Modeling the Risk of Wrong-Way Driving on Freeways and Toll Roads

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Wrong-way driving (WWD) is dangerous and poses a significant legal and safety risk when it occurs on limited access facilities. Most previous studies focused on WWD crashes to develop countermeasures. The combined risk of WWD citations and 911 calls, however, has been overlooked. Furthermore, because WWD crashes are rare and represent less than 3% of all crashes, such crashes are difficult to analyze. WWD prediction is an important assessment because it can help mitigate and reduce future occurrences. This paper builds on previous work pioneered by the authors in which WWD crashes were predicted with the use of WWD noncrash events (e.g., citations and 911 calls). These WWD noncrash events occur more frequently, and their data are widely available. The paper demonstrates how WWD 911 calls and citations, along with route characteristics, can be linked to WWD crashes and so target corridors for countermeasures. Two models were developed and applied in South Florida to identify WWD hot spots. The first model shows that WWD citations and 911 calls positively affect yearly crash prediction. The second model identifies hot spot segments in a route and predicts crashes during a 4-year period. This second model predicts crashes with the use of several variables, such as major interchanges per mile, directional interchanges per mile, and WWD 911 calls along the segment. The findings showed high WWD risk values on SR-821 (Homestead Extension) from Exits 20 to 39 and on SR-9 (I-95) from Exits 0 to 6B and Exits 7 to 14.

Wrong-way driving (WWD) is the result of driver error or behavior. It is especially dangerous on high-speed roadways, such as limited access facilities (Interstates and toll roads). WWD can result in head-on collisions on the main line of limited access facilities; these types of collisions often cause severe injuries and fatalities. When WWD crashes occur on limited access facilities, these events usually make news headlines that strike fear into those who use those roadways. Drivers on the main line may not be able to react in time or have the ability to avoid a wrong-way vehicle since the combined approach speed rates are very high. Many WWD crashes involve drivers under the influence and frequently occur during late night hours.

Data collected over several years indicate that WWD noncrash events, such as WWD citations and WWD 911 calls, occur much more frequently than crashes. While some WWD events lead to crashes, most of the time these events do not result in a crash. However, it is logical to assume that more frequent occurrences of WWD citations and 911 calls can lead to an increased risk of WWD crashes. While most of the previous studies focused on crashes to develop countermeasures, WWD citations and 911 calls together have been overlooked. The goal of the present research is to focus on WWD noncrash events and investigate relationships between these events and crashes through statistical prediction and modeling.

The authors of this paper pioneered the idea of linking WWD crashes to WWD citations and 911 calls and presented the work at the TRB annual meeting in 2015; the paper was published in the *Transportation Research Record* (*1*). A novel approach for evaluating the WWD crash risk was presented; statewide data were used and counties and routes in the state of Florida were ranked according to their WWD risk. The WWD risk value was defined as the addition of predicted WWD crashes to the actual WWD crashes. Since the predicted WWD crashes are based on WWD 911 calls and citations, the WWD risk values allow these noncrash events to be included in the analysis of WWD. At the same time, the WWD risk values take the actual counts of WWD crashes into consideration.

This paper will take the above previous efforts one step further and develop models to rank segments of routes in regard to their WWD risk to prioritize countermeasure treatments. The motivation of this research is to save agencies extensive cost by avoiding systemwide implementation of WWD countermeasures and selecting only the high-priority segments identified by the WWD risk model.

In applying the new method to the state of Florida, Rogers et al. found that South Florida is a major WWD hot spot (*1*). The Homestead Extension of the Florida Turnpike (HEFT)–State Road 821 was ranked first statewide for WWD risk. Numerous other roadways in Broward and Miami–Dade Counties ranked high relative to WWD risk. The models developed in this paper are localized and more focused on the WWD hottest spot region of South Florida. The models are applied to a selected group of limited access roadways to identify WWD high-risk segments within routes.

LITERATURE REVIEW

The study of WWD is not new. In the 1950s, the California Department of Transportation began examining freeways and median-related crashes (*2*). The use of WWD detection systems began in 1967 when California used road tubes and cameras to detect wrong-way vehicles (*3*). This system did not alert wrong-way drivers, but it allowed California transportation officials to see where WWD events occurred most frequently (*3*). The National Transportation Safety

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Board also analyzed characteristics of WWD crashes nationwide and found that the United States has an average of 260 fatal WWD crashes per year (2004–2009). These WWD crash averages have not changed in recent years (*4*). Most WWD crashes occur at night and on weekends and involve intoxicated or impaired drivers (*4*).

