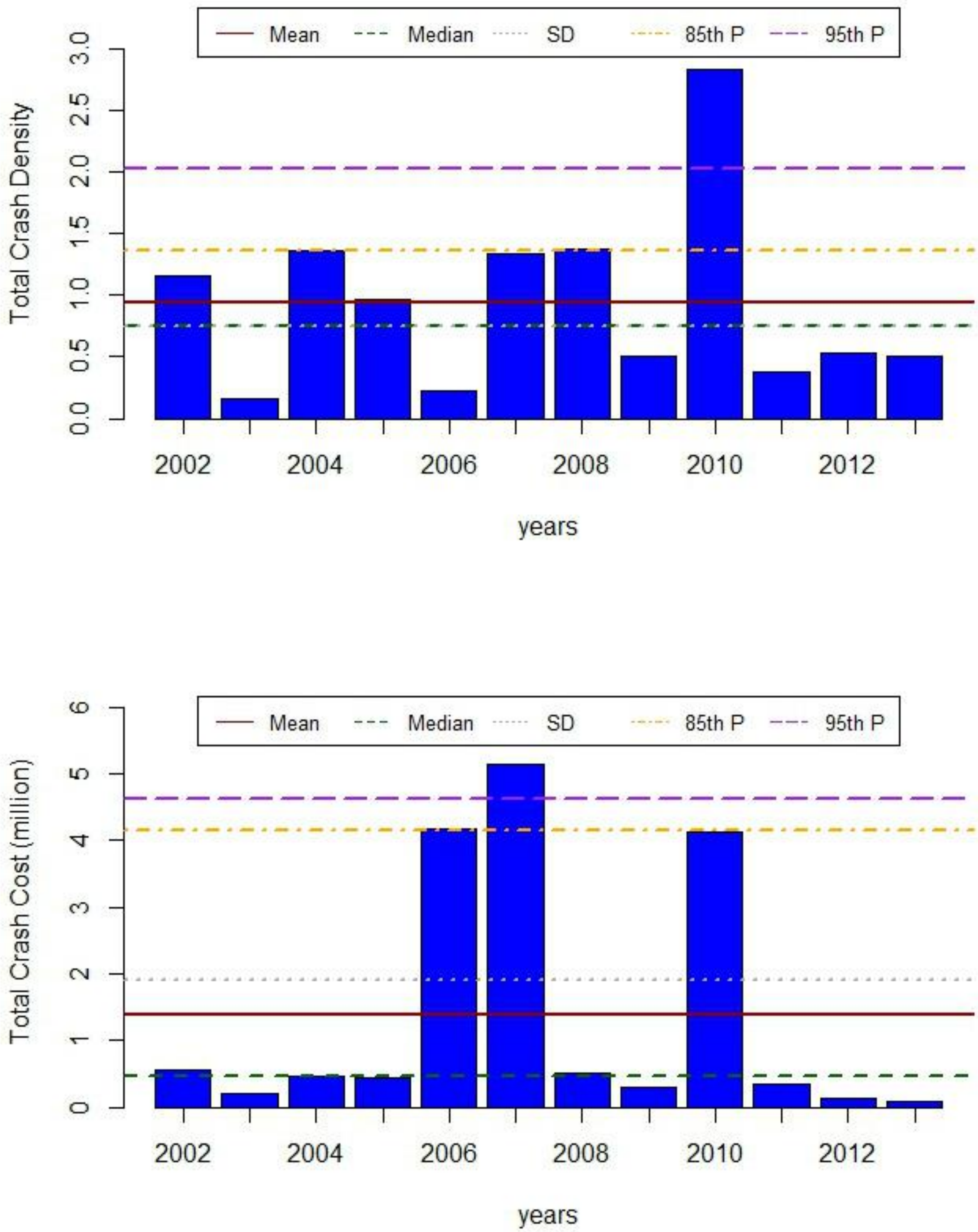
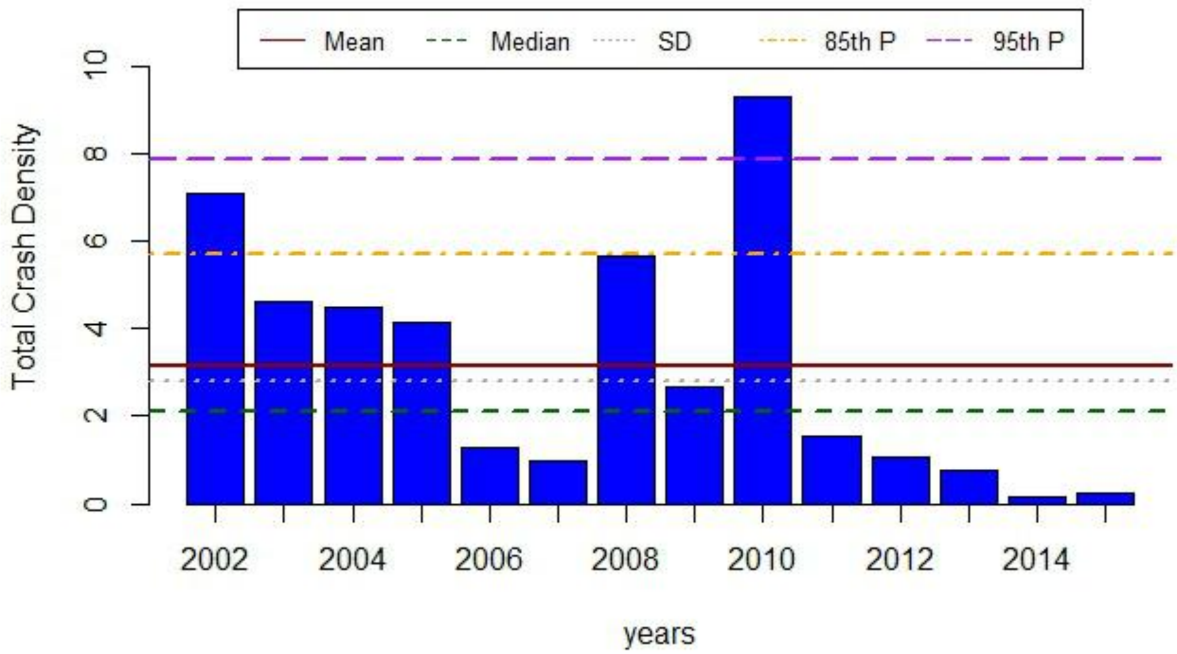


Figure 107 Crash Performance Measure: Carroll County



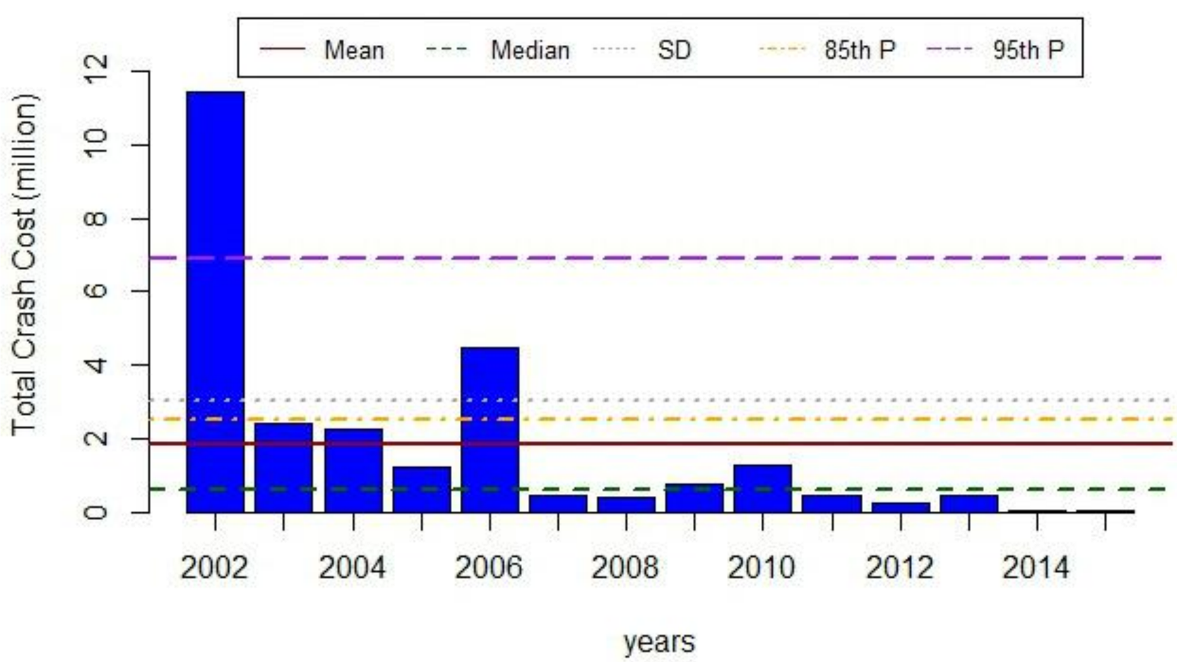
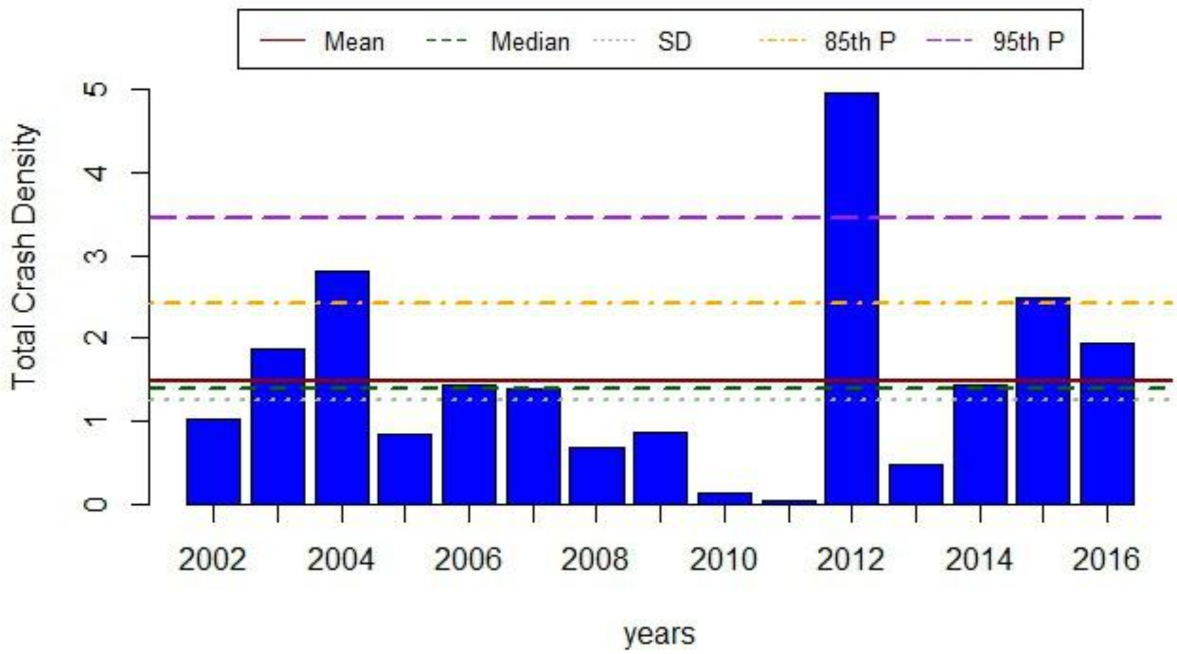


Figure 108 Crash Performance Measure: Carter County



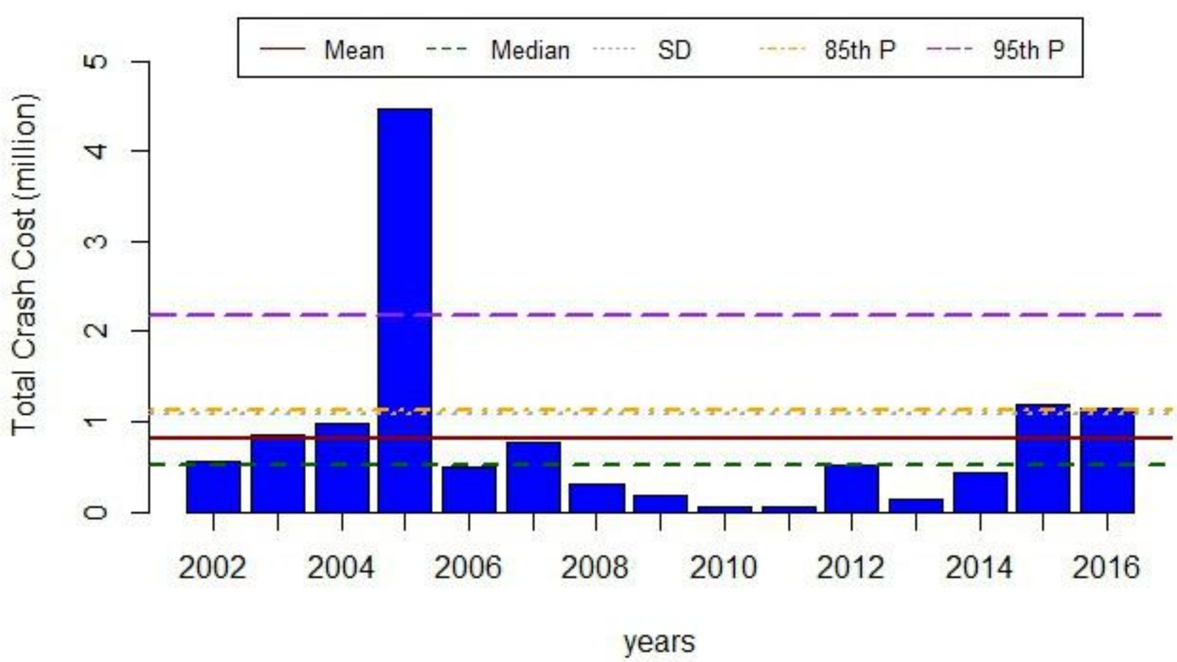
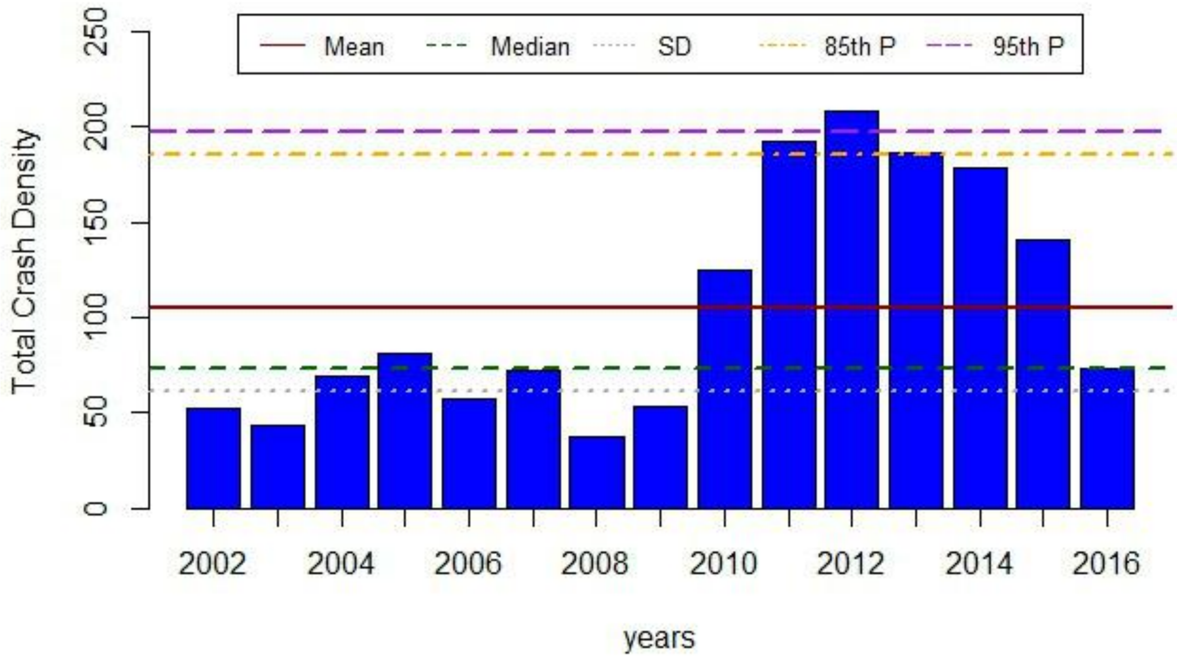


Figure 109 Crash Performance Measure: Cheatham County



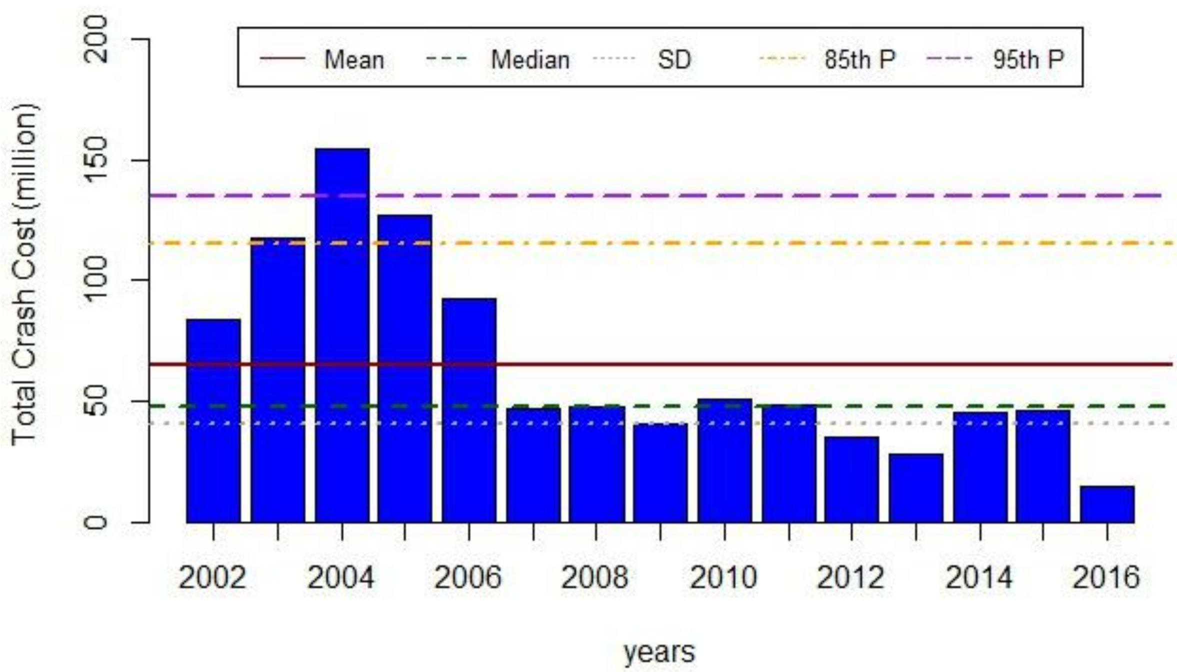
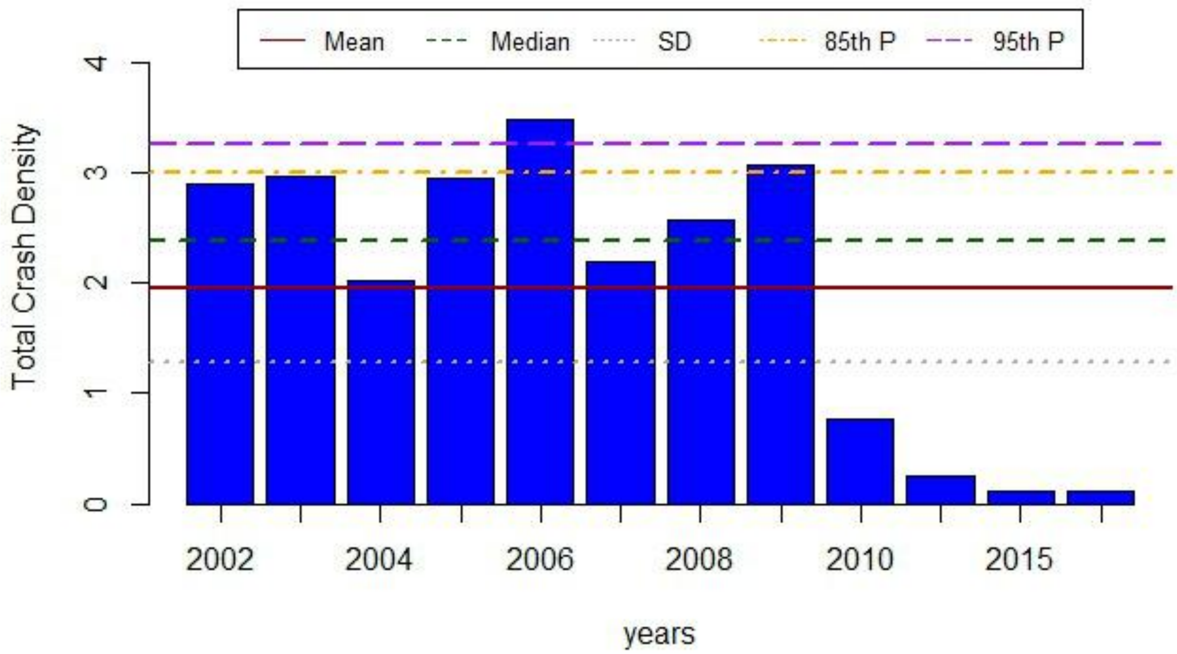


Figure 110 Crash Performance Measure: Chester County



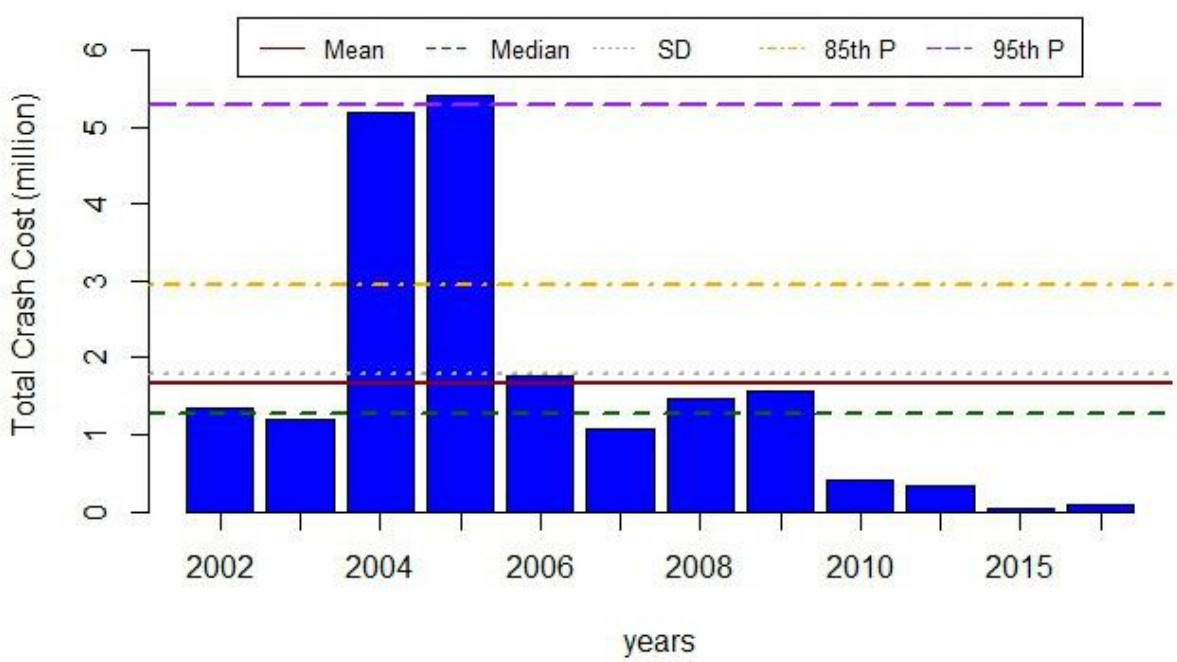


Figure 111 Crash Performance Measure: Claiborne County

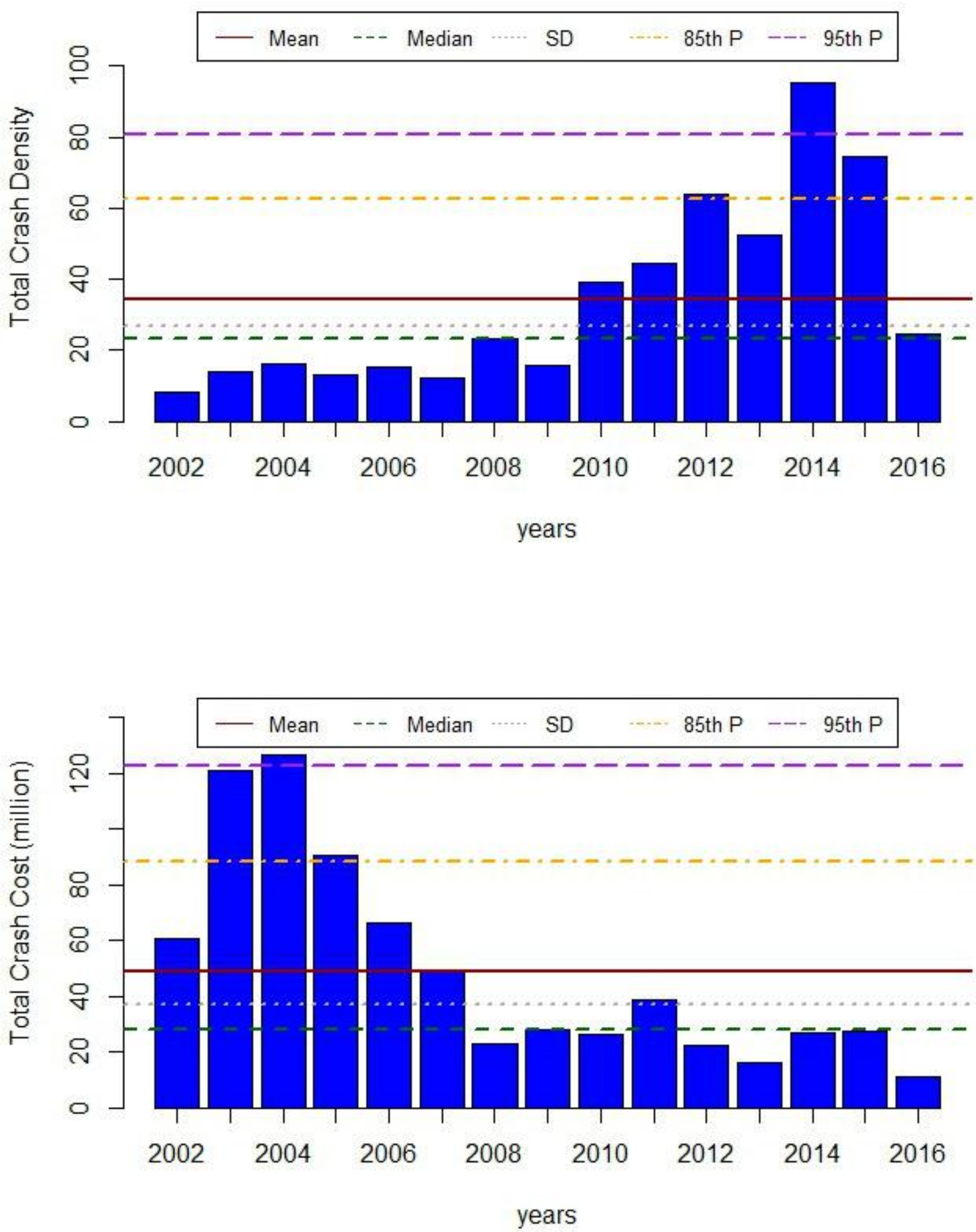
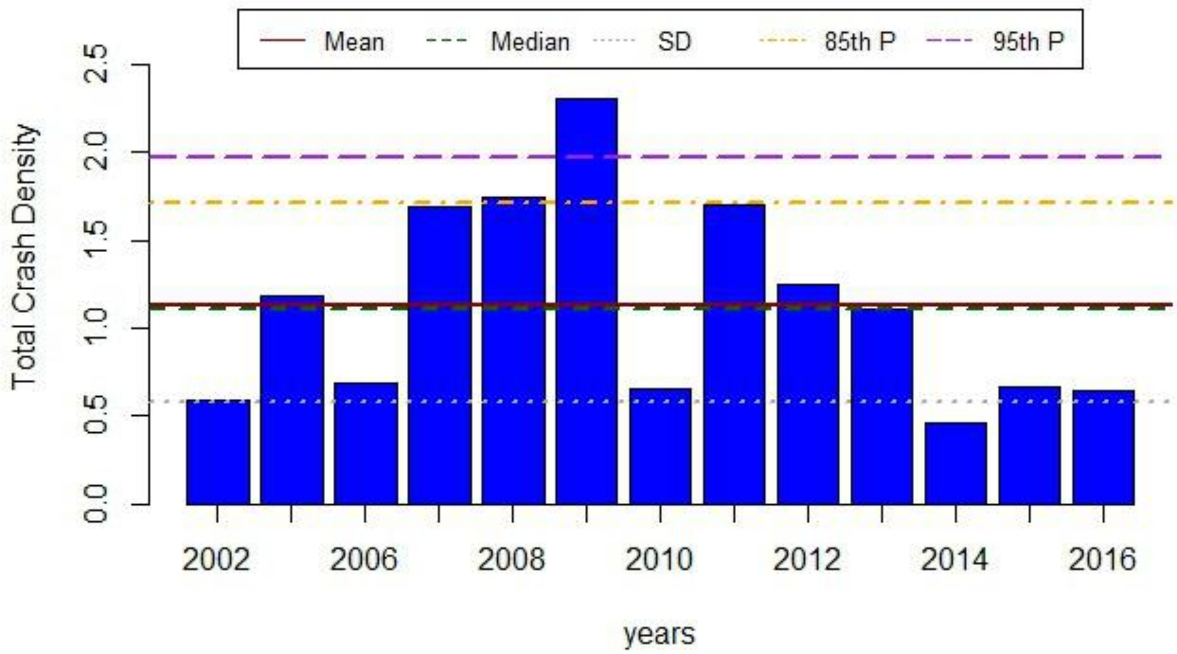


Figure 112 Crash Performance Measure: Clay County



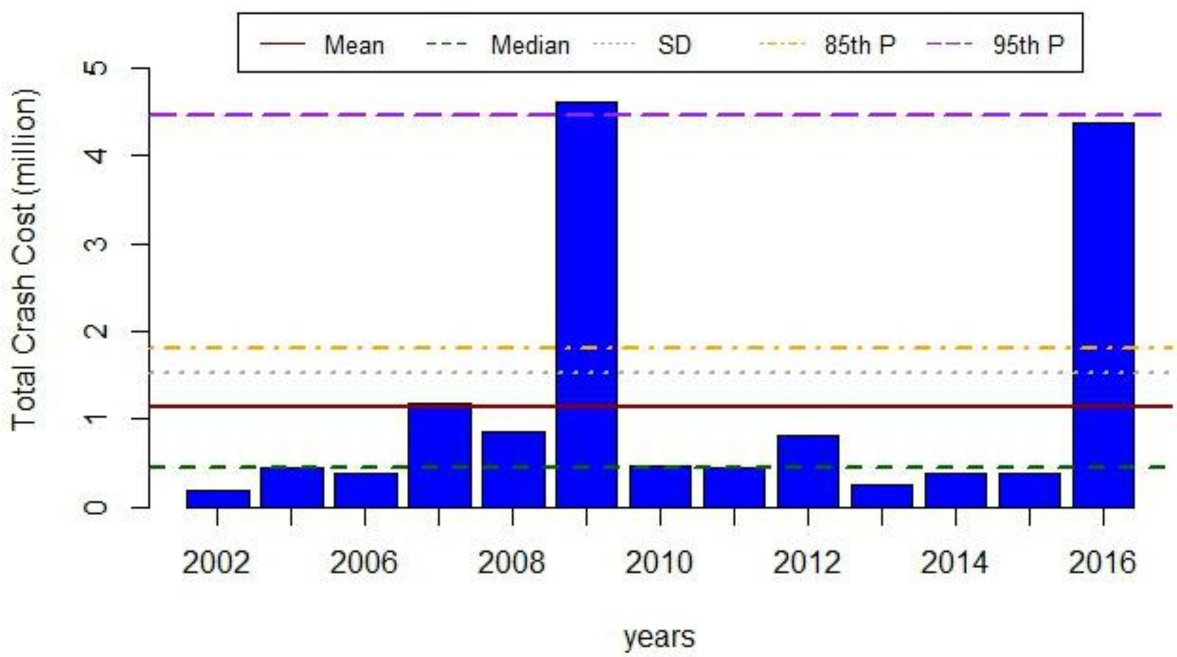
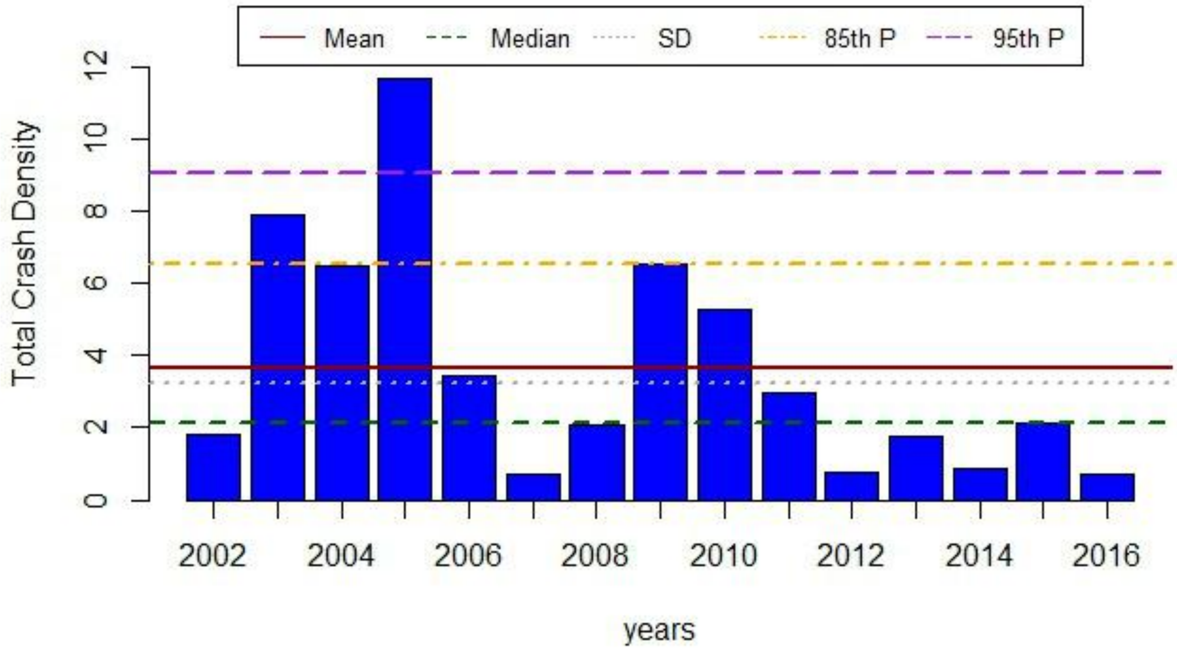


Figure 113 Crash Performance Measure: Cocke County



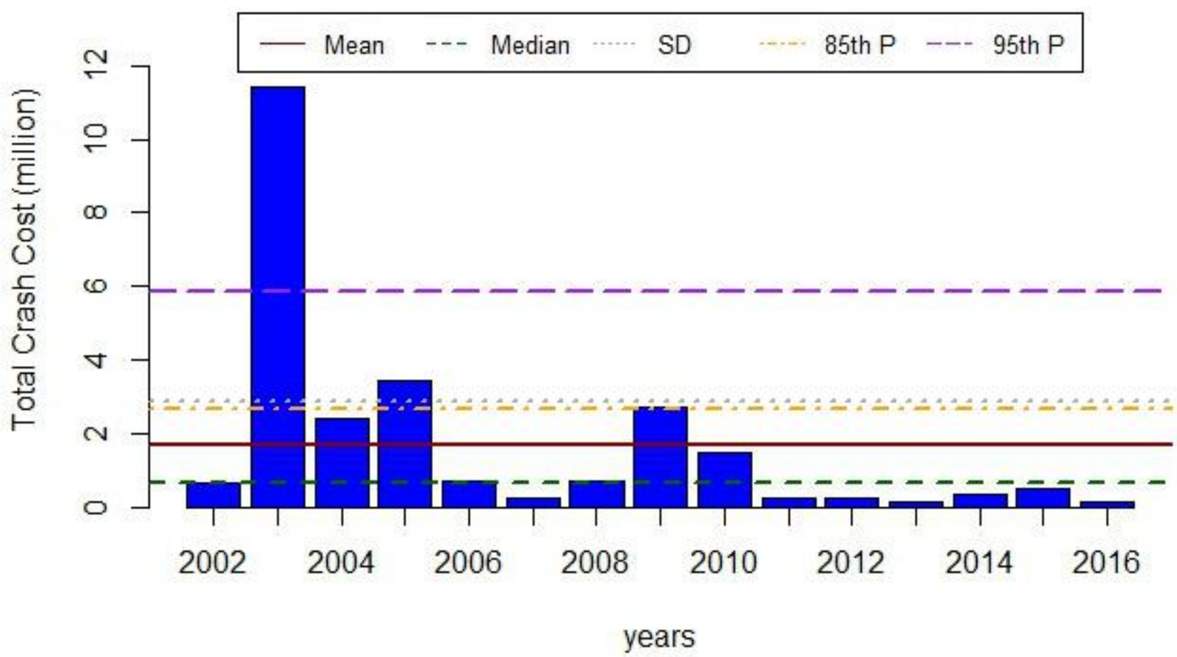


Figure 114 Crash Performance Measure: Coffee County

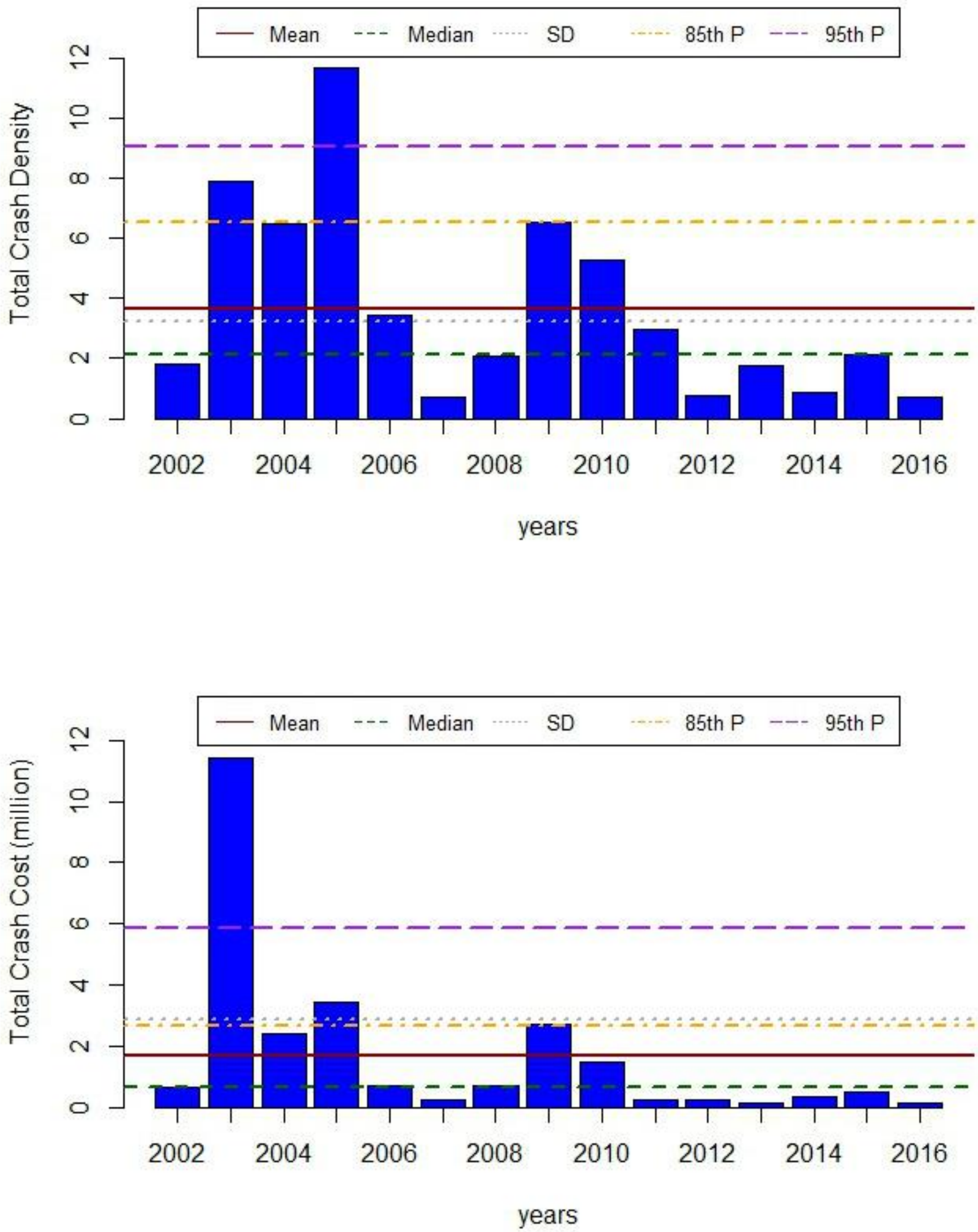
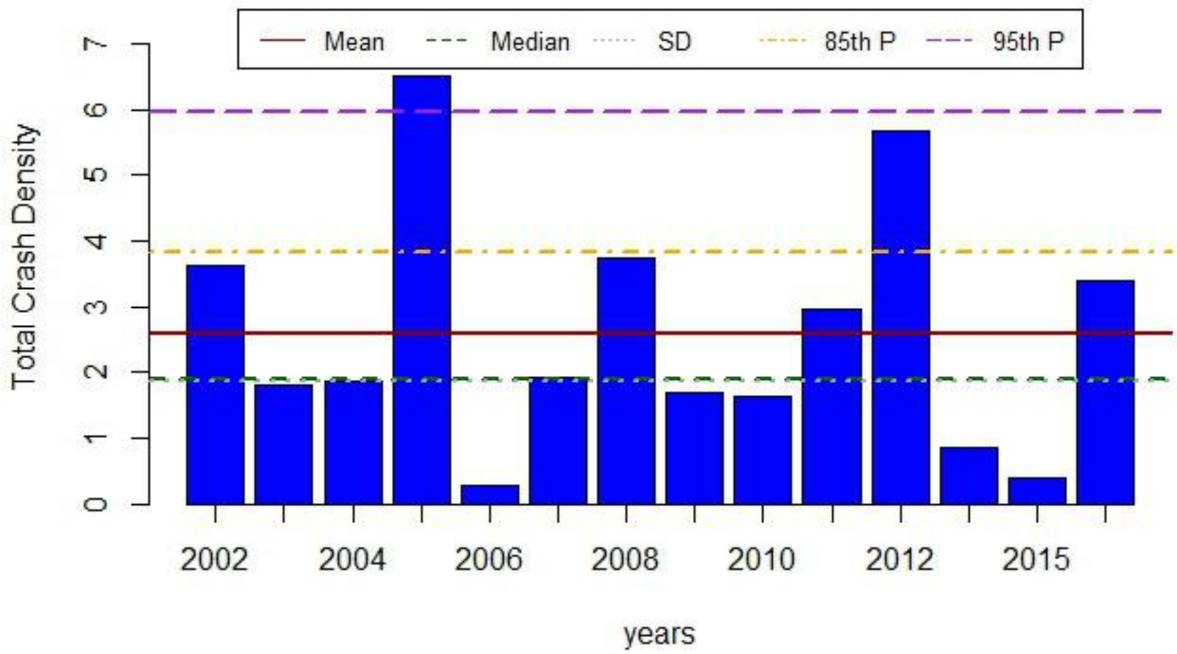


Figure 115 Crash Performance Measure: Crockett County



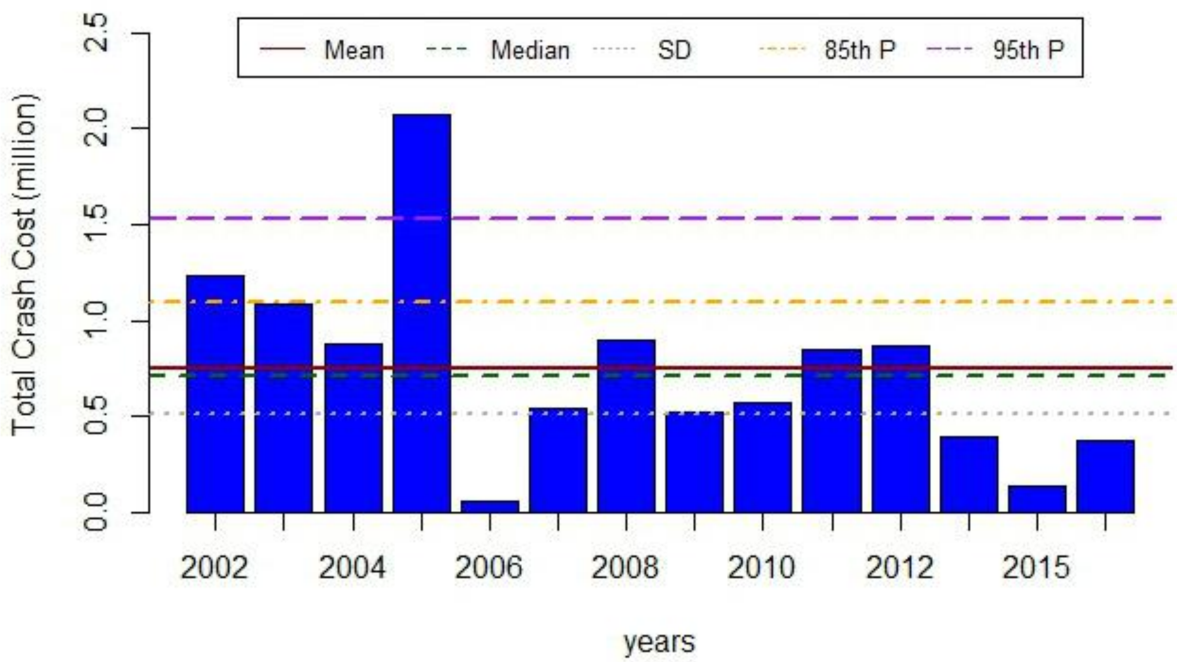


Figure 116 Crash Performance Measure: Cumberland County

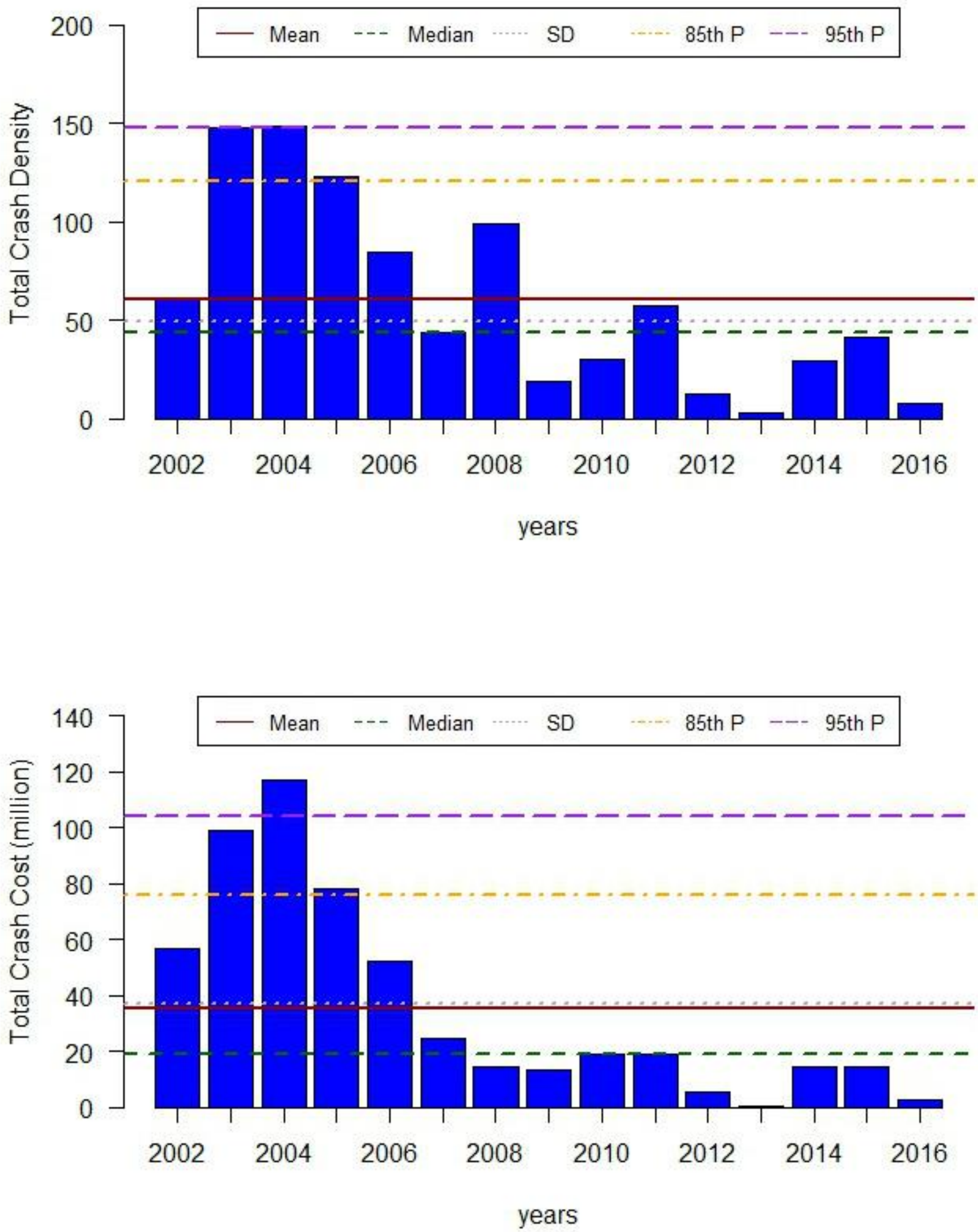
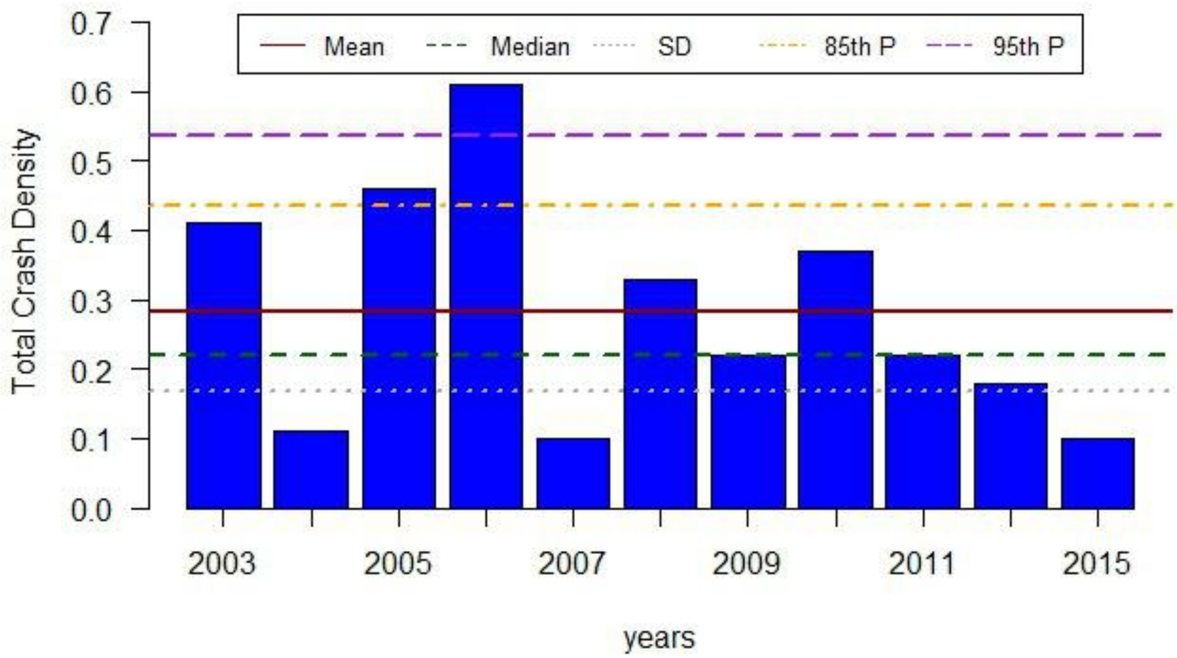