An Illinois study found 217 WWD crashes that resulted in 44 fatalities and 248 injuries on Illinois freeways from 2004 to 2009 (*5*). The majority of these crashes occurred between midnight and 5 a.m. and were caused by drivers under the influence (*5*). WWD research performed in Texas showed that the early morning period was found to have a five times higher probability of a WWD crash than the average throughout the day (*6, 7*). Wrong-way drivers were mostly elderly and male, and 60% of the crashes involved a driver under the influence of alcohol or drugs (*6, 7*). In San Antonio, Texas, there were 185 reports of WWD to the local traffic management center and 358 WWD-related calls to the San Antonio Police Department in 2011 (*7*). Eighty percent of the WWD traffic management center reports occurred during late night hours, with 45% occurring between 2 and 4 a.m. (*7*). This study was one of the first to examine WWD data besides WWD crashes. These traffic management center WWD reports and calls to the local police department were used to target corridors for countermeasures (*7*). A study in North Carolina of statewide freeway WWD crashes found that the crashes accounted for only 0.2% of freeway crashes, but accounted for 5.6% of freeway fatalities (*8*). Sixty percent of the WWD freeway crashes resulted in a fatality or serious injury, which was much higher than the 2.5% of the overall freeway crashes that resulted in a fatality or serious injury (*8*). The study also investigated driver impairment, age, race, familiarity with the region, and interchange design (*8*).

The only study known to examine WWD citations was a 1969 California Study, "Wrong-Way Accidents Are Reduced" (*3*). The paper surveyed traffic offenders charged with driving on the wrong side of a divided highway. One hundred sixty-eight wrong-way drivers were interviewed, and social information was gathered along with background information on the WWD event. The results demonstrated that a good portion of the cited WWD offenders had actions that resulted in a crash, had several prior arrests, and were classed socially as blue collar.

No previous study has examined WWD citations and WWD 911 calls in an attempt to predict WWD crashes and evaluate WWD crash risk. The authors of this paper were the first to develop this novel approach of analyzing WWD risk (*1, 9*).

The first WWD crash prediction model was developed with the use of WWD 911 calls and citations, which occur more frequently than crashes (*1*). A market basket analysis was used to determine the overlap between the three WWD data sets (crashes, citations, and 911 calls) for 2011 and 2012 on Florida Interstates and toll roads. Market basket analysis is defined as follows: "Affinity analysis is a data analysis and data mining technique that discovers co-occurrence relationships among activities performed by (or recorded about) specific individuals or groups" (*10*). The independent WWD events were then used to develop a generalized Poisson regression model that allowed the WWD 911 call, citation, and crash frequencies to be converted to WWD risk values. The counties and roadways were then ranked with respect to WWD risk values and densities. Miami–Dade County ranked first and Broward County ranked second in WWD risk.

Additional research was presented at the Road Safety and Simulation International Conference (*9*). The authors presented a generalized linear model (GLM), which included a newly added variable (squared time difference from the noon hour). This modified GLM was compared with another artificial neural network model that the authors had developed and with the original GLM published in Rogers et al. (*1*). The authors concluded that GLMs were more useful to assess WWD crash risk than artificial neural network models because the artificial neural network overfits data while GLMs are easier to interpret.

The previous GLMs were developed with the use of hourly data at the statewide level, and these were applied only to countywide route frequencies for citations and 911 calls to assess WWD crash risk. However, a more microscopic approach is needed to help agencies focus on route segments so countermeasures can be implemented at their WWD hot spots. The intent is to avoid blanket implementation of countermeasures all over the corridor because of budget constraints. If only the most critical segments are identified through modeling, agencies can save significantly on the implementation of effective countermeasures.

RESEARCH OBJECTIVES

The following are the primary objectives of this paper:

1. Develop a new WWD crash prediction model (Model 1) at the route level that uses yearly WWD crashes, citations, and 911 calls data in a region. This new model can be used for identifying hot spot corridors, which are vulnerable for WWD crash risk. The purpose of this model is to help agencies identify WWD high-risk routes in their jurisdictions.
2. Develop a microscopic model (Model 2) at the segment level in a hot spot route, which uses yearly WWD data and considers segment characteristics—such as interchange type—to identify hot spot WWD segments in a route. The purpose of this model is to help agencies prioritize countermeasure implementation in the WWD high-risk routes.
3. Apply the two models to real-life corridors and routes in South Florida.

METHOD

The development of these two new WWD crash prediction models is described in the following steps:

- Geolocate WWD crash, citation, and 911 call data events.
- Develop a market basket analysis to remove overlapping events to ensure the use of independent data points in the models.
- Collect route data and categorize interchange types for the segment and route models.
- Discuss data preparation and key decisions made in model development.
- Develop two unique generalized Poisson regression models (from here on called "Model 1" for routes and "Model 2" for segments) linking WWD citations to WWD crashes and WWD 911 calls to WWD crashes.
- Apply the WWD crash prediction values from these models, and compare them with the actual crashes at the route level for Model 1 and at the segment level for Model 2.
- Develop crash risk values based on these models to rank routes and segments within a route in relation to WWD crash risk.