Figure 117 Crash Performance Measure: Davidson County



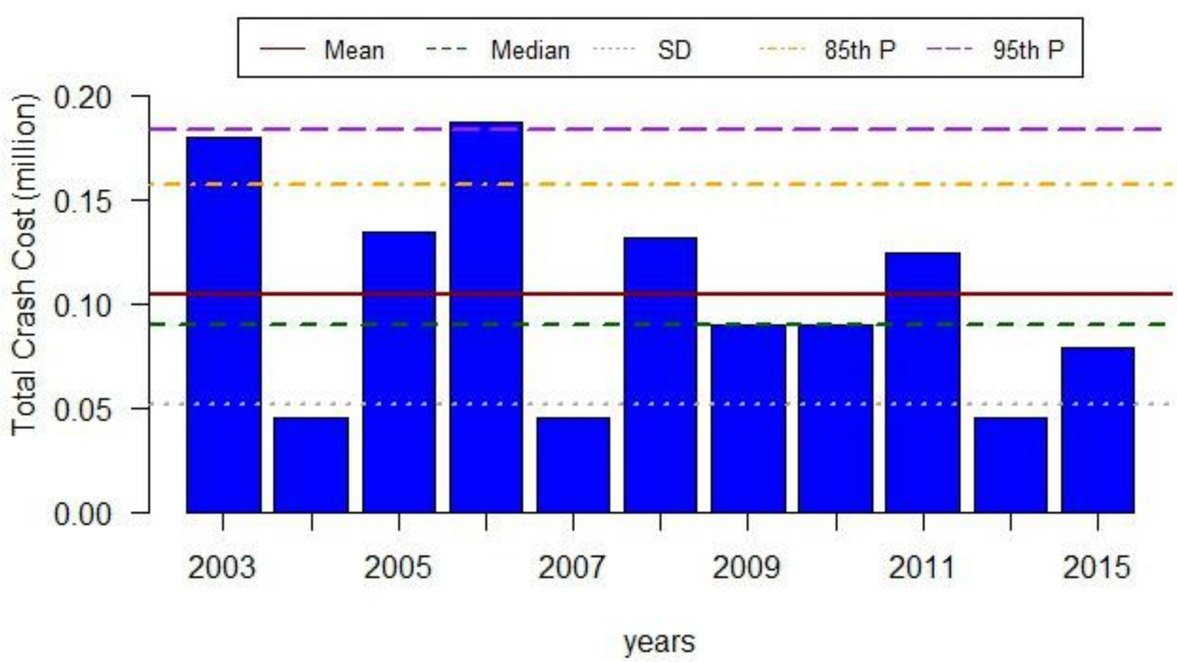


Figure 118 Crash Performance Measure: Decatur County

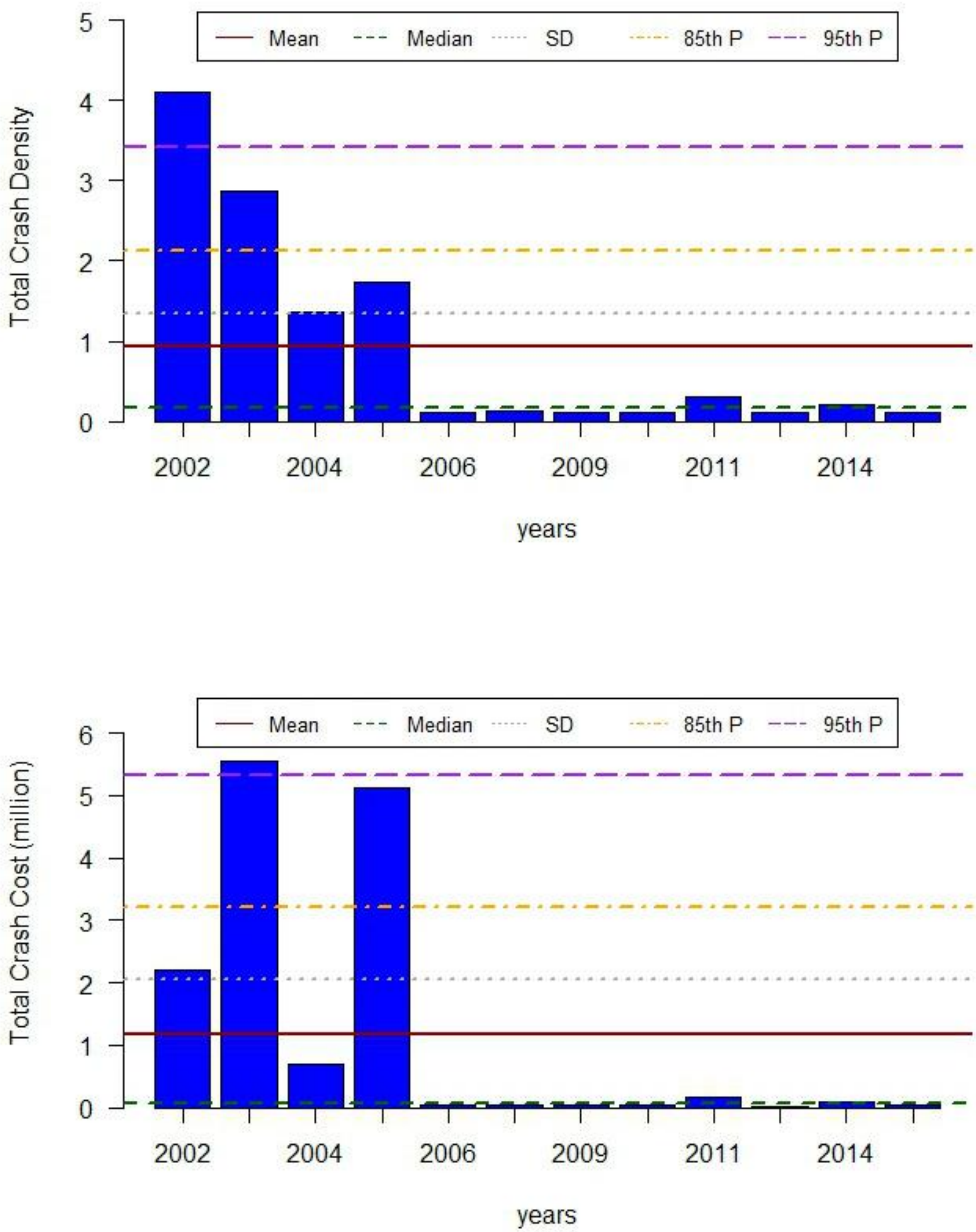
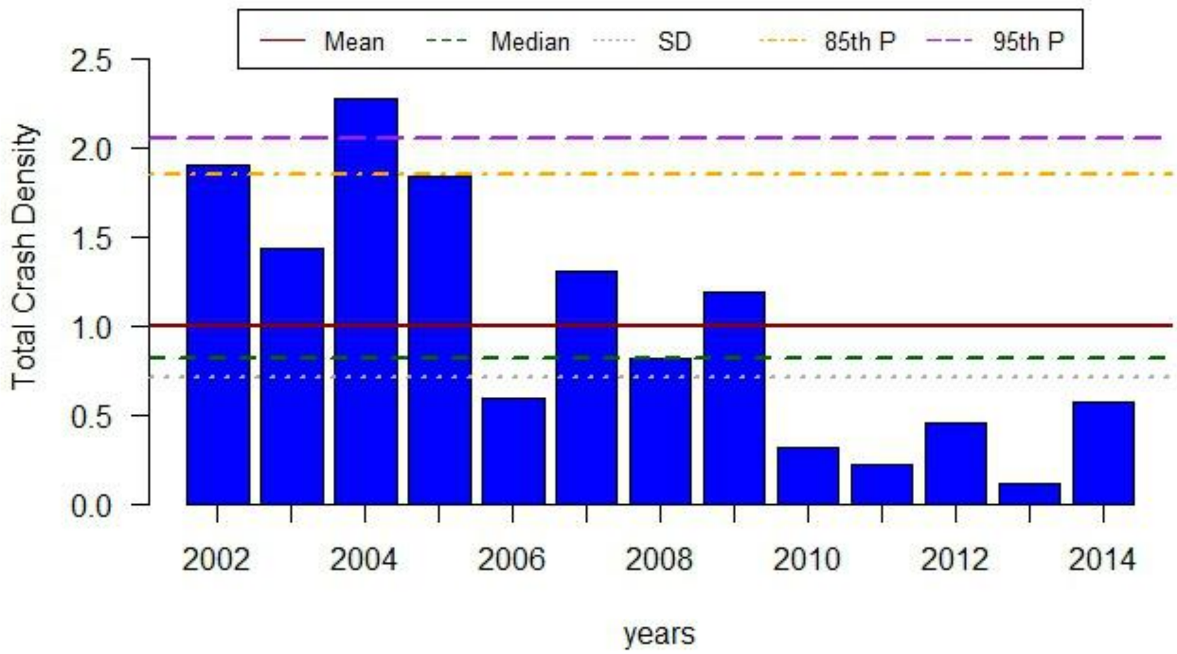


Figure 119 Crash Performance Measure: DeKalb County



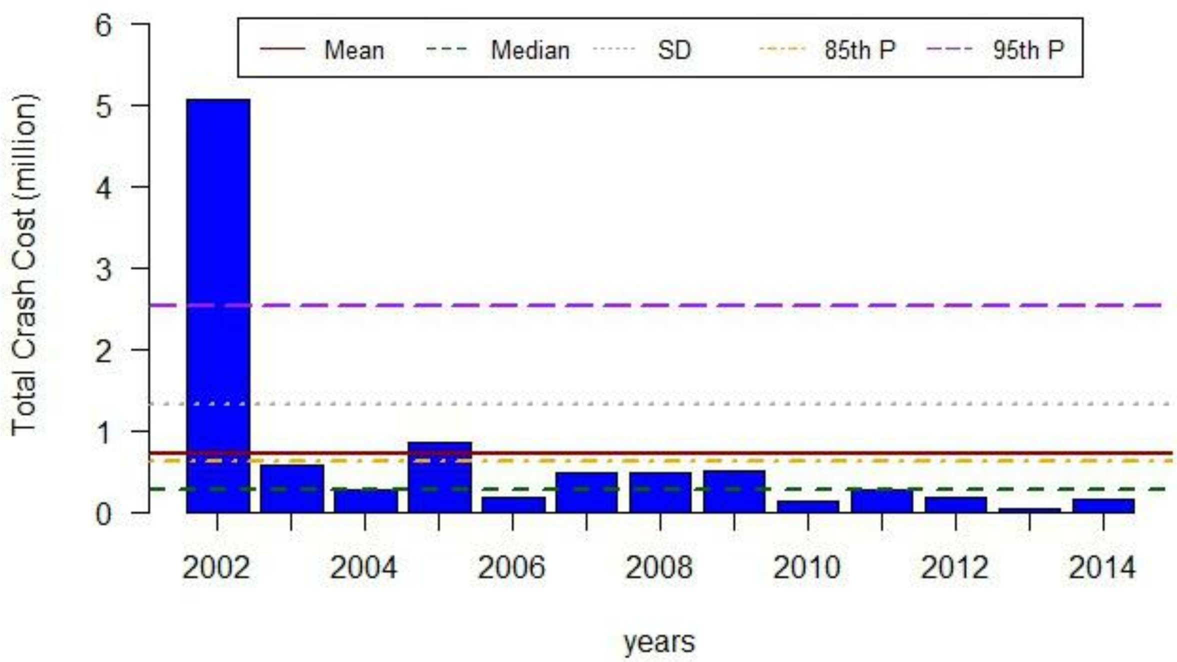
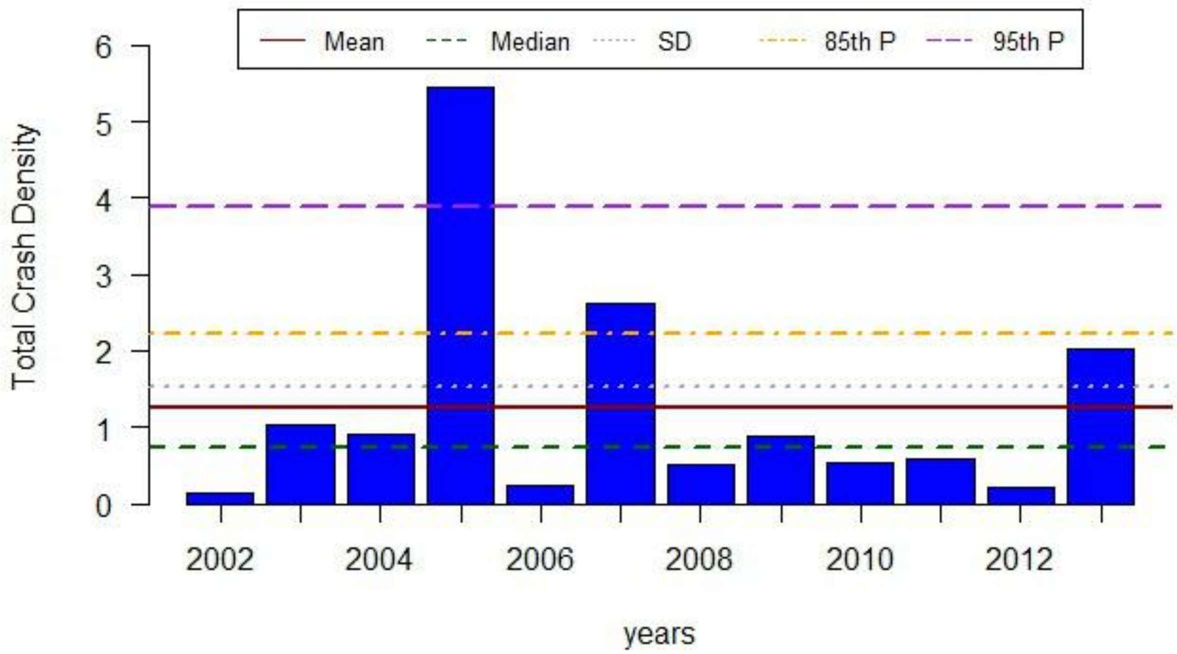


Figure 120 Crash Performance Measure: Dickson County



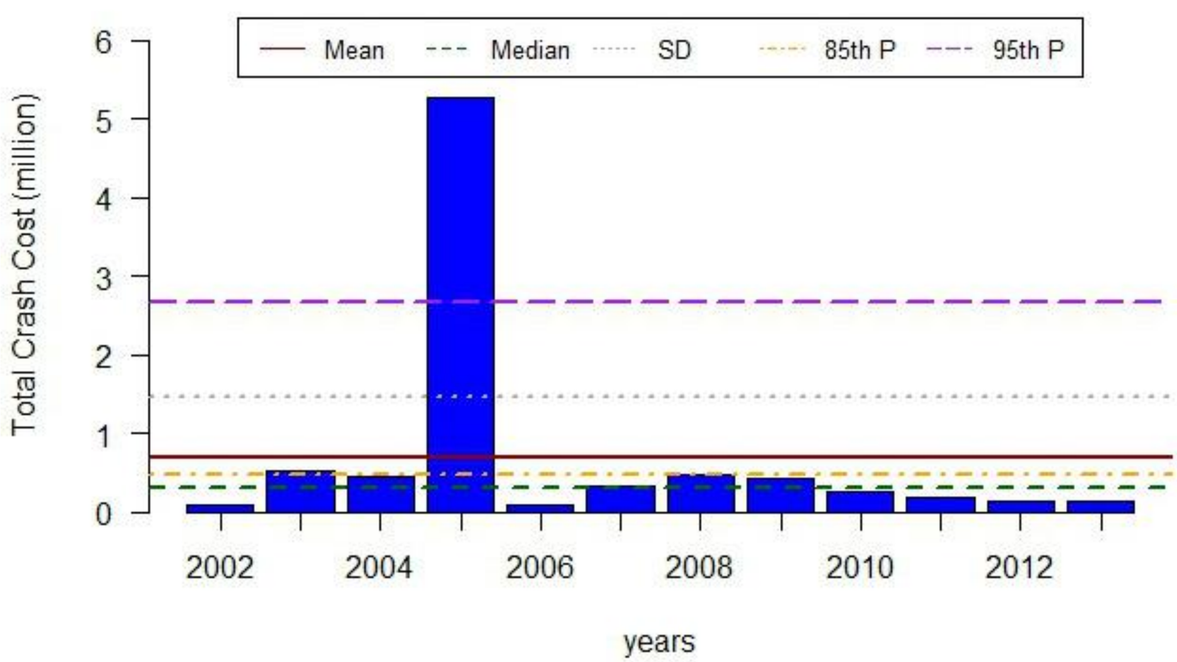


Figure 121 Crash Performance Measure: Dyer County

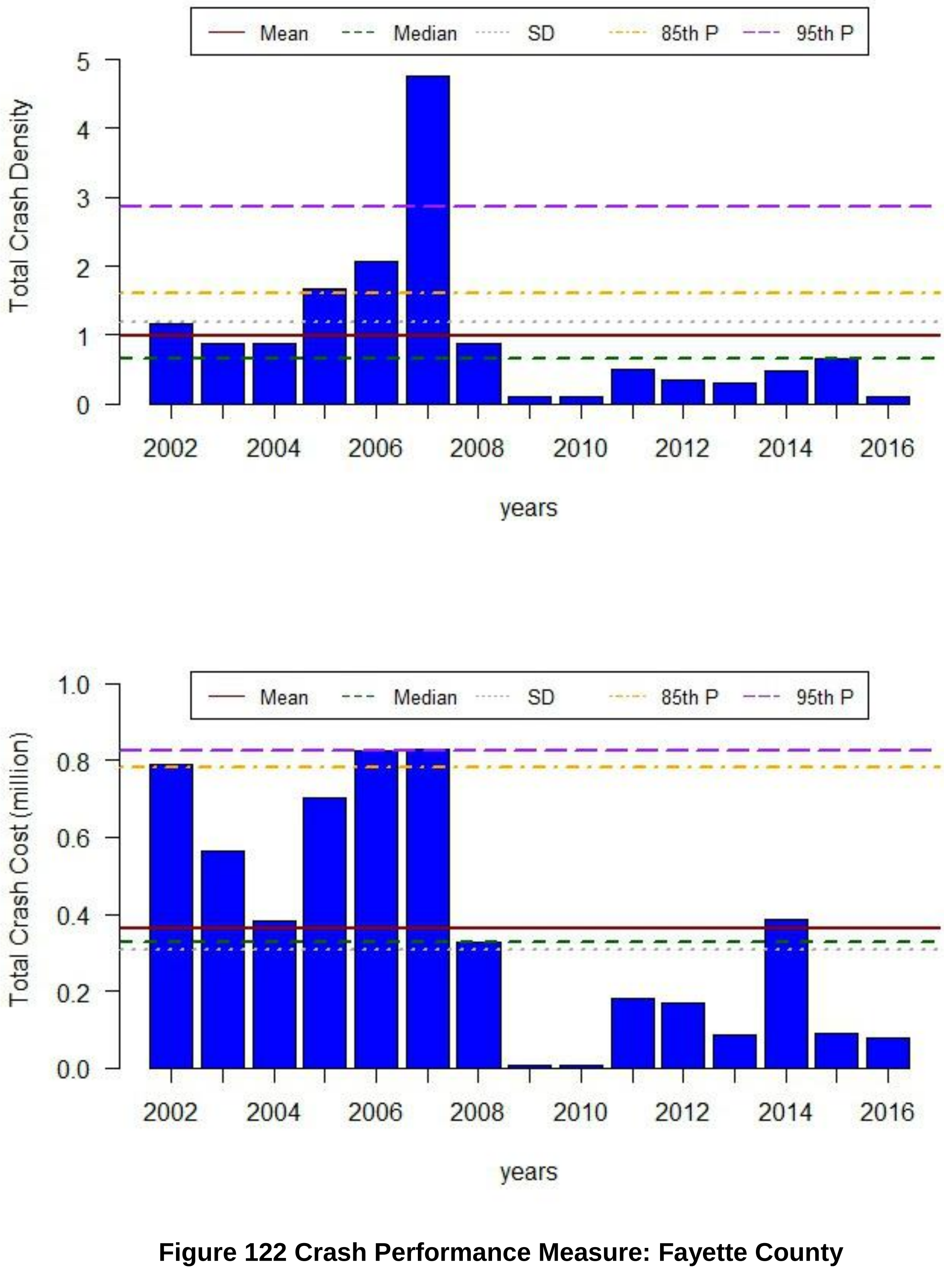
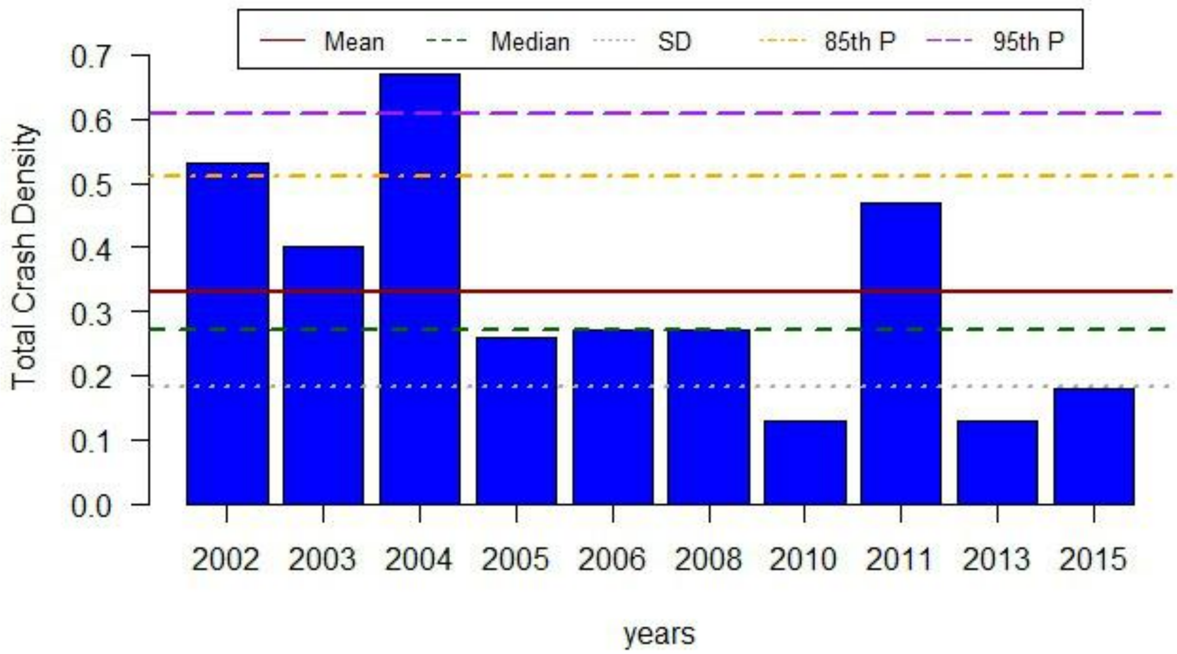


Figure 122 Crash Performance Measure: Fayette County



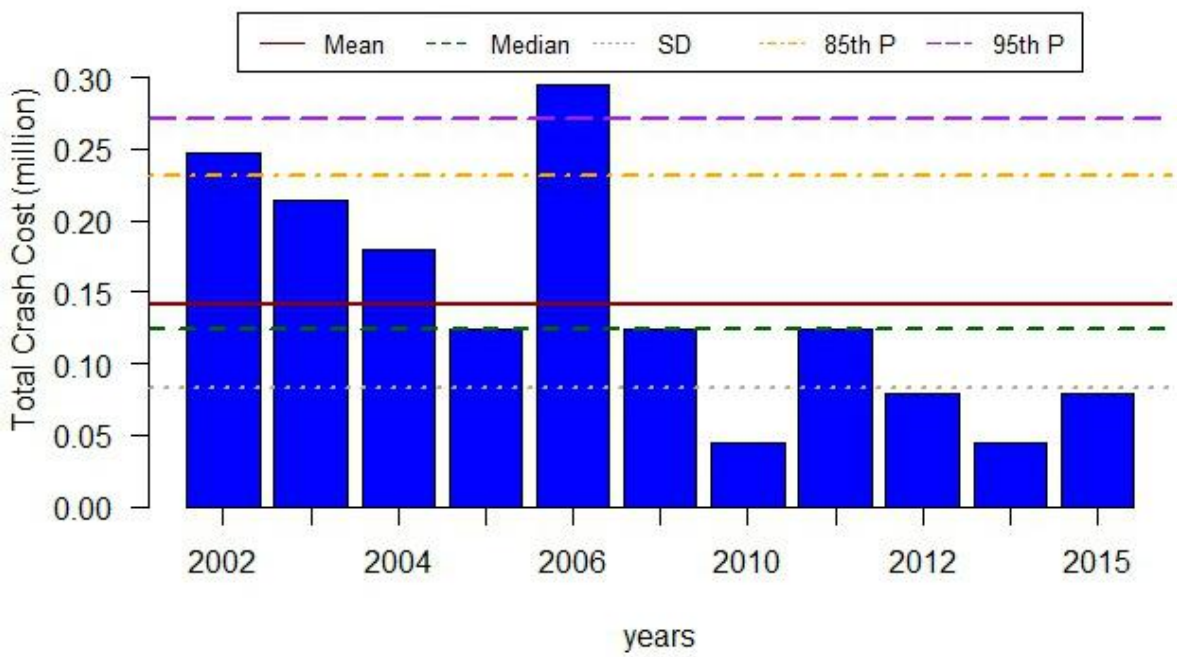
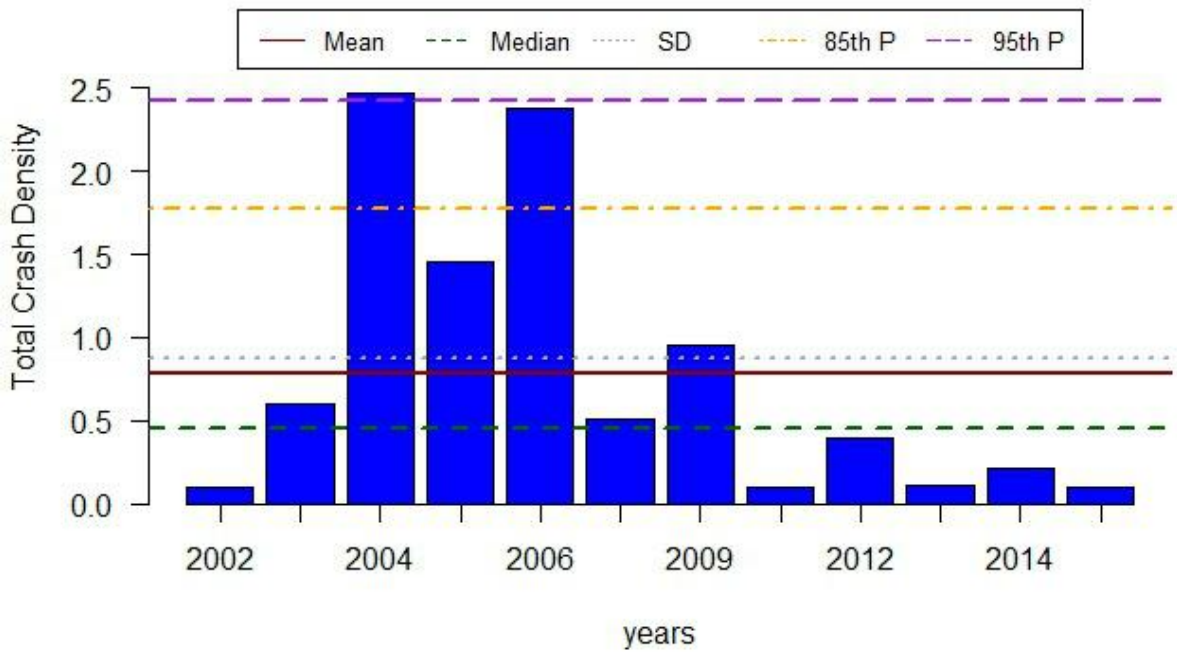


Figure 123 Crash Performance Measure: Fentress County



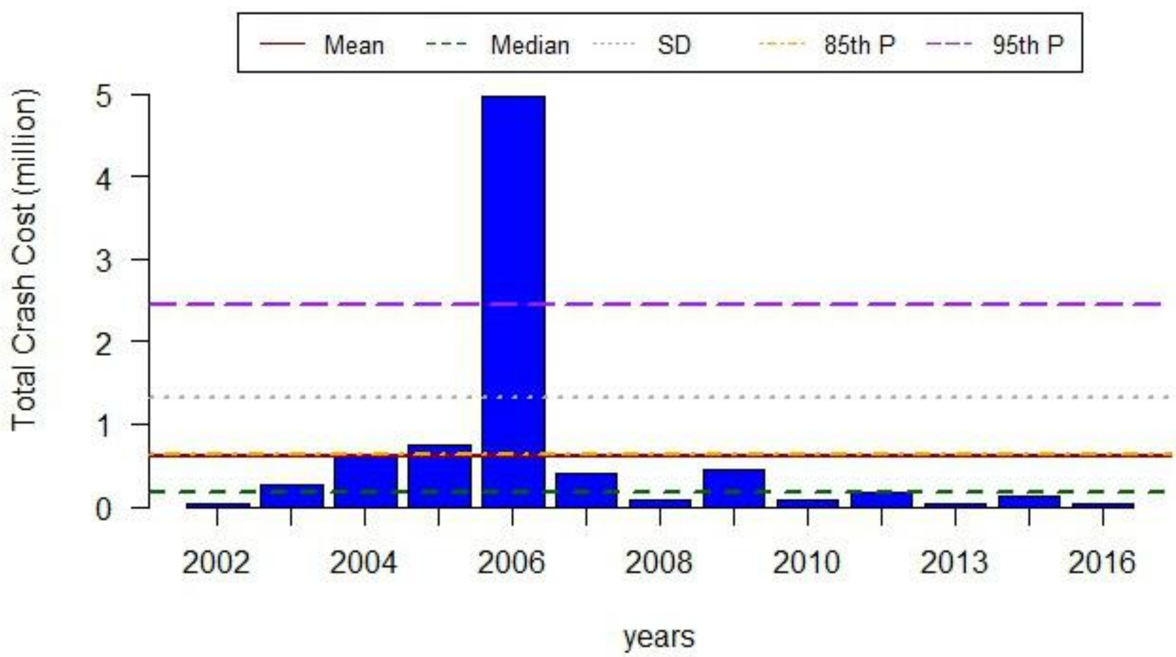


Figure 124 Crash Performance Measure: Franklin County

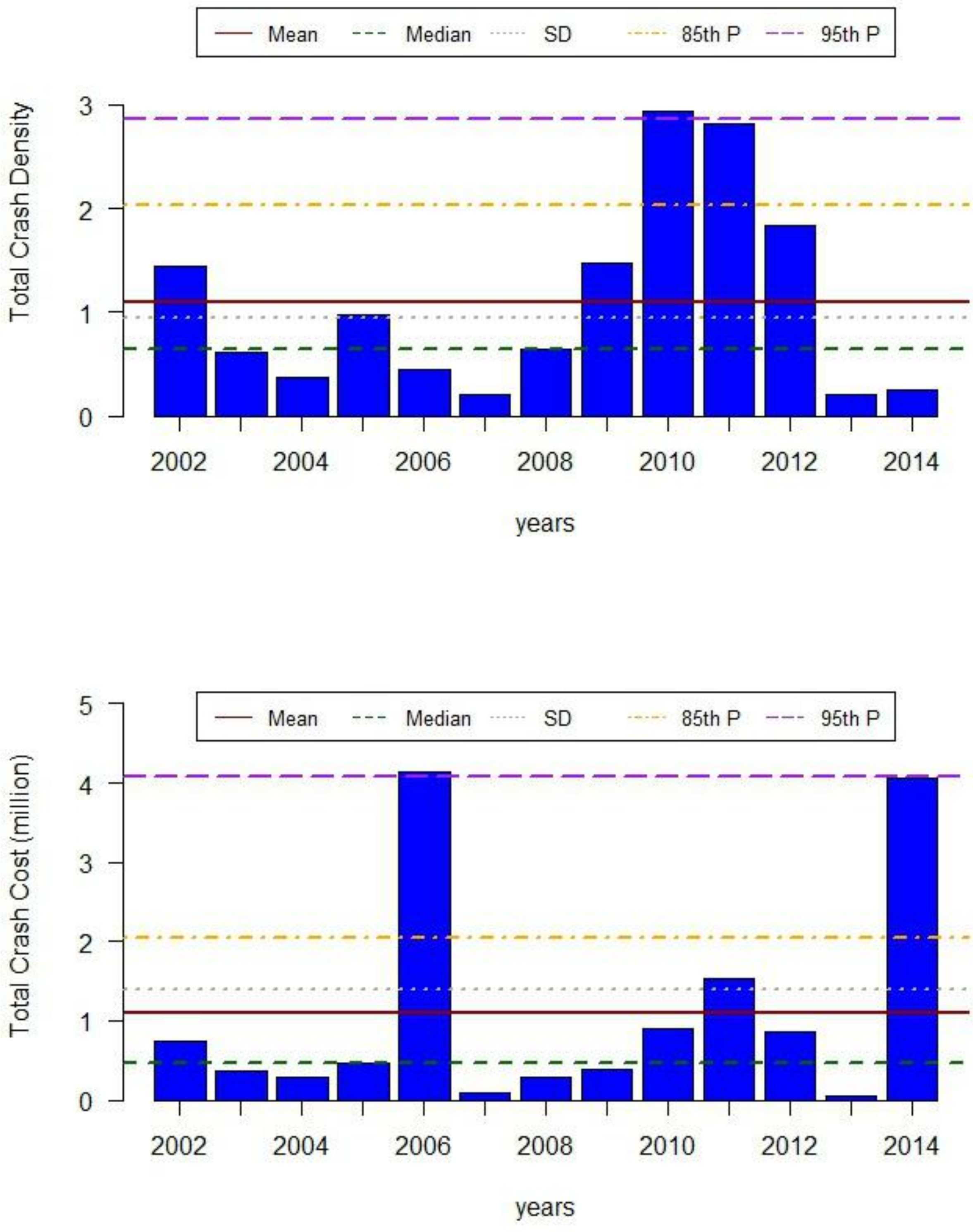
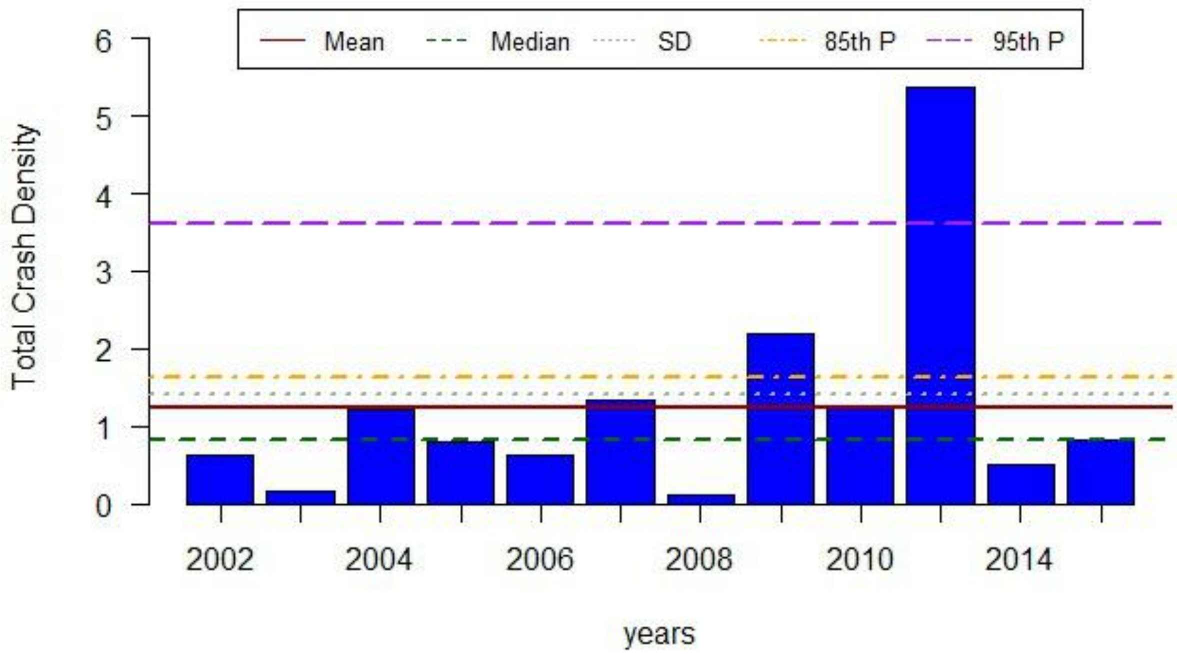


Figure 125 Crash Performance Measure: Gibson County



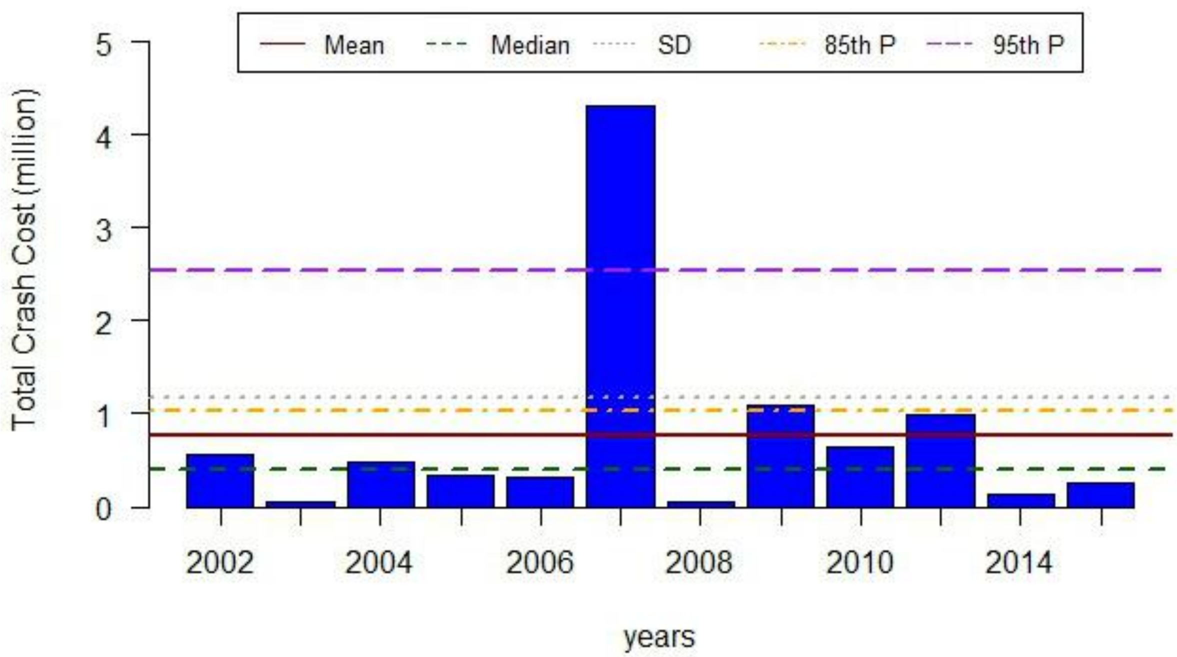
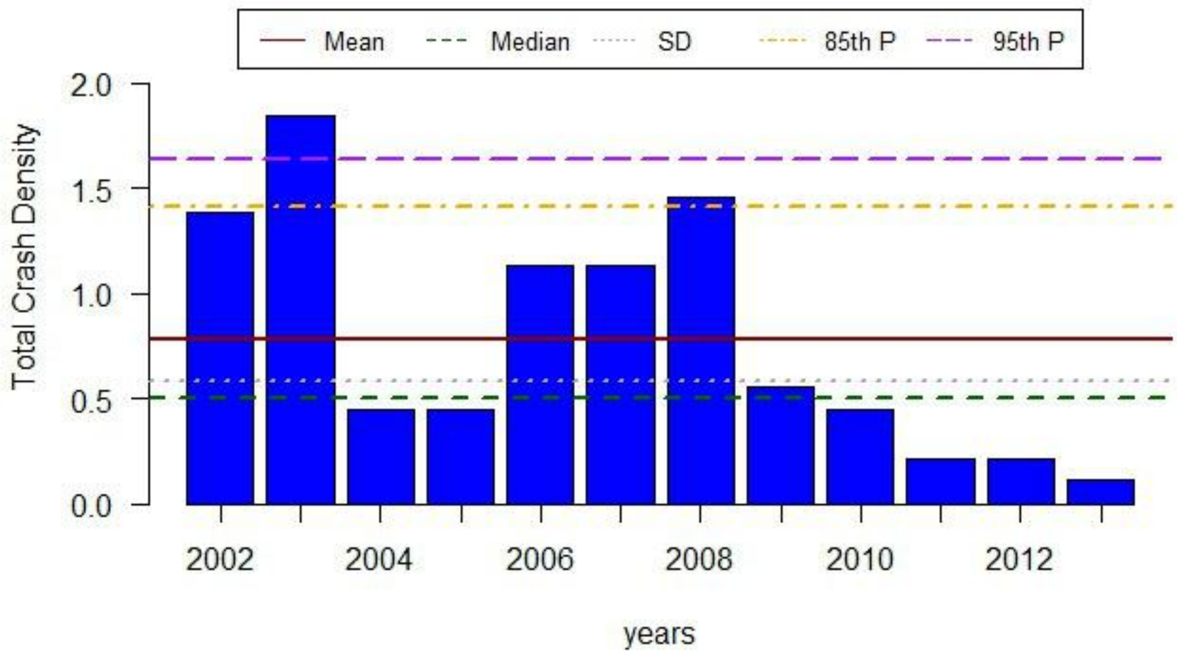


Figure 126 Crash Performance Measure: Giles County



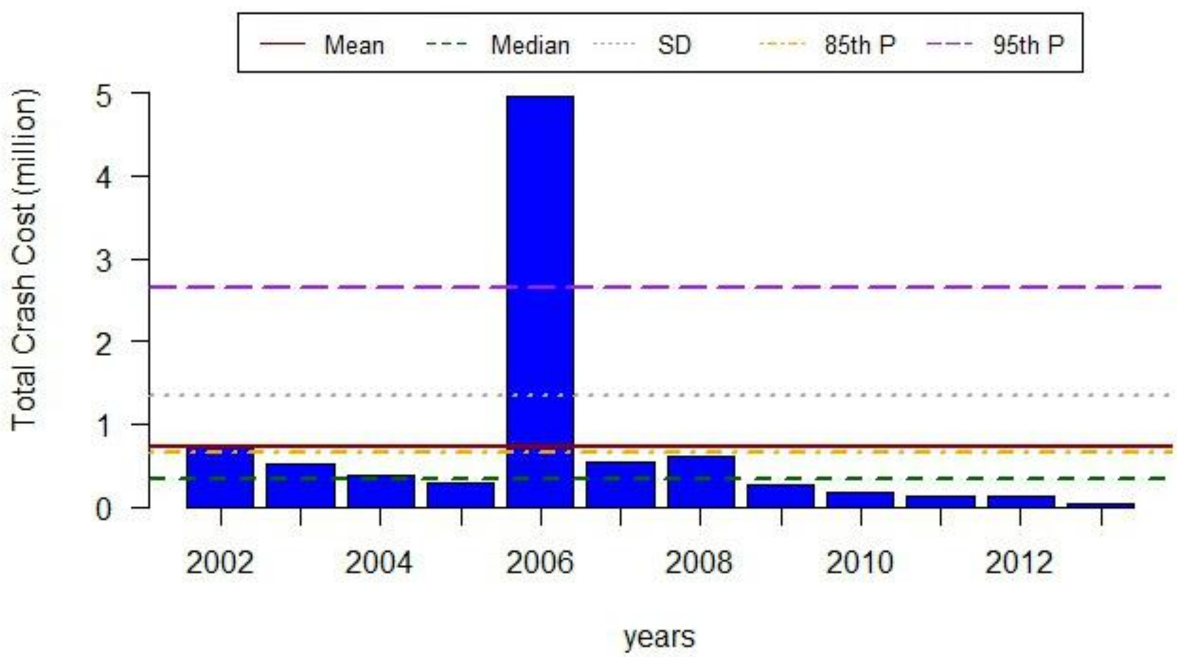


Figure 127 Crash Performance Measure: Grainger County

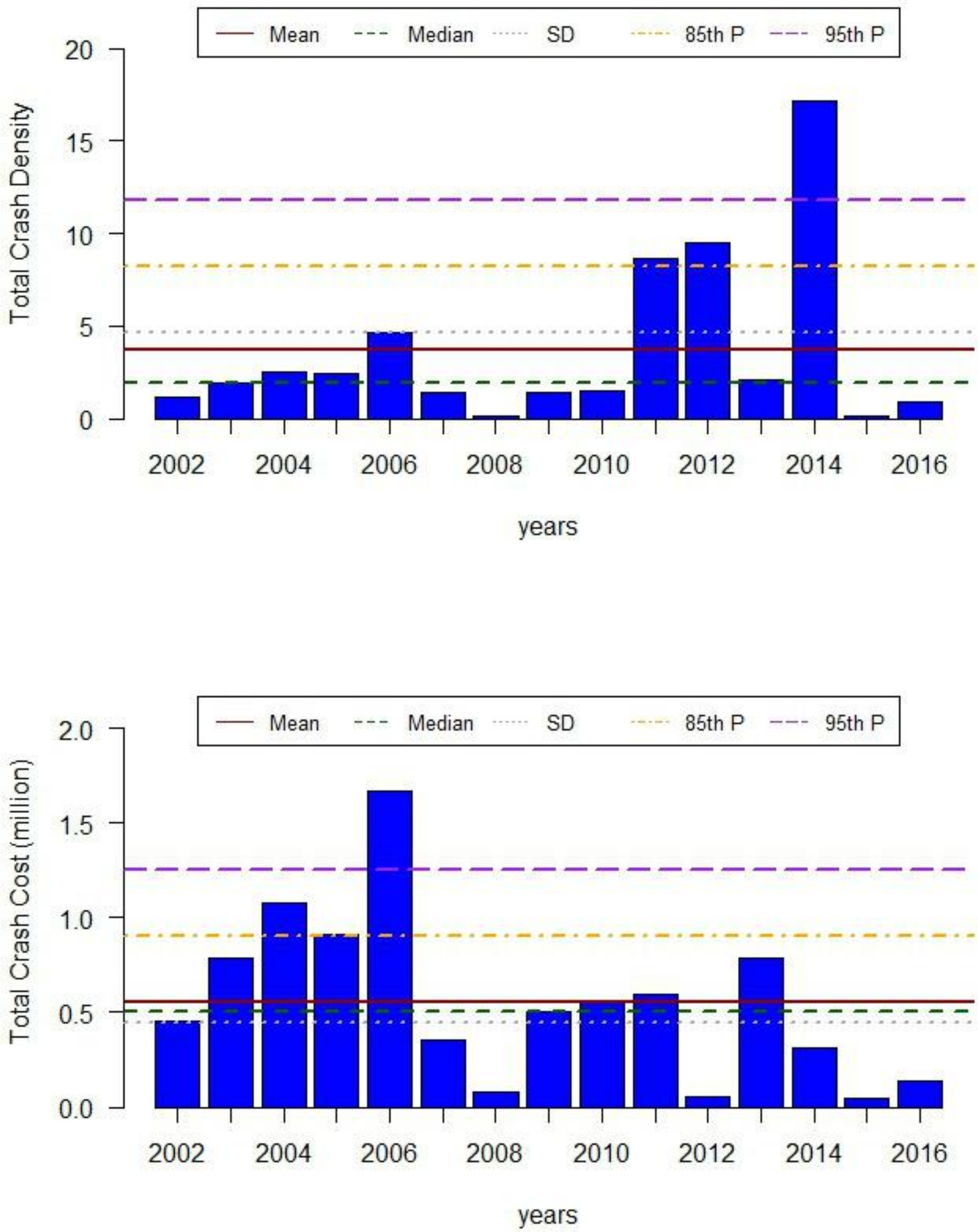
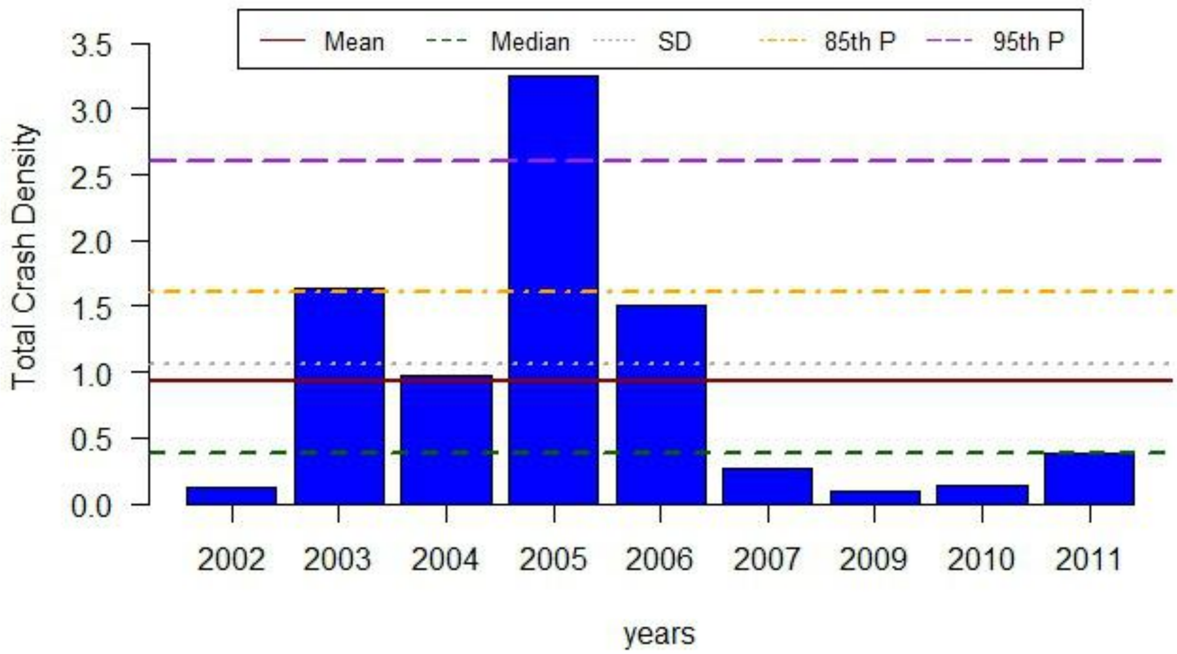


Figure 128 Crash Performance Measure: Greene County



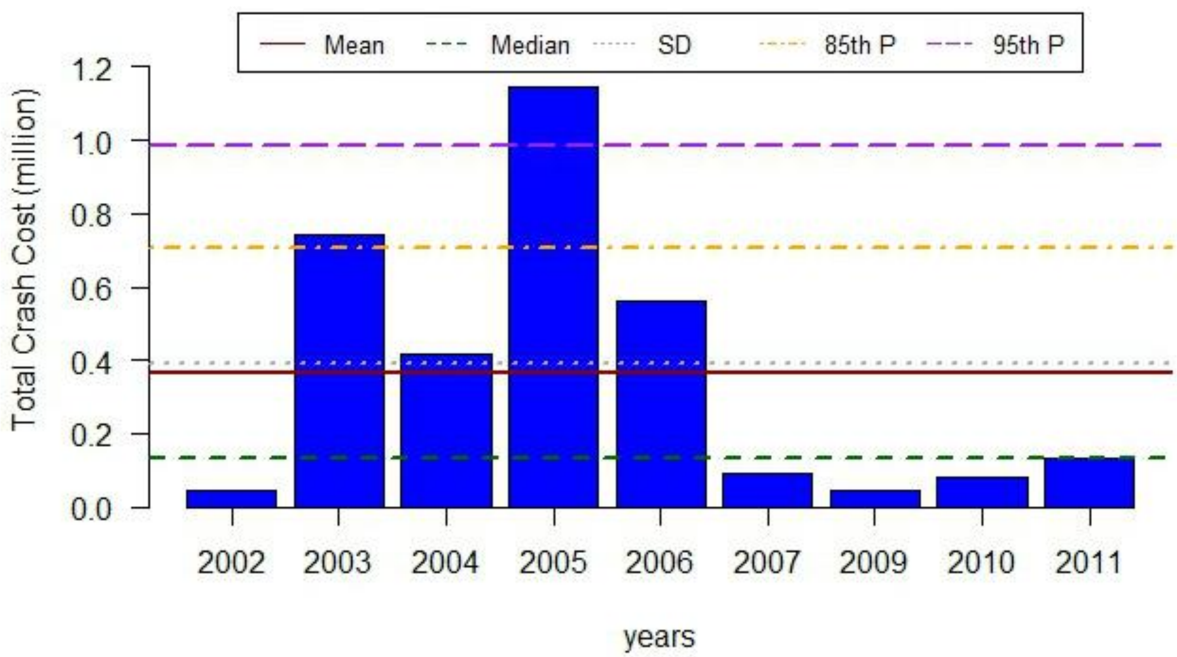
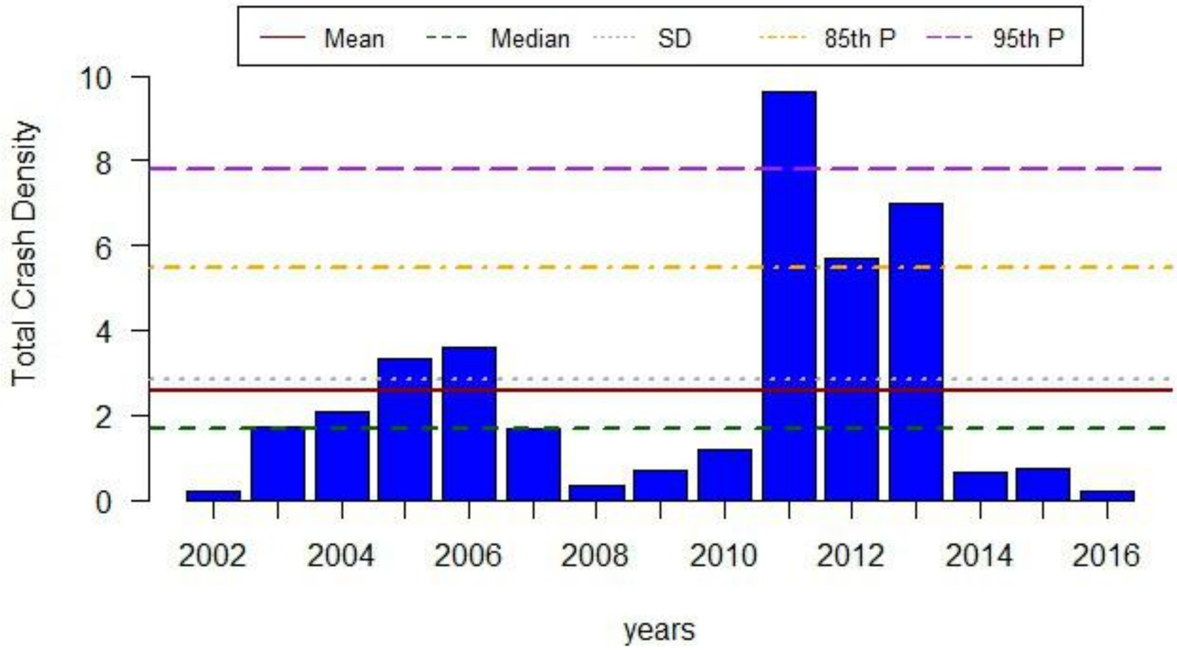


Figure 129 Crash Performance Measure: Grundy County



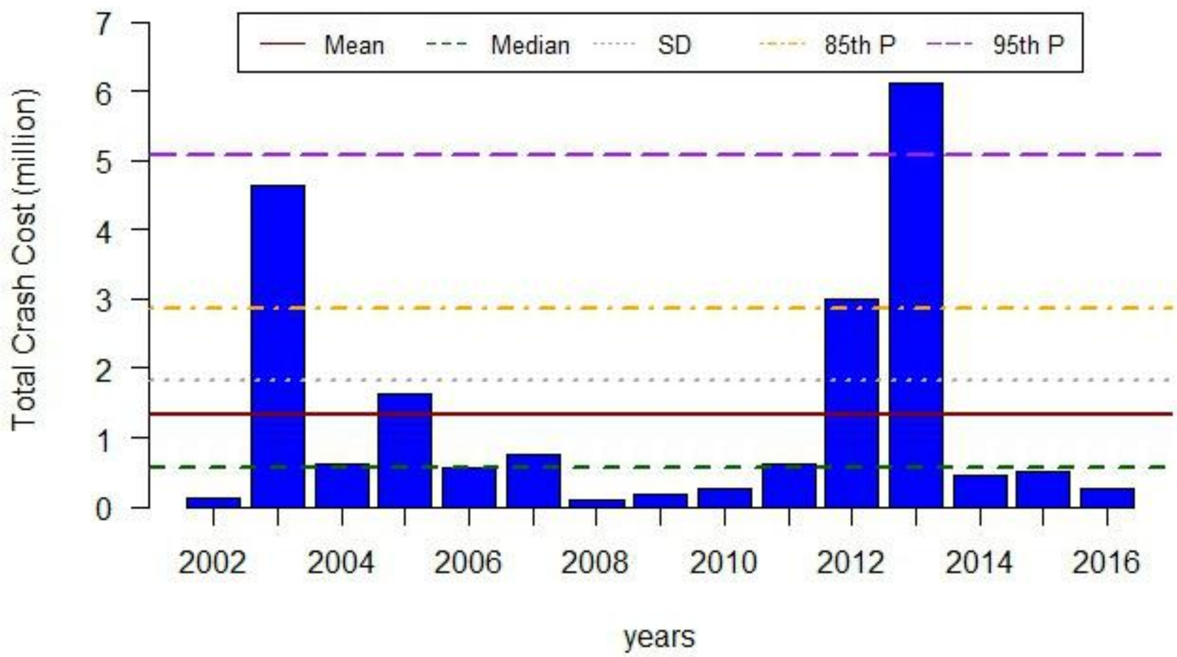
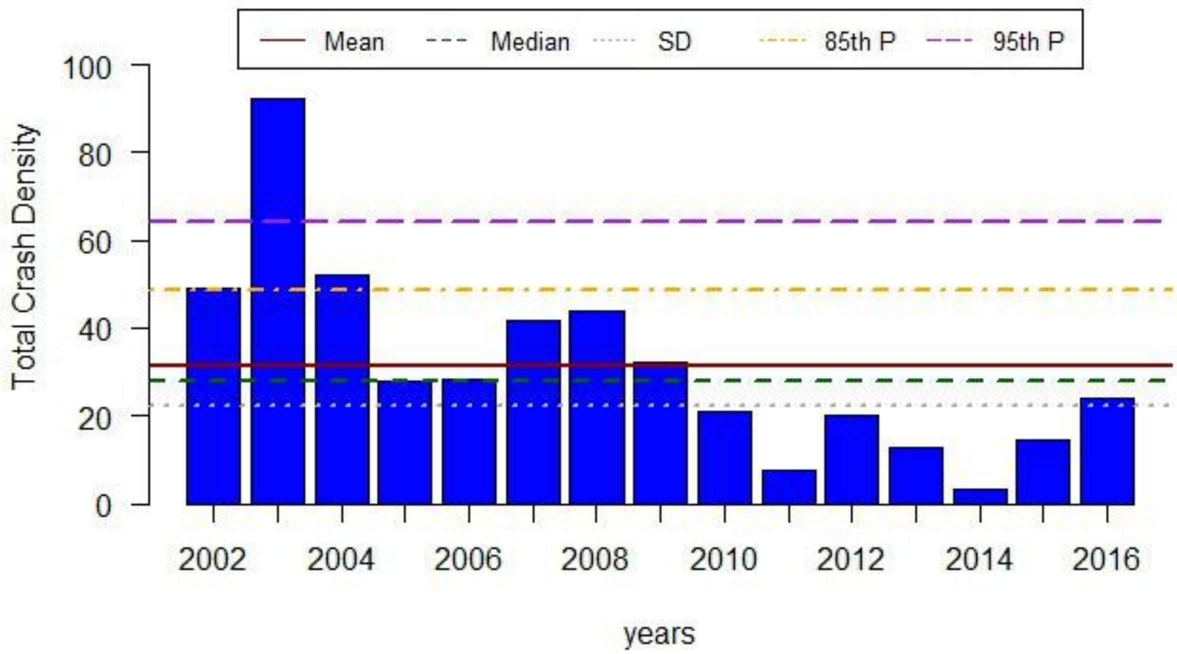


Figure 130 Crash Performance Measure: Hamblen County



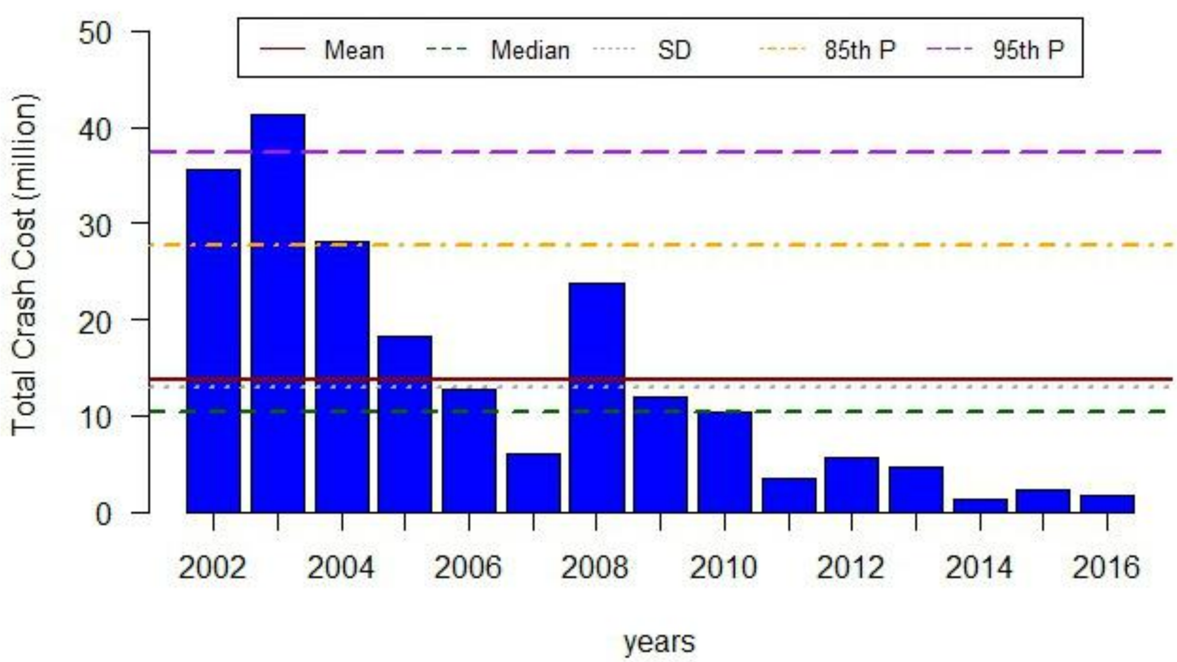
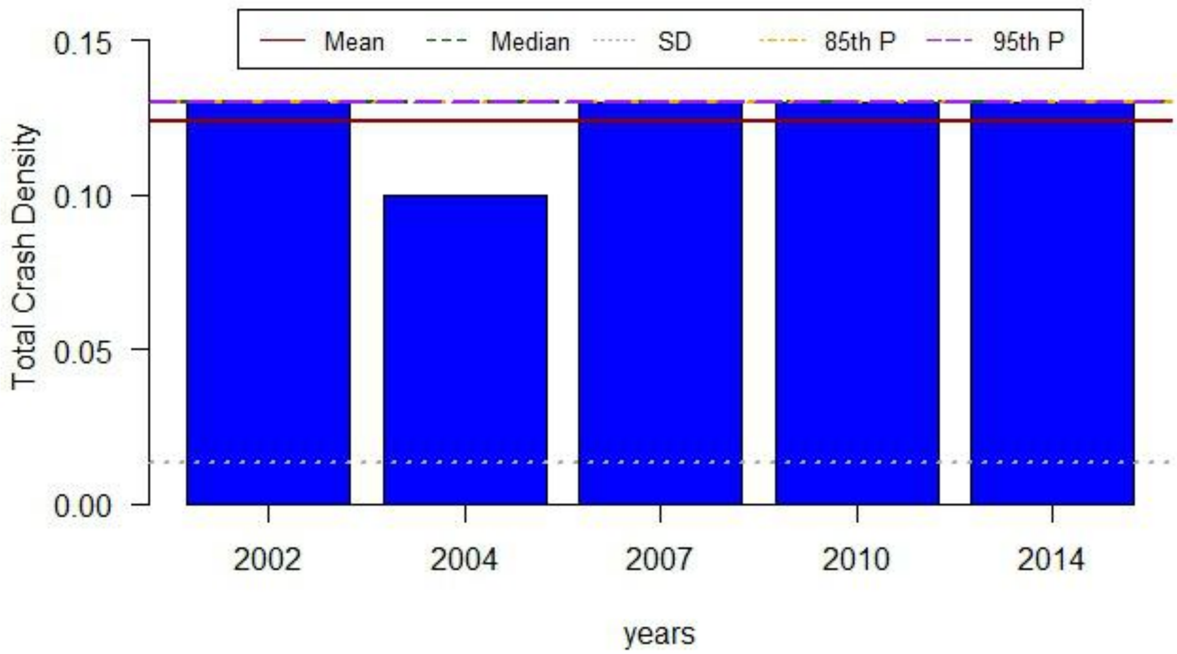


Figure 131 Crash Performance Measure: Hamilton County



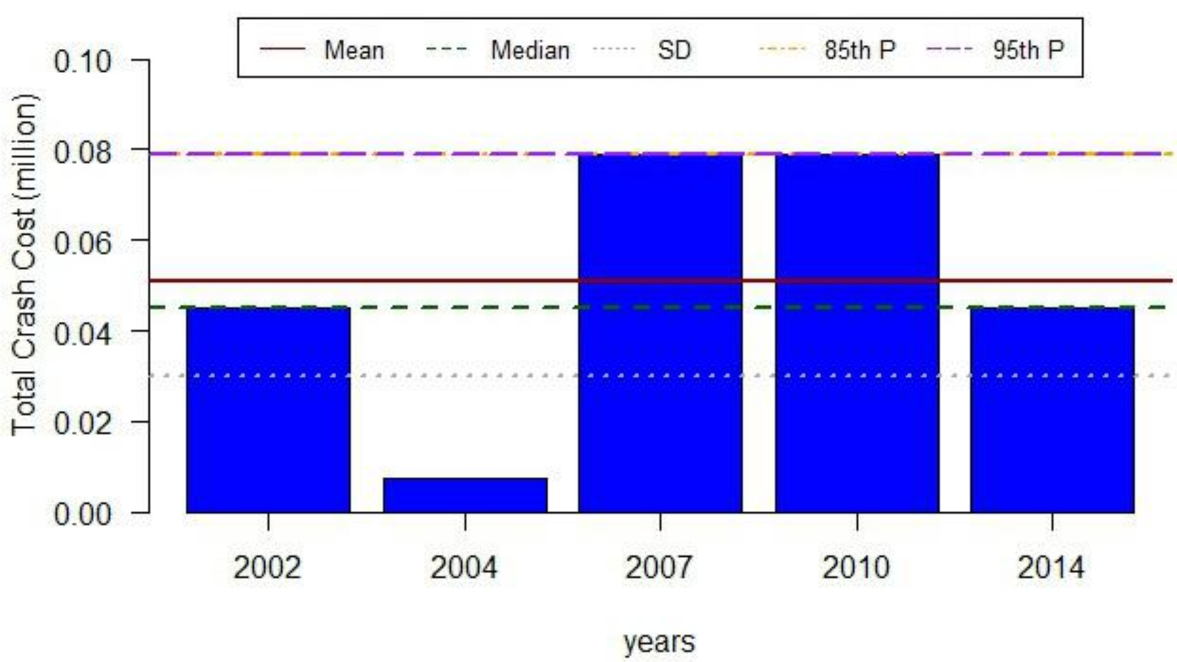
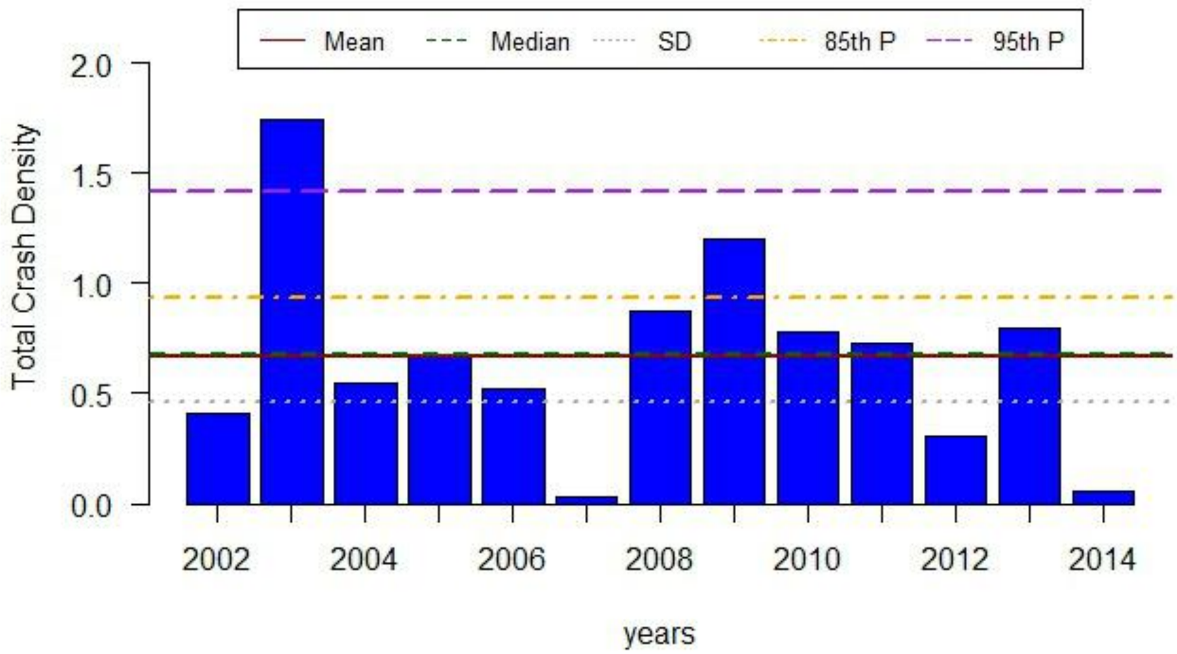


Figure 132 Crash Performance Measure: Hancock County



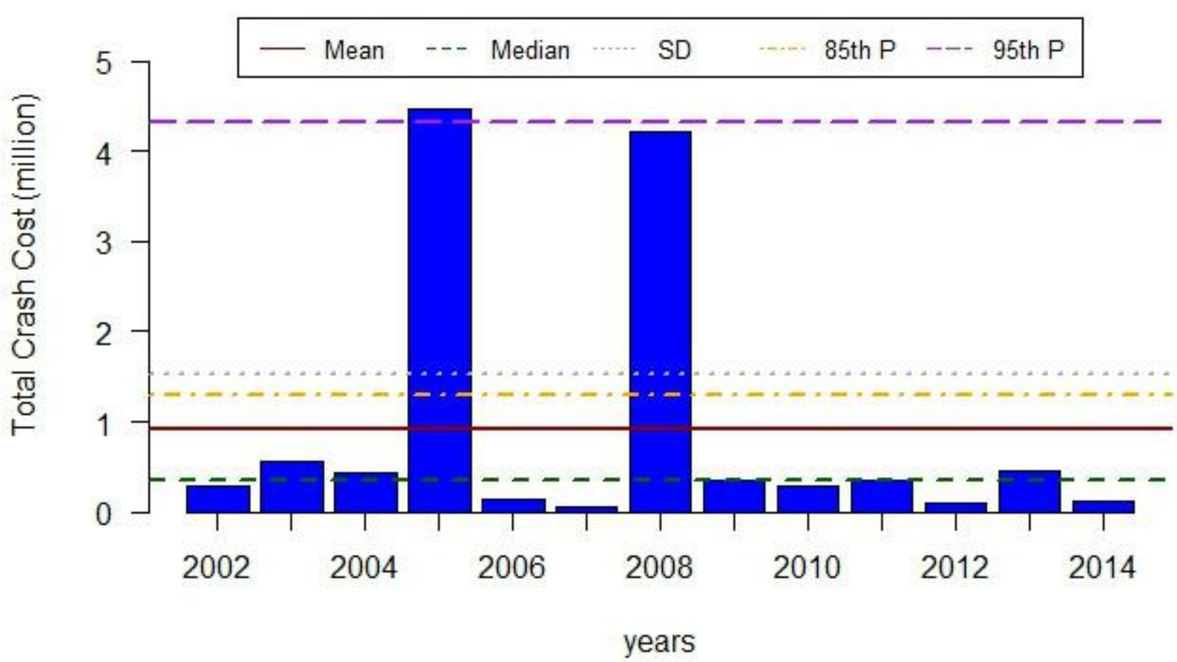


Figure 133 Crash Performance Measure: Hardeman County

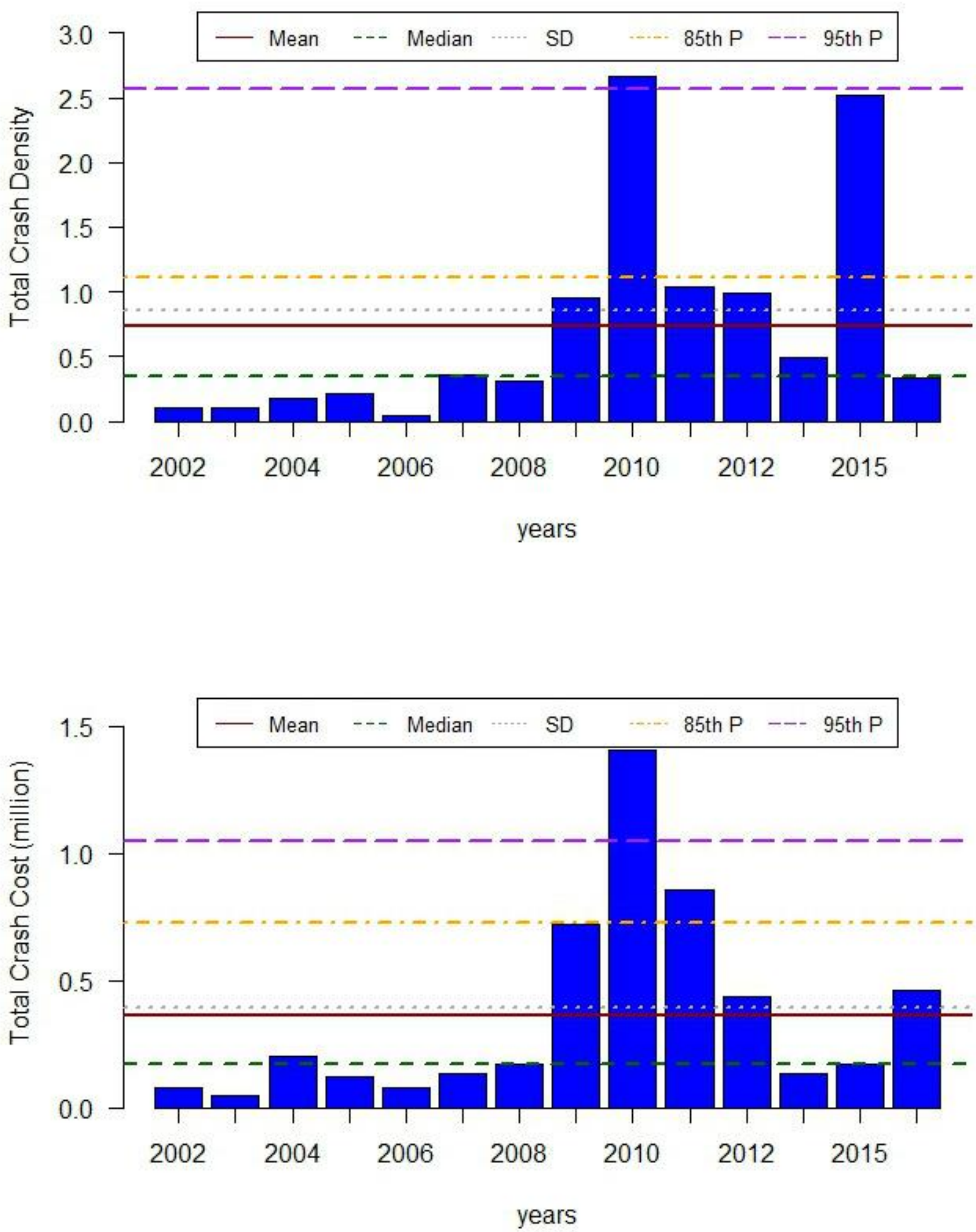
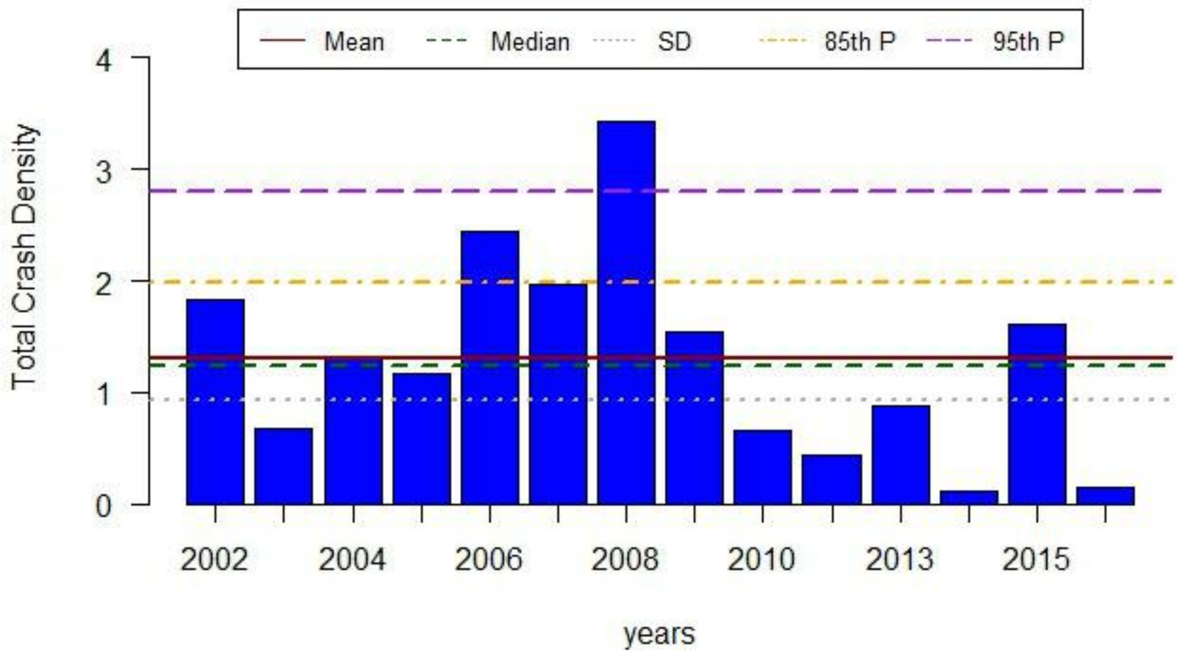


Figure 134 Crash Performance Measure: Hardin County



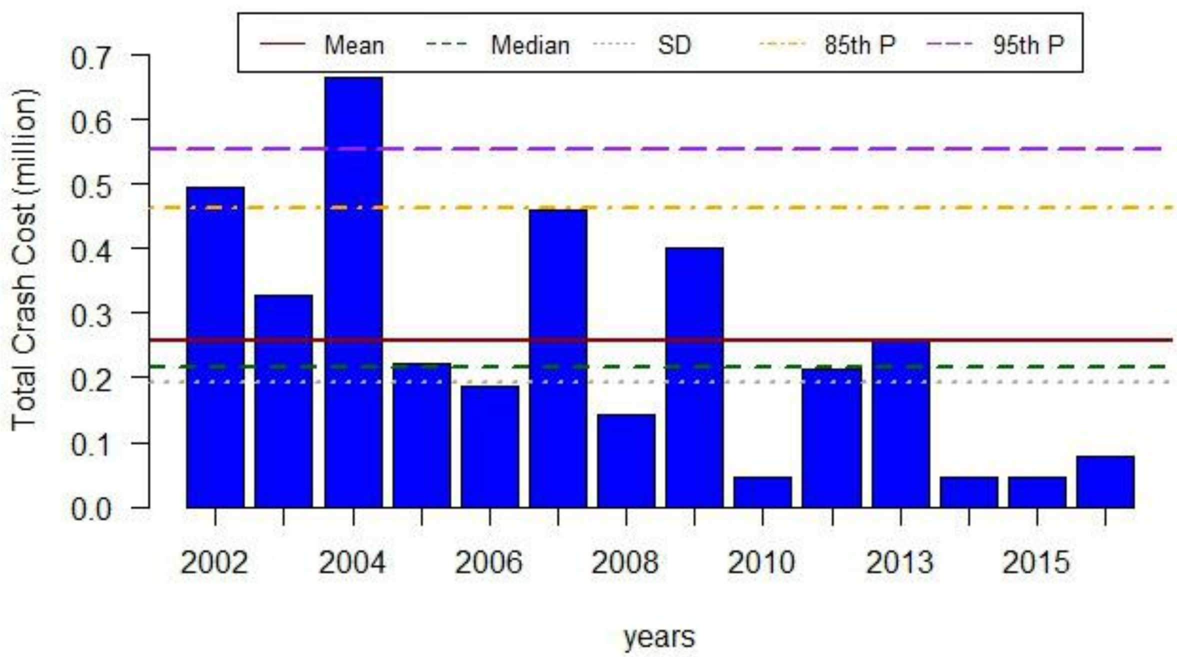
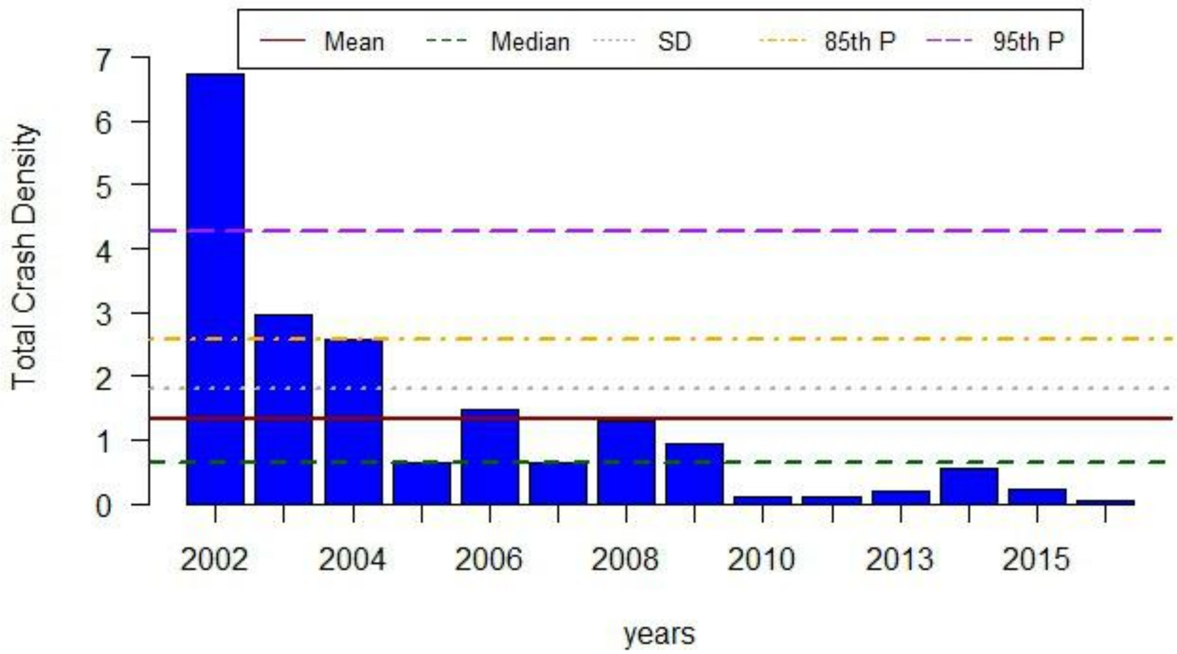


Figure 135 Crash Performance Measure: Hawkins County



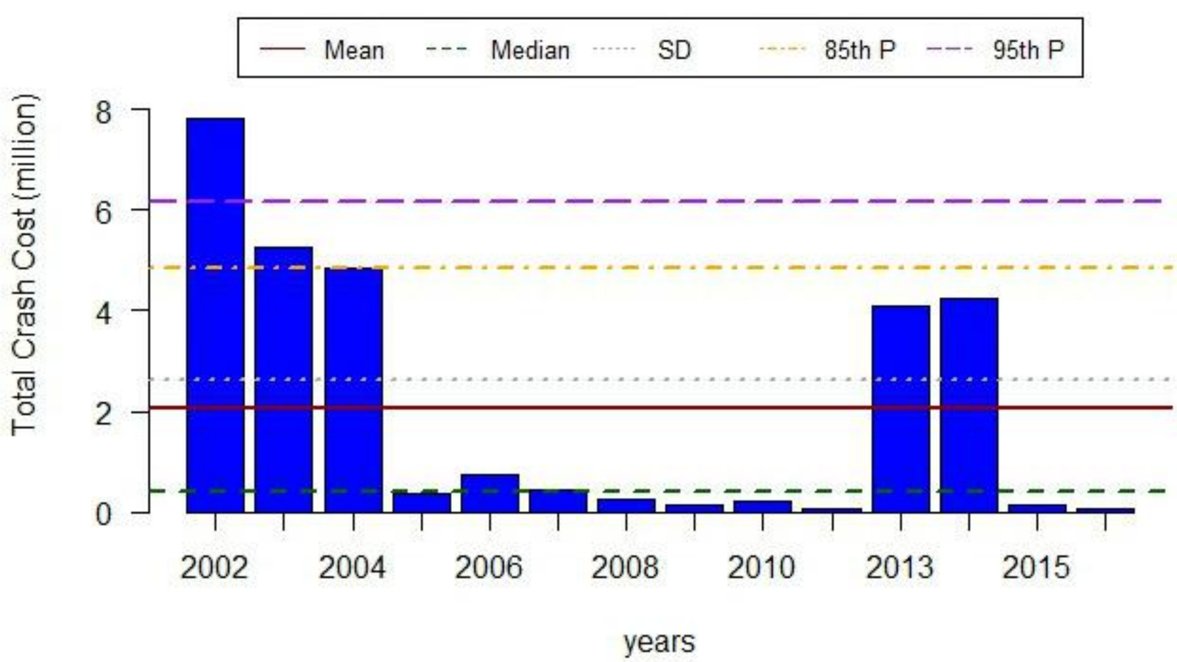


Figure 136 Crash Performance Measure: Haywood County

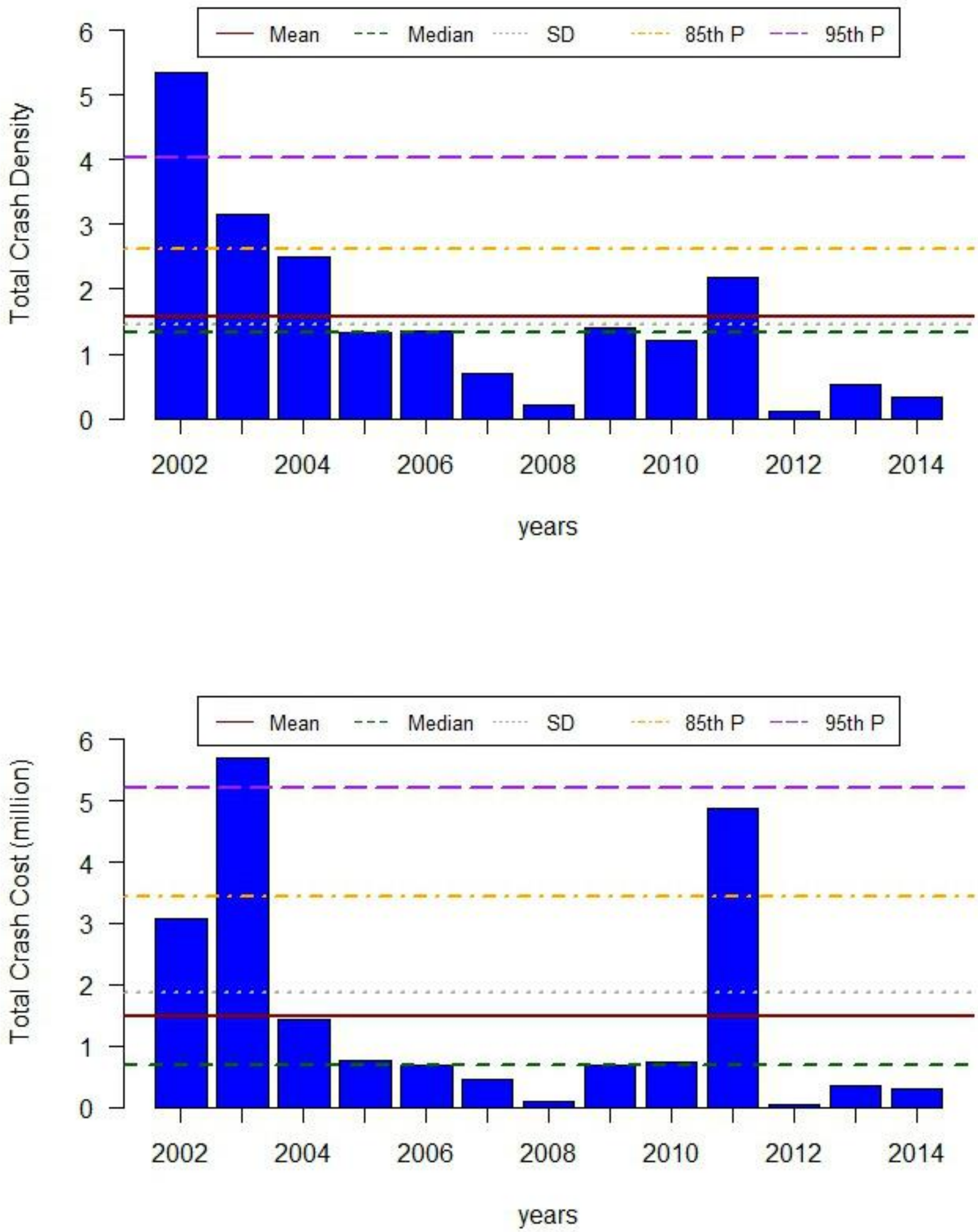
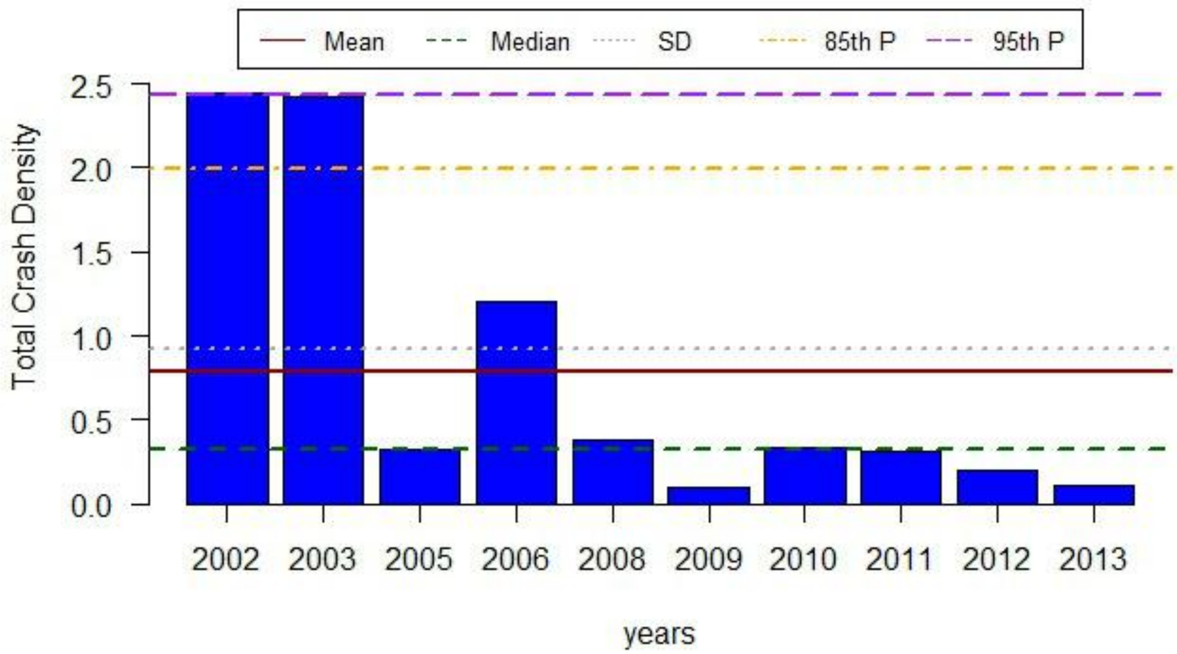


Figure 137 Crash Performance Measure: Henderson County



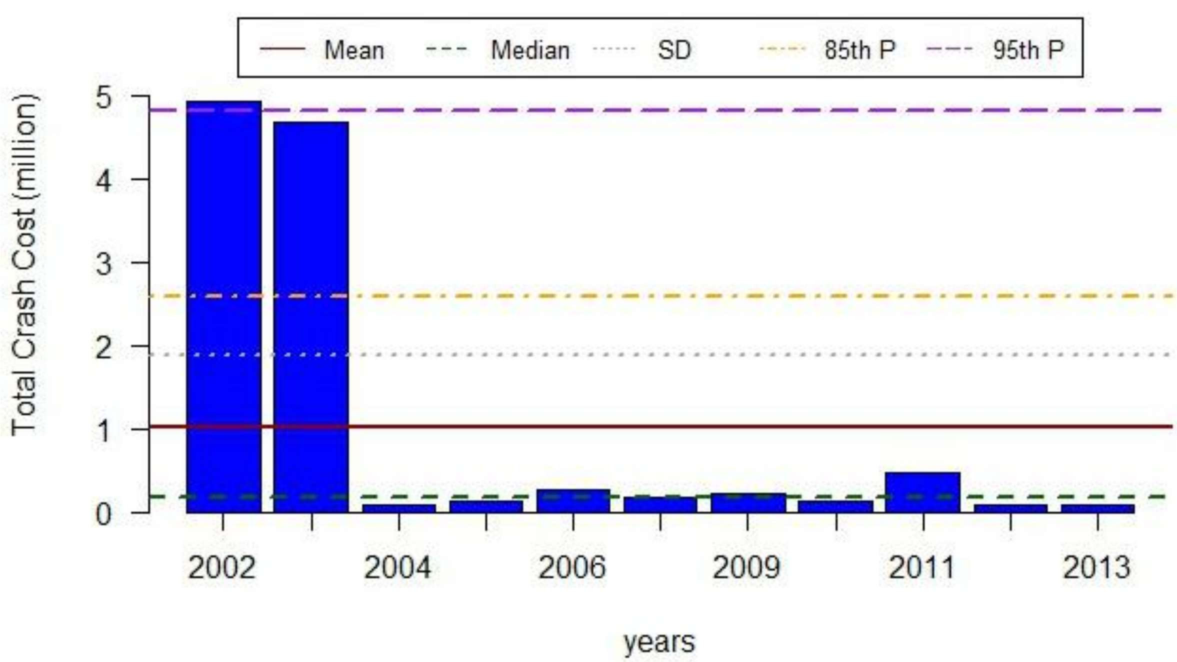
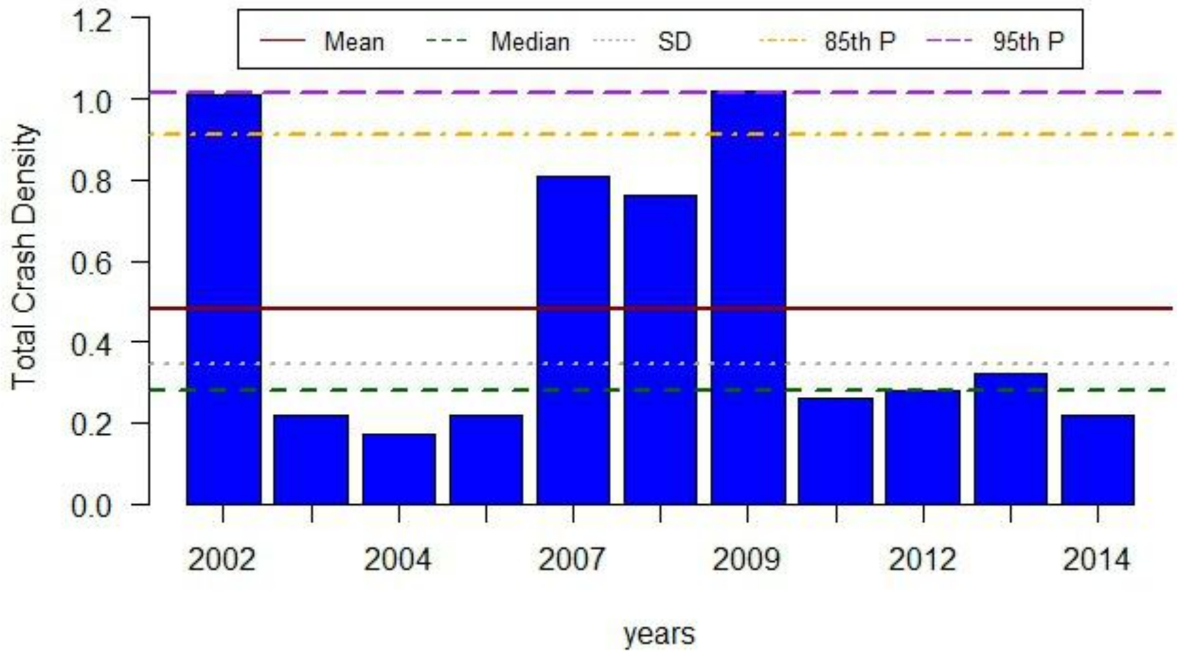


Figure 138 Crash Performance Measure: Henry County



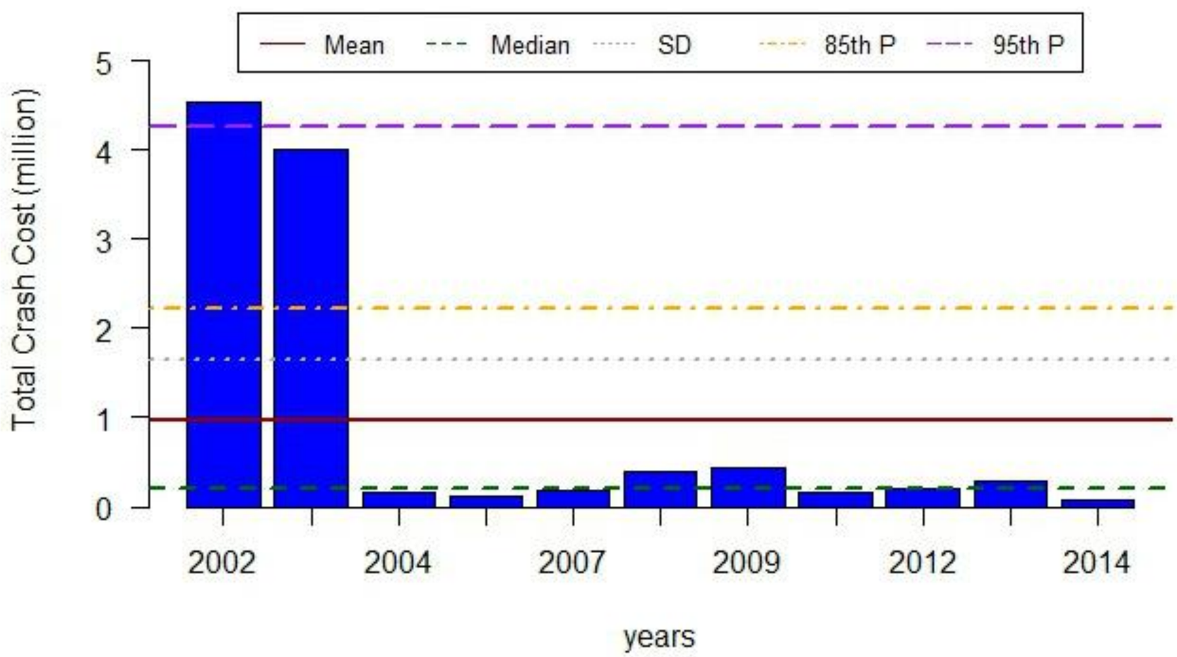
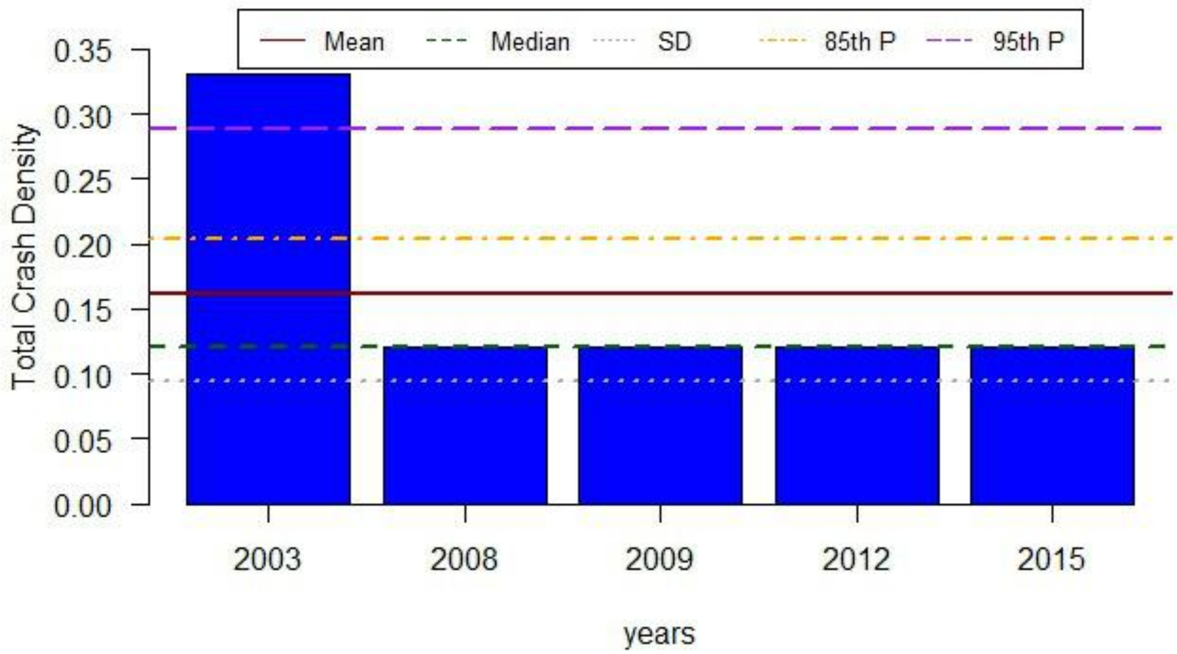


Figure 139 Crash Performance Measure: Hickman County



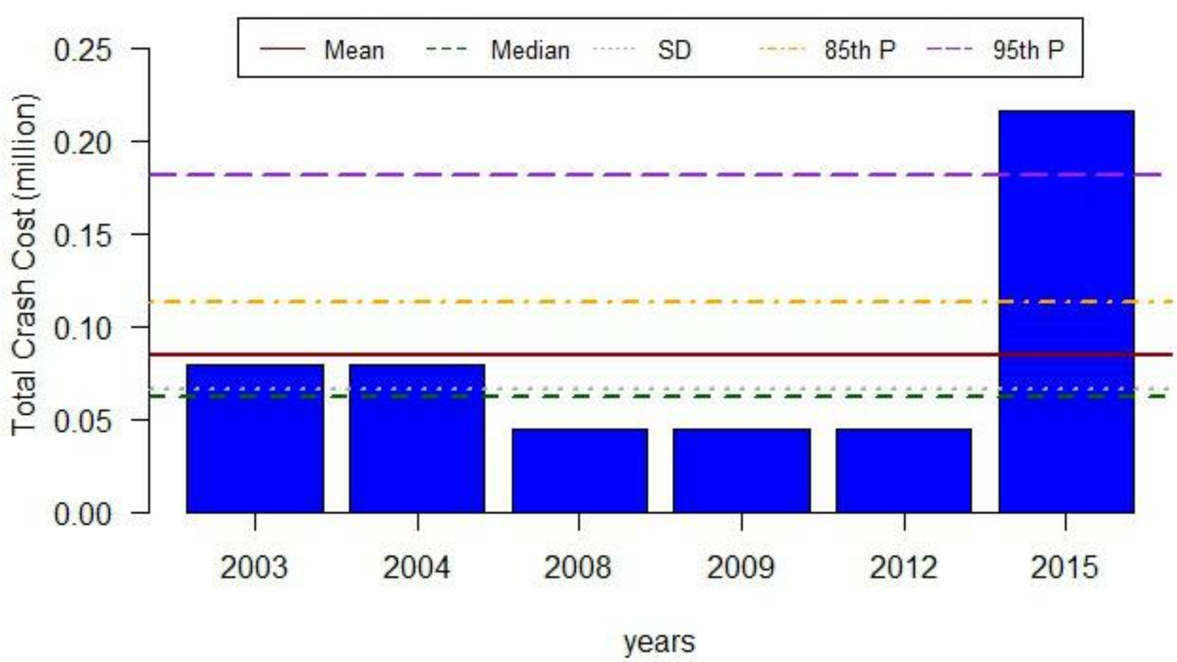


Figure 140 Crash Performance Measure: Houston County

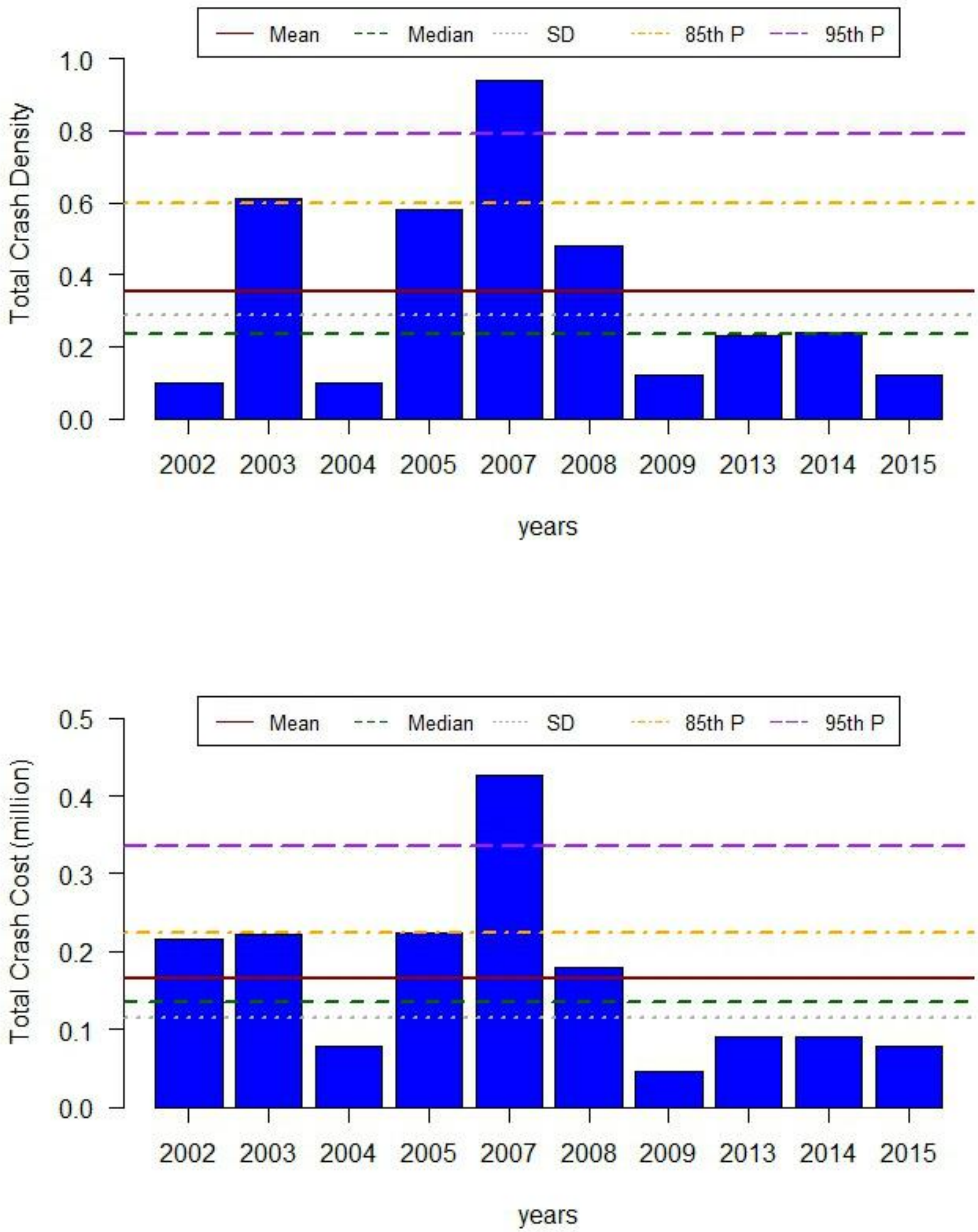
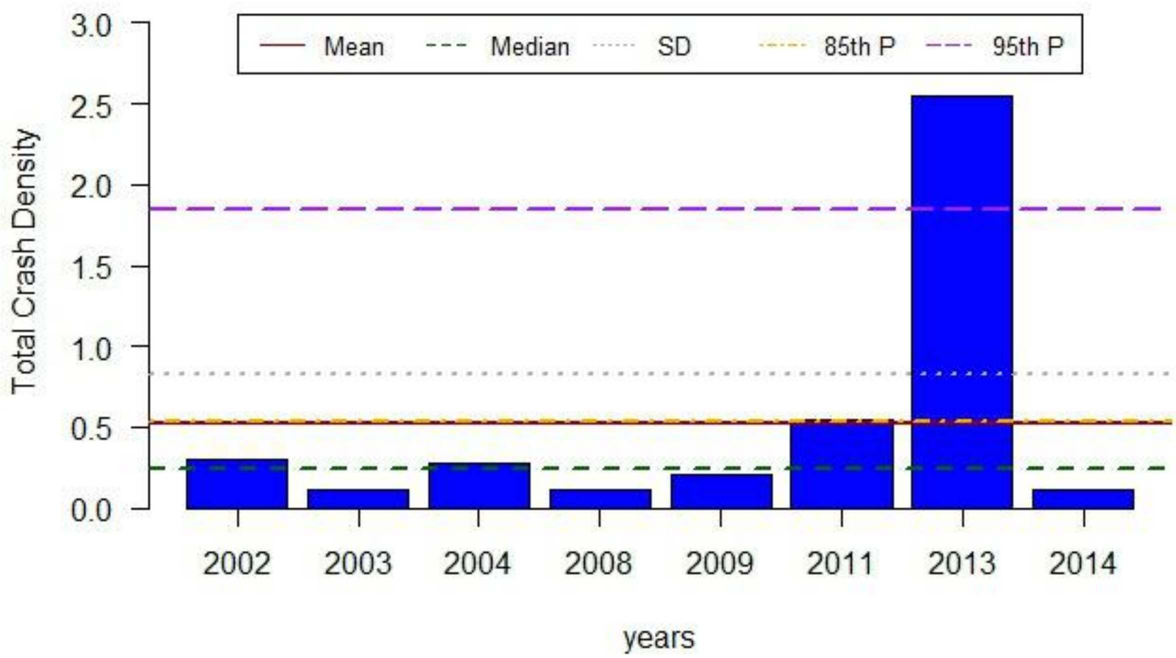


Figure 141 Crash Performance Measure: Humphreys County



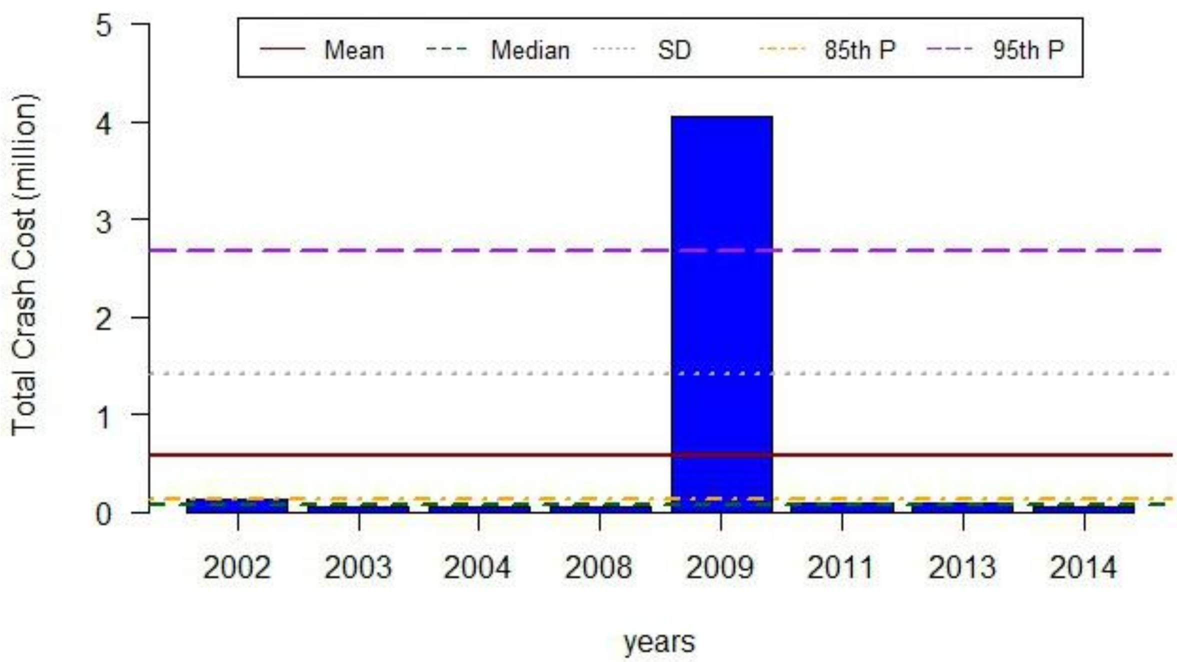
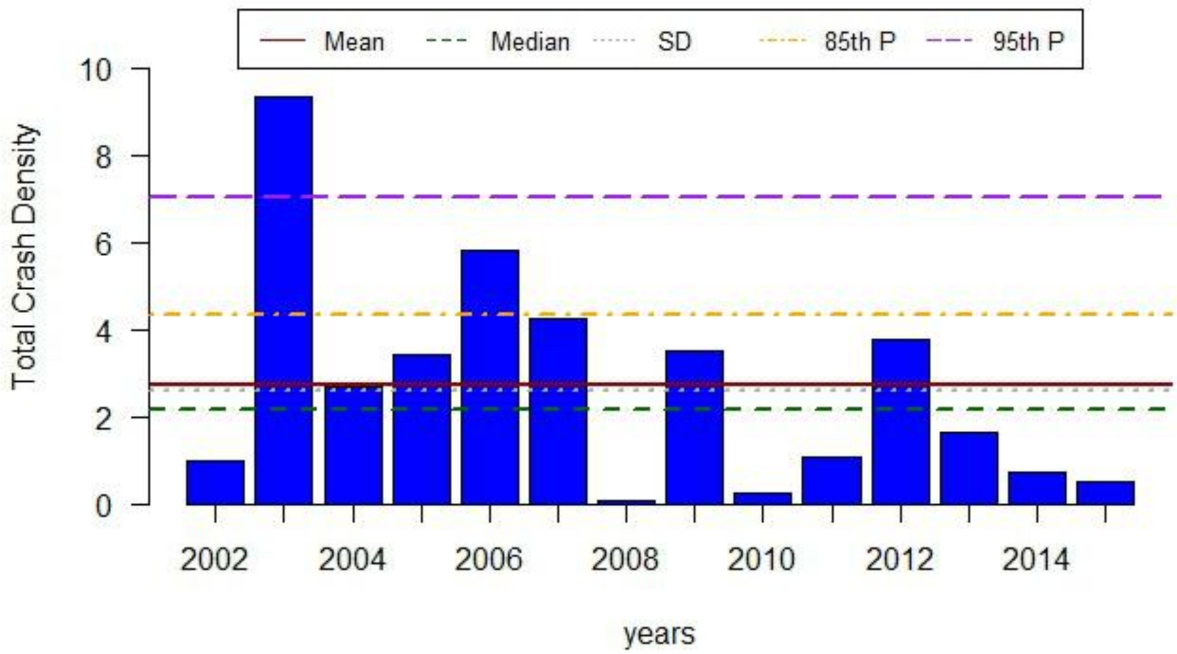