Data Description and Exploration

The previously developed WWD risk model showed that Miami–Dade County ranked first and Broward County ranked second for WWD risk values (*1*). Therefore, this paper is focused on these counties' Interstates, expressways, and toll roads to develop two new WWD crash prediction models. Routes were selected because of length and counts of WWD crashes.

WWD crash data were filtered to Broward and Miami–Dade Counties. WWD citations and 911 call data were obtained through the Florida Highway Patrol's Central Office. The citation data consisted of violations of Florida Statute 316.090(1), which is "driving the wrong direction on a divided highway." Florida Highway Patrol 911 call data were obtained from the computer-aided dispatch center. Citation data with geographic information system were available from 2011 to 2014.

Routes Used for Modeling

- SR-821 (HEFT)—Florida Turnpike Enterprise (FTE),
- SR-826 (Palmetto Expressway),
- SR-862 (I-595),
- SR-869 (Sawgrass Expressway)—FTE,
- SR-9 and SR-9A (I-95),
- SR-91 (Turnpike Main Line)—FTE, and
- SR-93 (I-75).

Interchange Types

The Florida DOT's Interchange Report was used to set up exits and mile marker segments for routes and event counts (*11*). Annual average daily traffic (AADT) and daily vehicle miles traveled information was gathered from the Florida DOT's Office of Traffic Statistics (*11–14*). AADTs were averaged at the interchange junctions, and simple interchange classifications were used for modeling, including the following [for definitions, see FHWA (*15*)]:

- Full diamond—standard four-leg diamond interchange,
- Other diamond—any diamond other than the standard four-leg diamond interchange,
- Partial cloverleaf—any partial cloverleaf interchange,
- Major directional—any complex directional interchange with two or more major routes,
- Two- to three-leg directional—any directional interchange with two or three legs,
- Trumpet—any trumpet style interchange (these are common on SR-91),
- Single or slip ramps—single ramp entrance or exit or a slip ramp alone, and
- Other—includes interchange types not defined by the above terms.

Segments Within Routes

Segments within a route were formulated such that a segment would include seven interchanges within its boundaries. Seven segments were used because the choice of seven produced a cumulative average count of three WWD crashes during a 4-year period. This approach is beneficial for modeling purposes in instances in which the aim is to have nonzero crash segments in the modeled data.

AADT Data

The following AADT variables were explored for modeling:

- AADT on toll road or Interstate (refers to the average main-line AADT of the seven interchanges in the segment) and
- AADT at interchange on road (refers to average AADT for surface streets at all seven interchanges in the segment).

WWD Data Points Mapped

Figure 1 shows Google Maps with WWD data points used to develop the WWD crash prediction models. All WWD crashes are shown in Figure 1*a,* all WWD citations are shown in Figure *1b,* and all WWD 911 calls are shown in Figure 1*c.* The combined WWD event counts by hour are shown in Figure 1*d.*

AFFINITY OR MARKET BASKET ANALYSIS OF WWD DATA

To evaluate routes with respect to WWD, it was necessary to determine the number of WWD driving events in all three data sets (crashes, citations, and 911 calls). Any overlapping between data sets—as well as within data sets—was discovered with the use of an affinity or market basket analysis. A market basket analysis allows for the discovery of connections between different groups of data.

Table 1 shows the market basket analysis of the three data sets from 2011 to 2014 in Miami–Dade and Broward Counties. There were 469 data points for WWD 911 calls, 96 data points for WWD citations, and 36 data points for WWD crashes. Some data points were related to the same WWD event, whether by overlapping between data sets or multiple data points in the same data set. For example, one event listed as "crash, citation, 911" in the table contained the following data points: "1/26/11, 2:57, SR-826, Latitude 25.7177, Longitude −80.3181, Miami–Dade" (crash data point); "1/26/11, 2:57, SR-826, Latitude 25.71773, Longitude −80.3181, Miami–Dade" (citation data point); "1/26/11, 2:47, SR-826, Latitude 25.70293, Longitude −80.318, Miami–Dade" (911 call data point). In addition, seven citation data points stated there was a crash, but no crash data point match was found (these data points were labeled "citation, no crash match").

In each data set, there were also points that referred to the same WWD event because these data points had times and dates close to one another on the same roadway. For example, two 911 call data points were commonly linked to the same event, so these were labeled "911 – 2." All overlaps were removed before the statistical modeling. Doing so was necessary to ensure that the variables were independent.