Figure 142 Crash Performance Measure: Jackson County



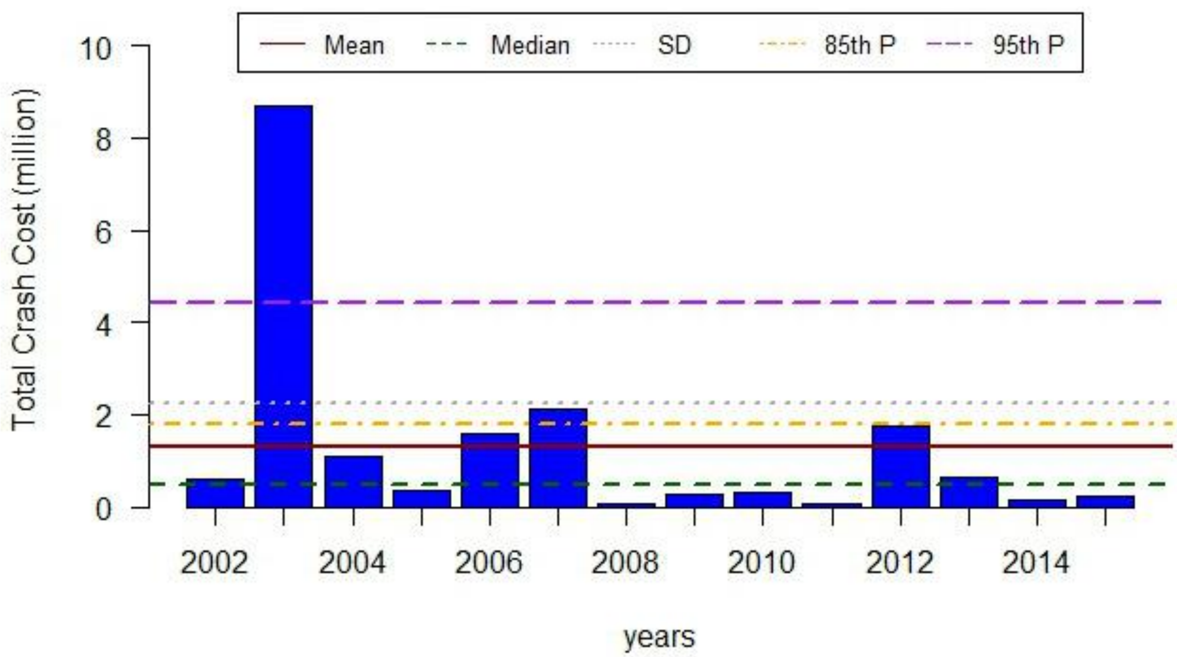
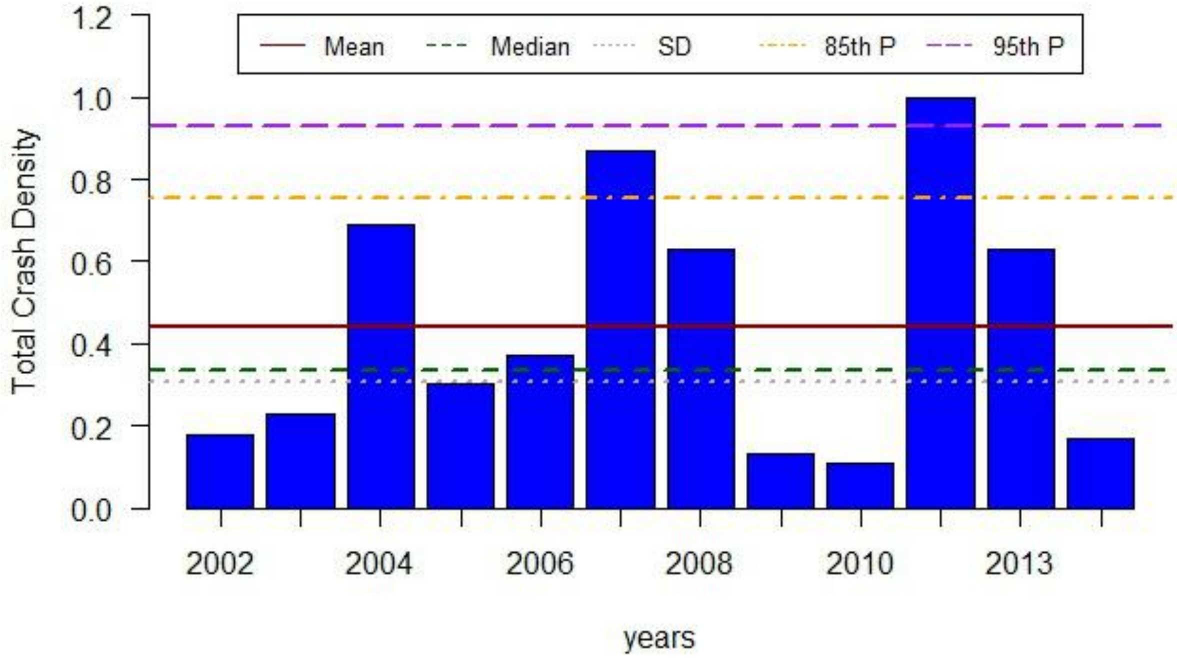


Figure 143 Crash Performance Measure: Jefferson County



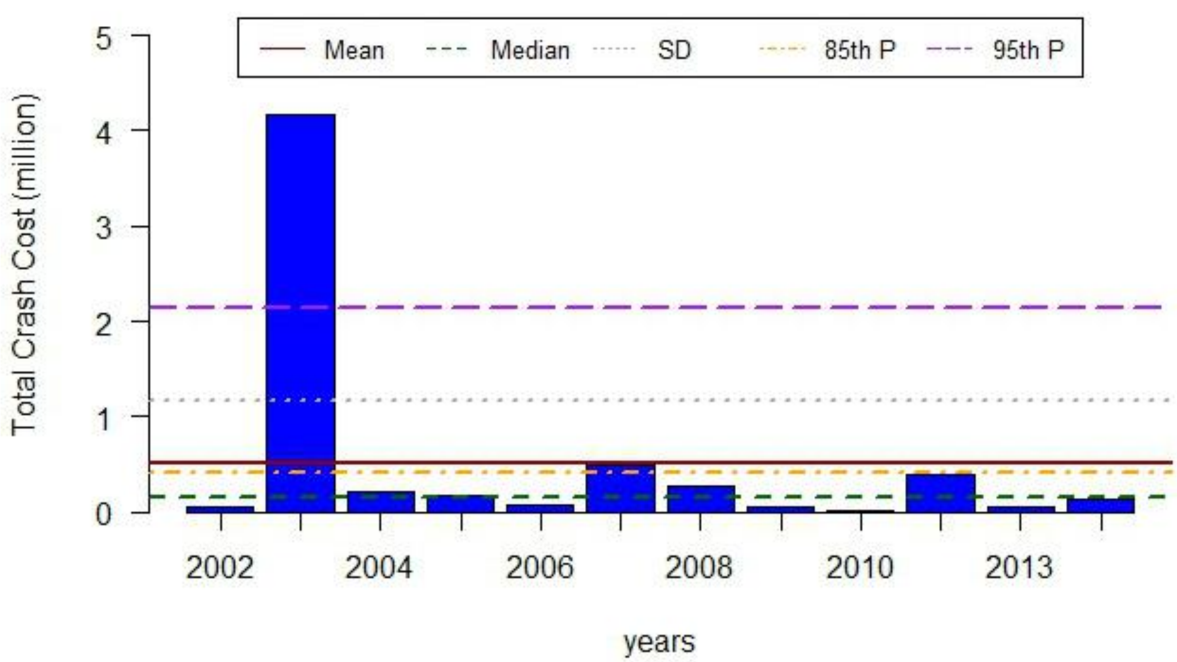
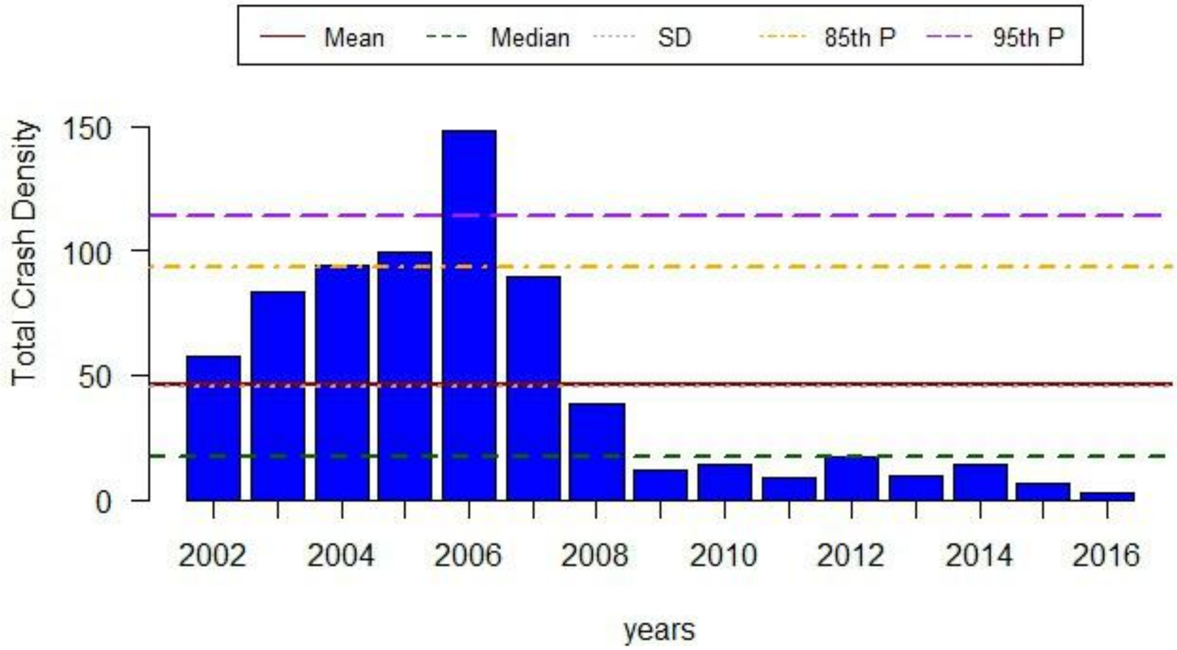


Figure 144 Crash Performance Measure: Johnson County



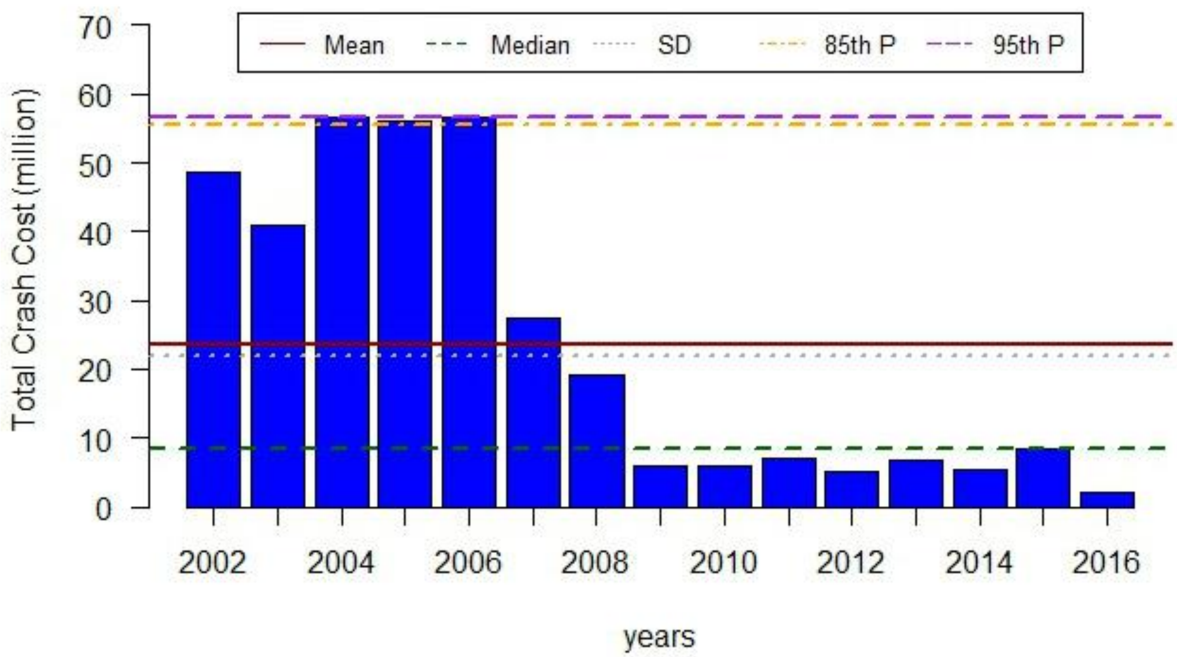
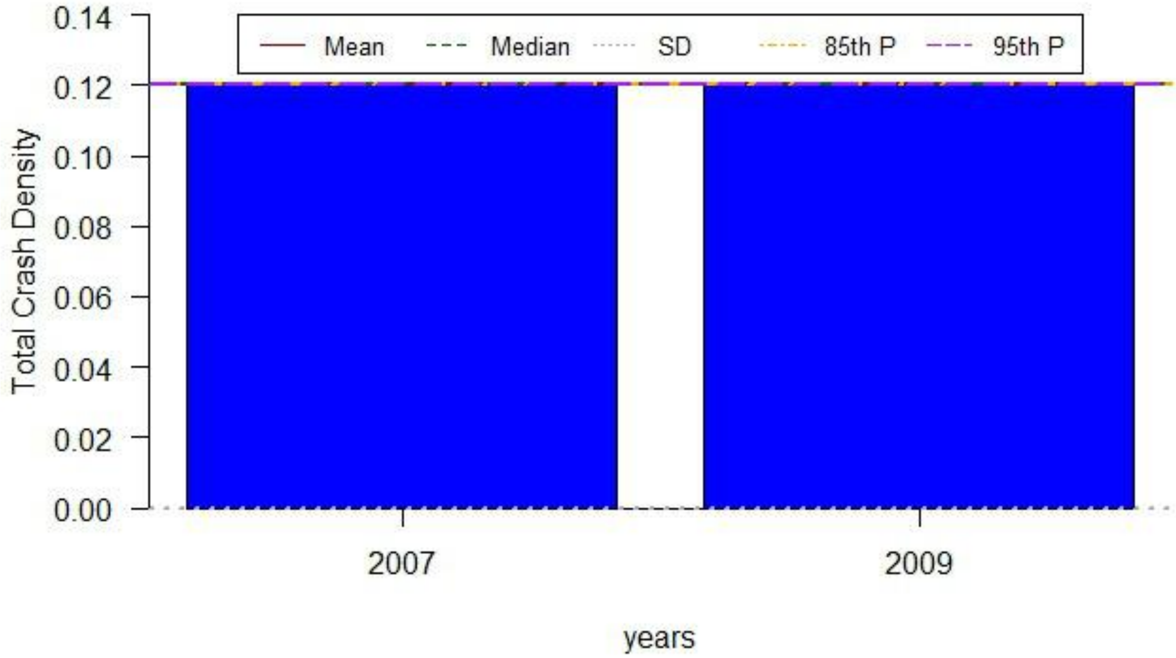


Figure 145 Crash Performance Measure: Knox County



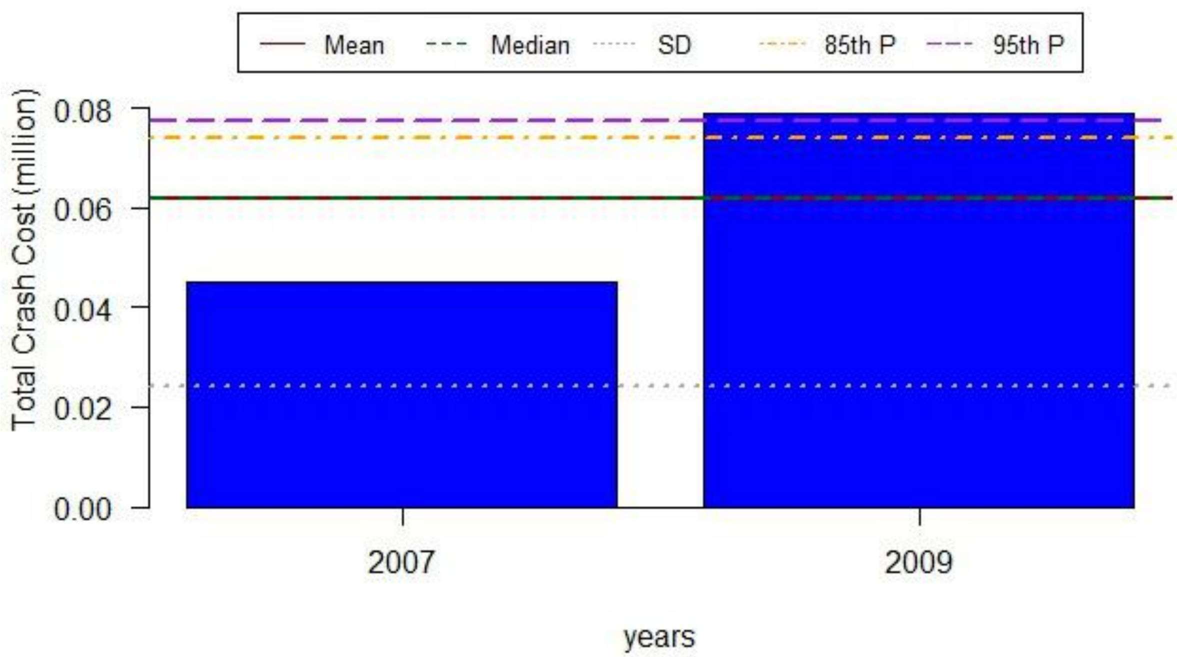
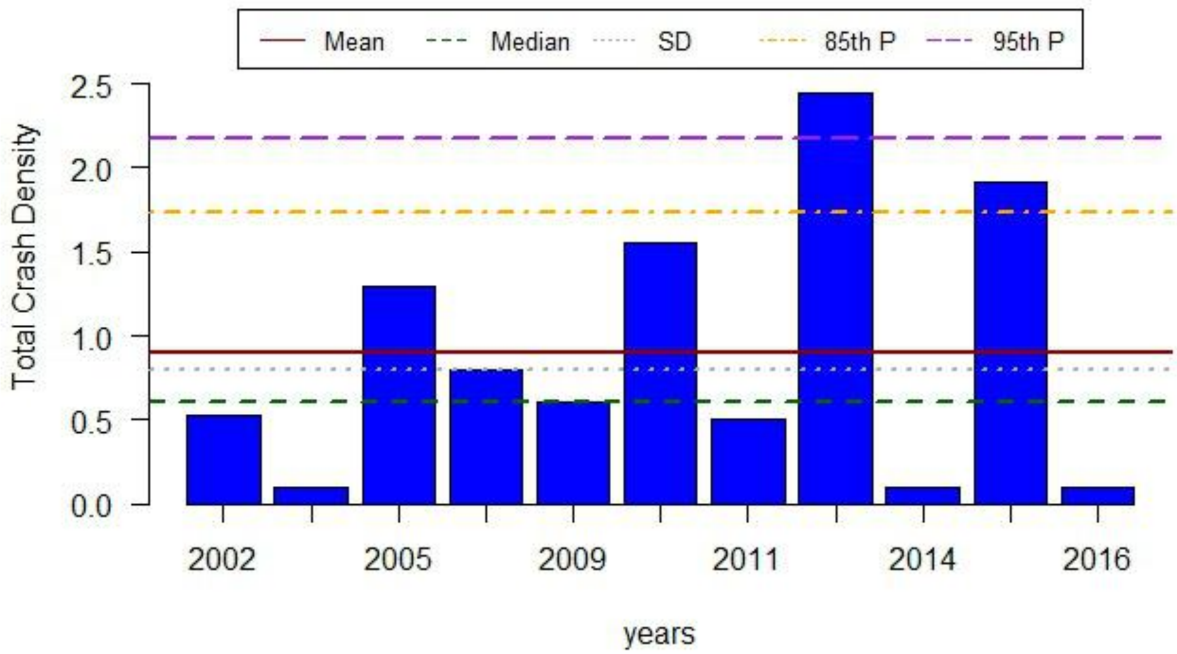


Figure 146 Crash Performance Measure: Lake County



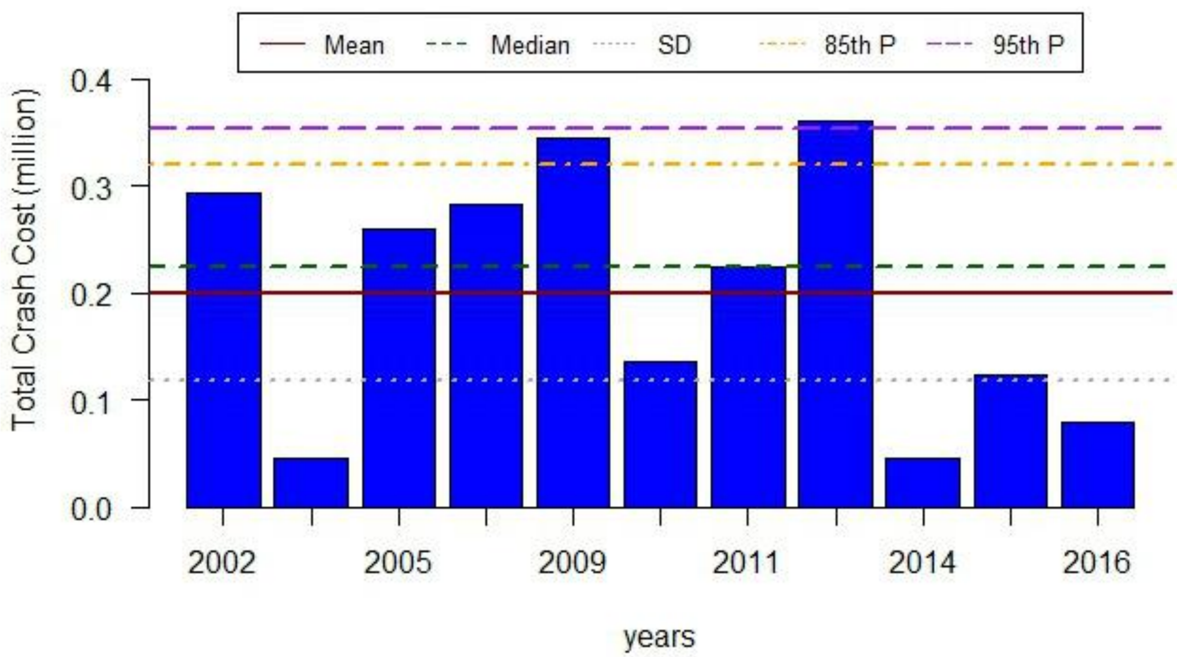
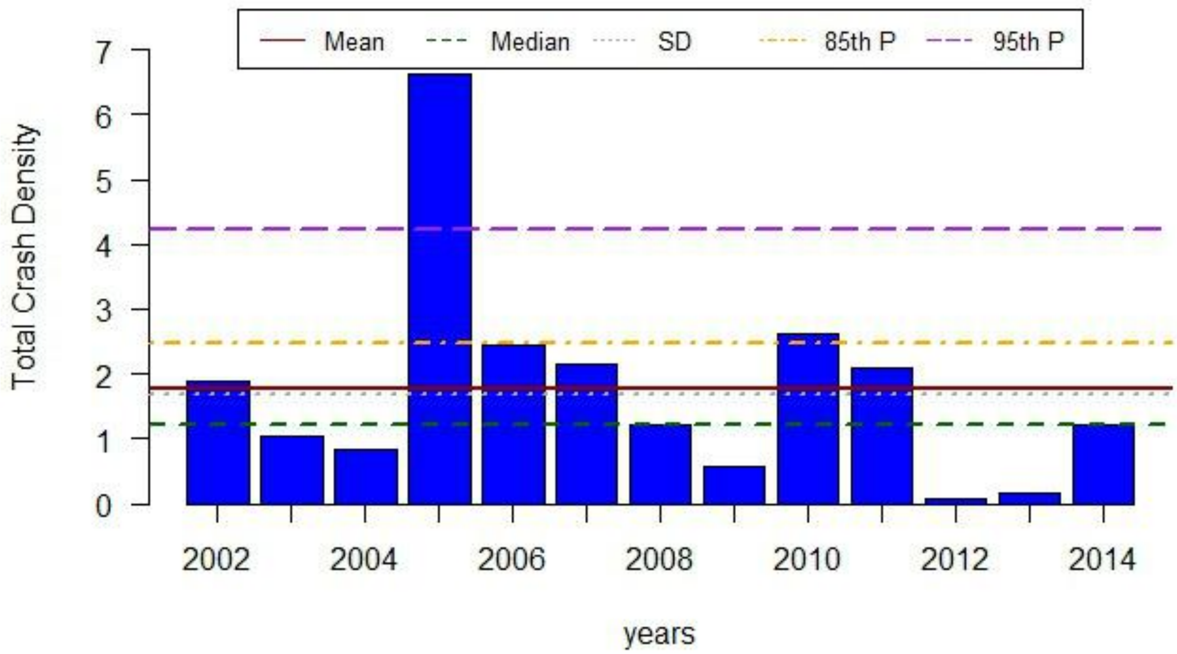


Figure 147 Crash Performance Measure: Lauderdale County



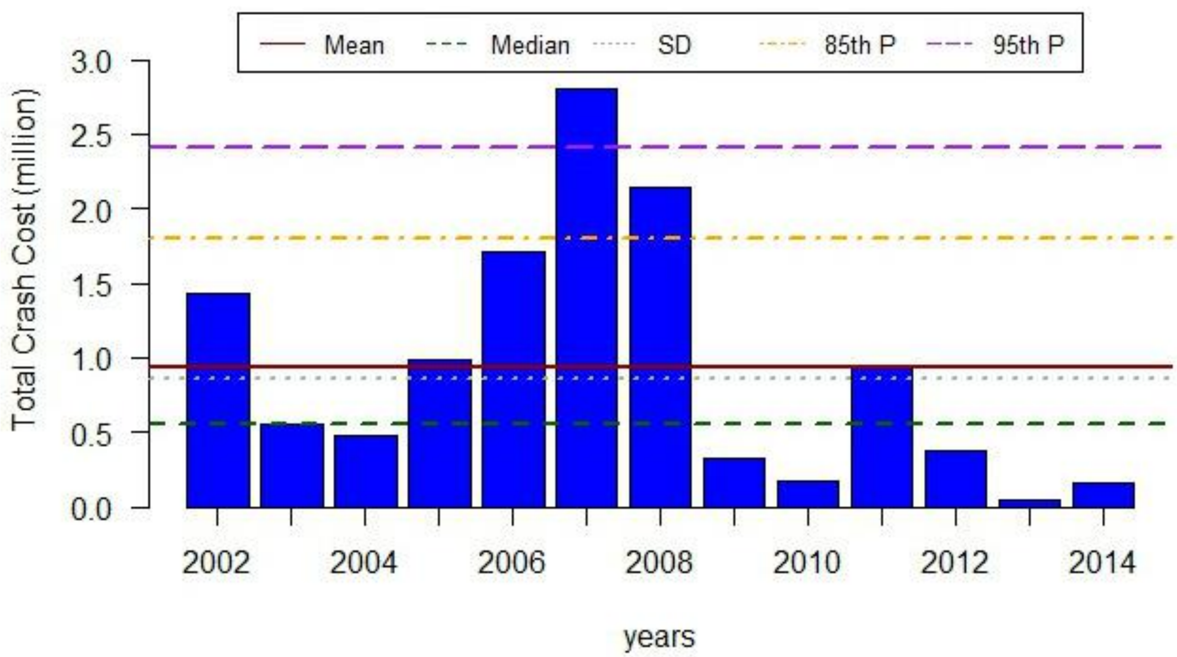
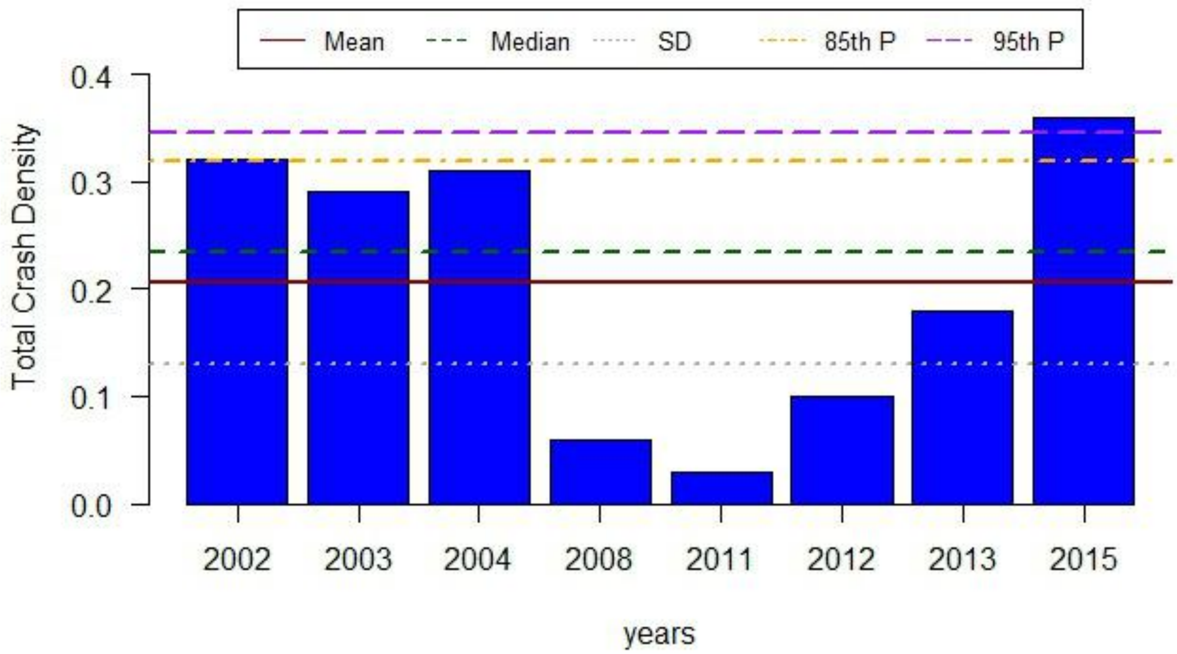


Figure 148 Crash Performance Measure: Lawrence County



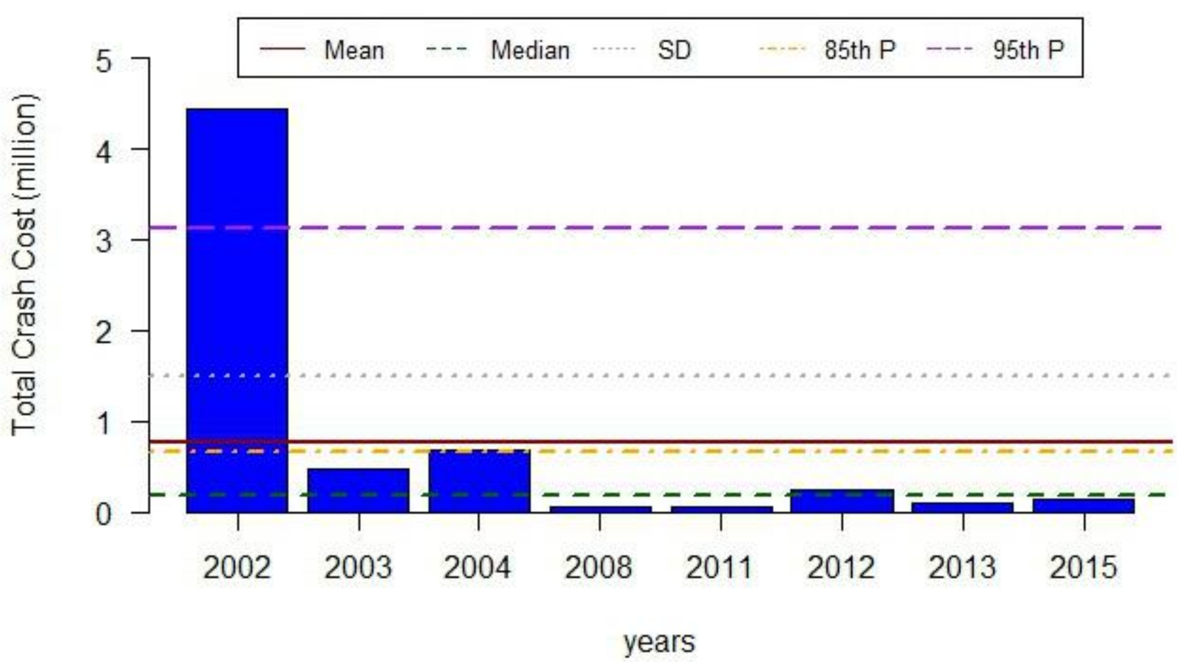
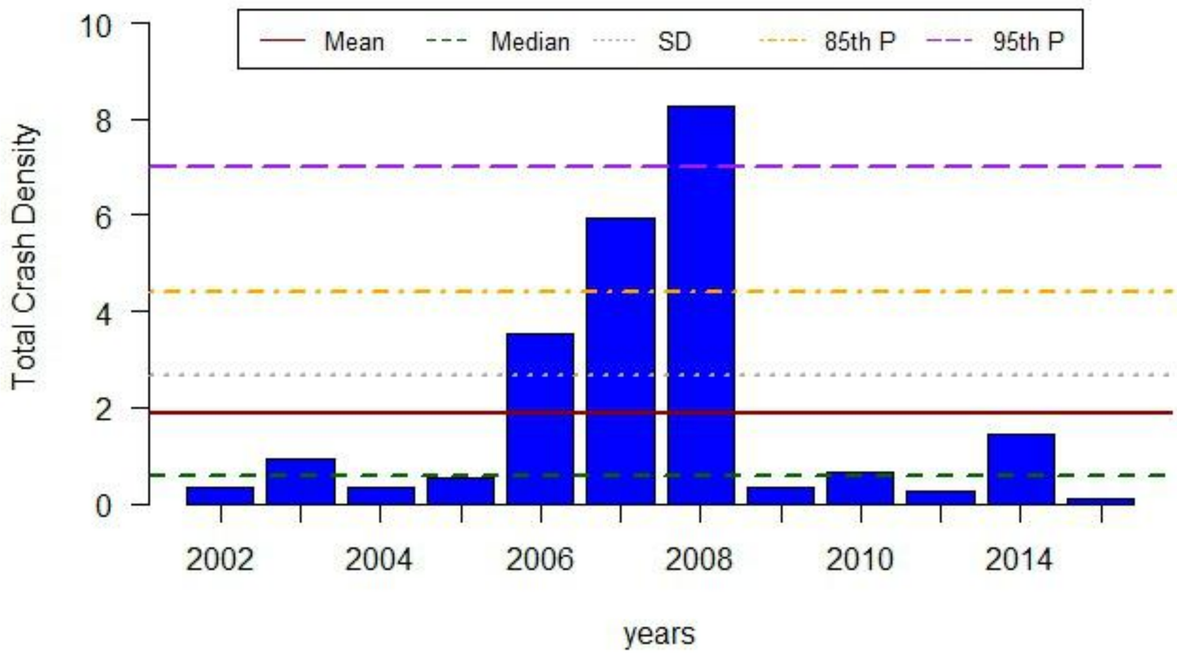


Figure 149 Crash Performance Measure: Lewis County



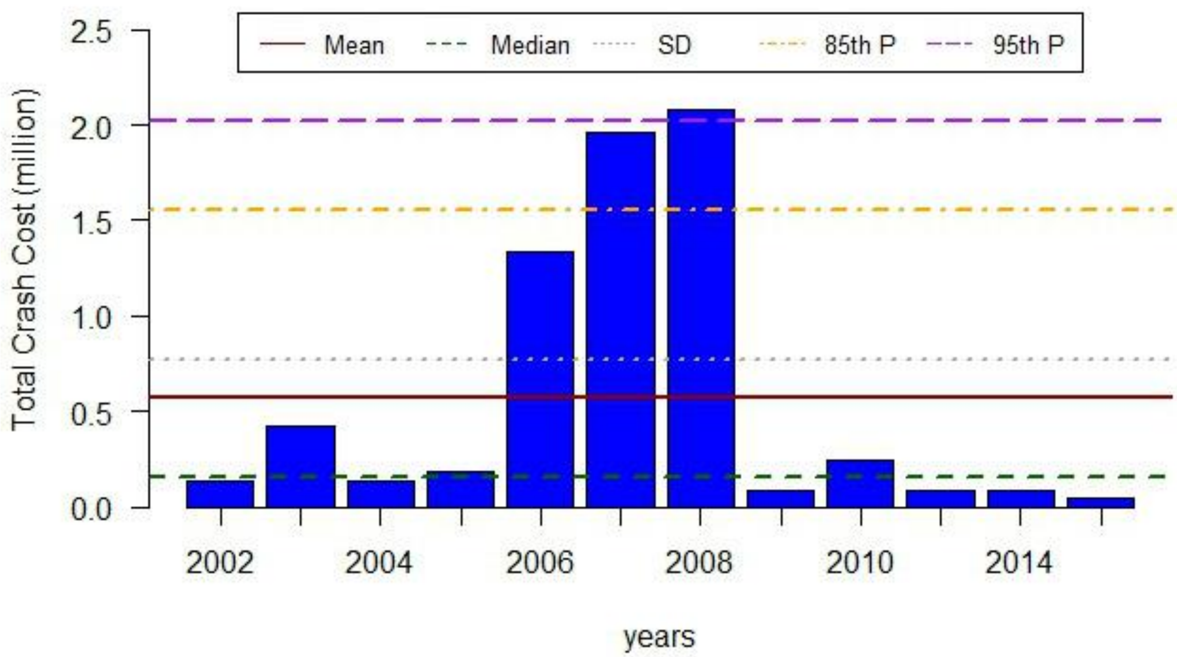


Figure 150 Crash Performance Measure: Lincoln County

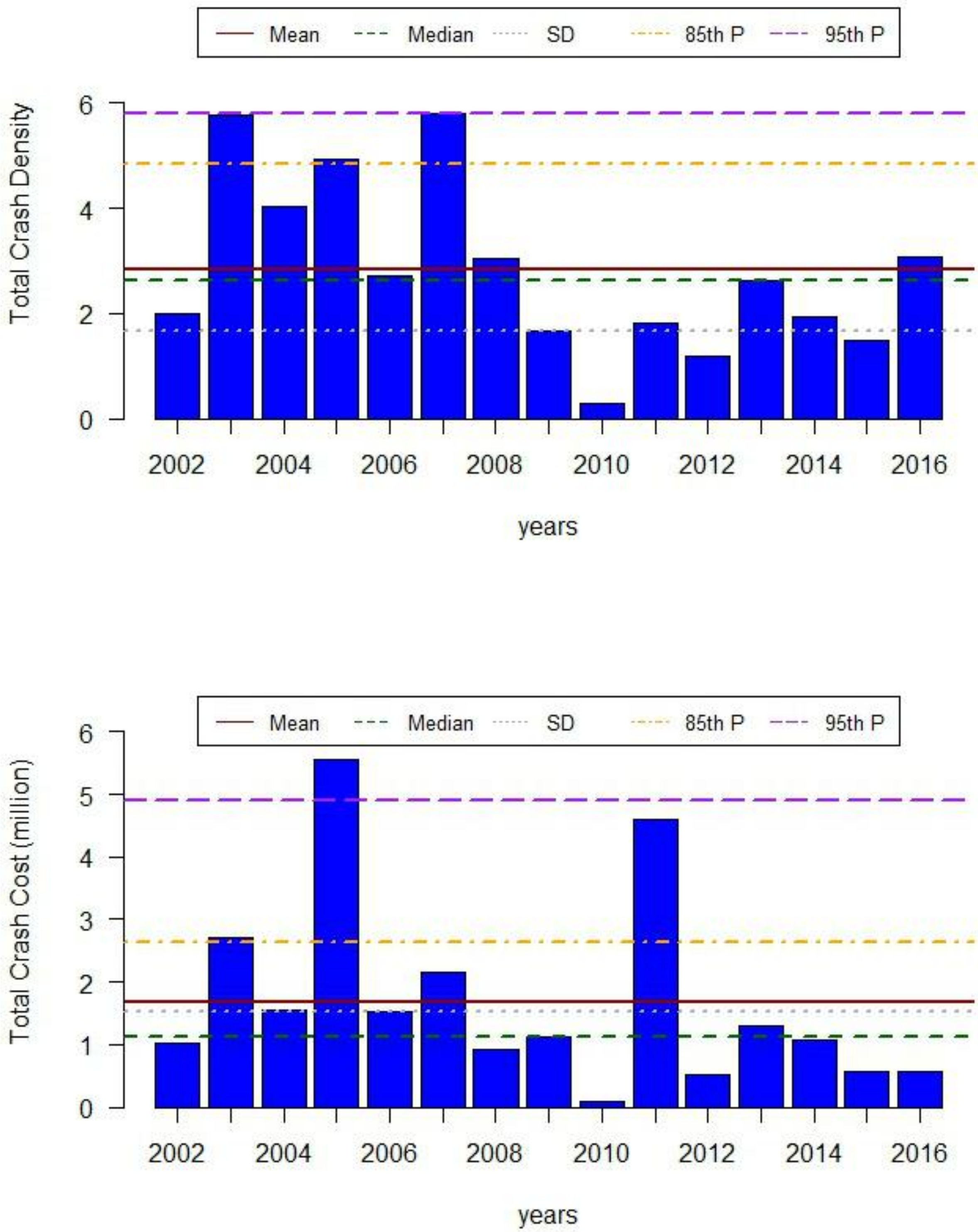
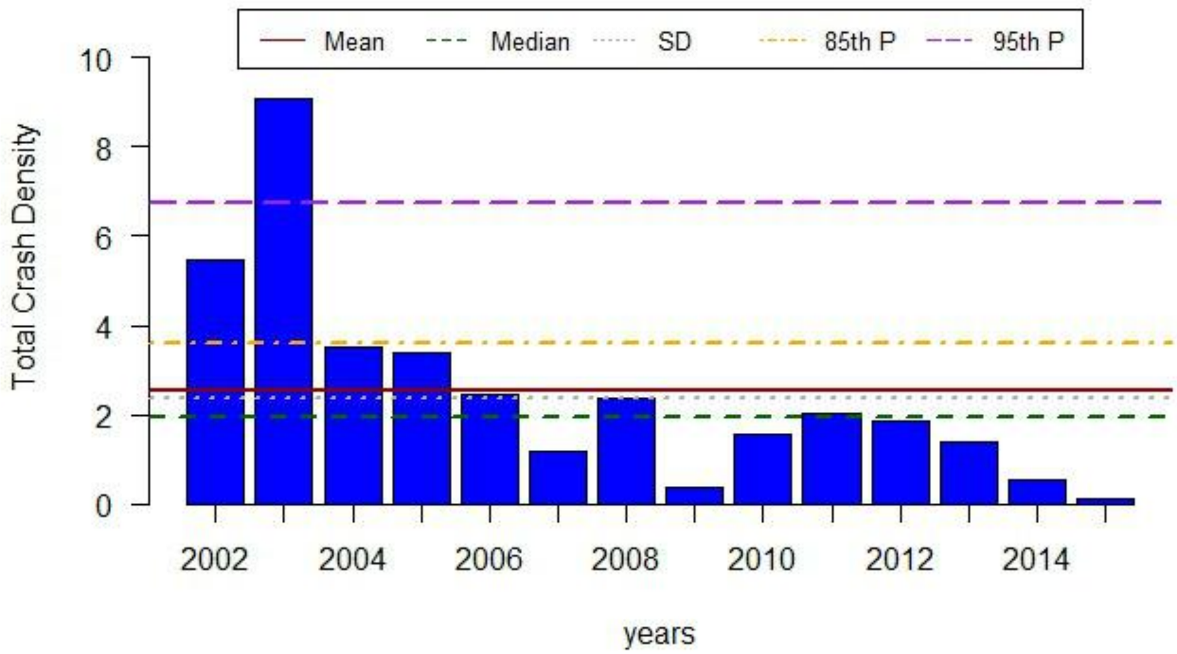


Figure 151 Crash Performance Measure: Loudon County



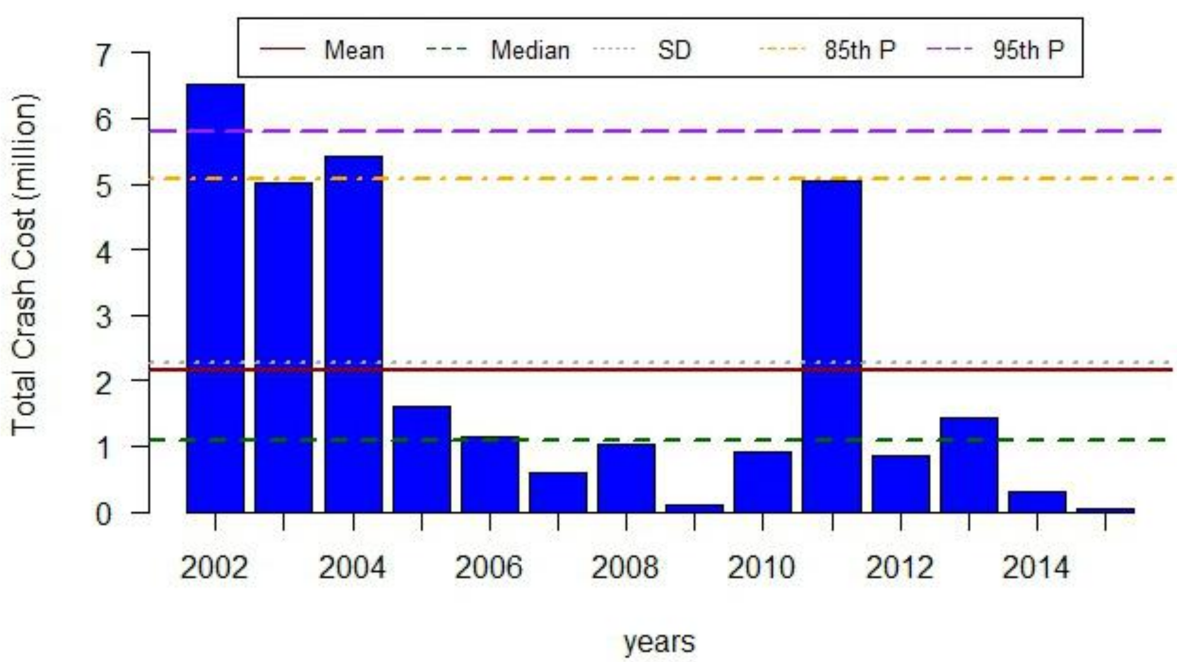
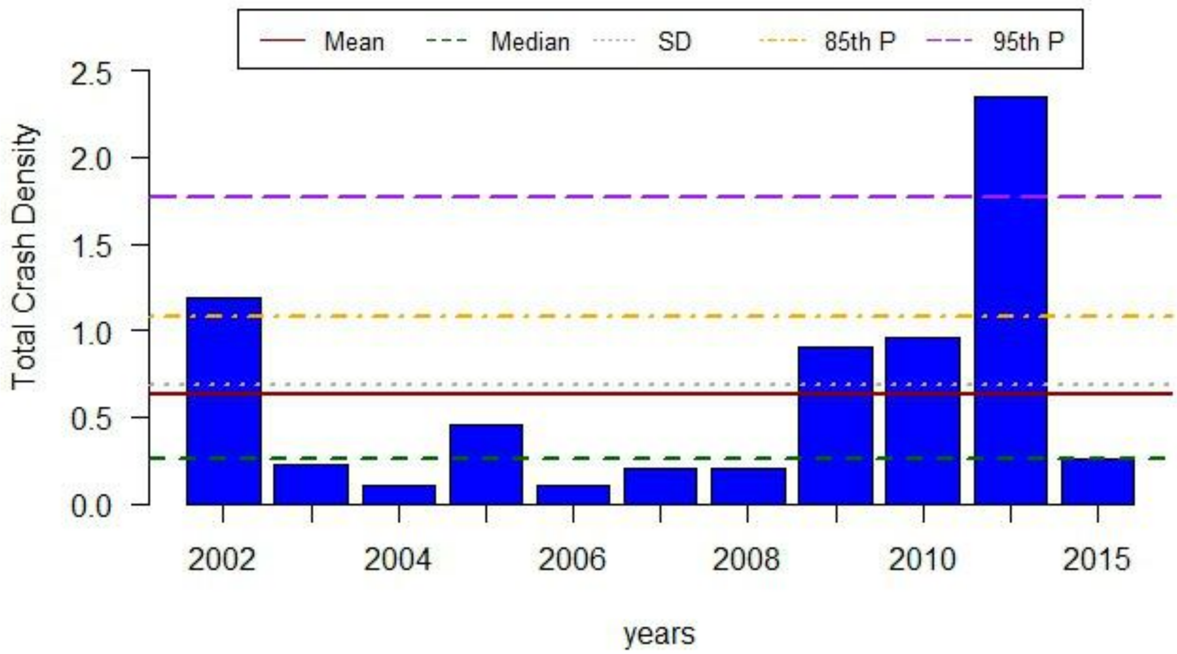


Figure 152 Crash Performance Measure: McMinn County



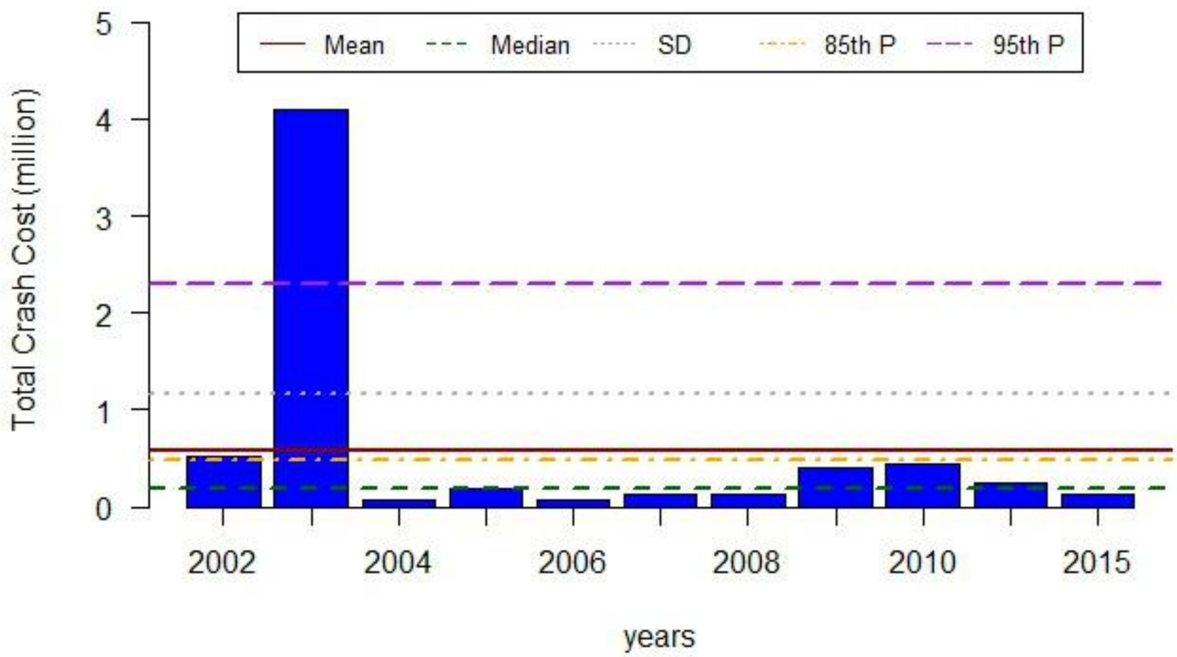
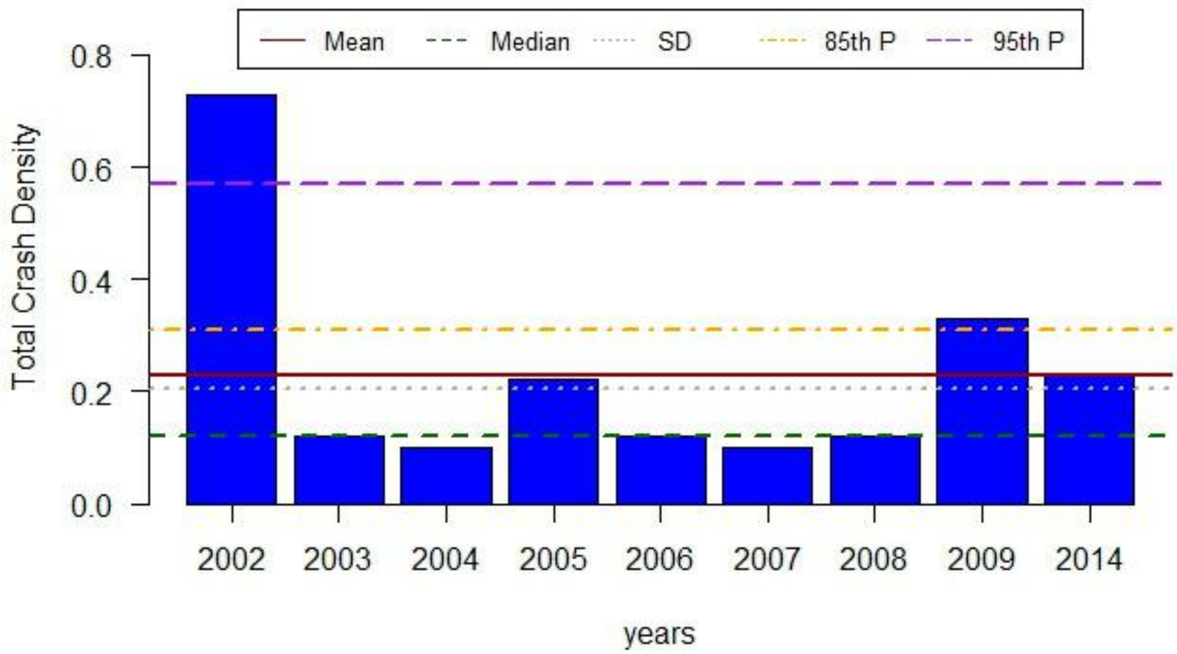


Figure 153 Crash Performance Measure: McNairy County



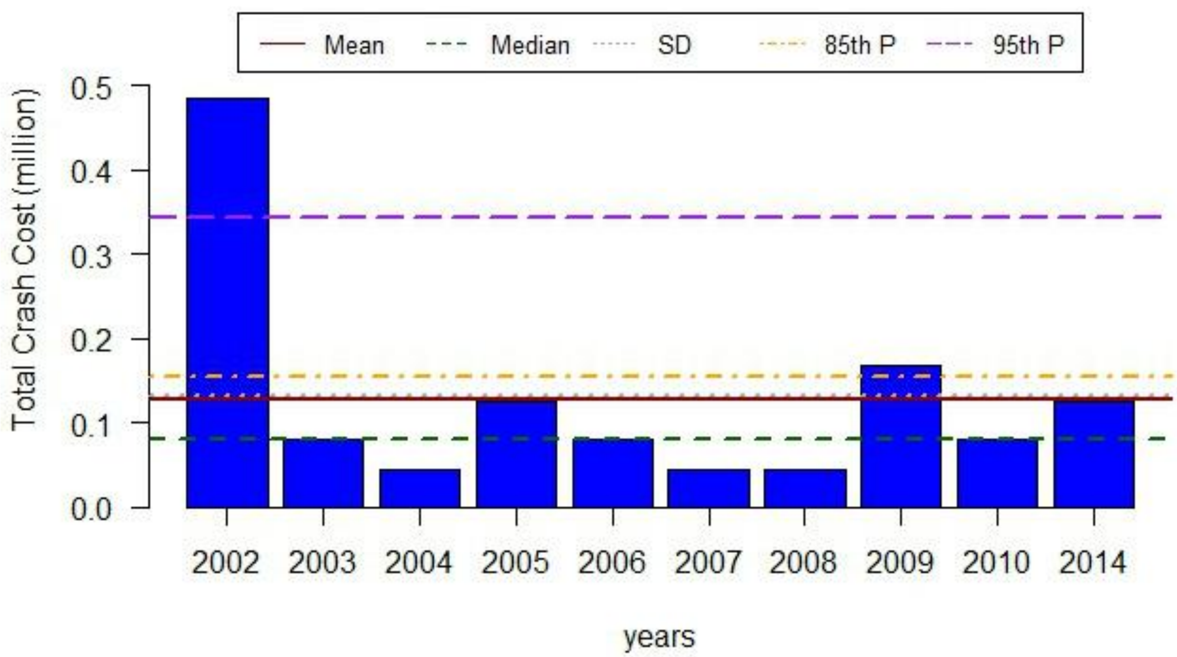
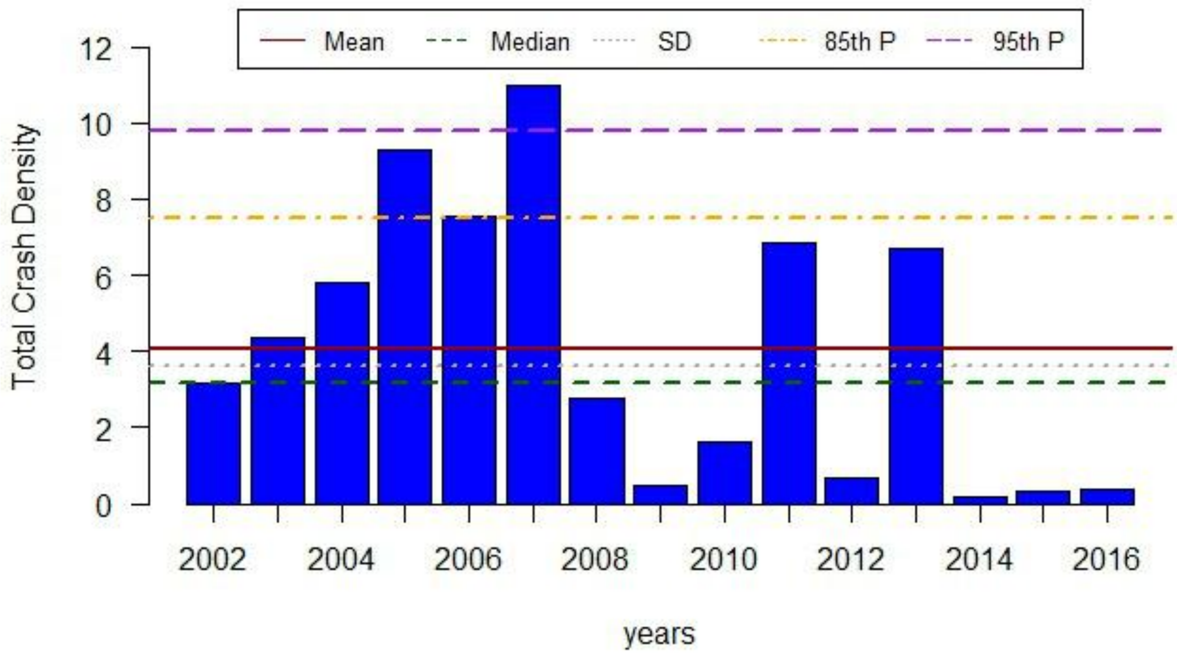


Figure 154 Crash Performance Measure: Macon County



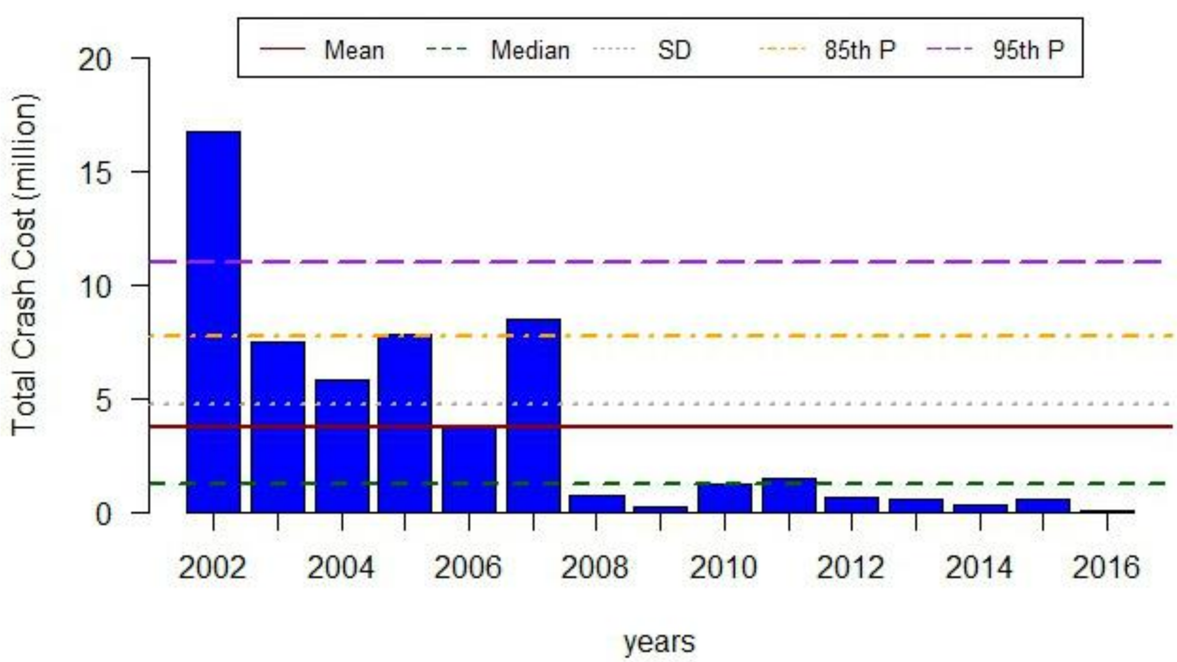
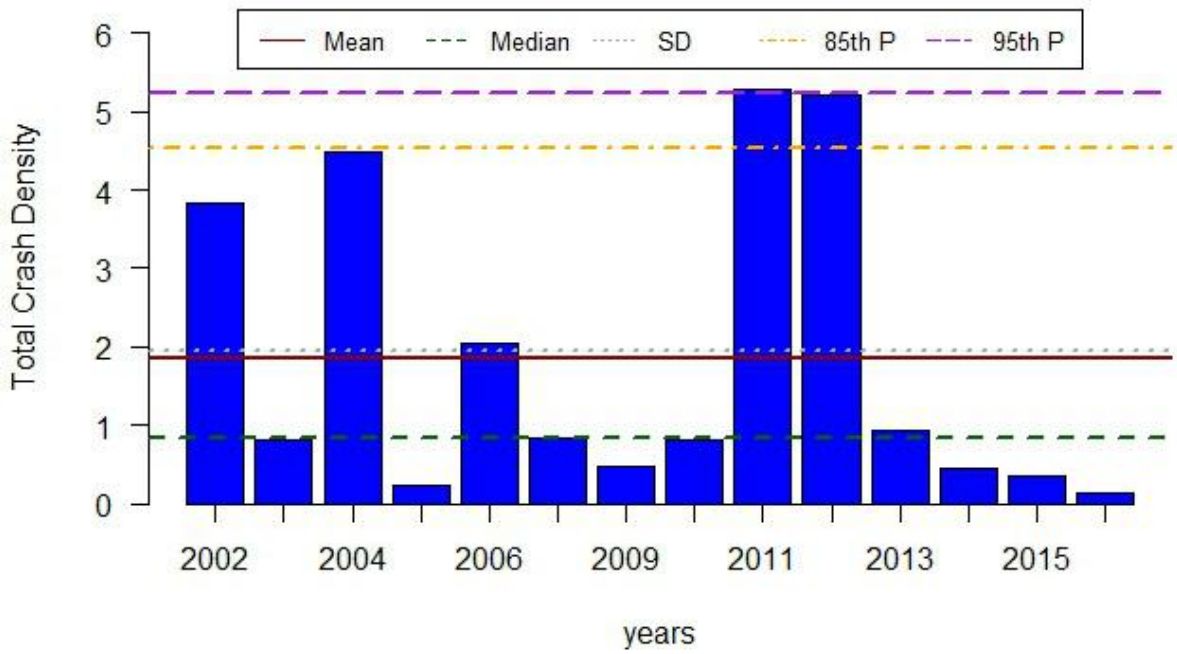


Figure 155 Crash Performance Measure: Madison County



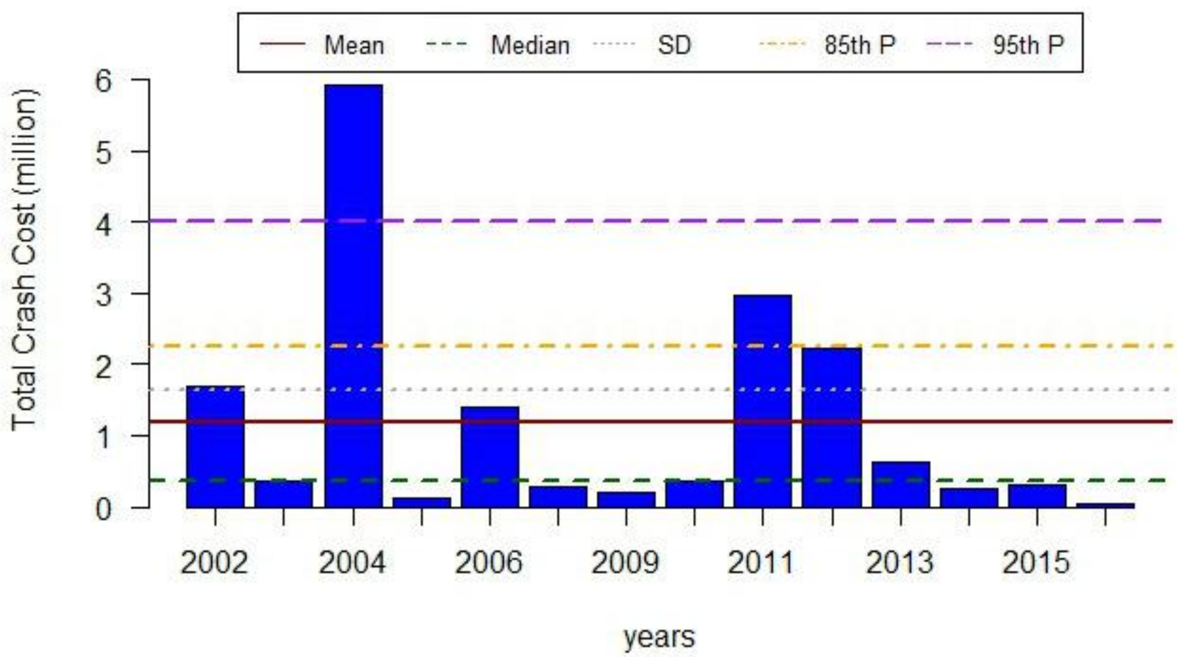


Figure 156 Crash Performance Measure: Marion County

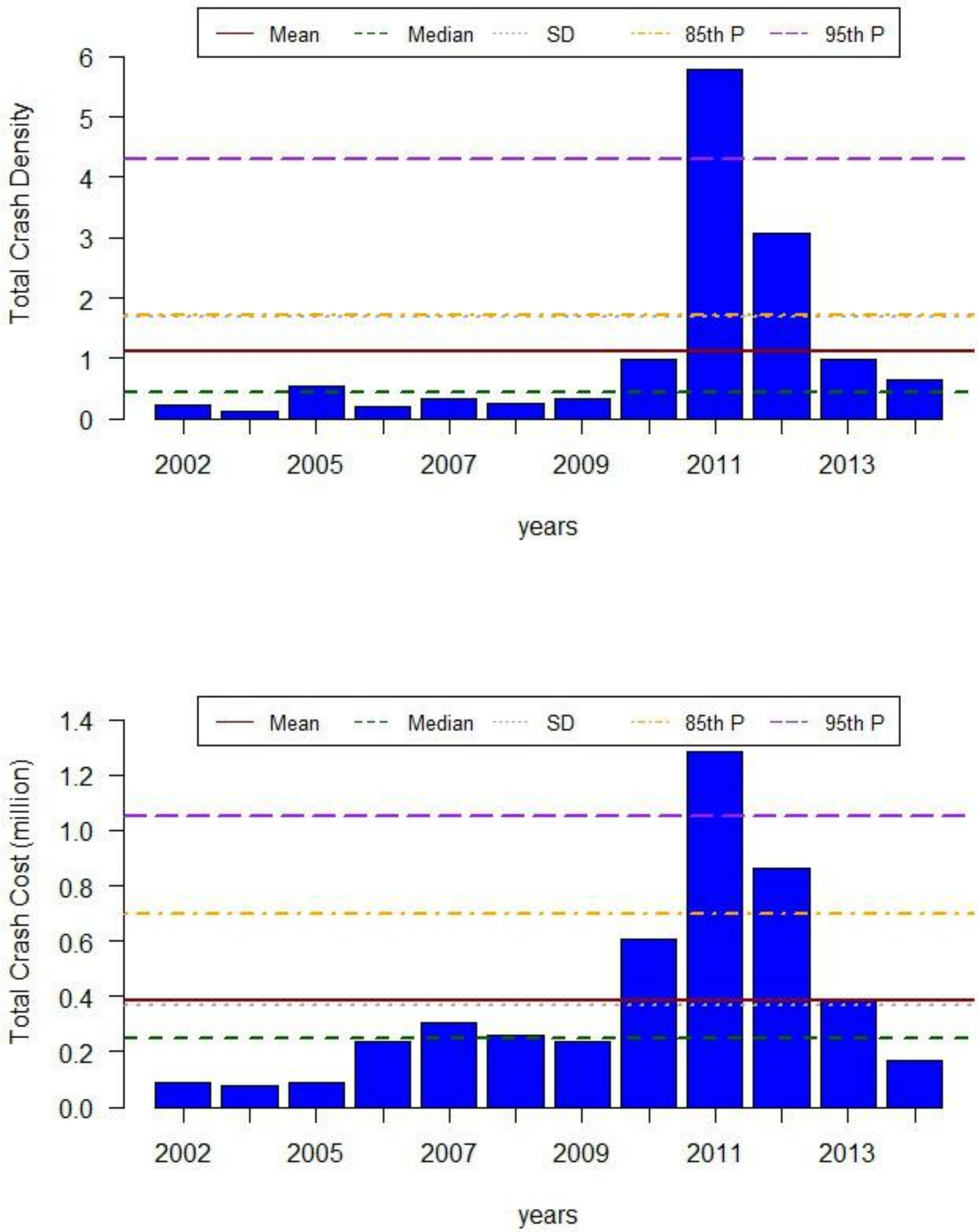
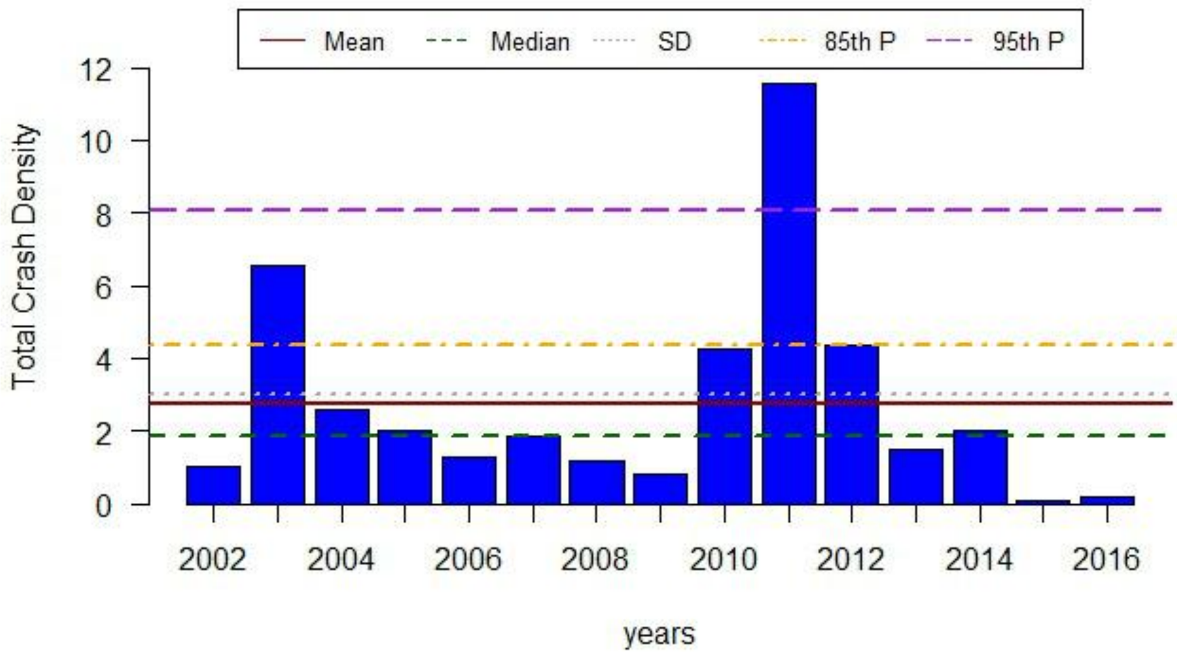


Figure 157 Crash Performance Measure: Marshall County



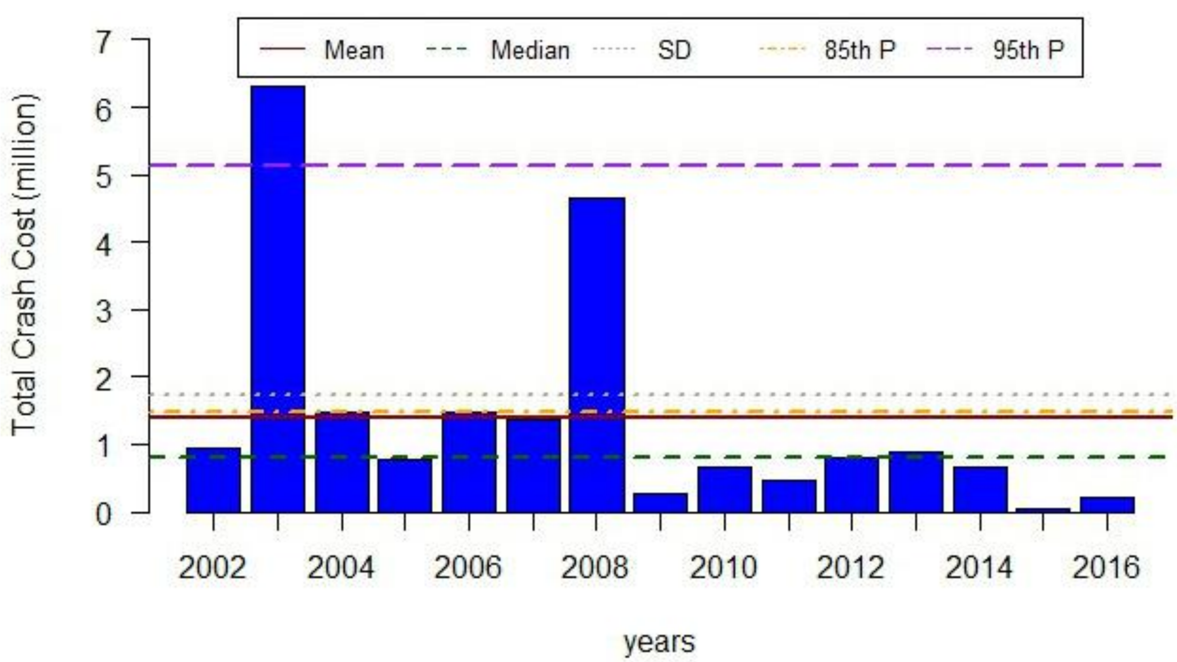
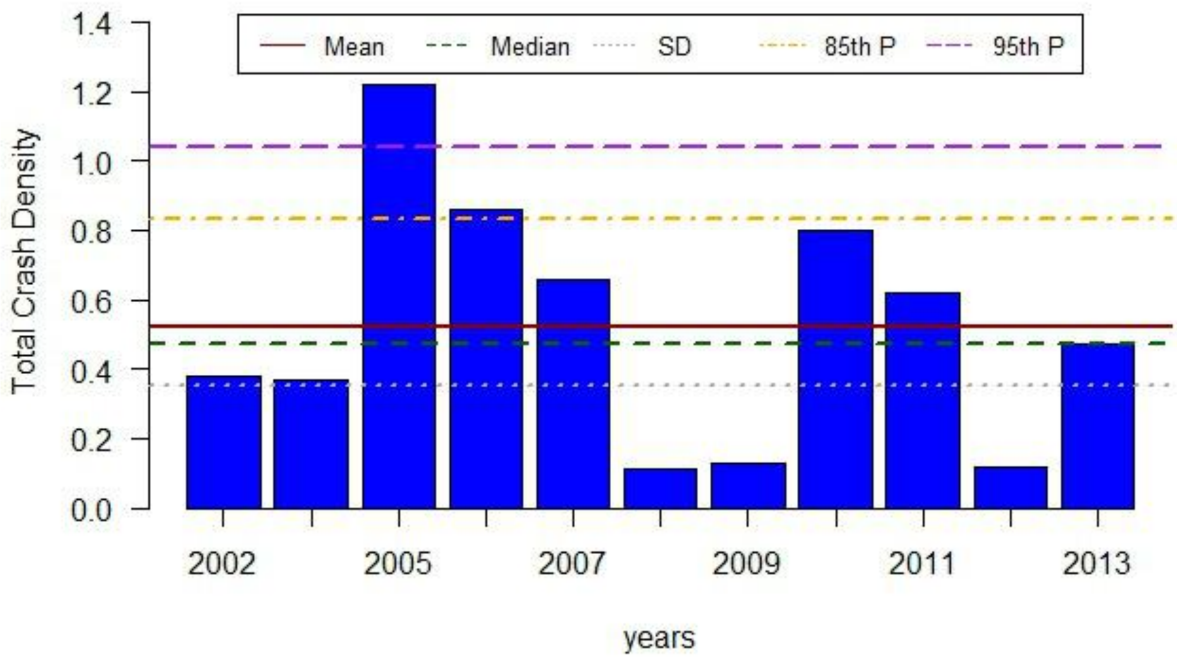


Figure 158 Crash Performance Measure: Maury County



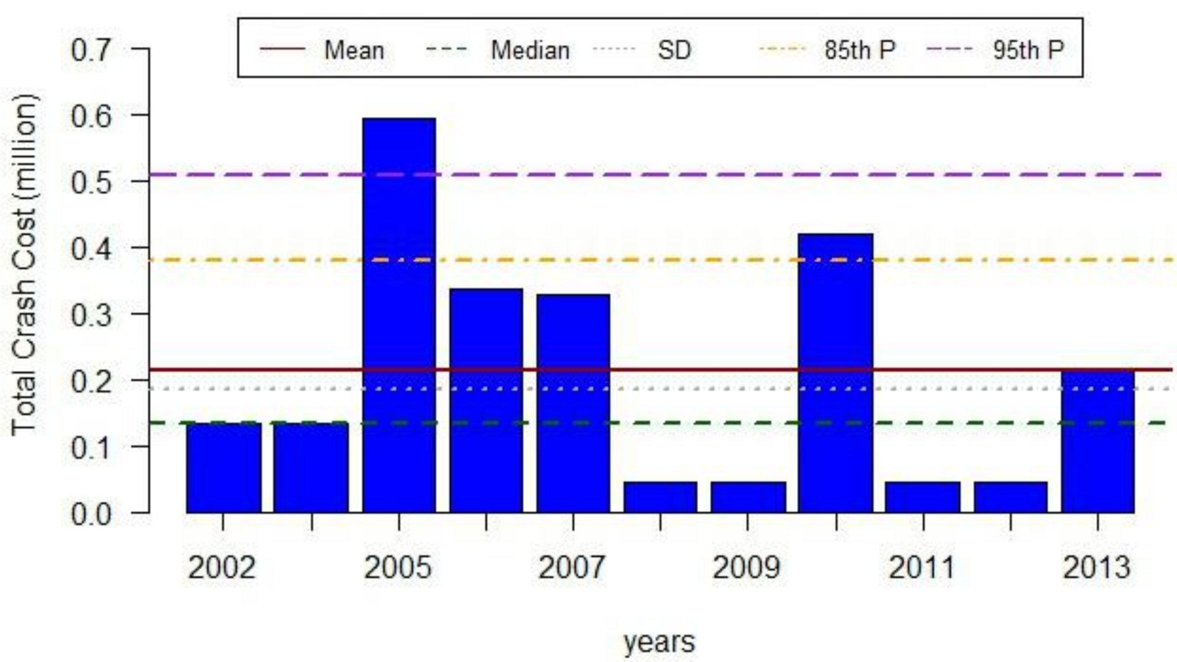
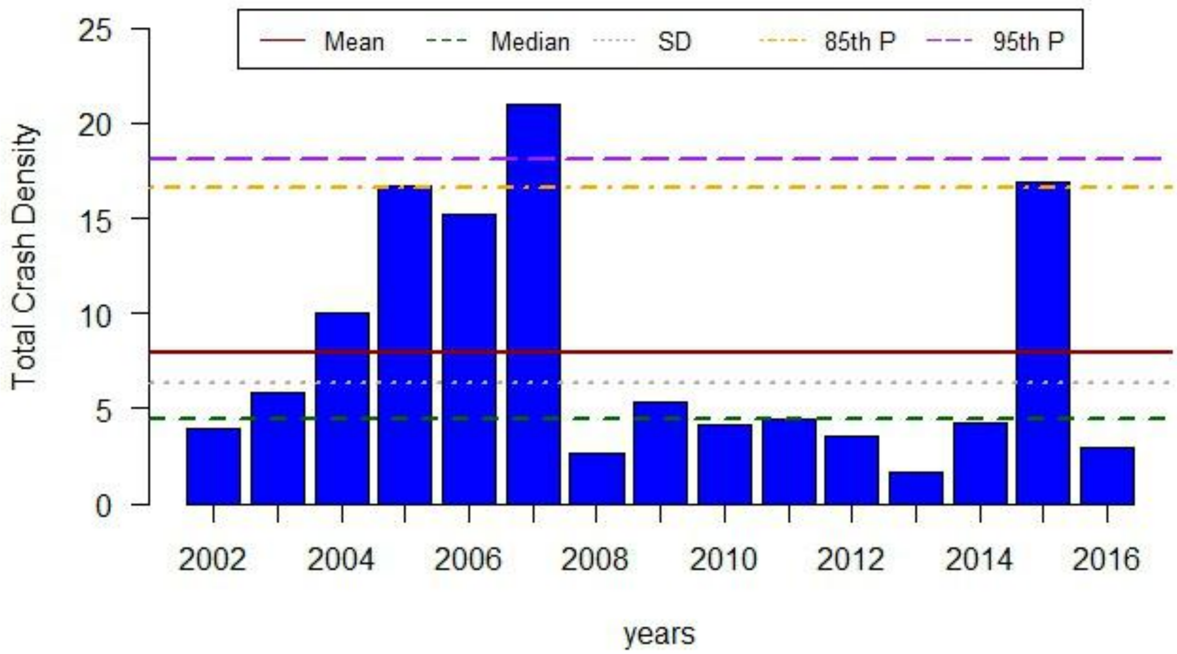


Figure 159 Crash Performance Measure: Meigs County



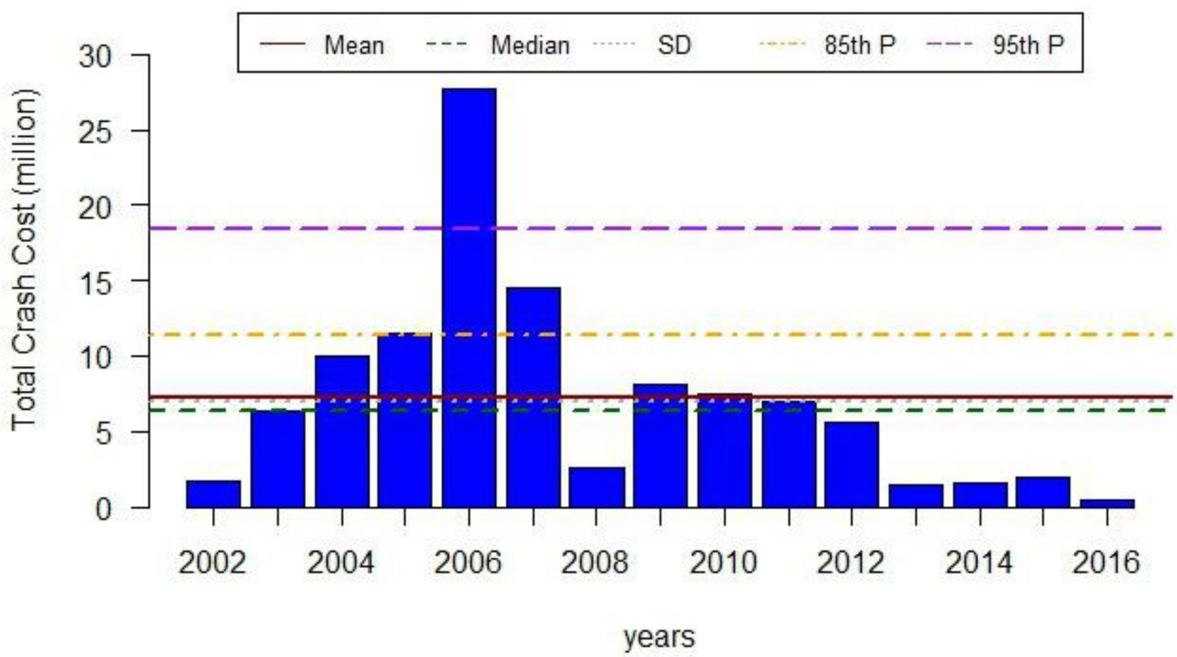
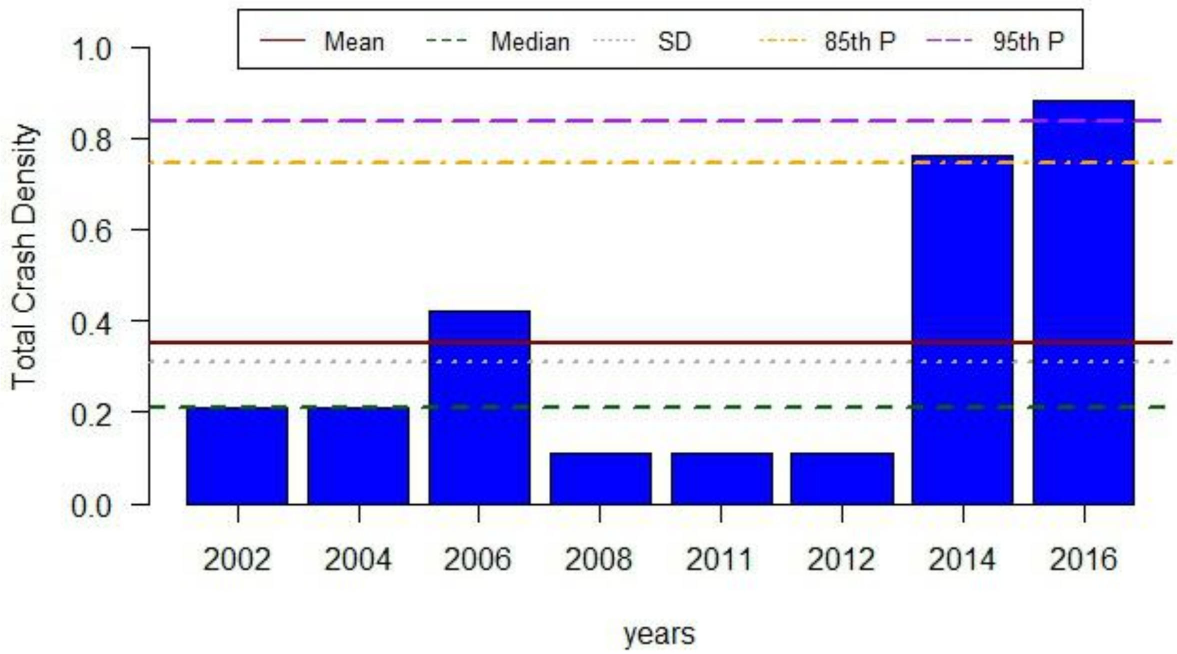


Figure 160 Crash Performance Measure: Montgomery County



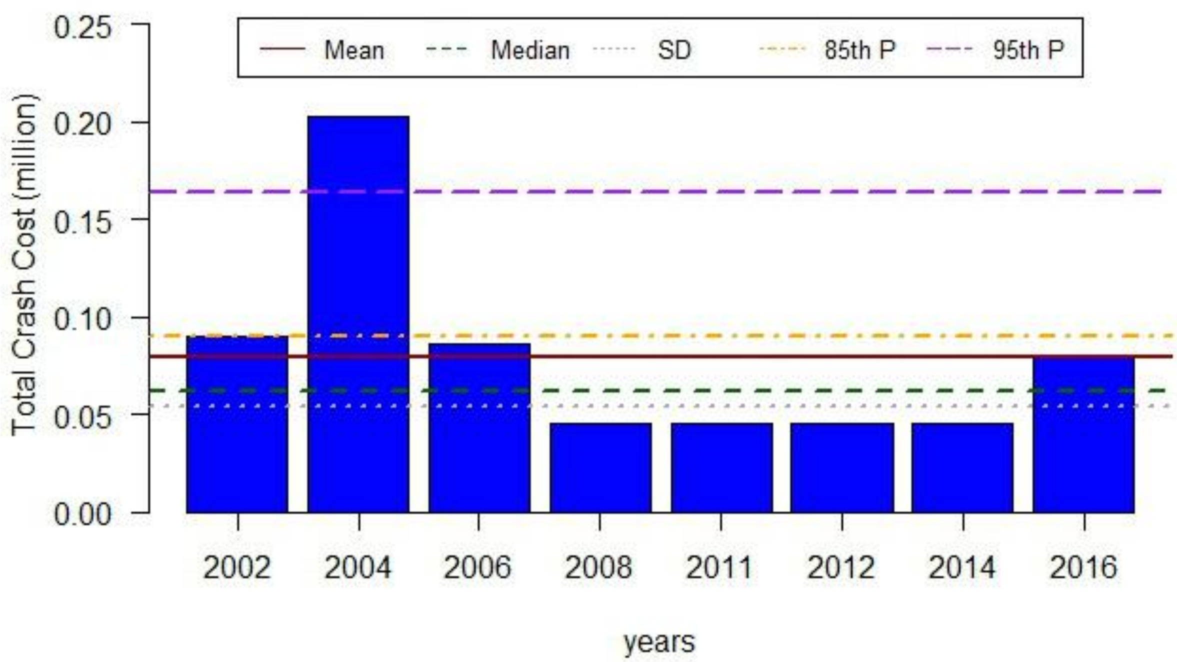


Figure 161 Crash Performance Measure: Moore County

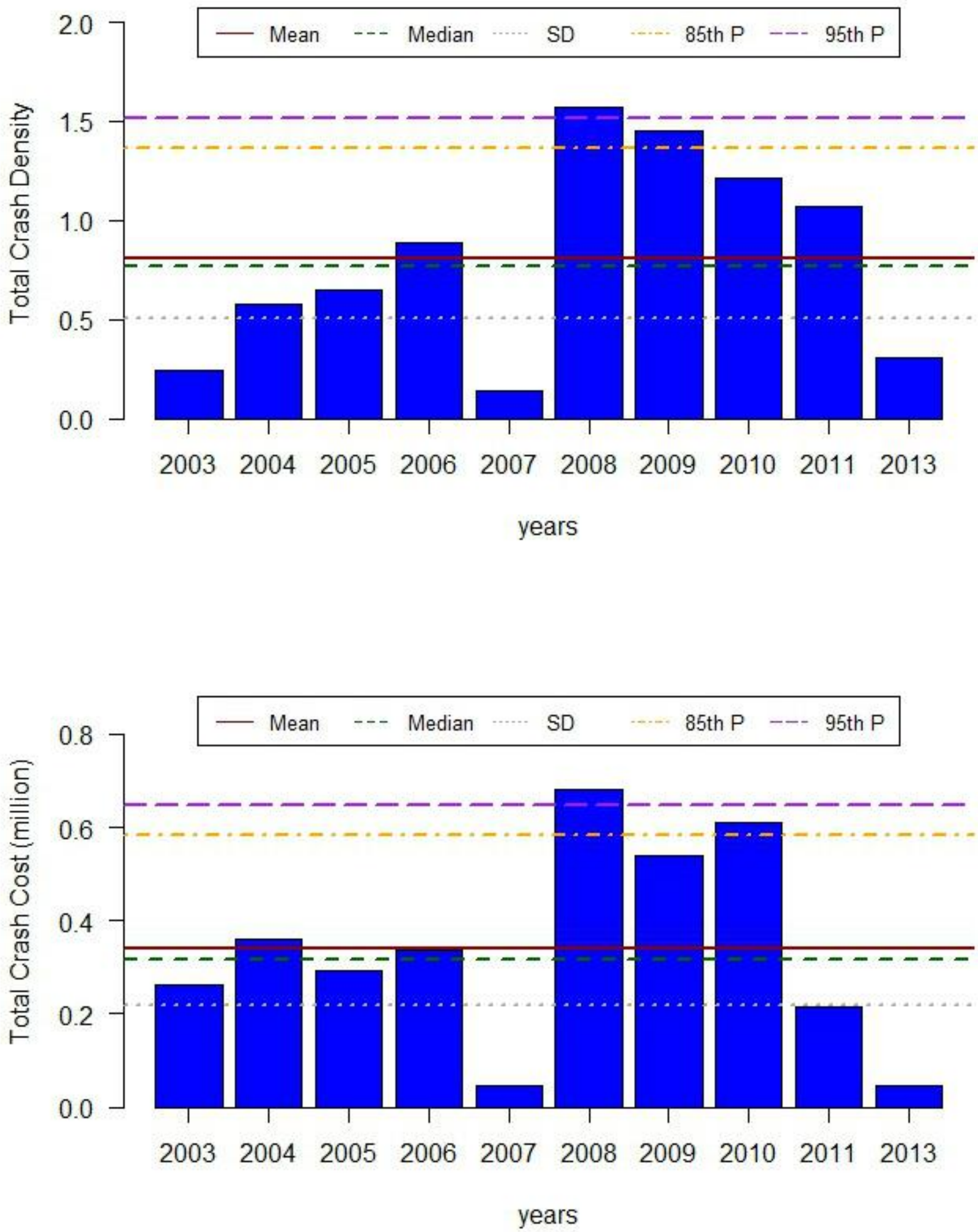
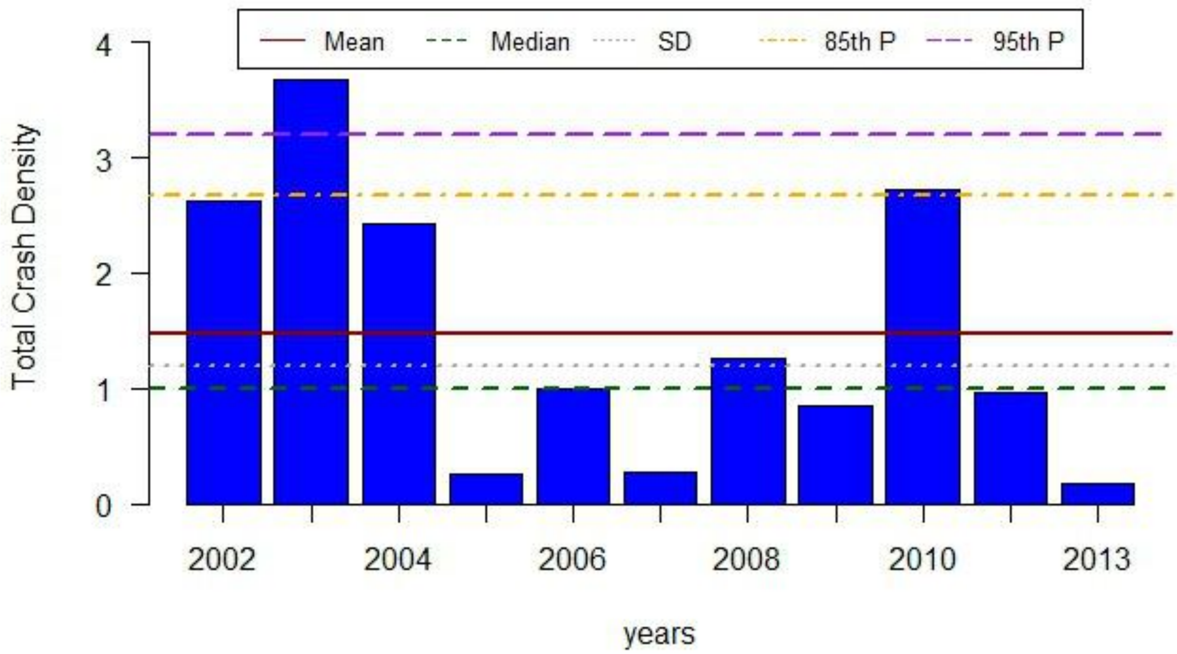


Figure 162 Crash Performance Measure: Morgan County



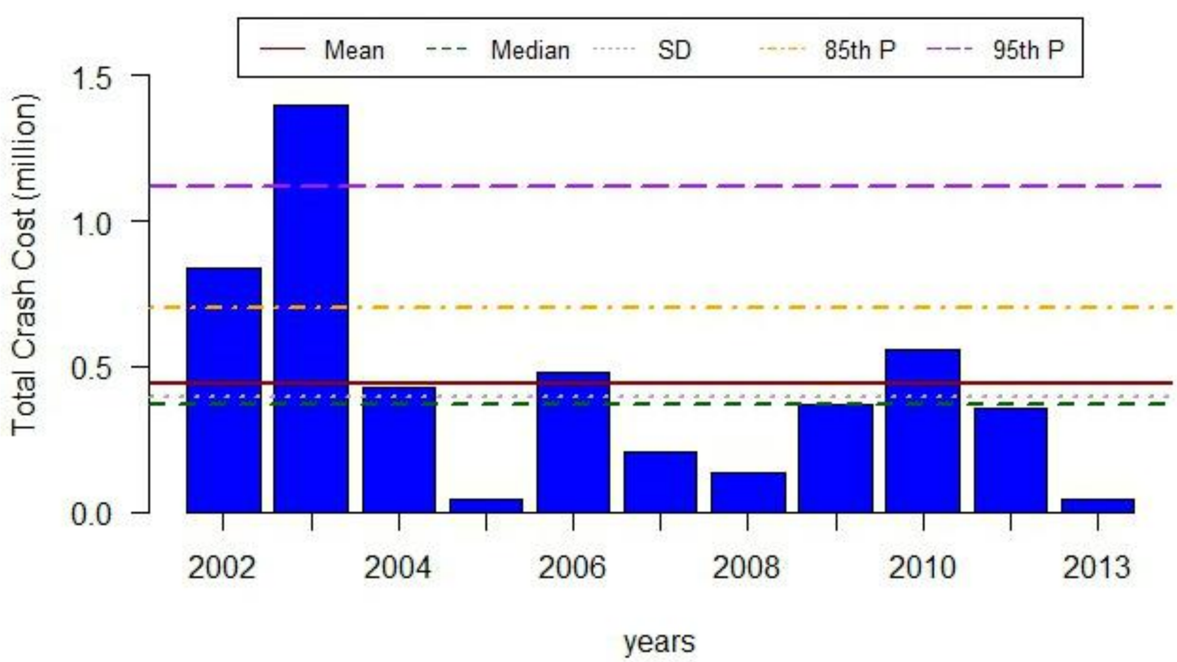
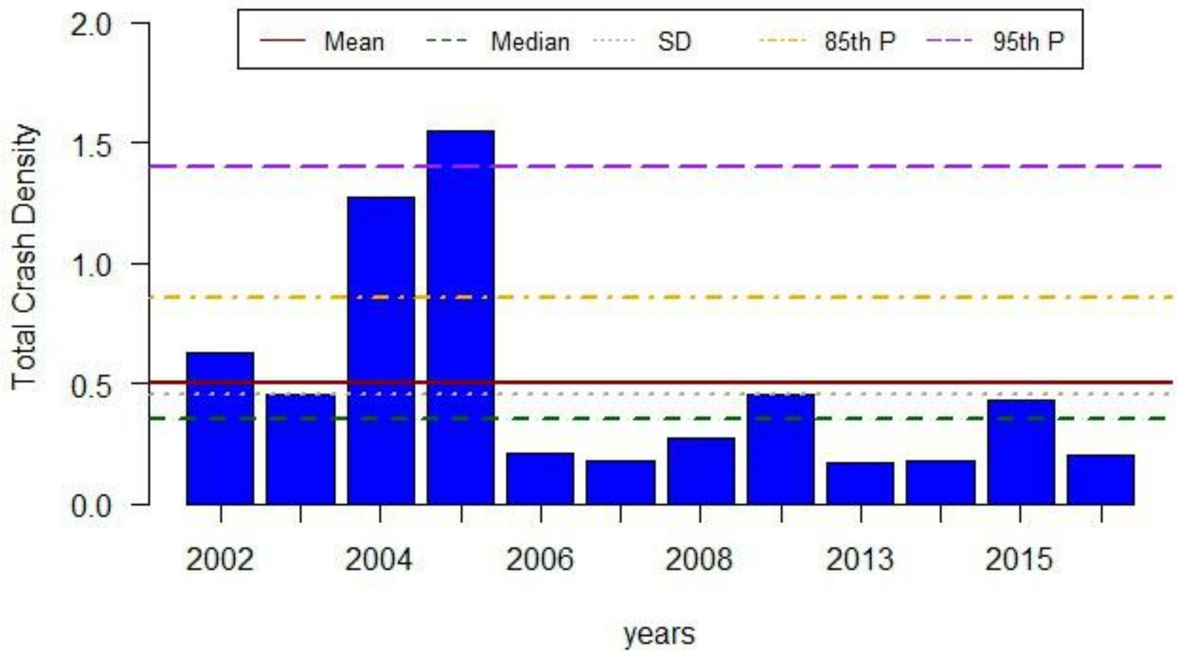


Figure 163 Crash Performance Measure: Obion County



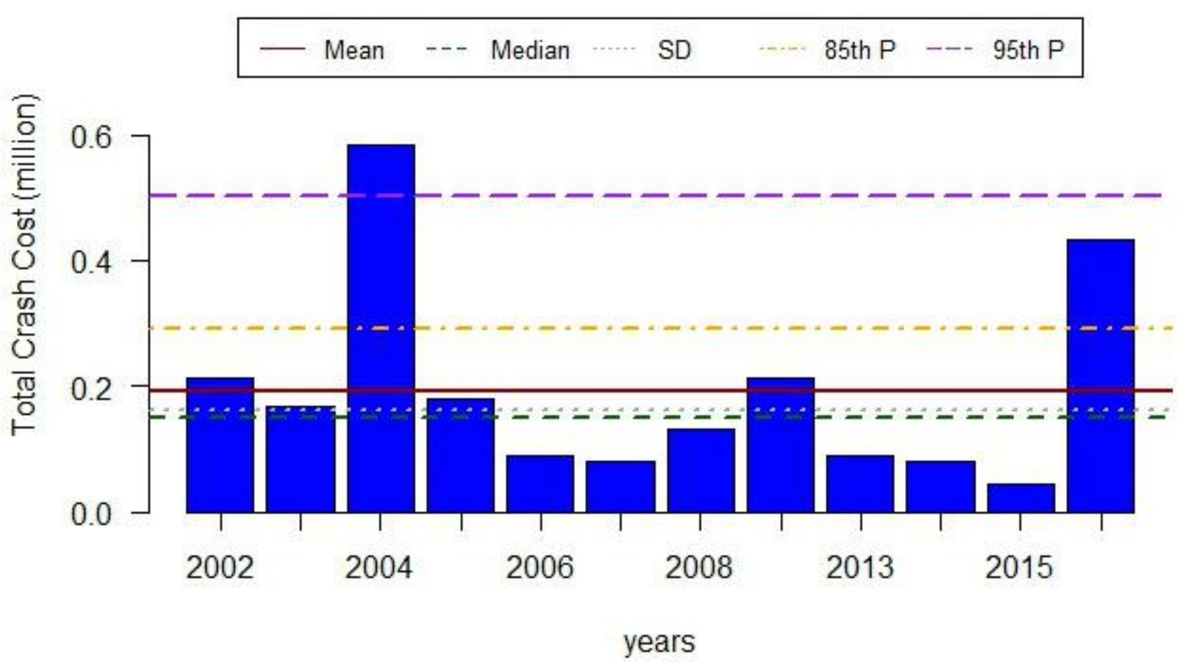
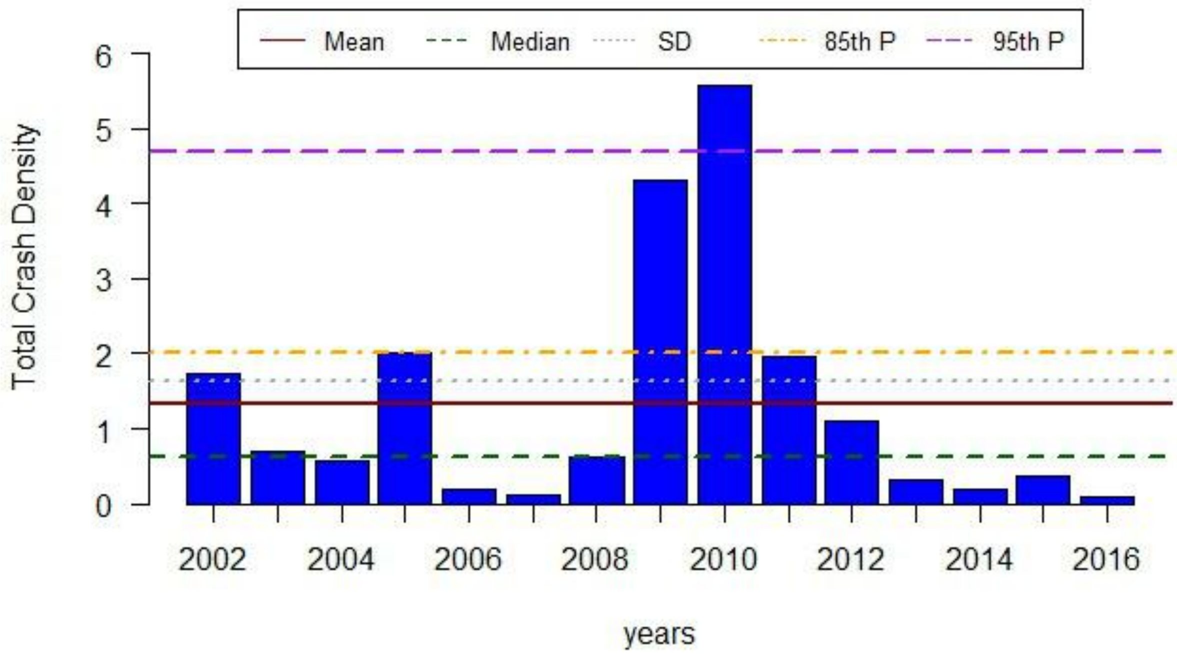


Figure 164 Crash Performance Measure: Overton County

Figure 165 Crash Performance Measure: Perry County



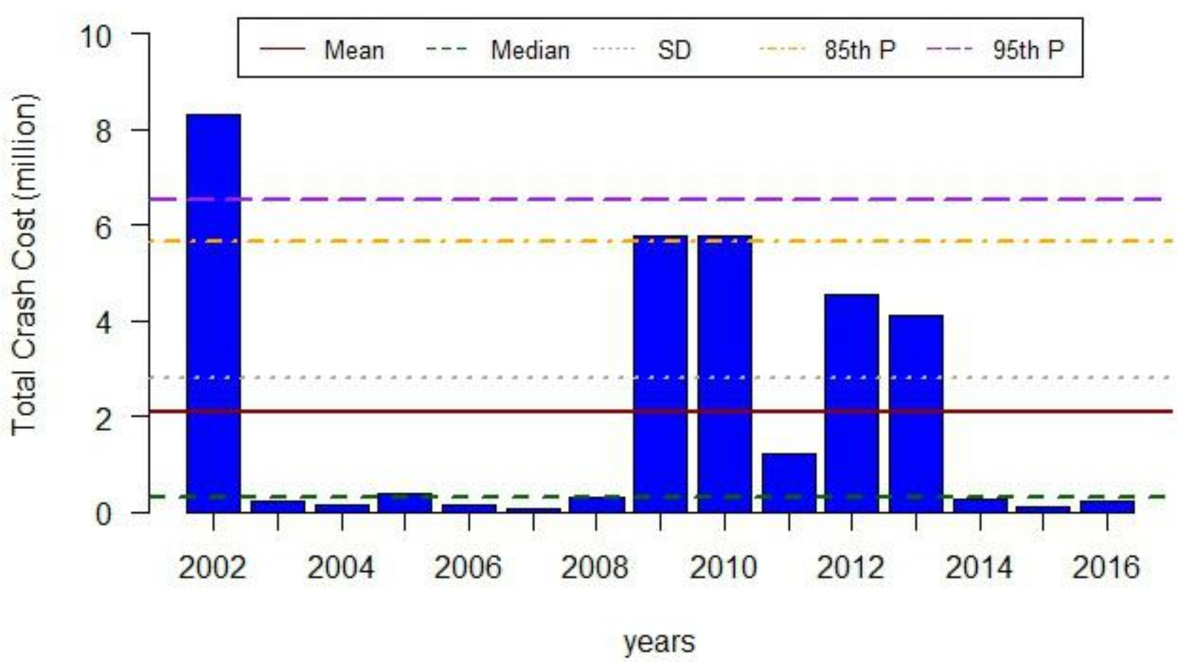
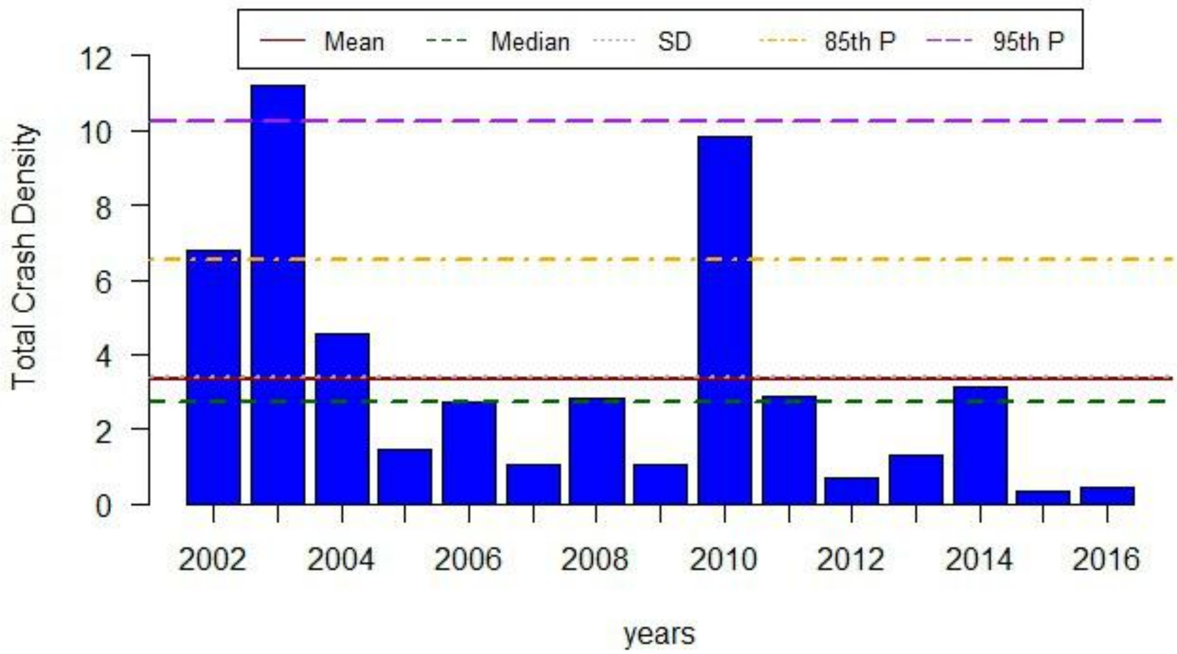


Figure 166 Crash Performance Measure: Polk County



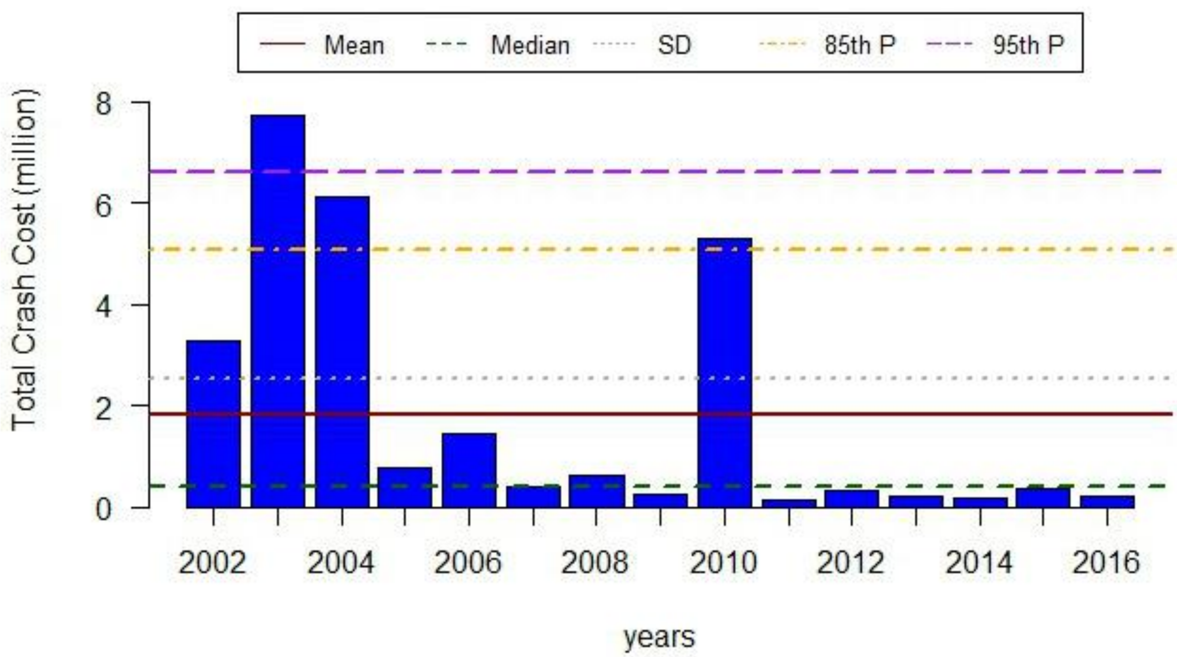
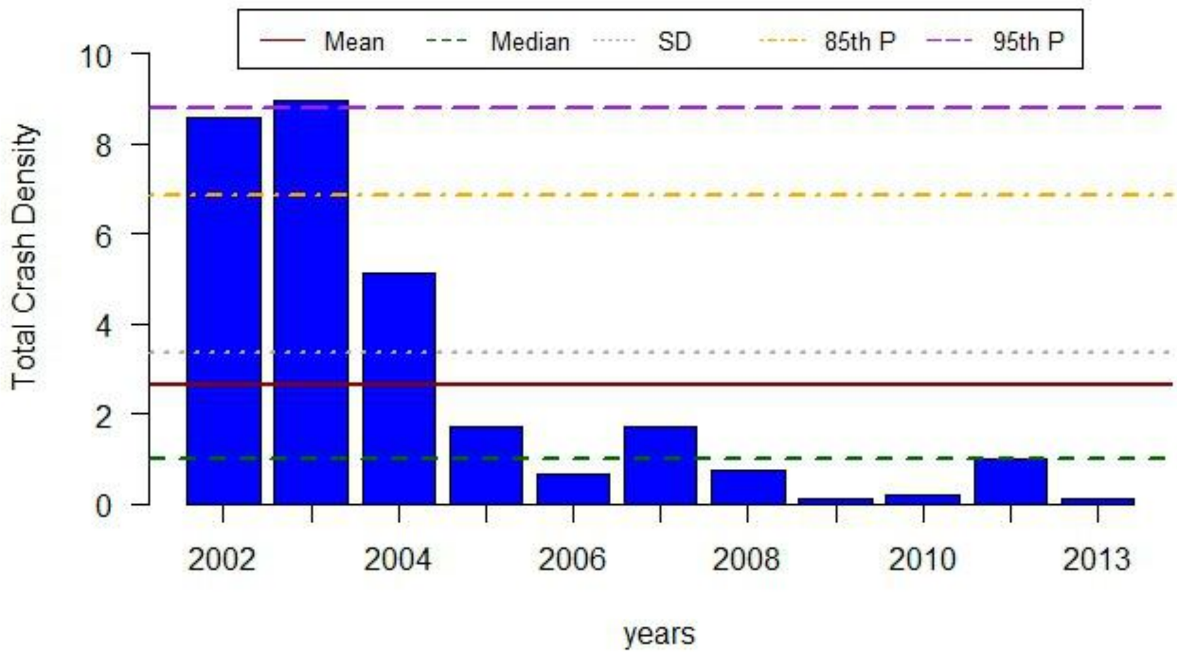


Figure 167 Crash Performance Measure: Putnam County



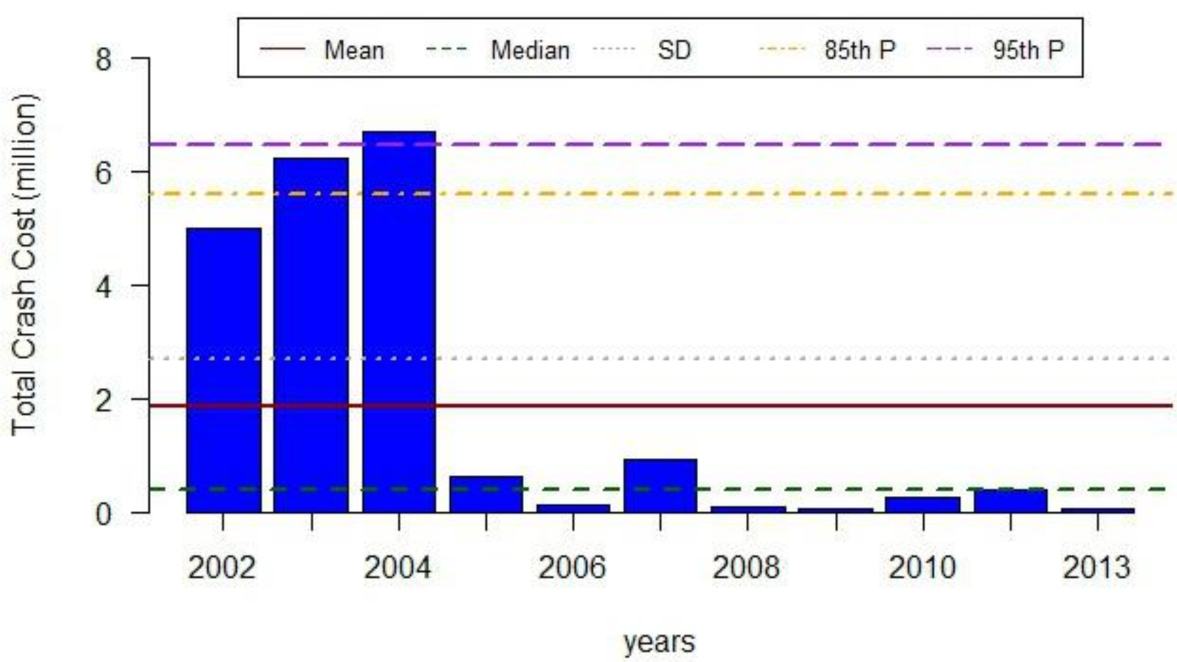
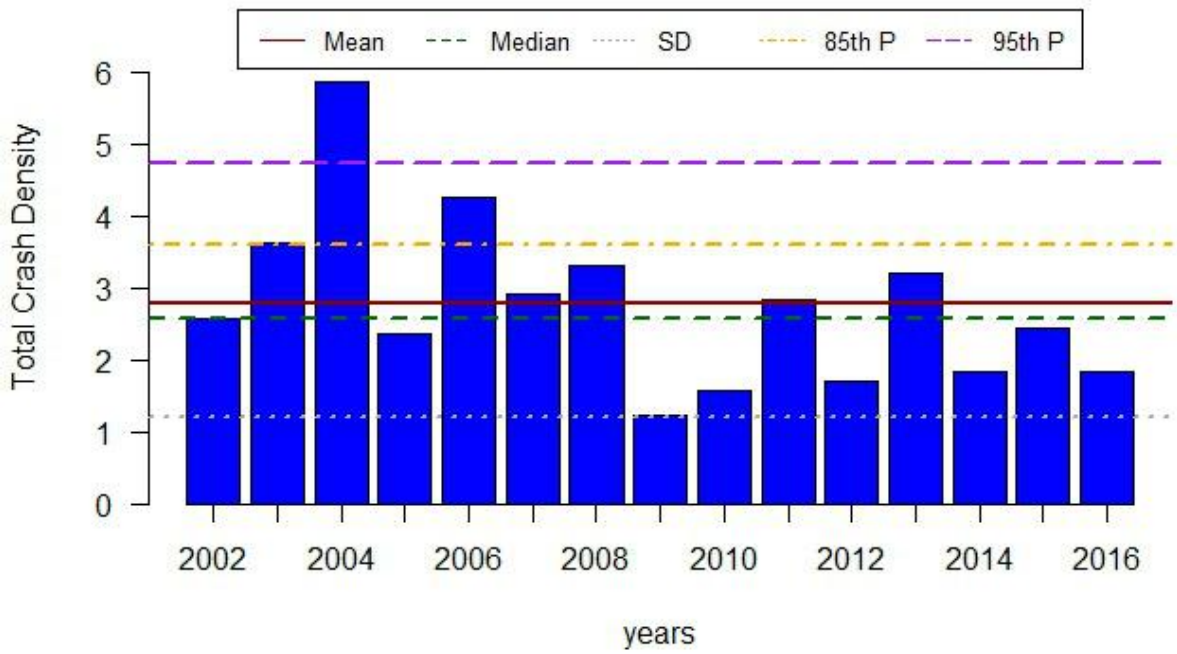


Figure 168 Crash Performance Measure: Rhea County



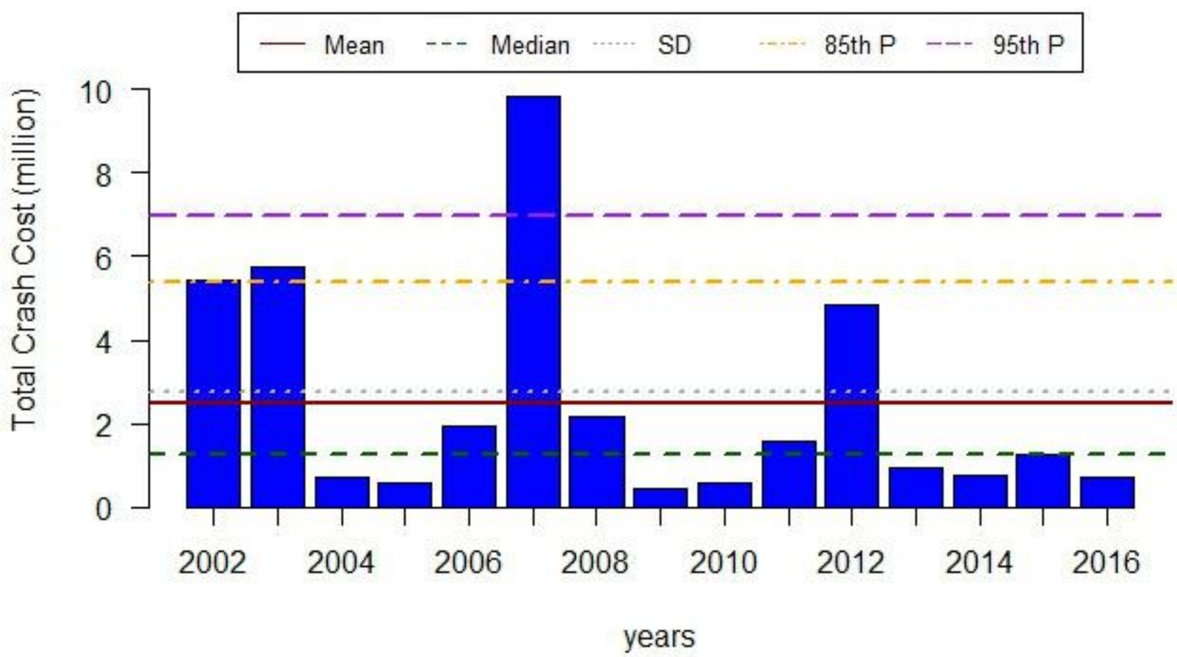
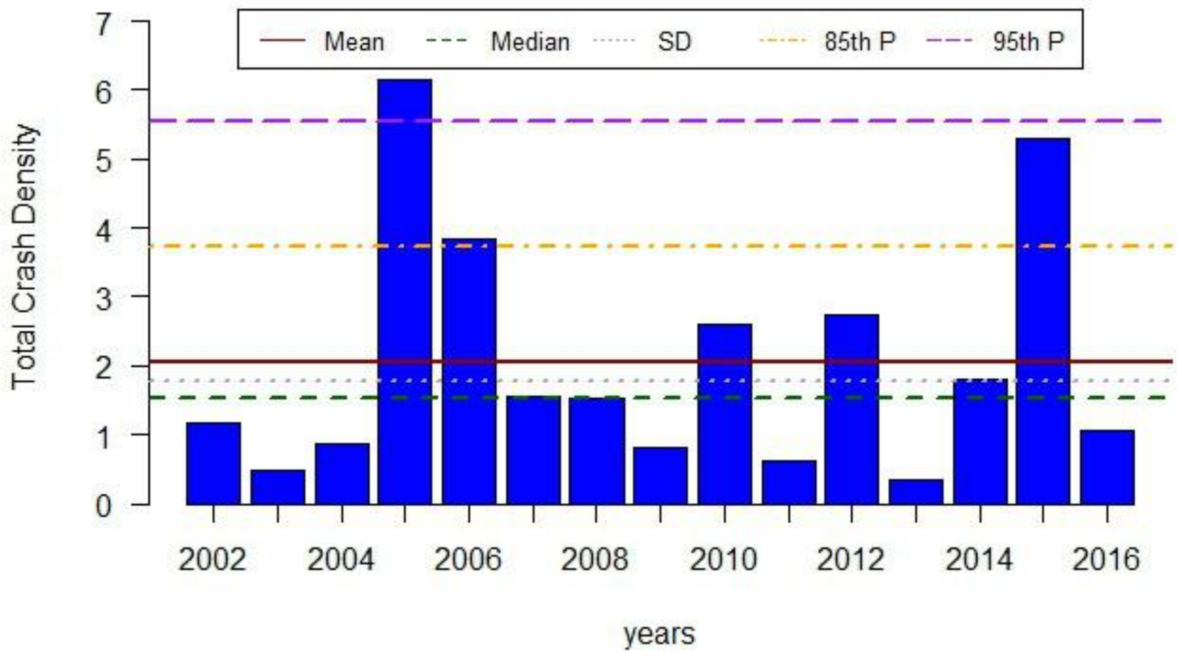


Figure 169 Crash Performance Measure: Roane County



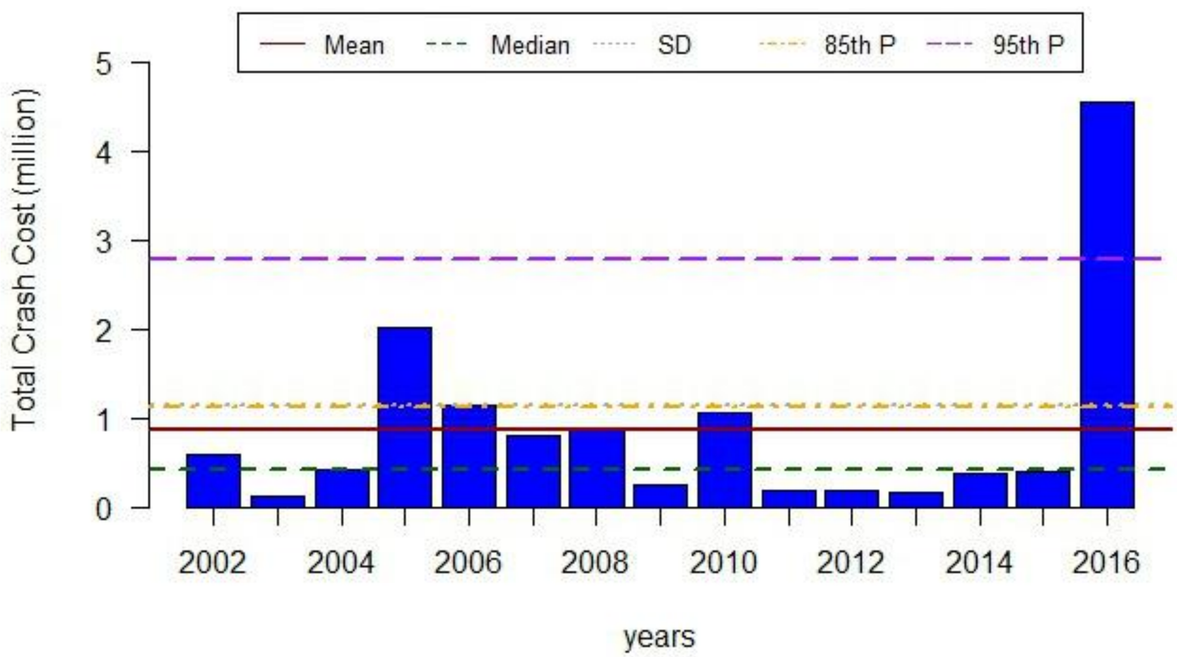
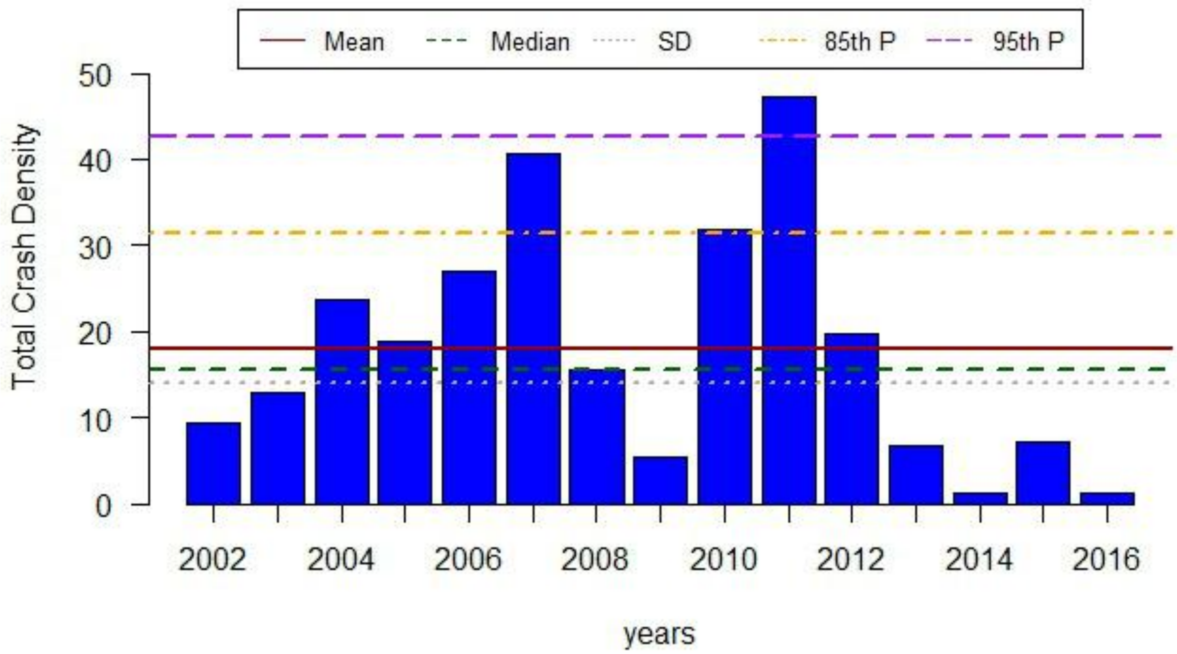


Figure 170 Crash Performance Measure: Robertson County



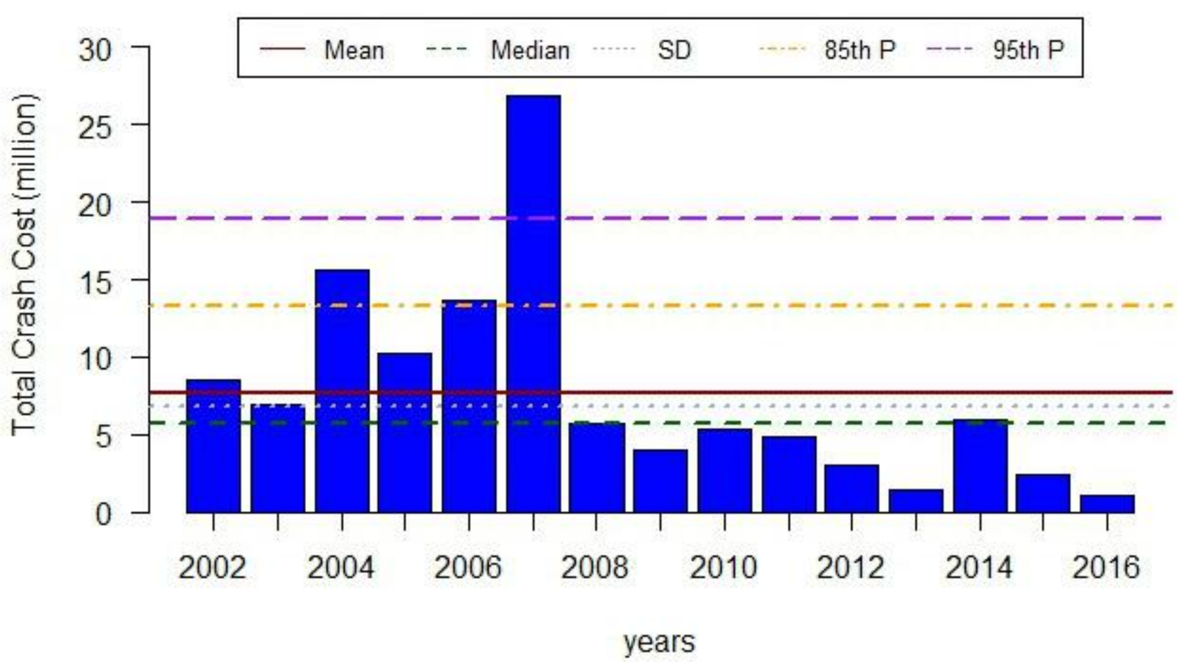
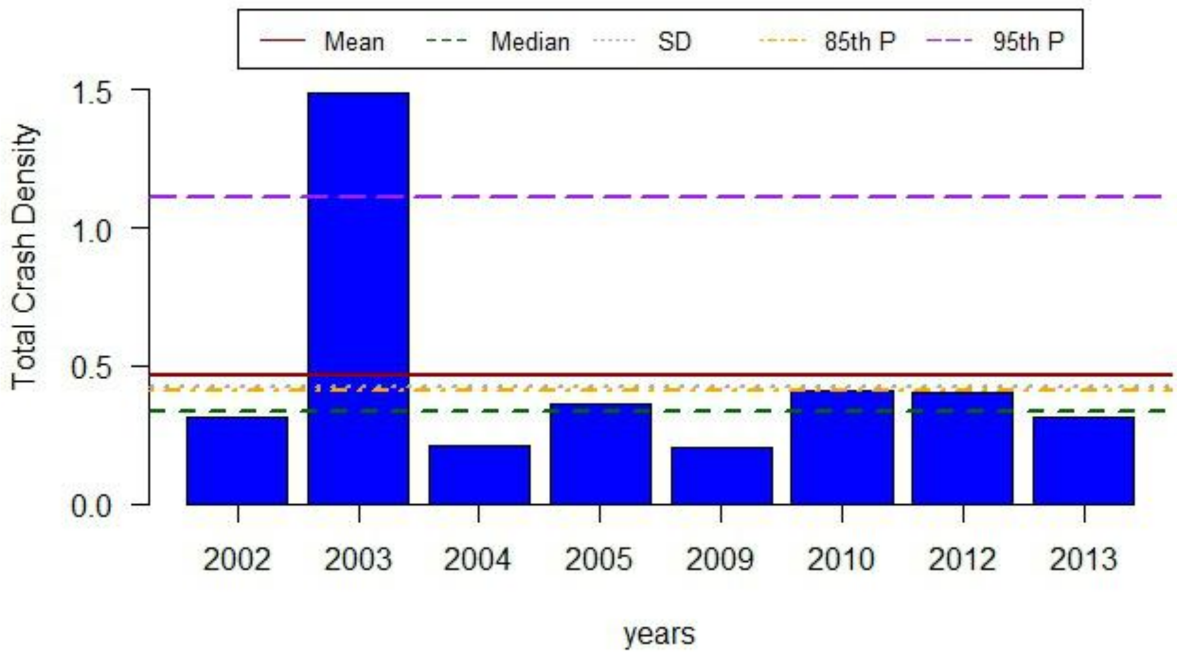


Figure 171 Crash Performance Measure: Rutherford County



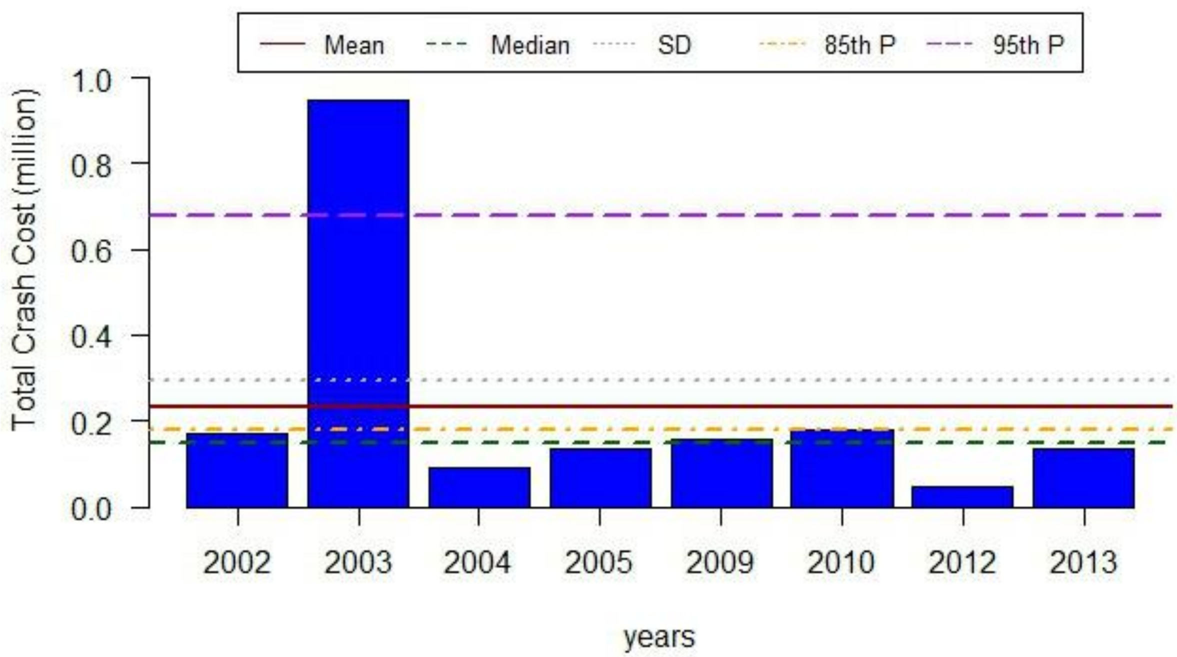
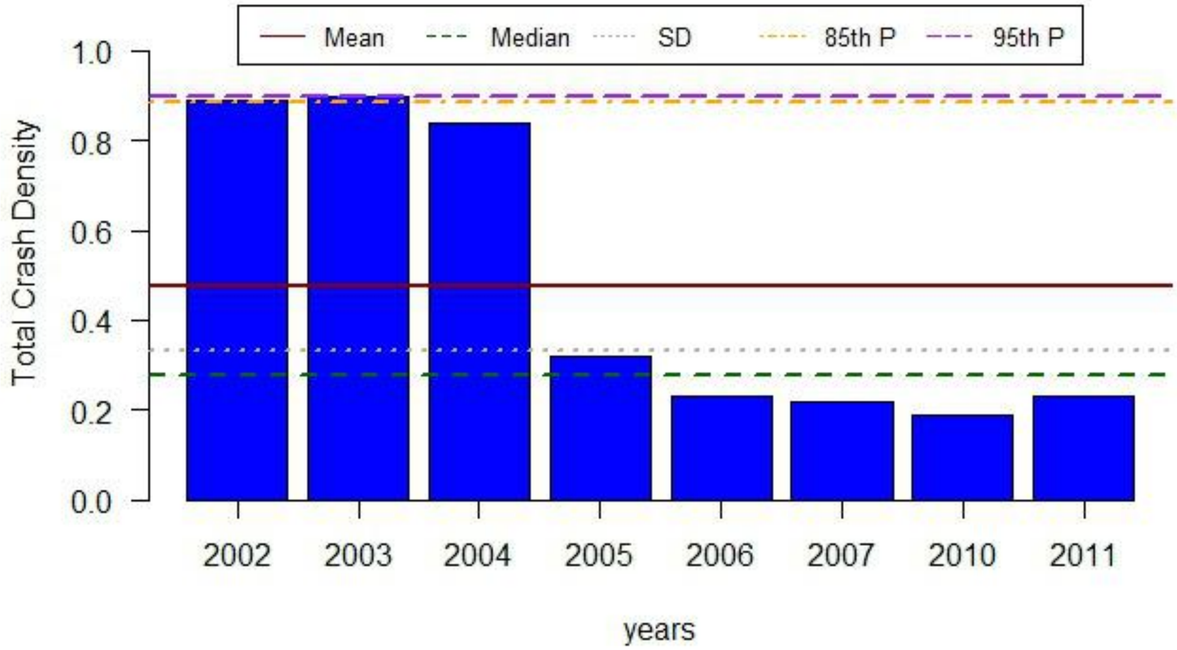


Figure 172 Crash Performance Measure: Scott County



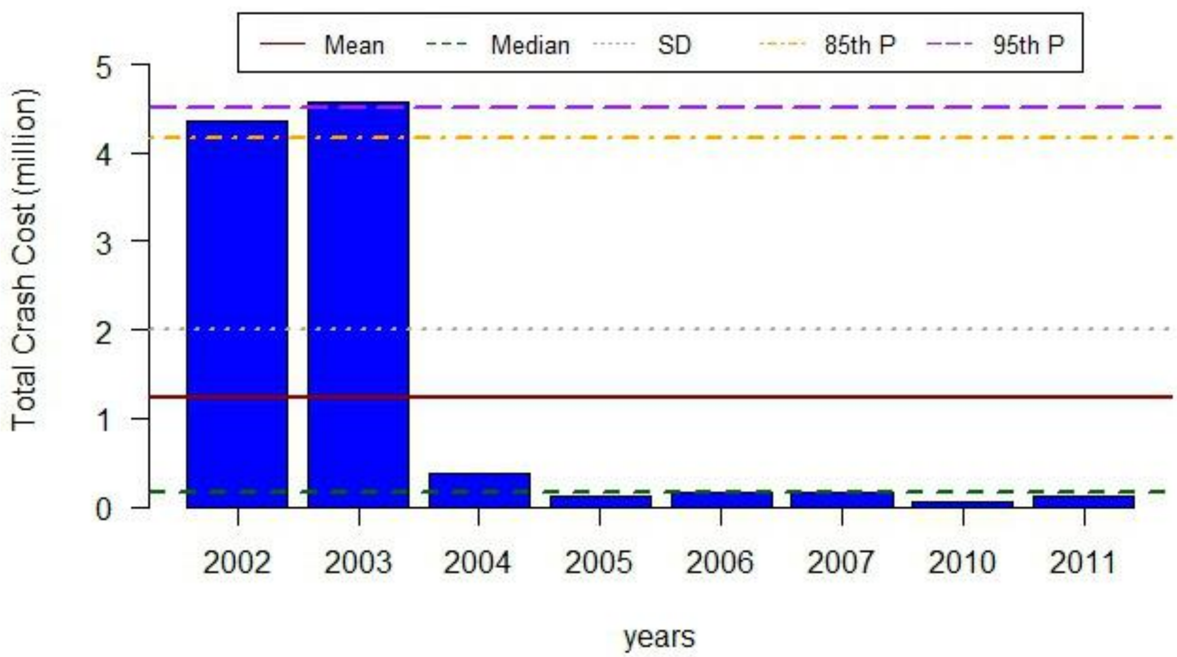


Figure 173 Crash Performance Measure: Sequatchie County

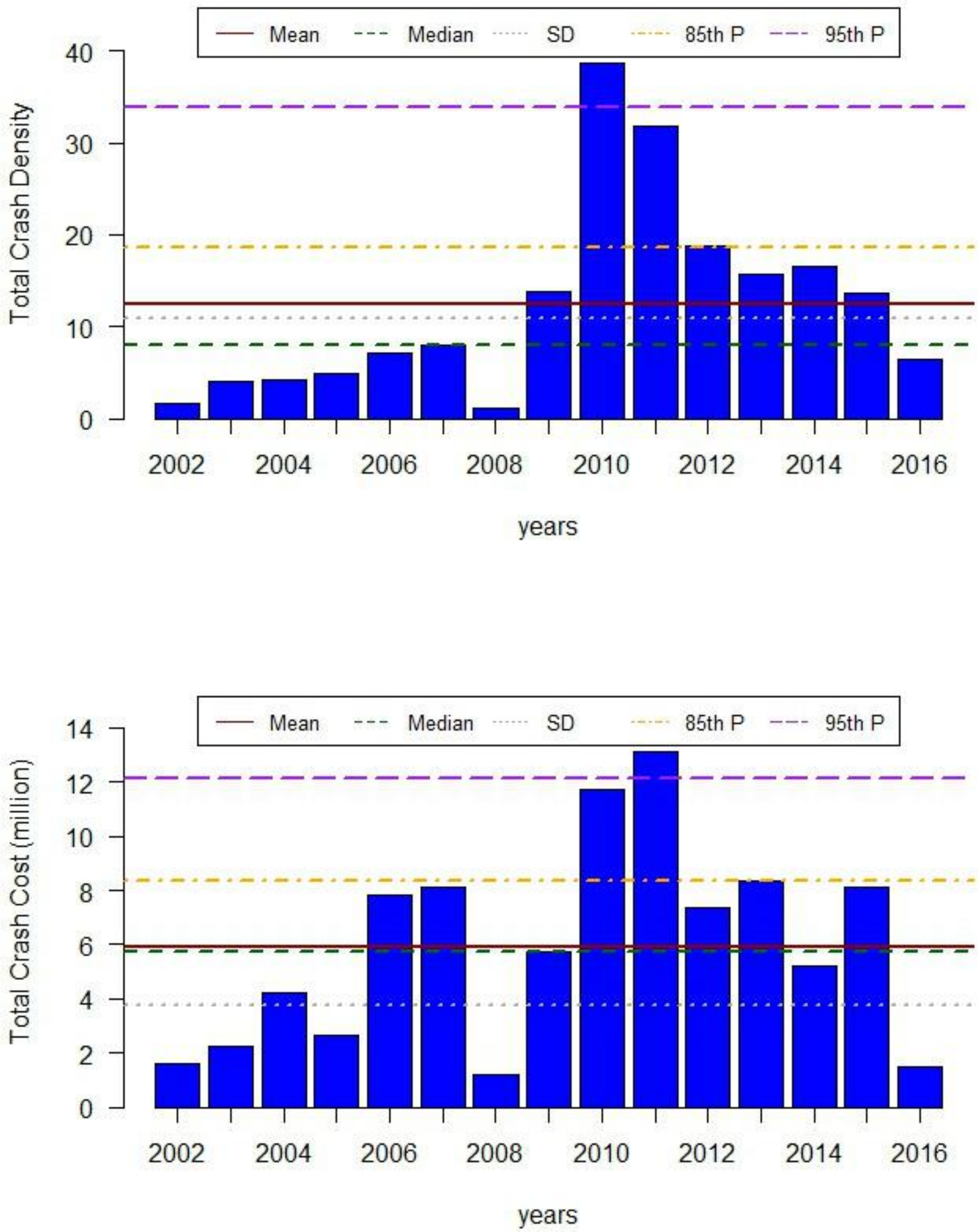
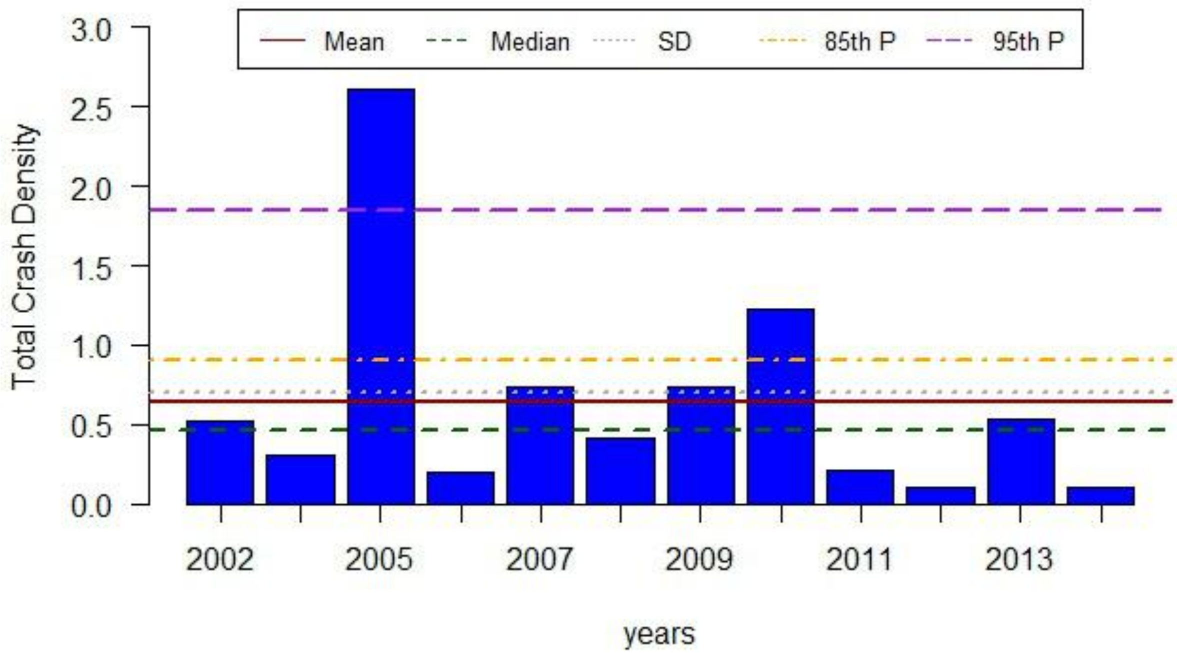


Figure 174 Crash Performance Measure: Sevier County



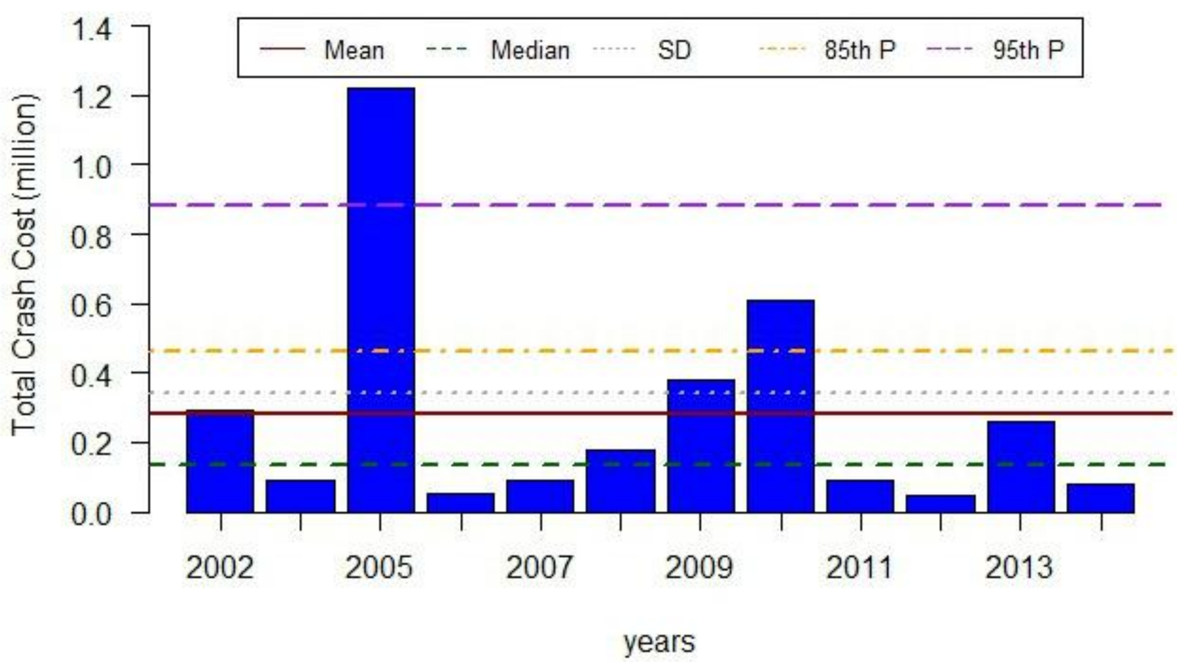
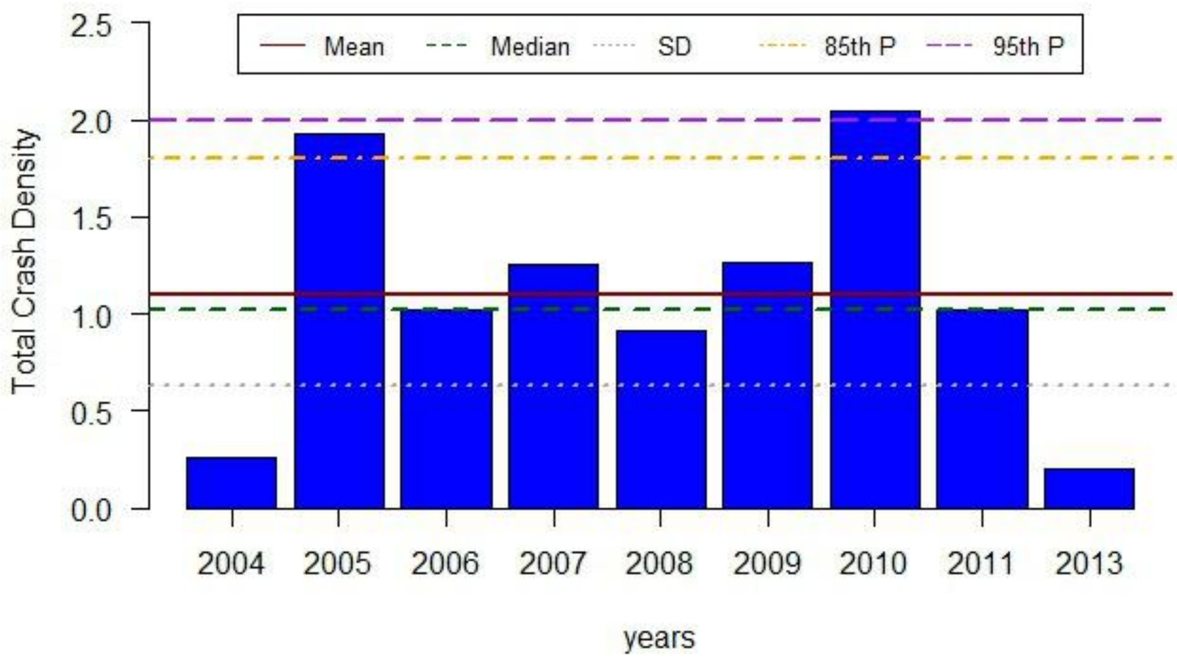


Figure 175 Crash Performance Measure: Smith County



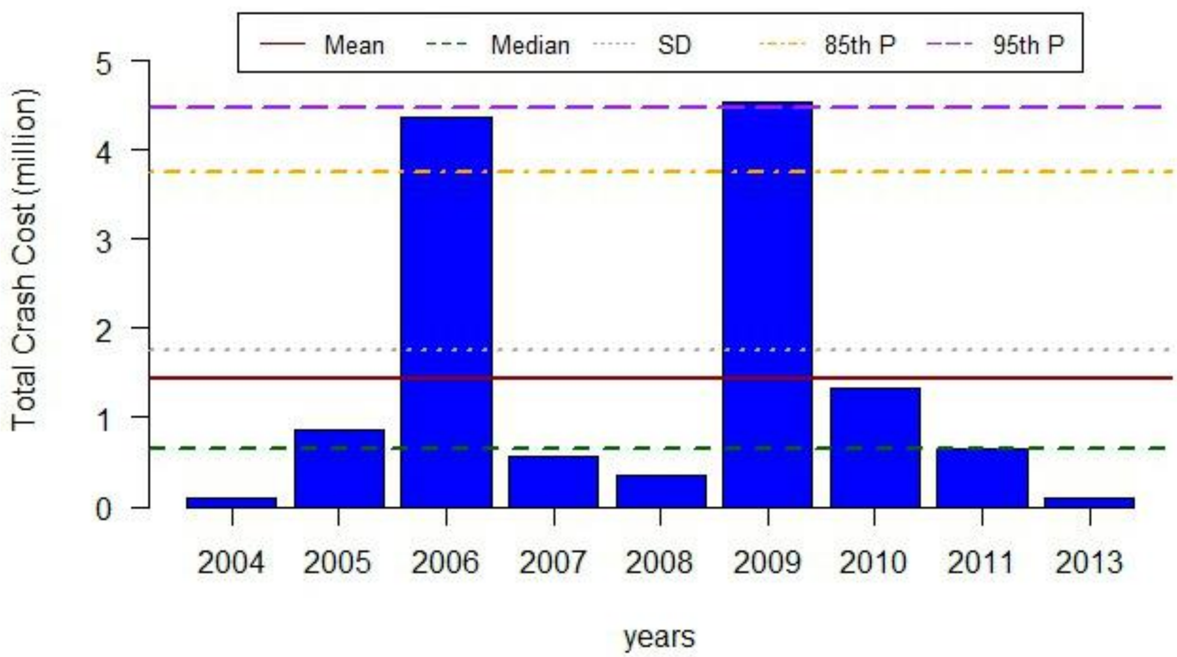
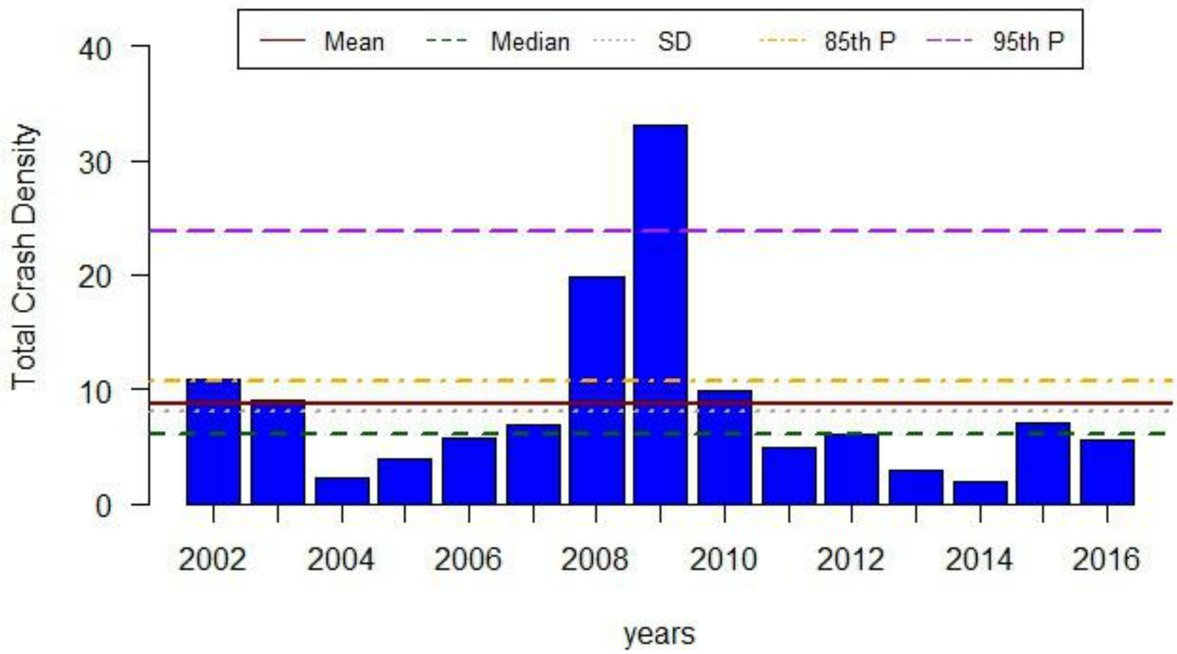


Figure 176 Crash Performance Measure: Stewart County



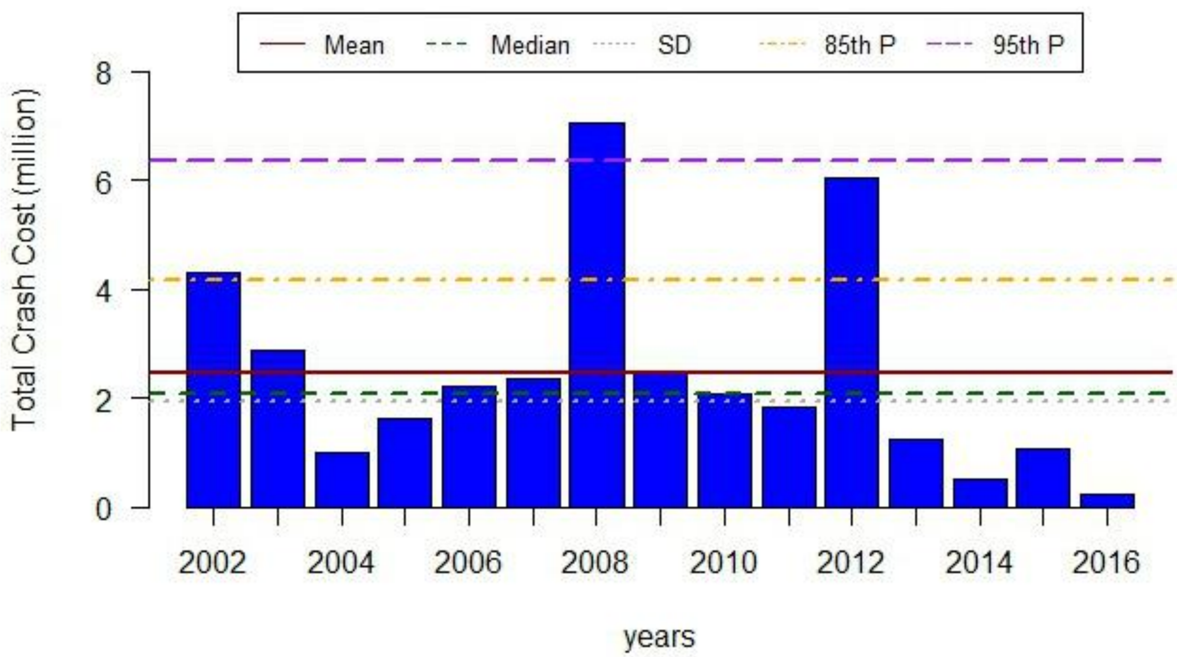
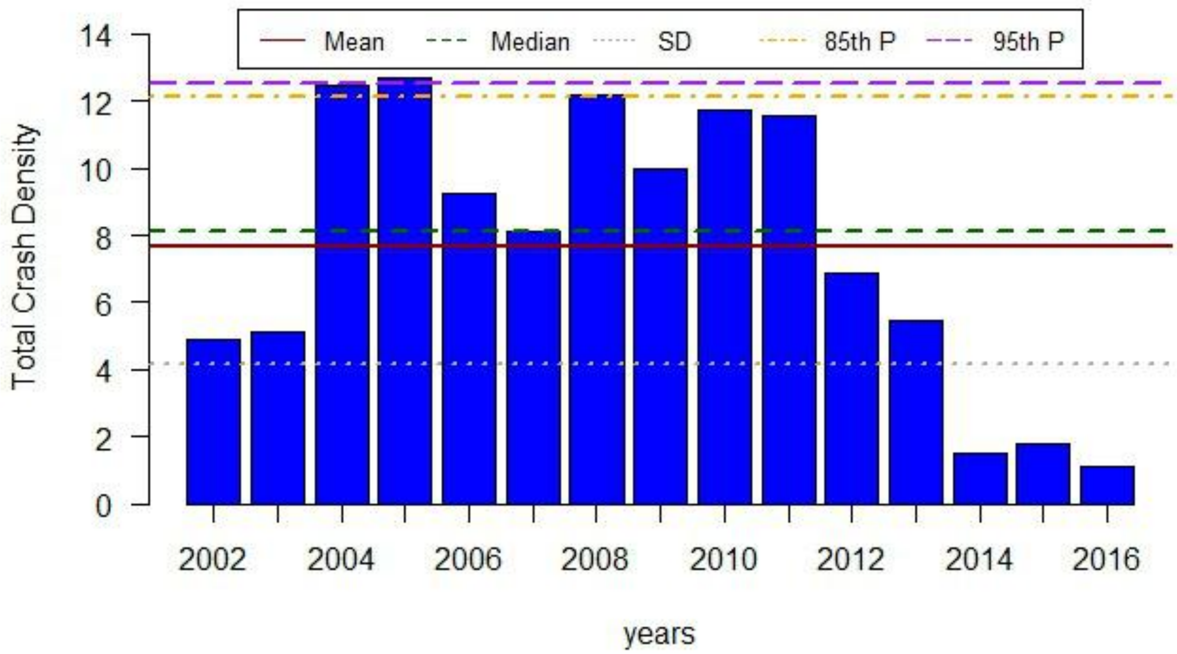


Figure 177 Crash Performance Measure: Sullivan County



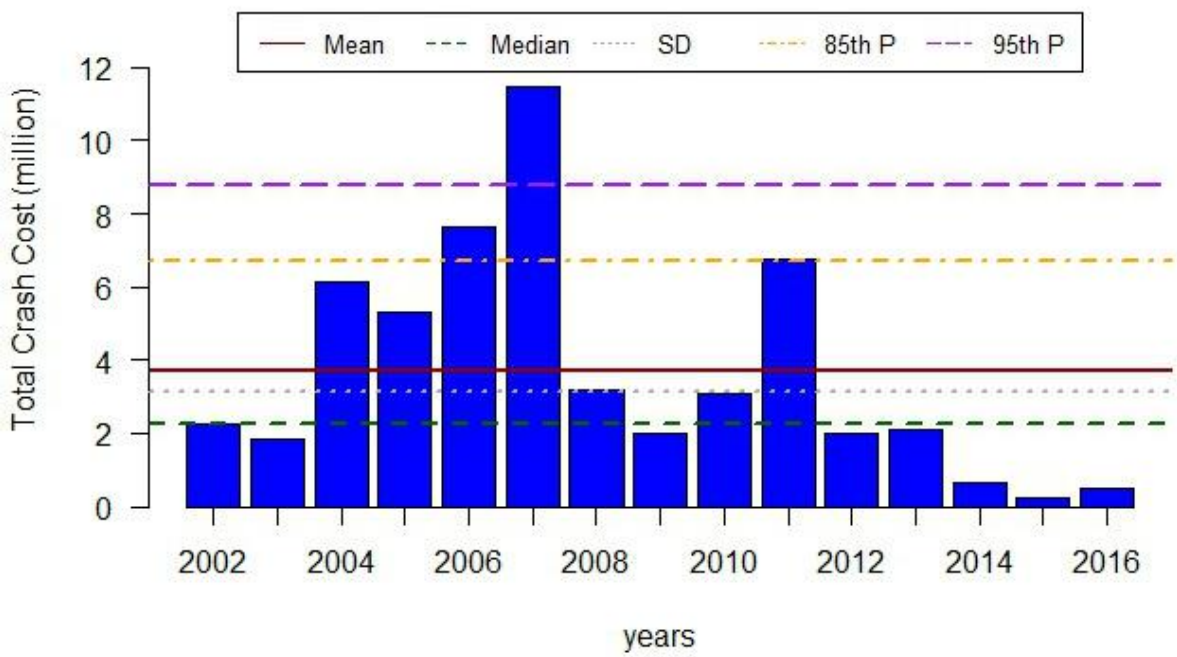


Figure 178 Crash Performance Measure: Sumner County

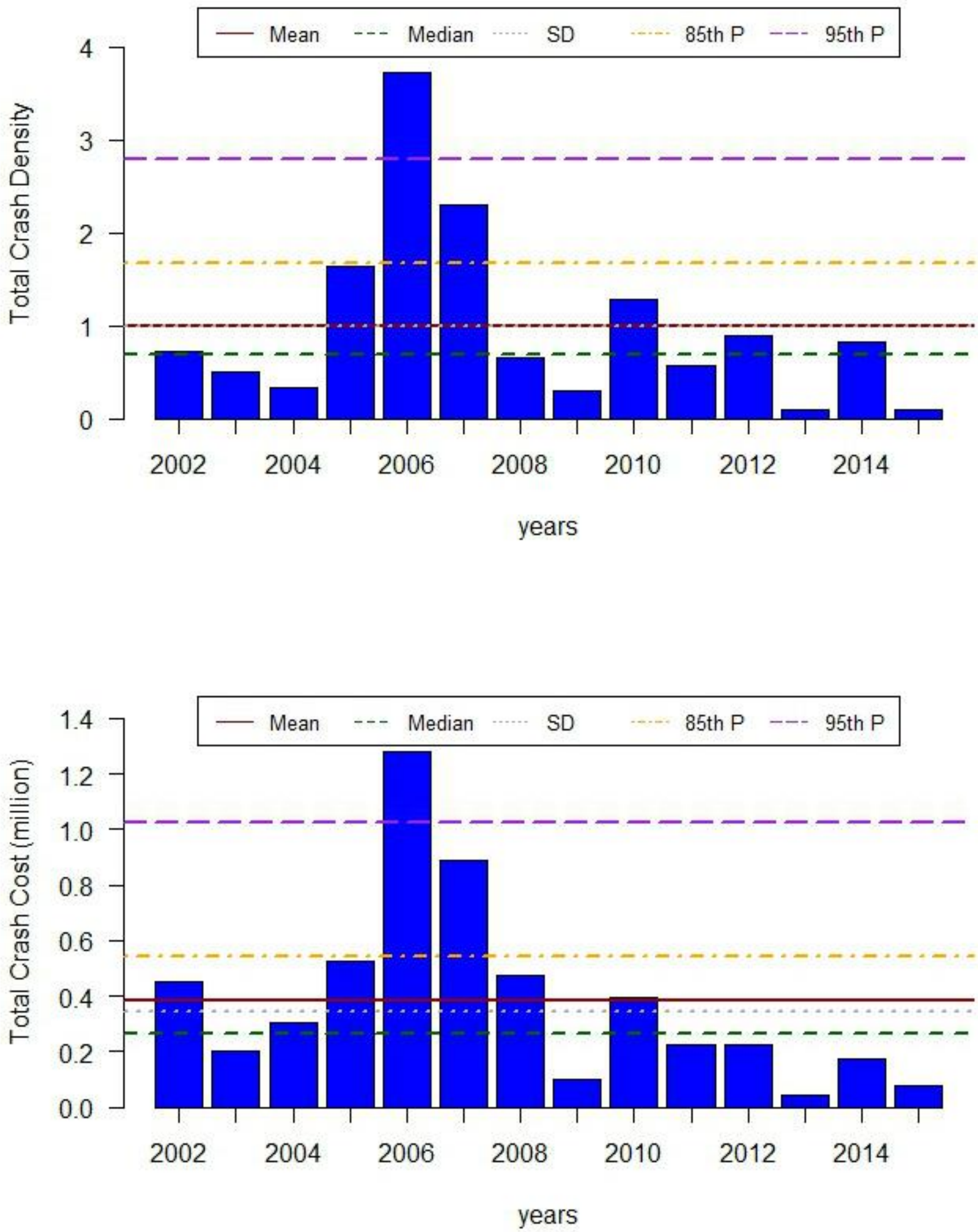
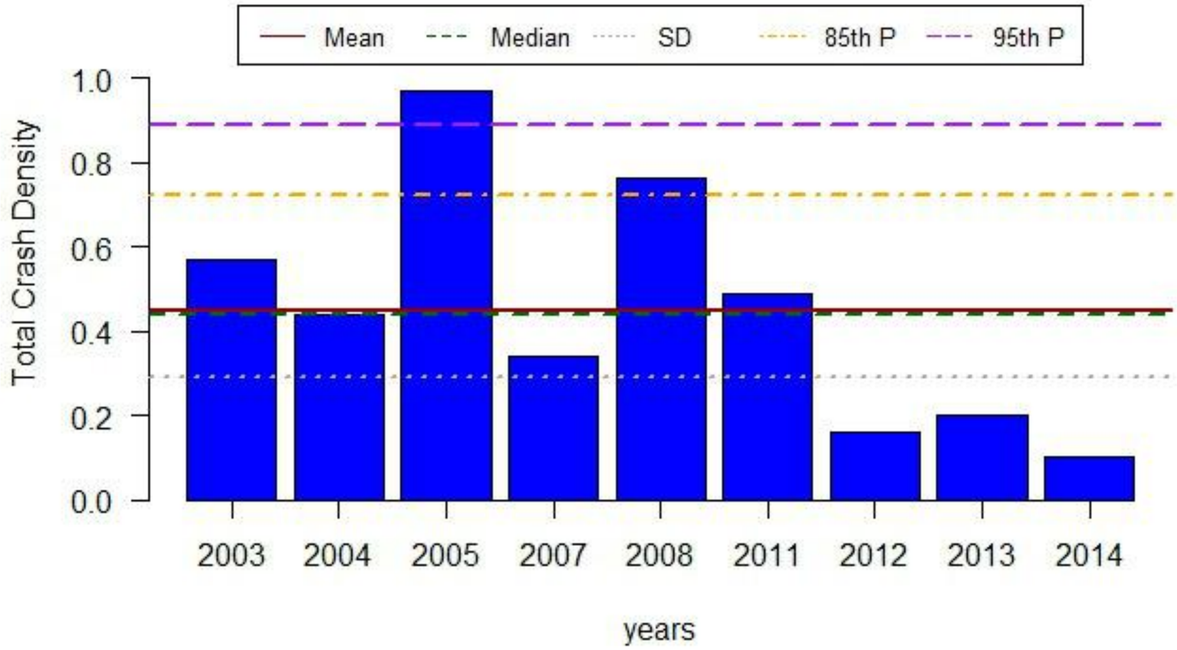


Figure 179 Crash Performance Measure: Tipton County



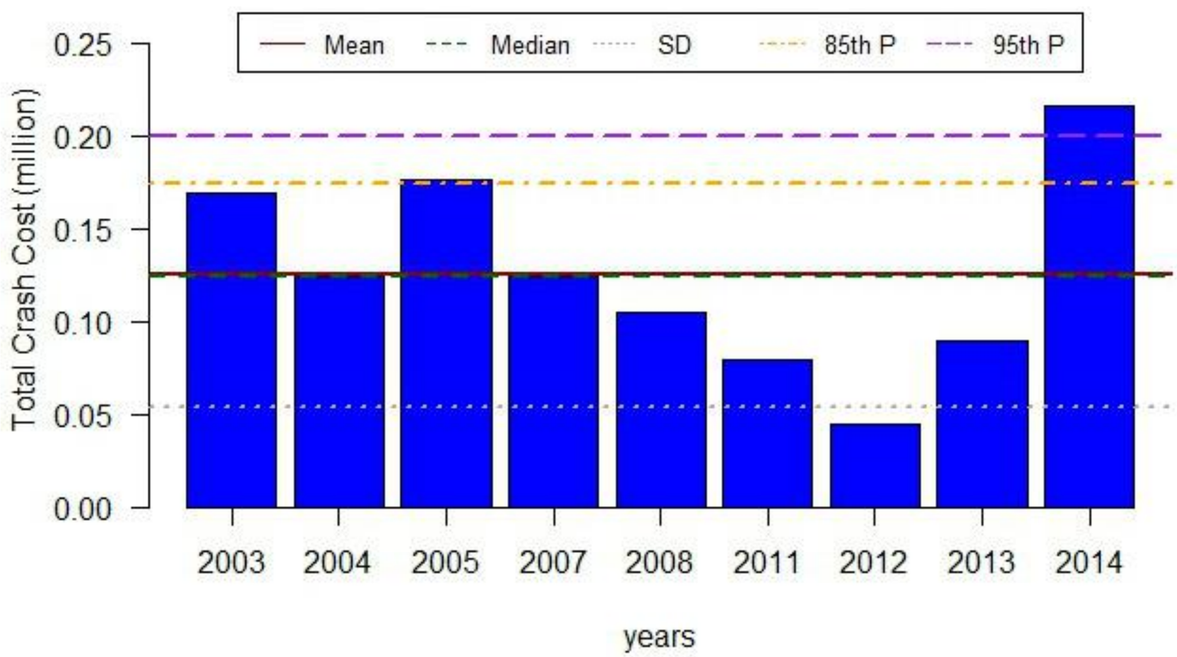


Figure 180 Crash Performance Measure: Trousdale County

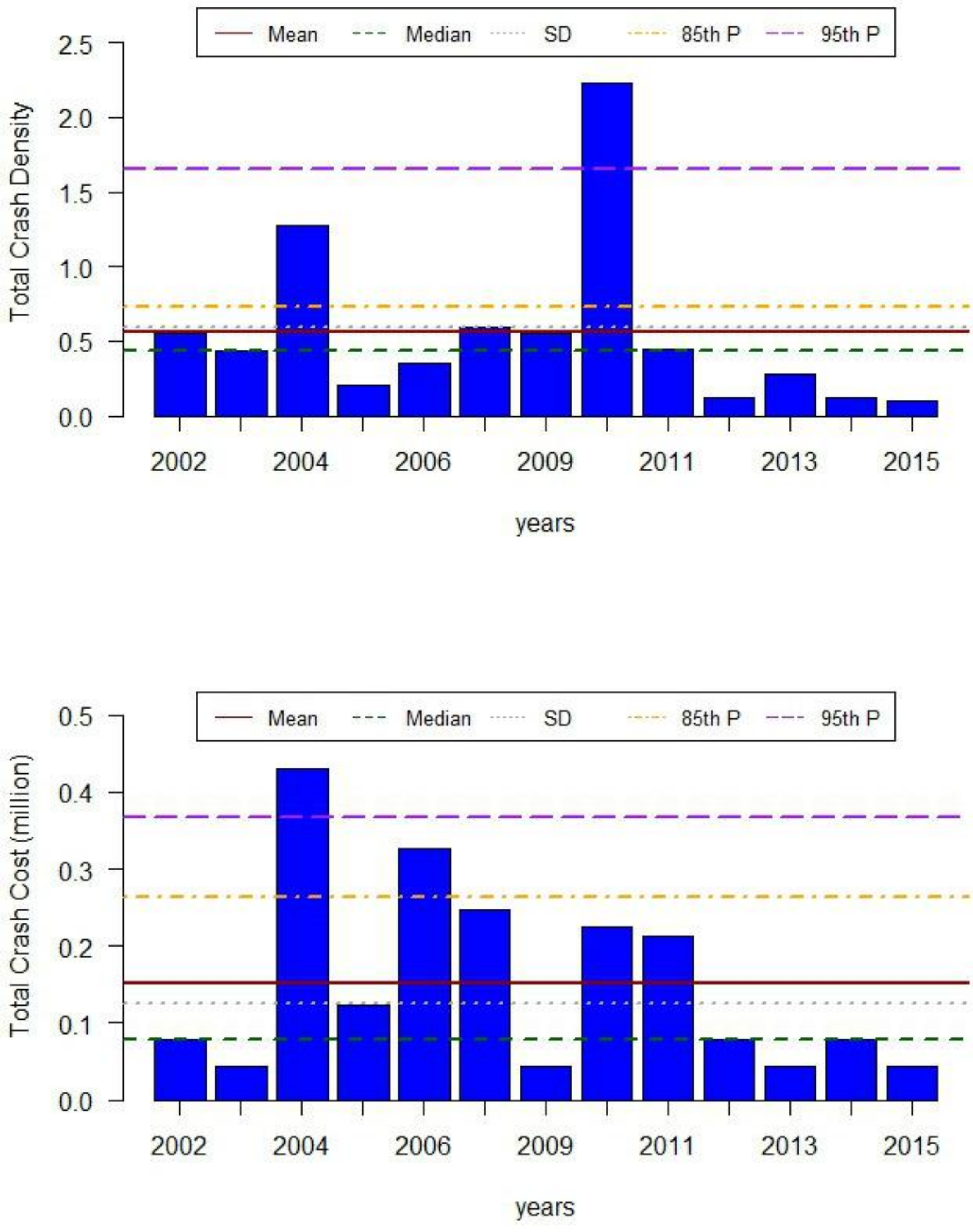
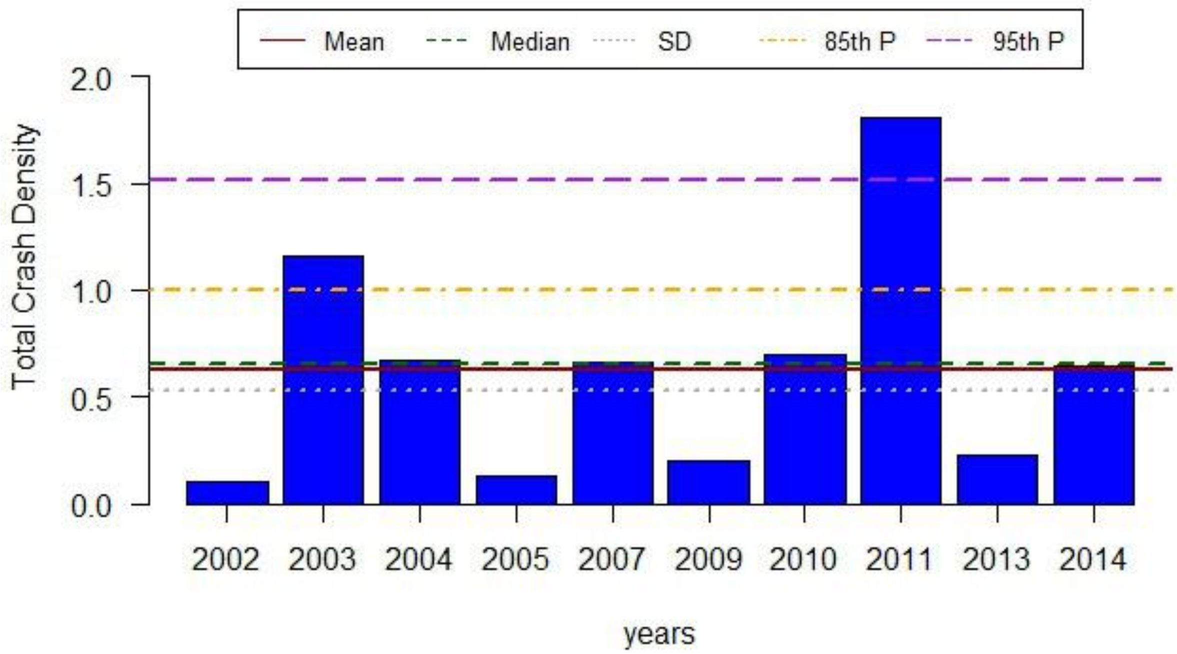


Figure 181 Crash Performance Measure: Unicoi County



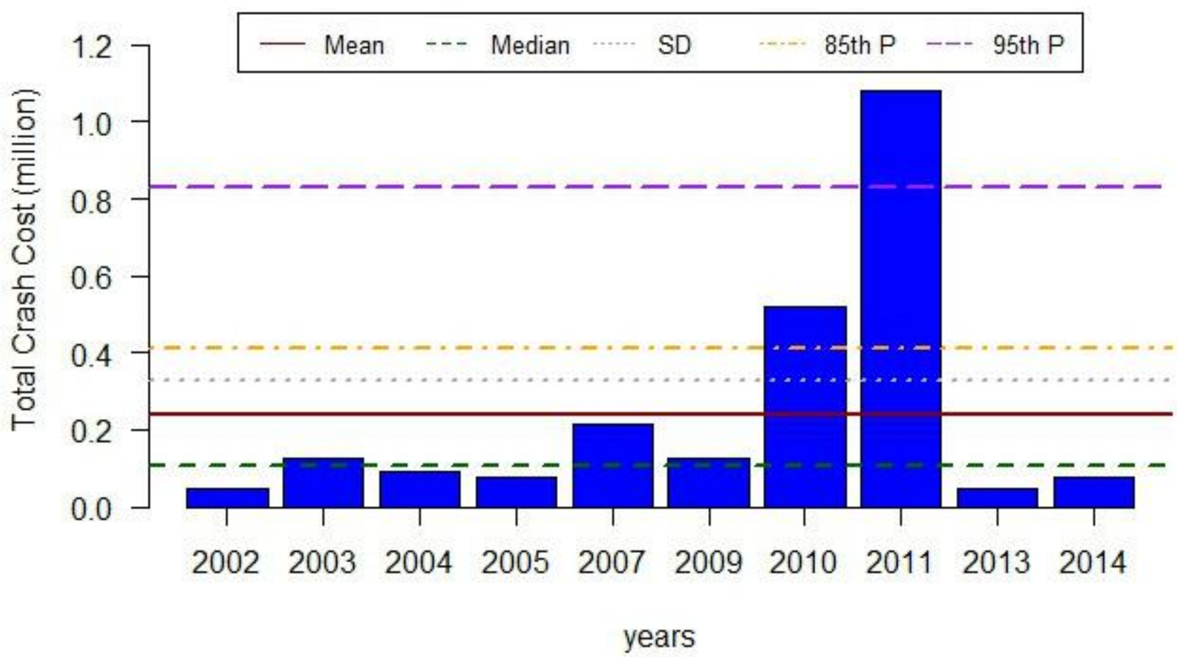
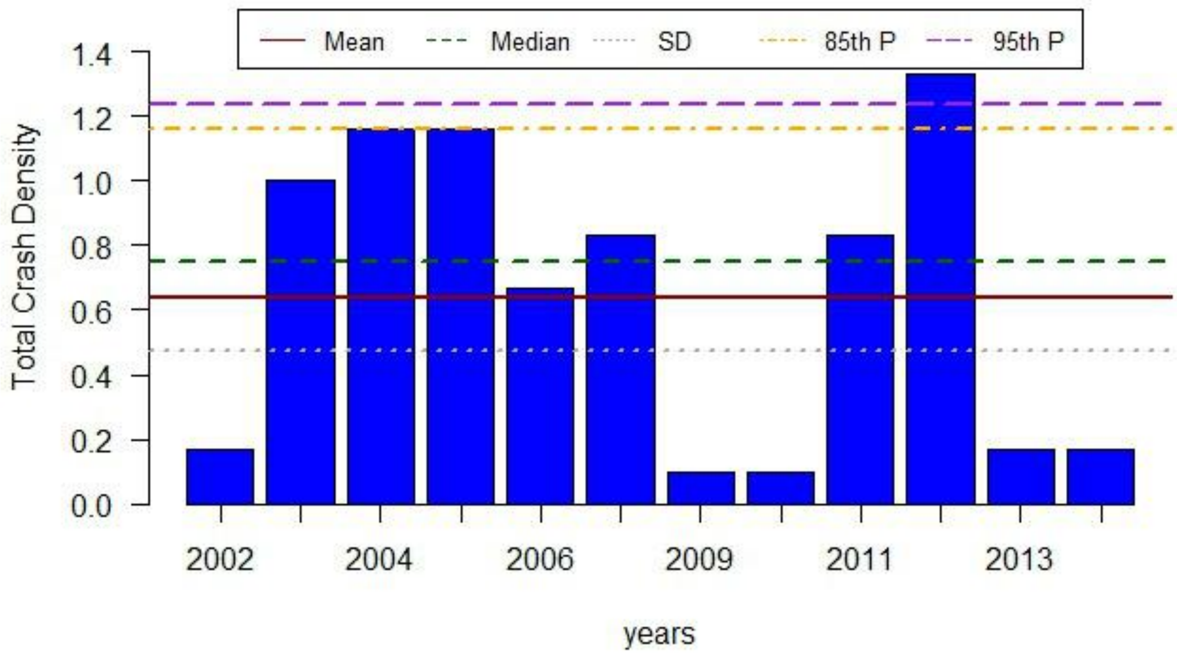


Figure 182 Crash Performance Measure: Union County



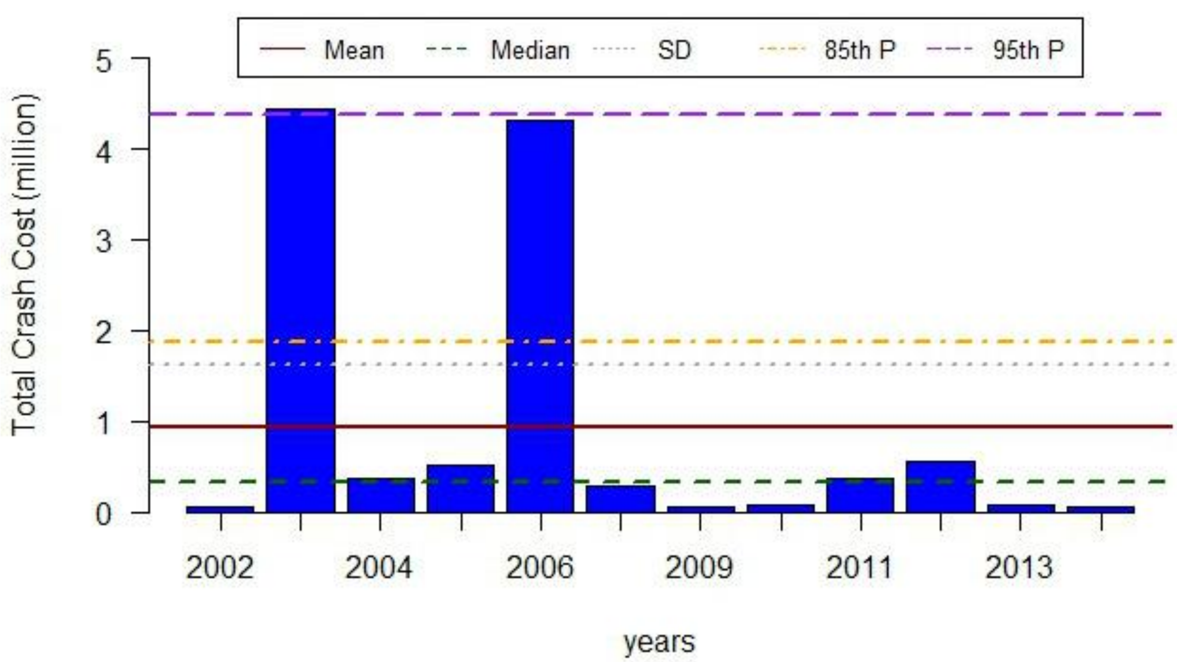
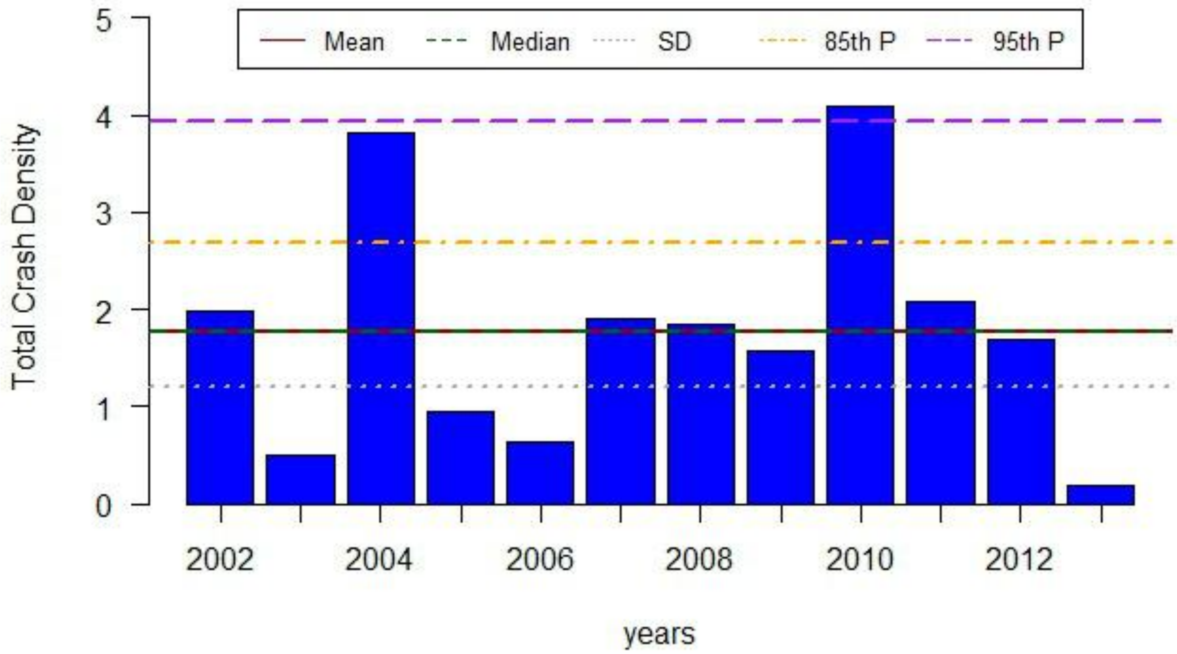


Figure 183 Crash Performance Measure: Van Buren County



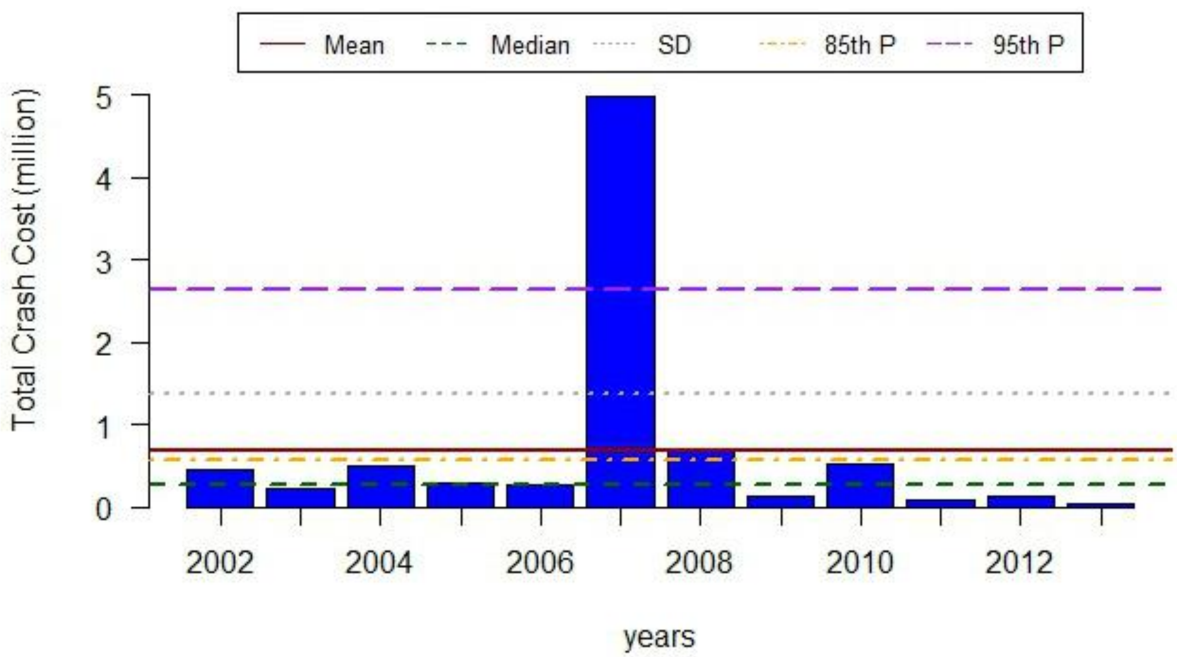


Figure 184 Crash Performance Measure: Warren County

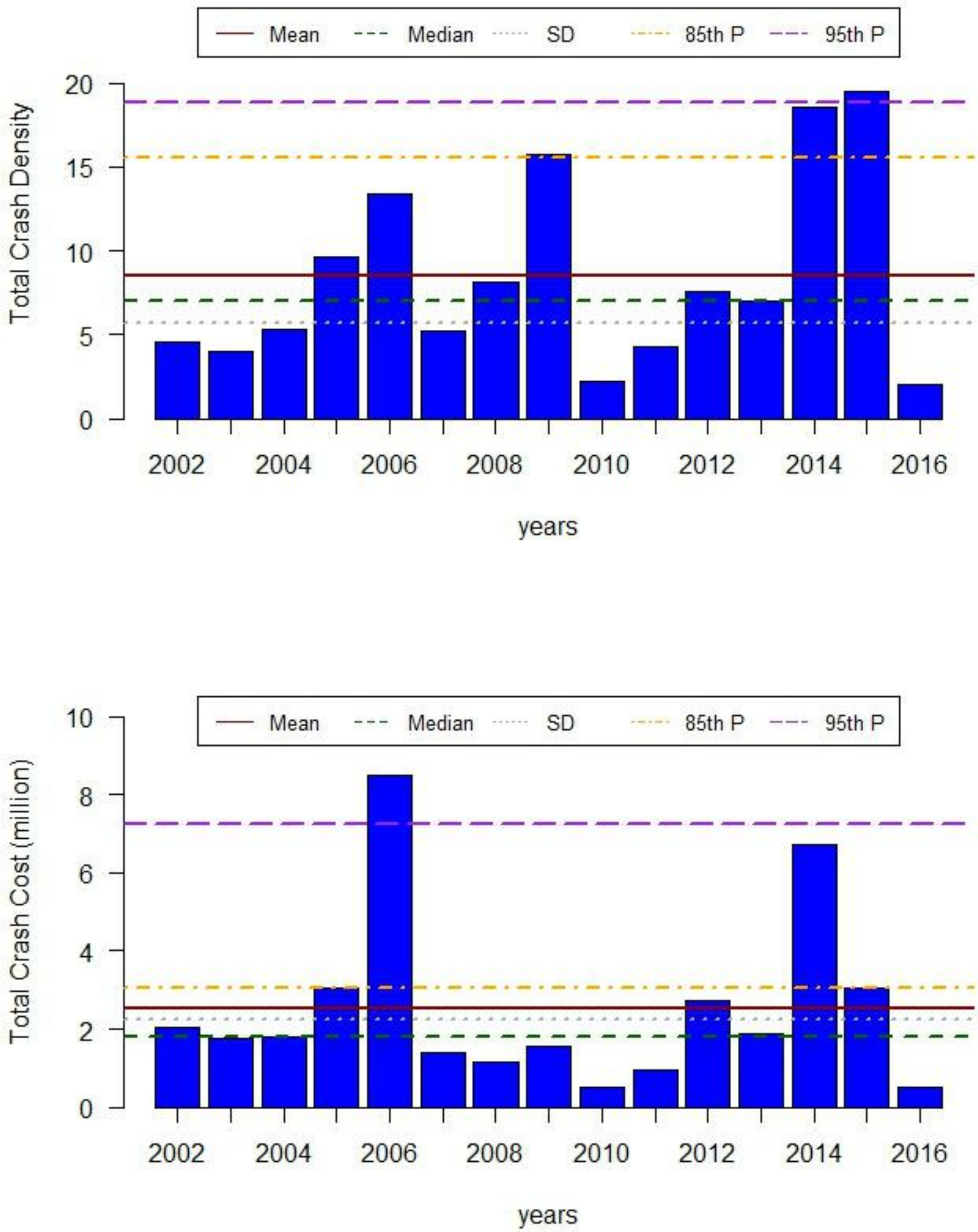
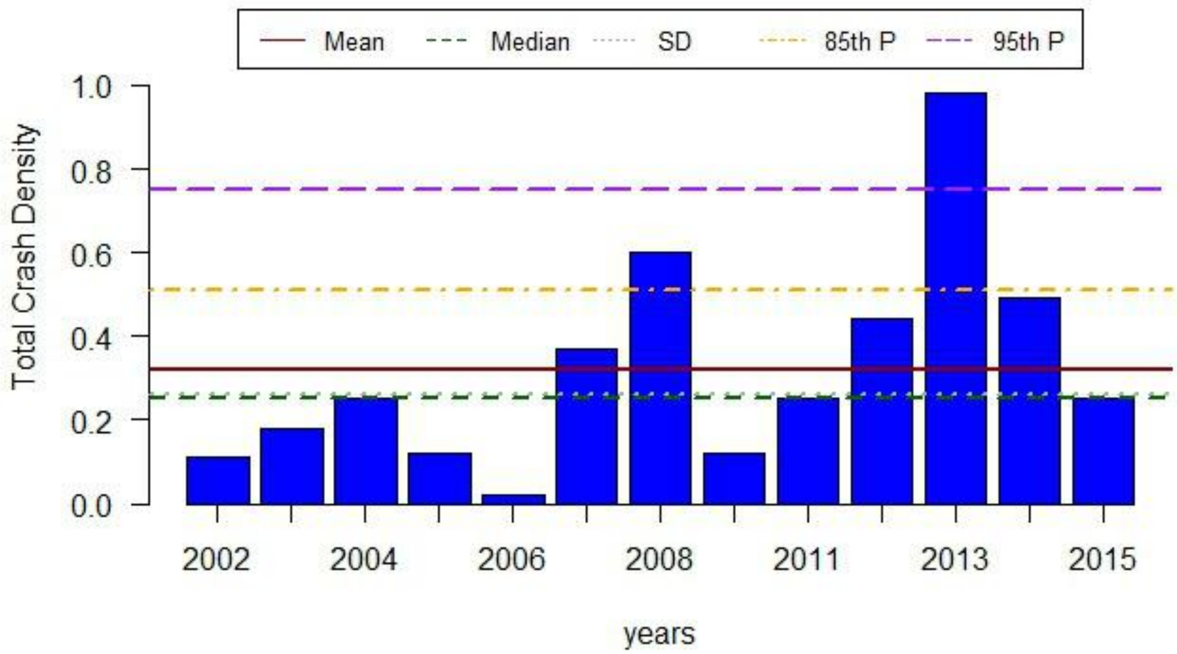


Figure 185 Crash Performance Measure: Washington County



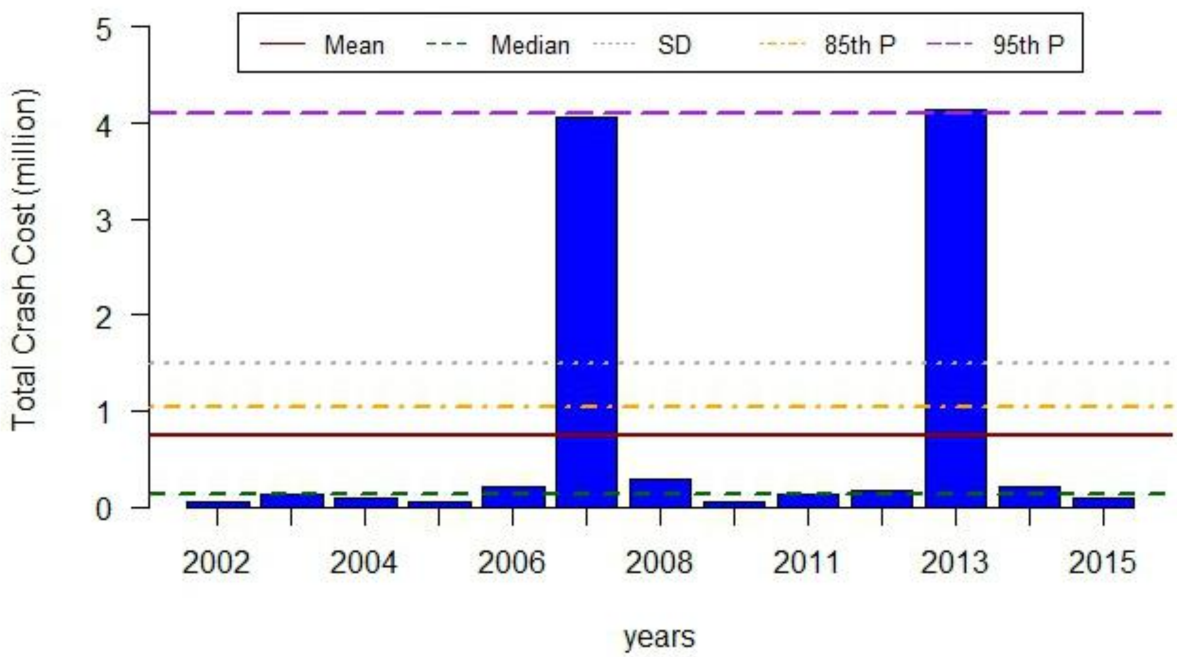
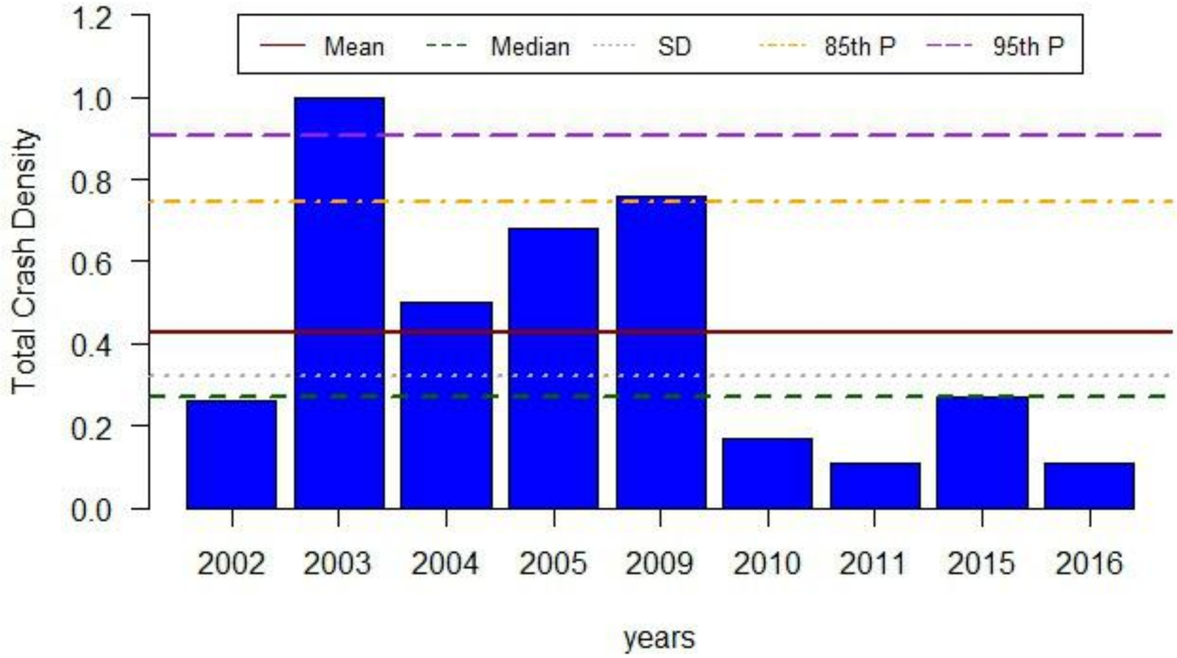


Figure 186 Crash Performance Measure: Wayne County



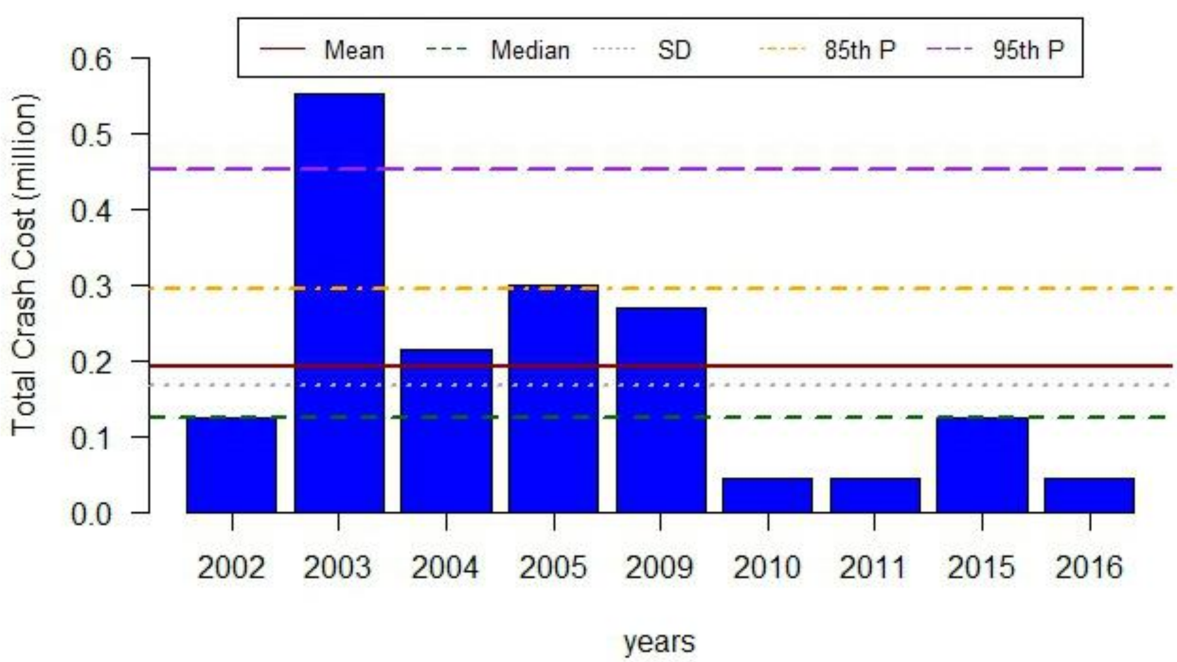


Figure 187 Crash Performance Measure: Weakley County

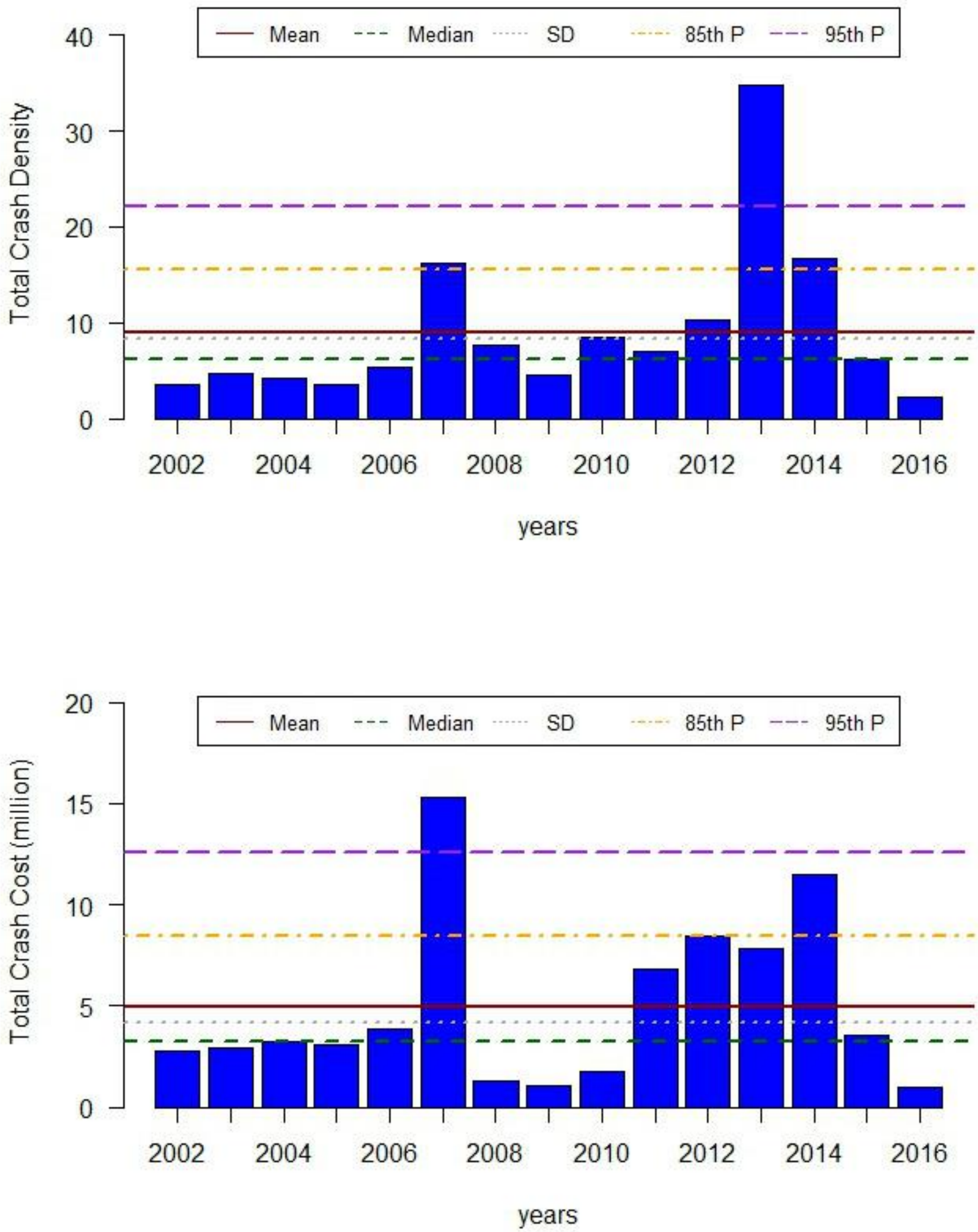
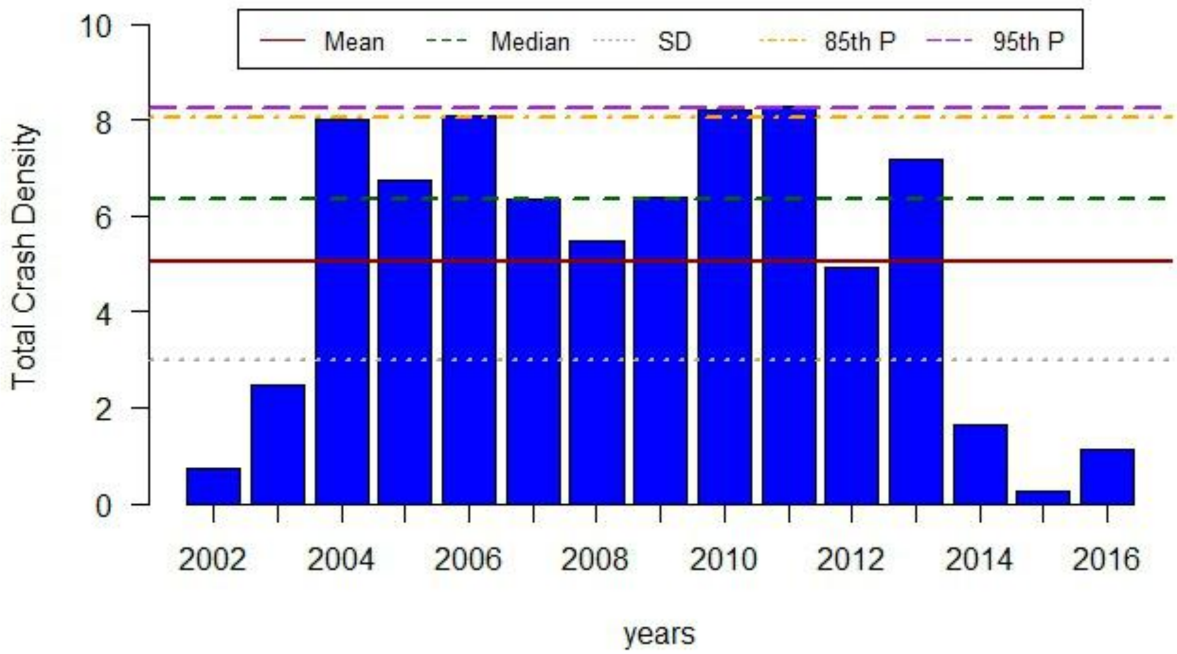


Figure 188 Crash Performance Measure: Williamson County



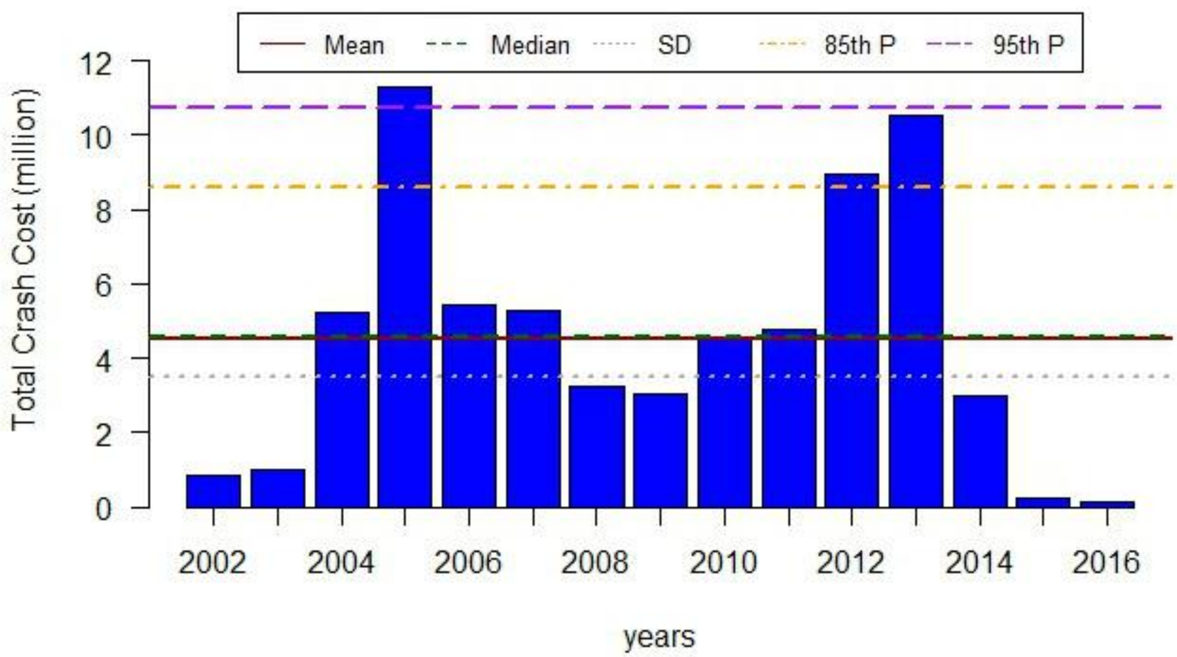


Figure 189 Crash Performance Measure: Wilson County

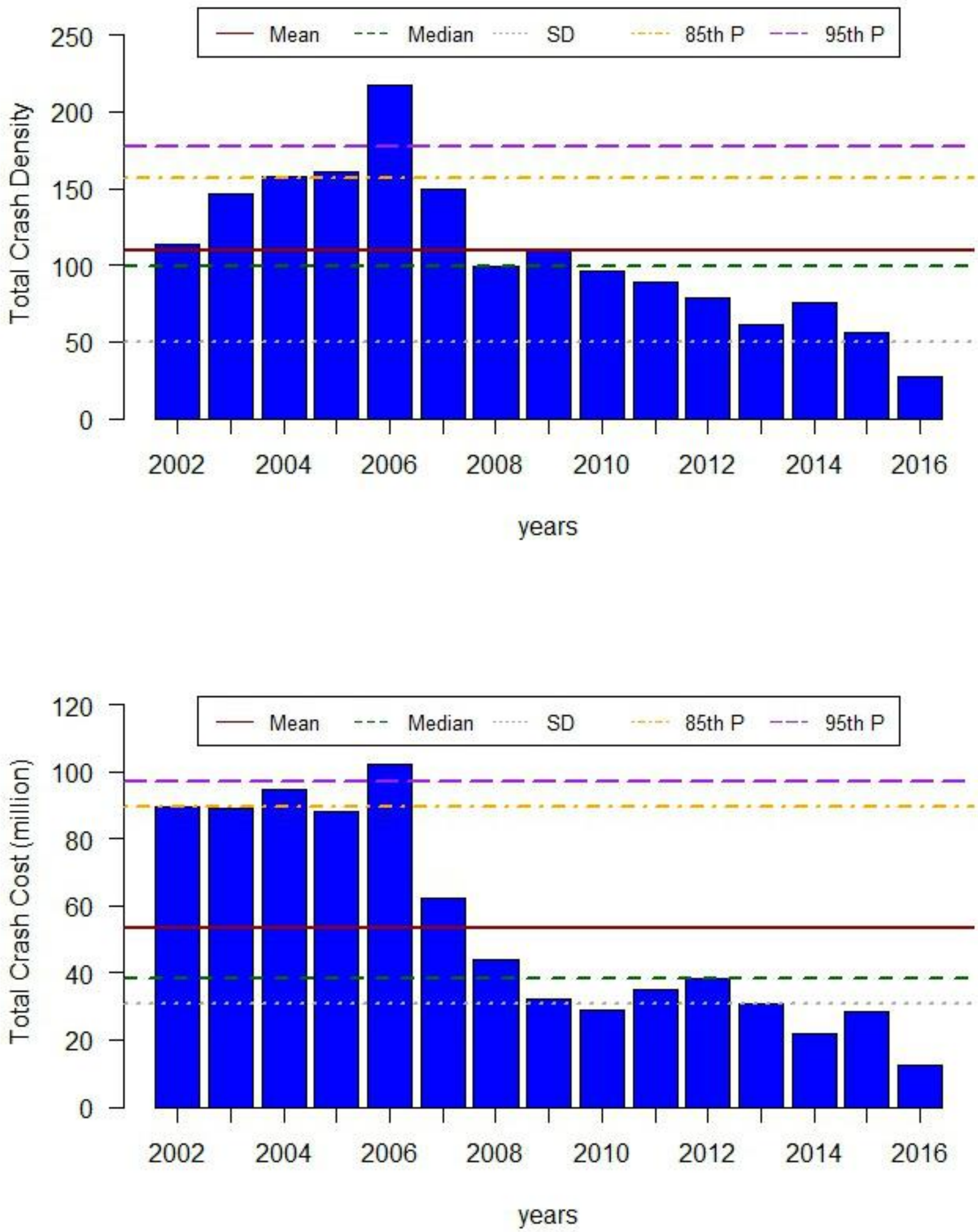


Figure 190 Crash Performance Measure: Region 1

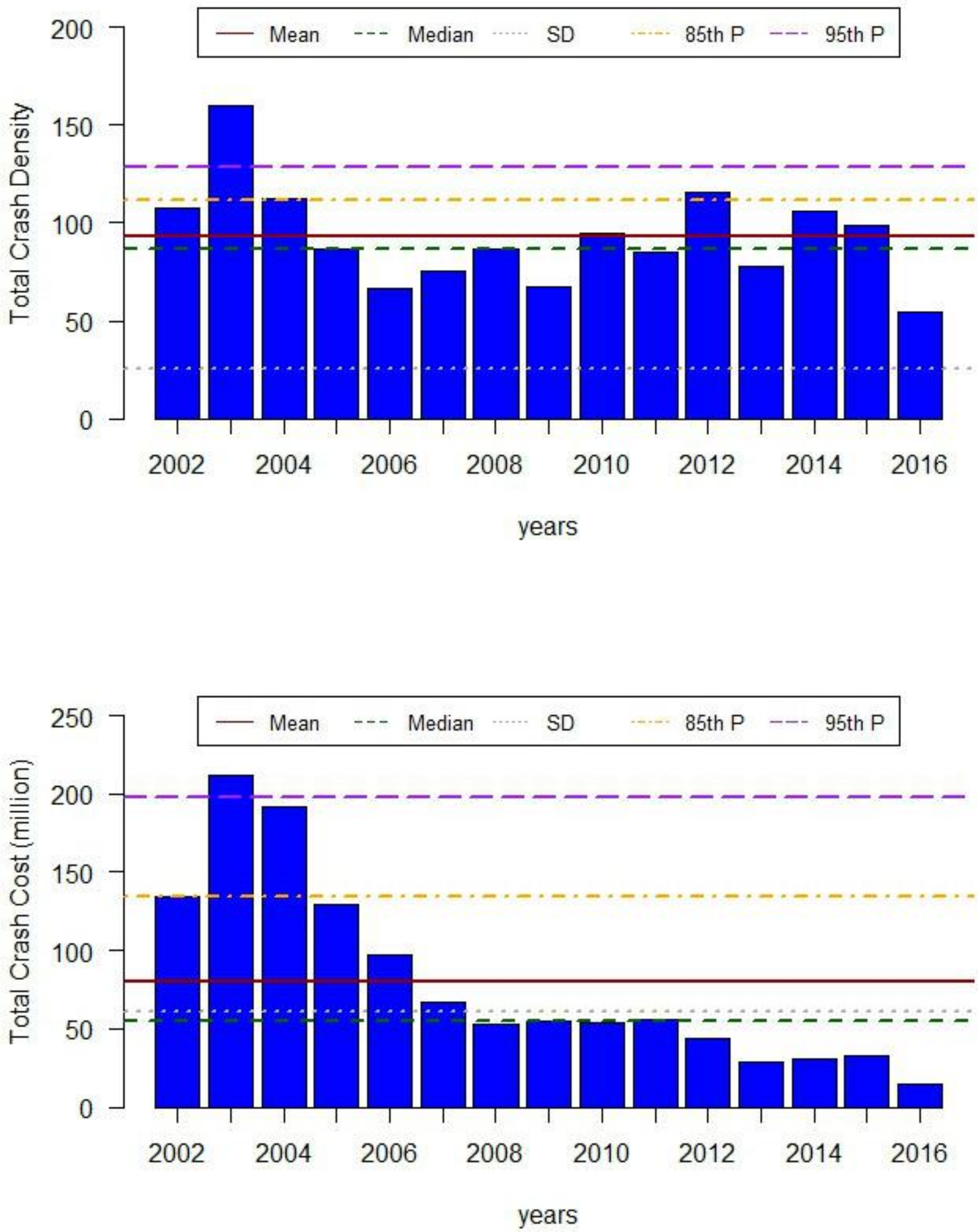
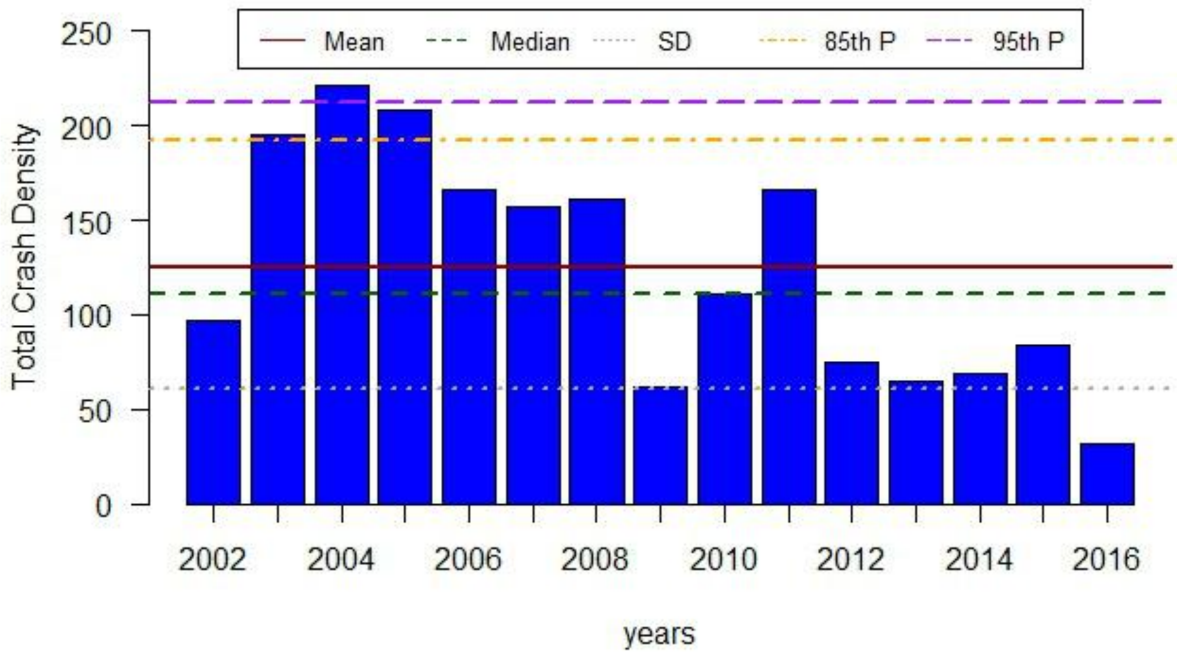


Figure 191 Crash Performance Measure: Region 2



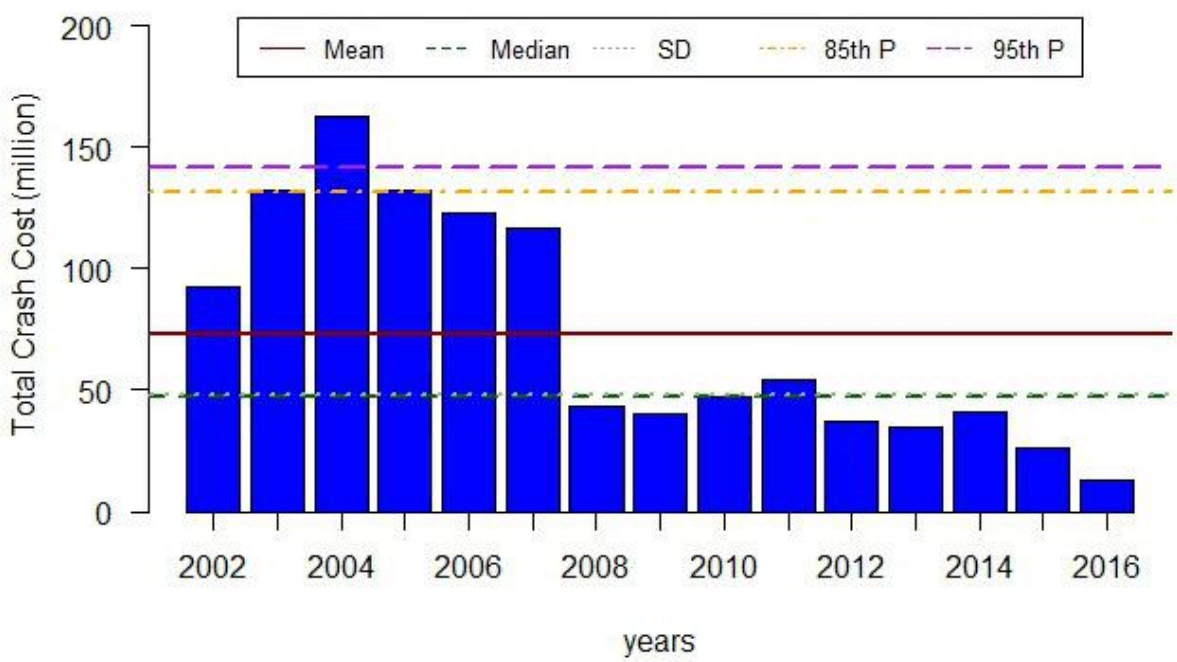
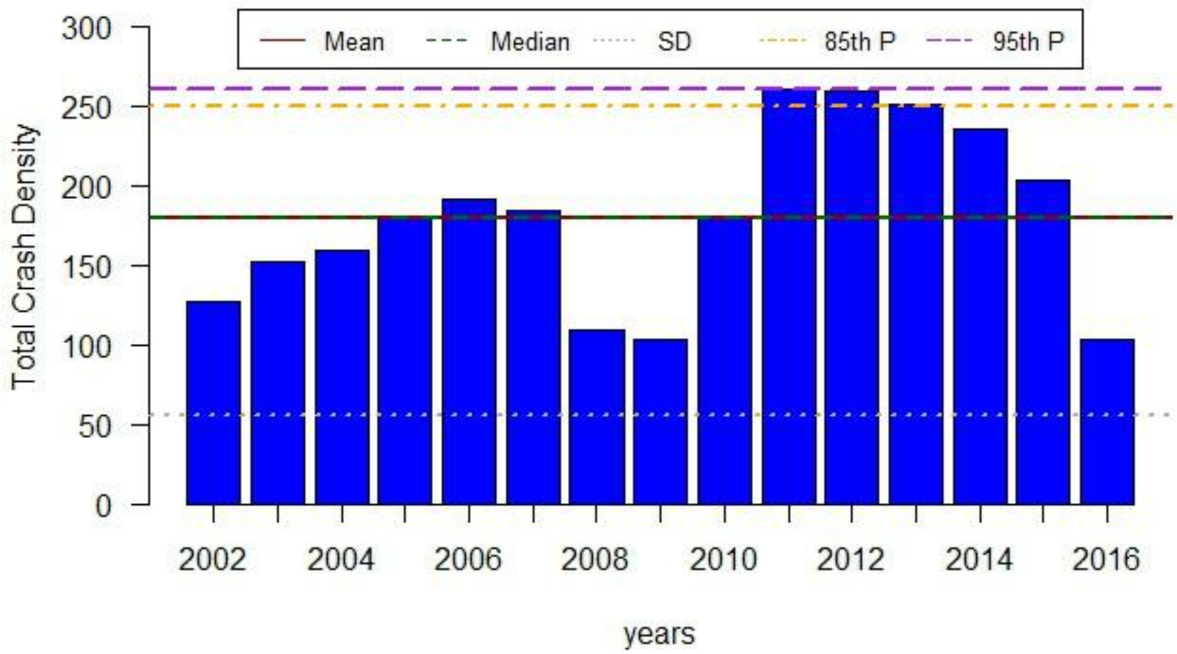


Figure 192 Crash Performance Measure: Region 3



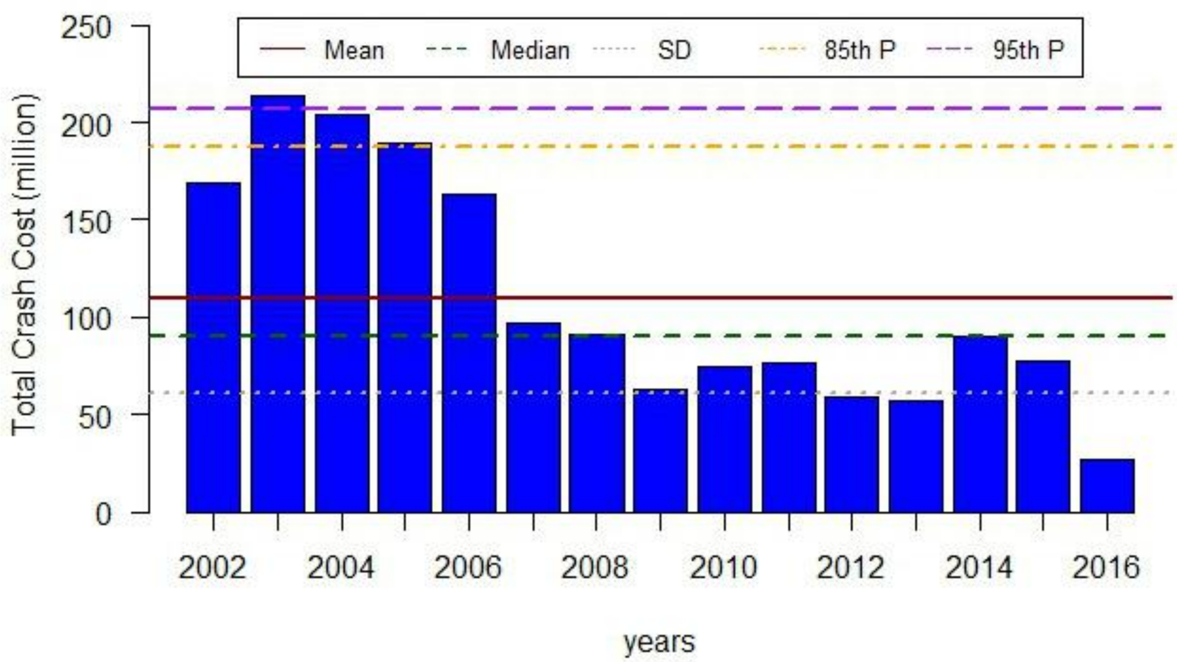


Figure 193 Crash Performance Measure: Region 4

APPENDIX F: WORK ZONE CRASH PERFORMANCE MEASURES BY YEAR

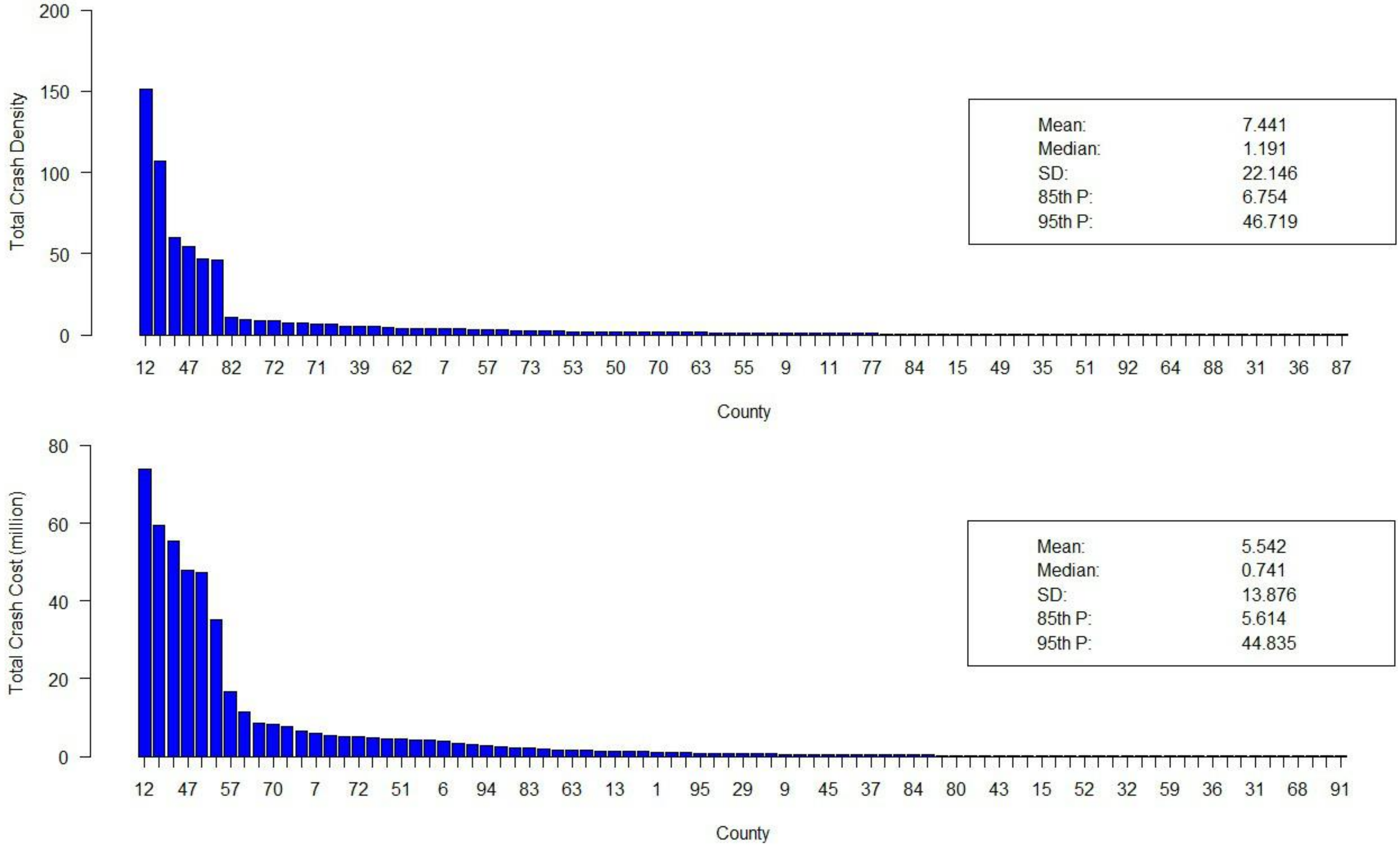


Figure 194 Crash Performance Measure: Year 2002

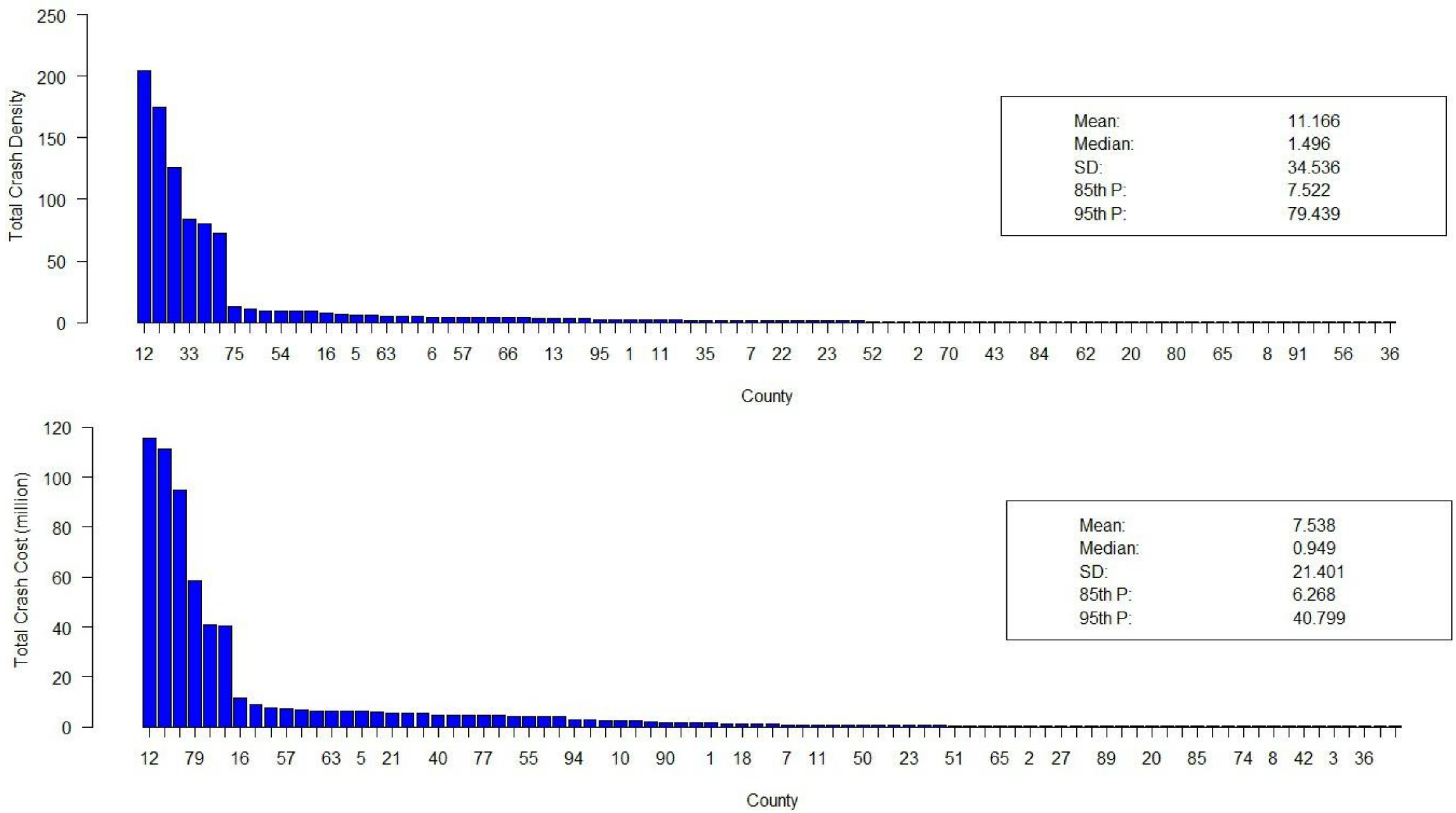


Figure 195 Crash Performance Measure: Year 2003

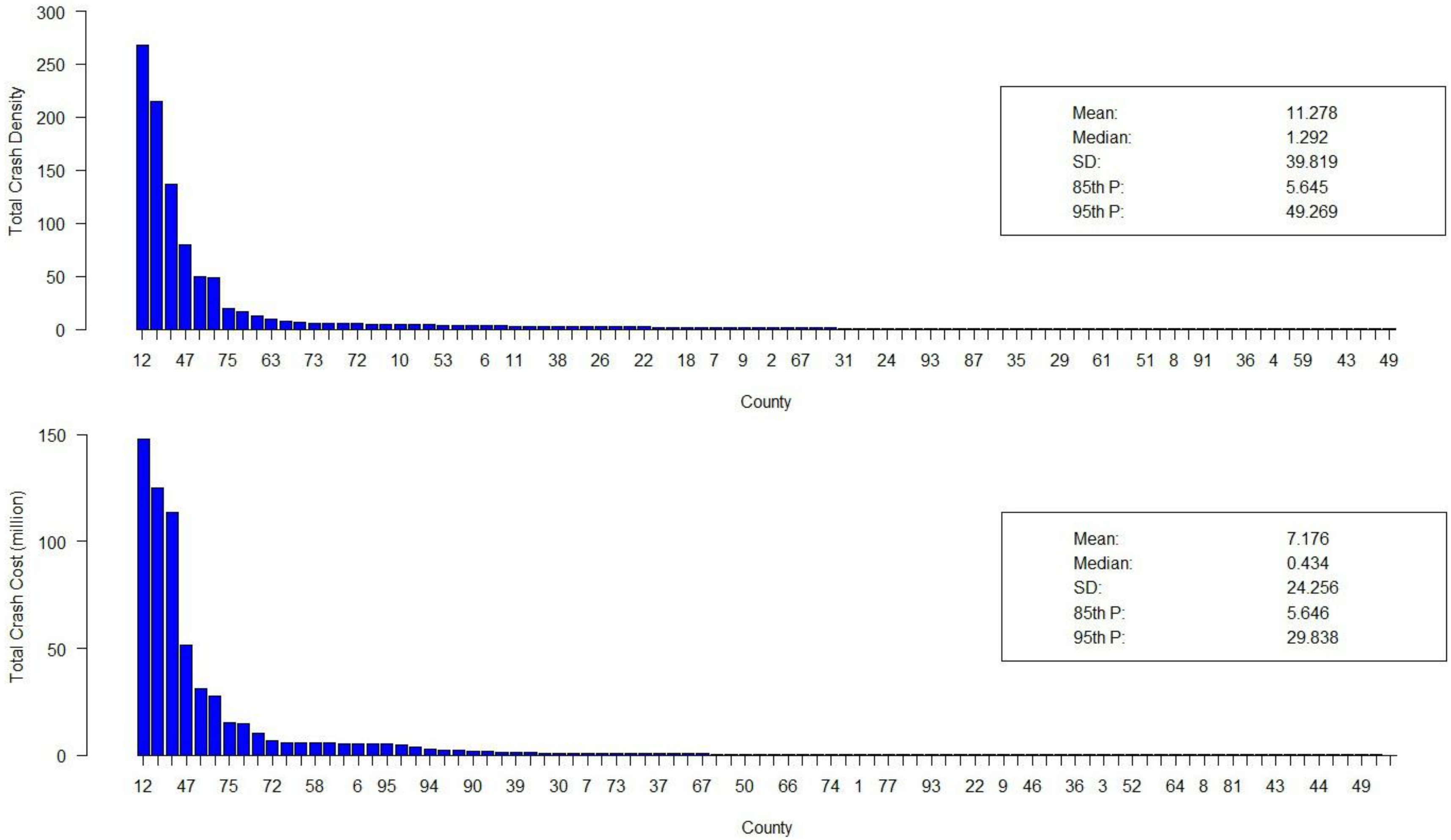


Figure 196 Crash Performance Measure: Year 2004

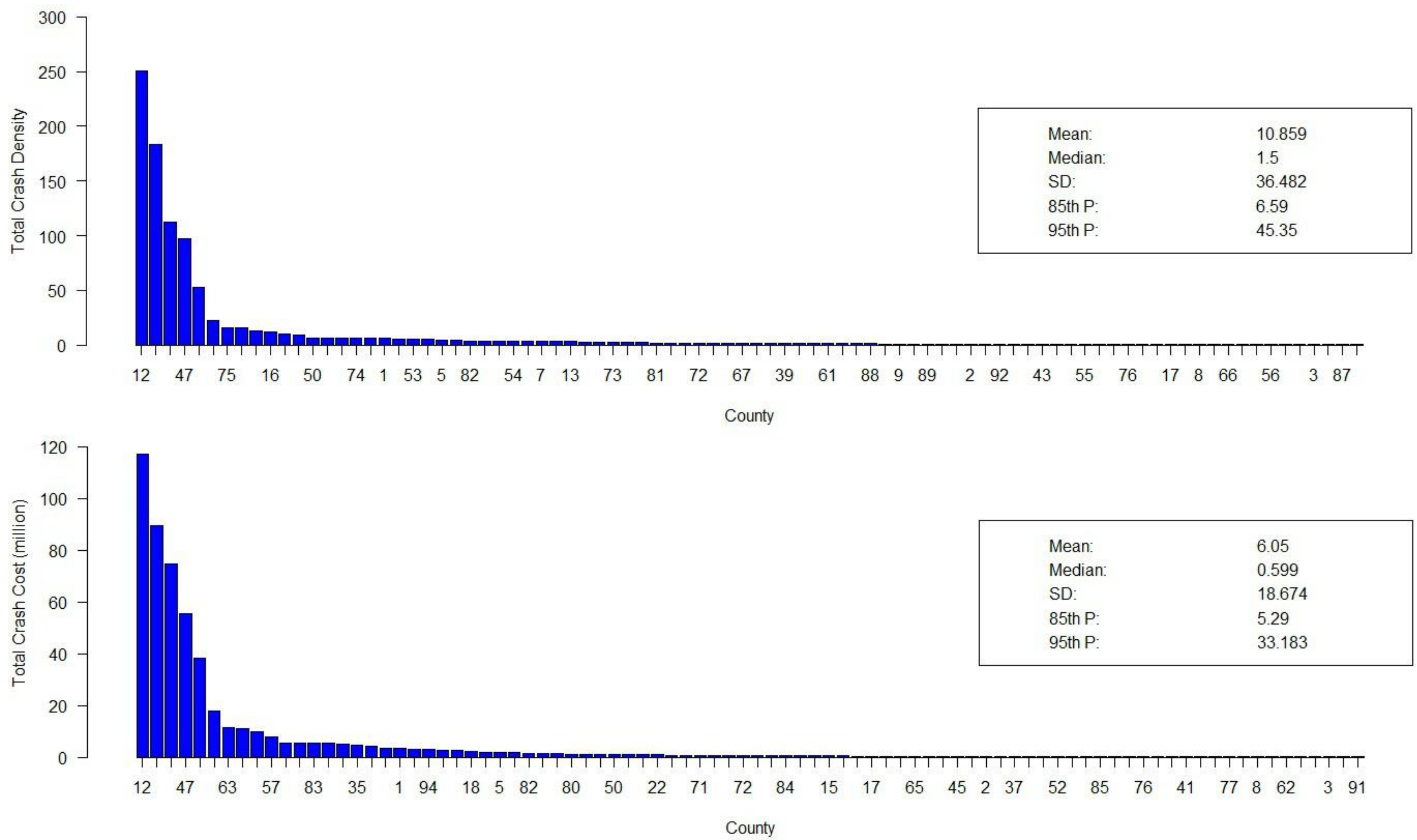


Figure 197 Crash Performance Measure: Year 2005

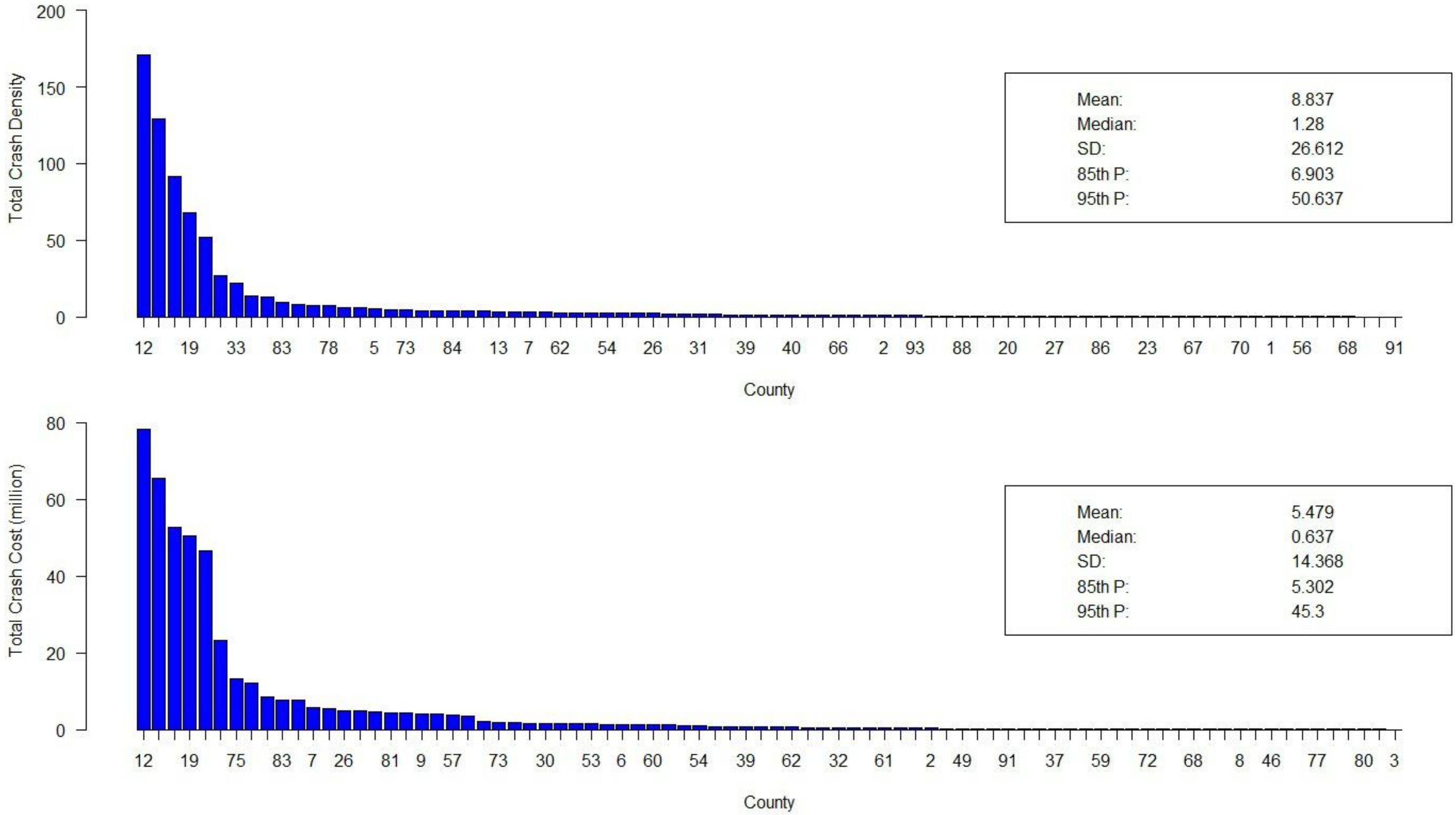


Figure 198 Crash Performance Measure: Year 2006

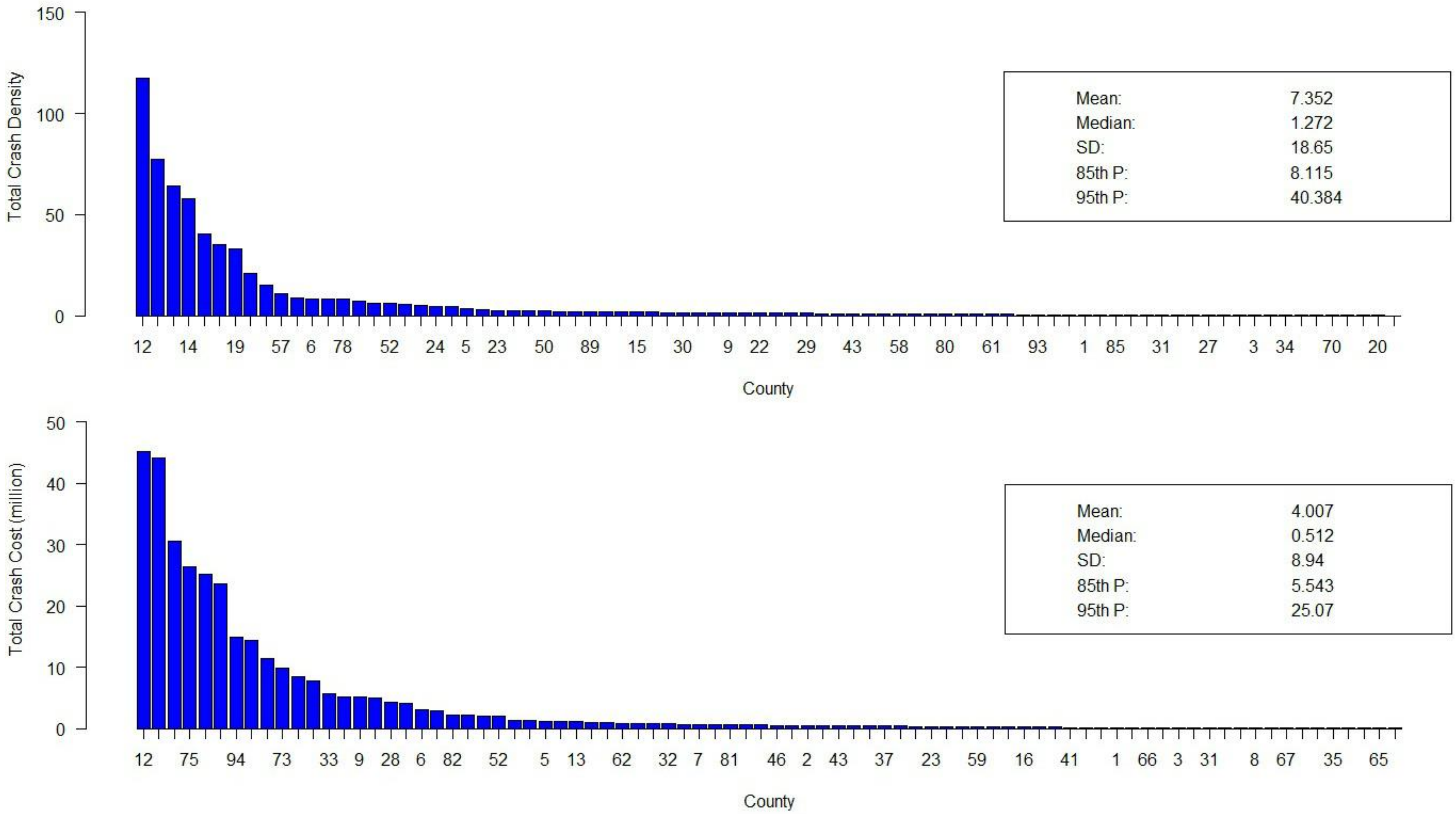


Figure 199 Crash Performance Measure: Year 2007

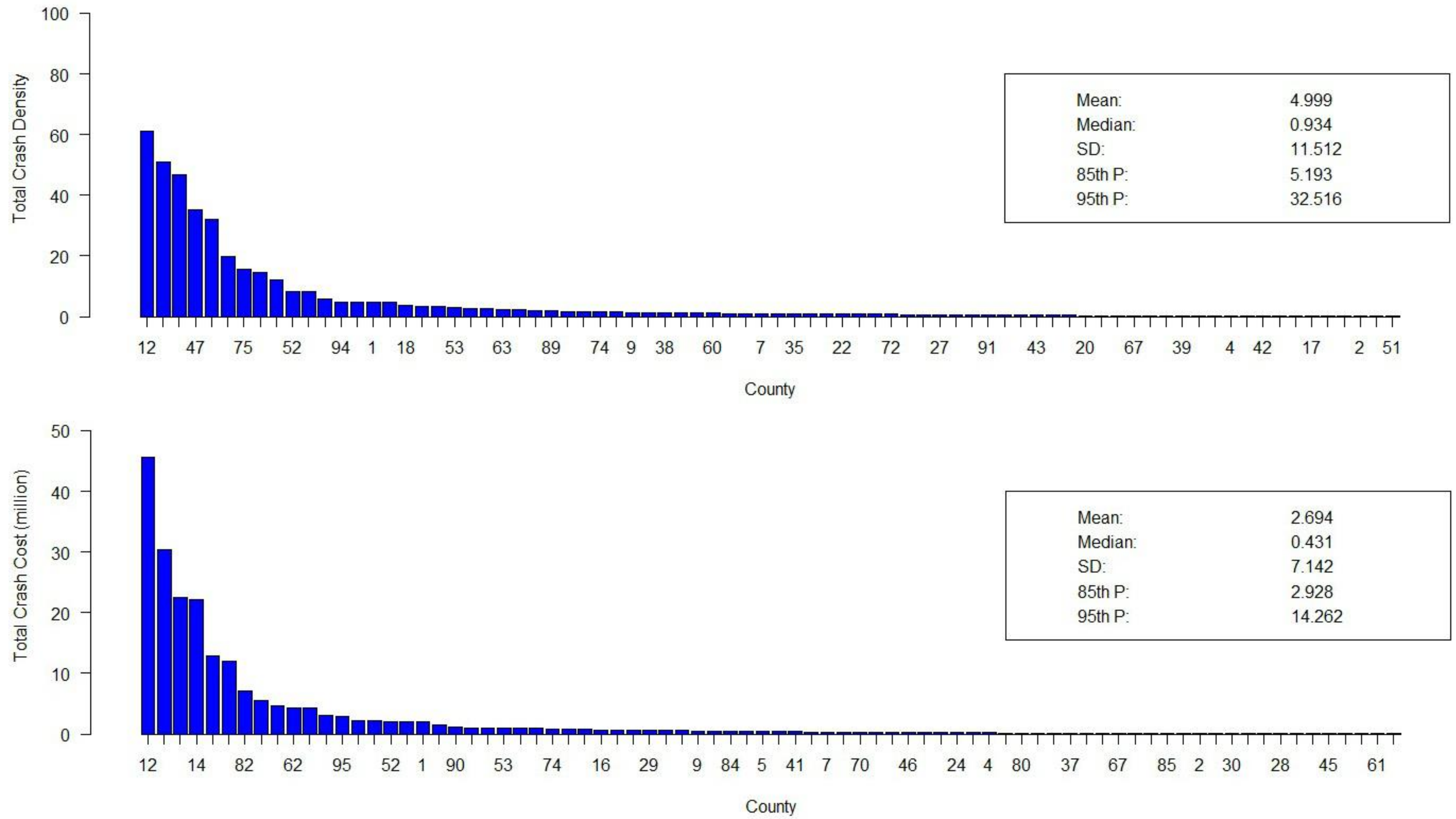


Figure 200 Crash Performance Measure: Year 2008

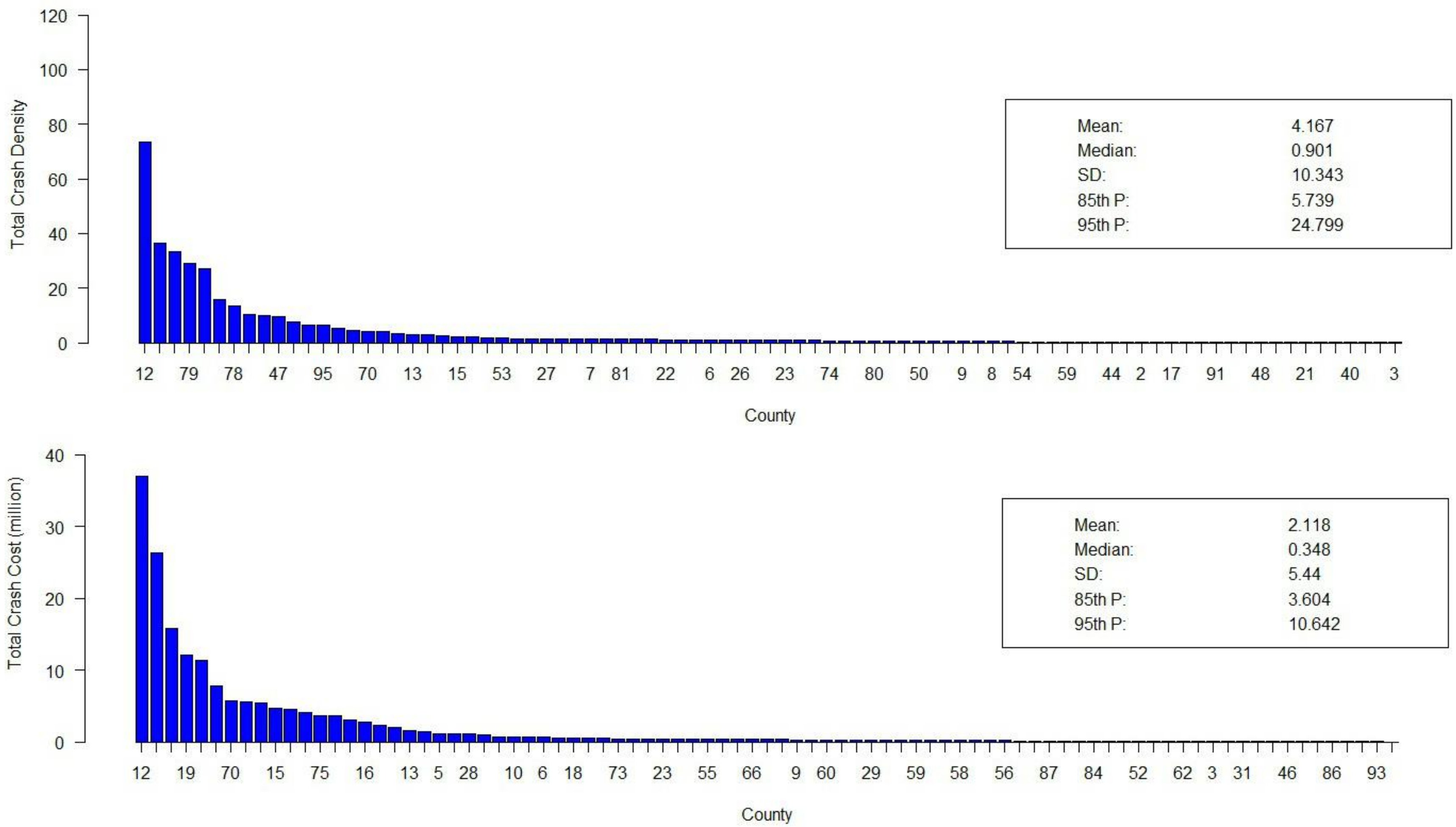


Figure 201 Crash Performance Measure: Year 2009

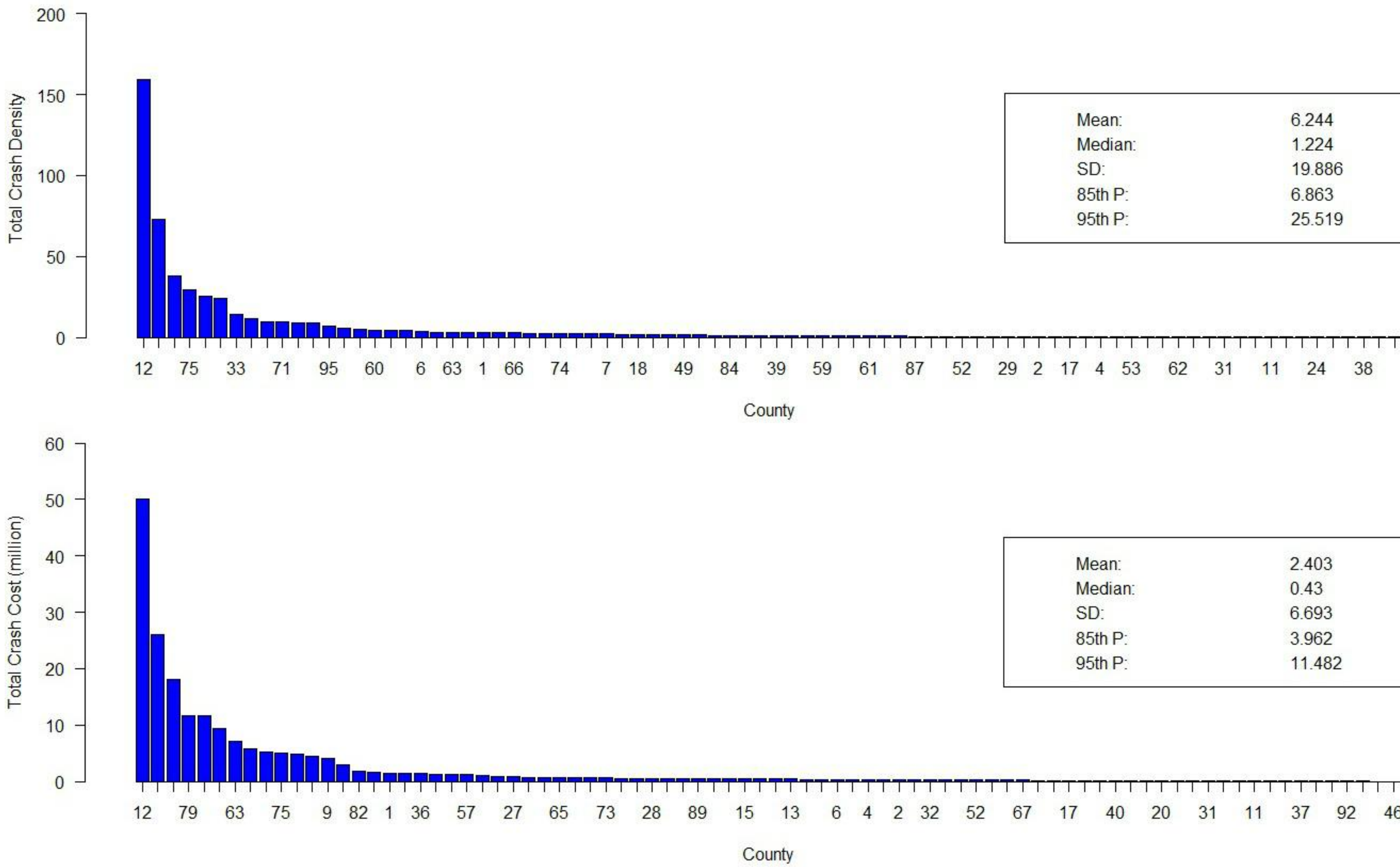


Figure 202 Crash Performance Measure: Year 2010

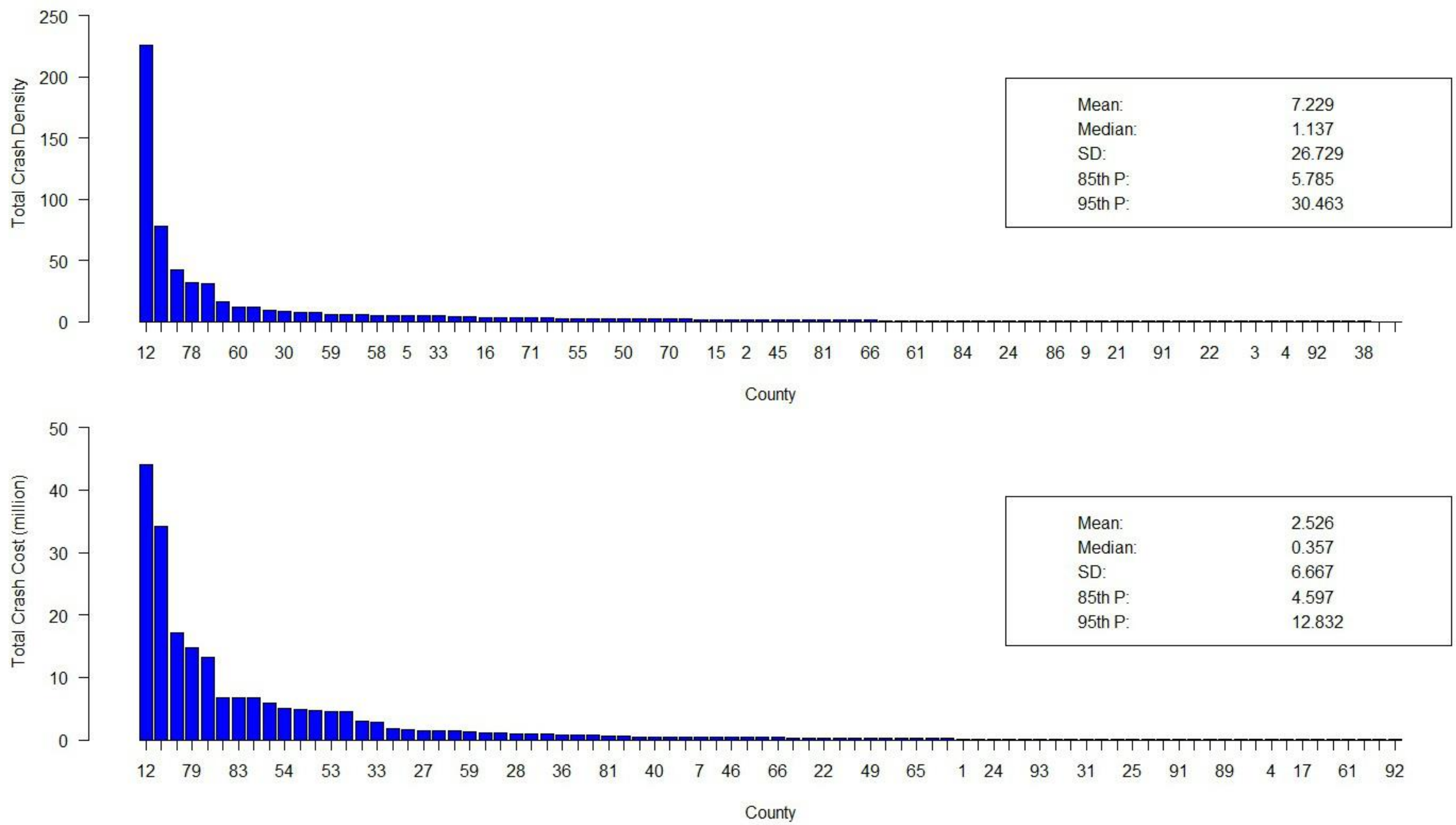


Figure 203 Crash Performance Measure: Year 2011

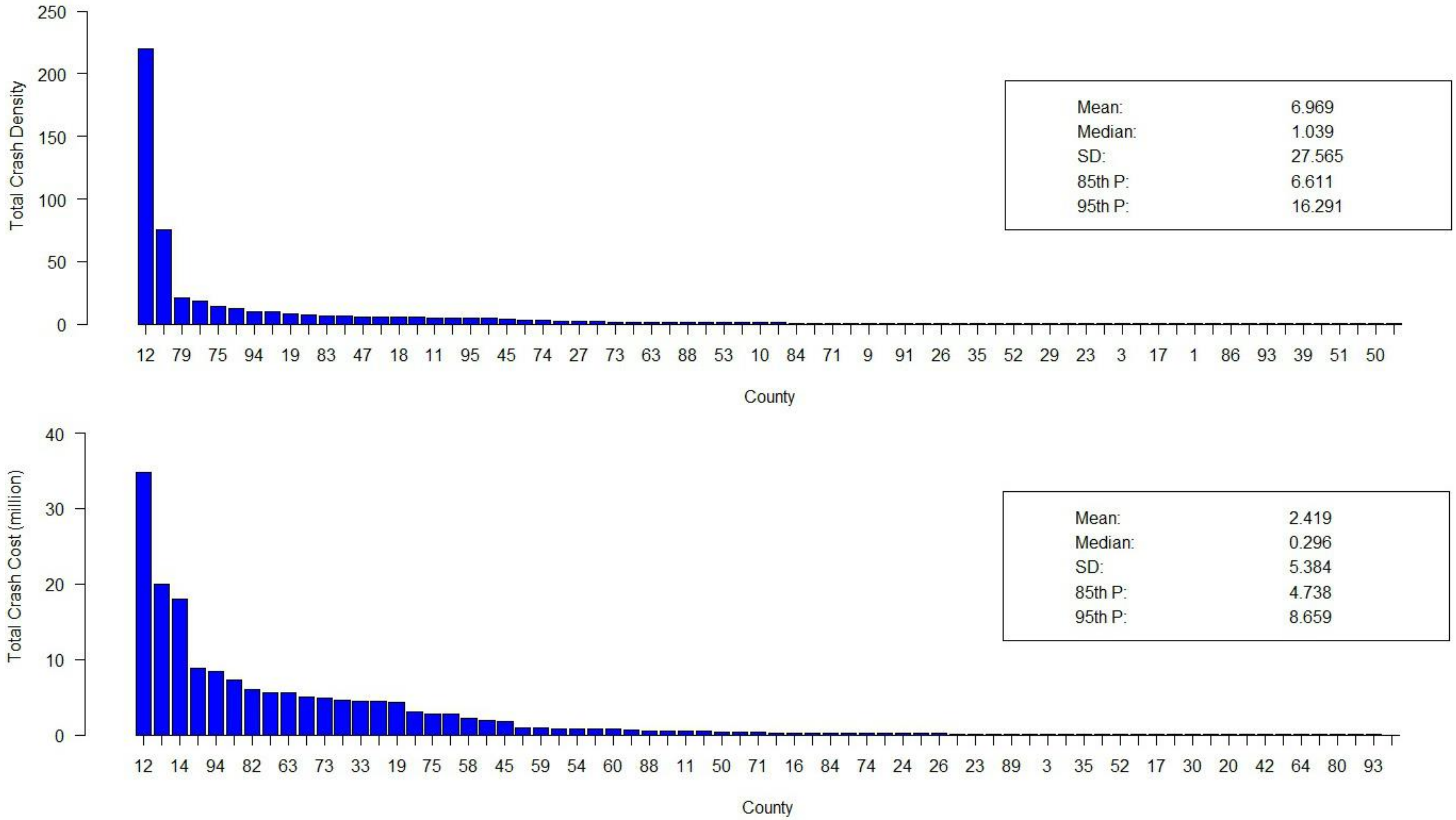
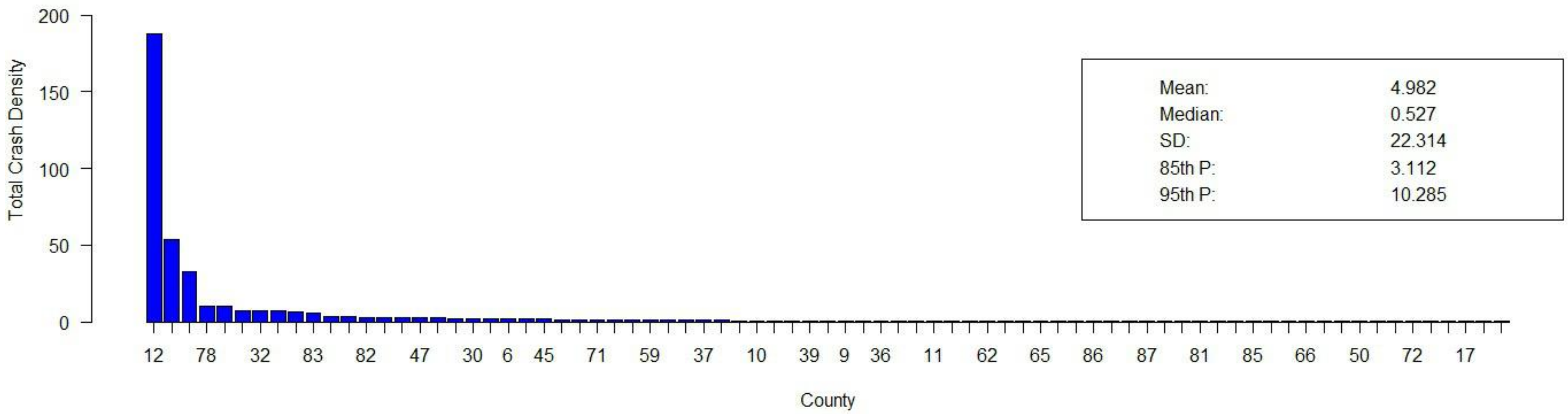


Figure 204 Crash Performance Measure: Year 2012



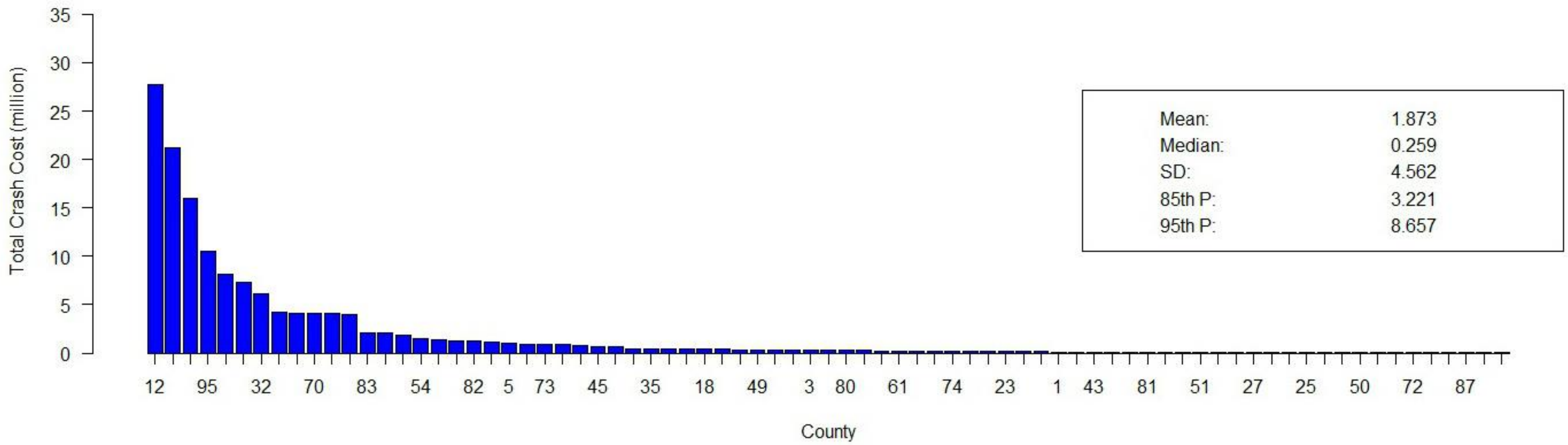


Figure 205 Crash Performance Measure: Year 2013

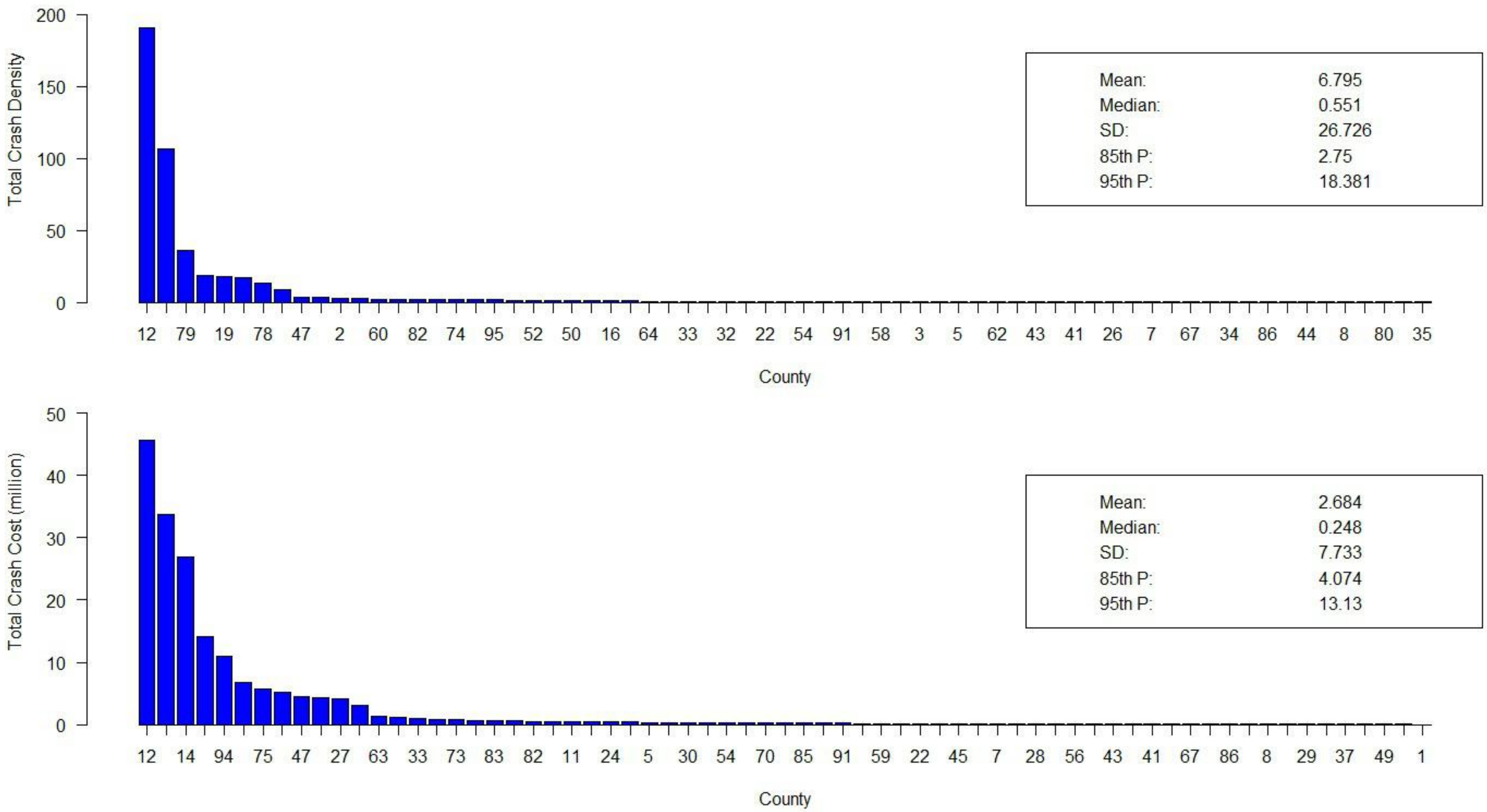


Figure 206 Crash Performance Measure: Year 2014