DATA PREPARATION FOR MODELING

After events were mapped, it was decided to filter out SR-93 (I-75) on the western half in Broward County past US-27. There were large numbers of 911 calls in this area but no WWD crashes. Daytime

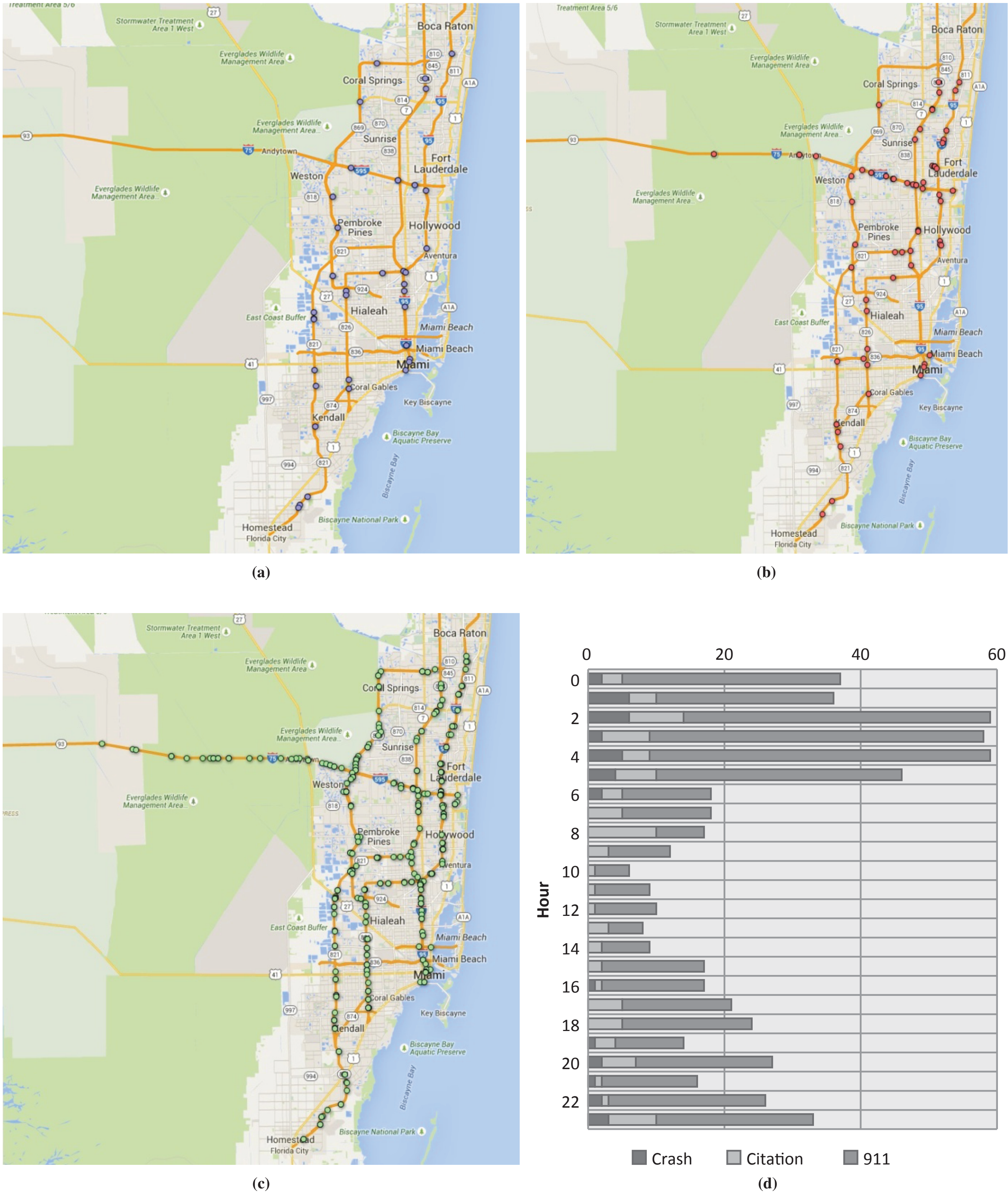


FIGURE 1 WWD events from 2011 to 2014 in Broward and Miami–Dade Counties: (a) WWD crash events, (b) WWD citation events, (c) WWD 911 call events, and (d) WWD events by hour.

TABLE 1 Market Basket Analysis of WWD Crash Data, Citation Data, and 911 Call Data

Market Basket Combination	911 Call Data Points	Citation Data Points	Crash Data Points
911 only	459	na	na
Citation only	na	74	na
Crash only	na	na	23
911 and citation overlap	4	4	na
911–2 and citation overlap	2	1	na
911 and crash overlap	3	na	3
Citation, no crash match	na	7	na
Citation and crash overlap	na	9	9
911, citation, and crash overlap	1	1	1
Total data points	469	96	36
Associated WWD events	418	83	36

NOTE: na = not applicable.

events—from 7:00 to 18:00—were eliminated because only one WWD crash occurred in the daytime during the 4-year period. Therefore, WWD events from 19:00 to 6:00 were used. The sample size was 28 data points, and after the outliers (SR-91 2014 and SR-93 2013) were removed, the sample was reduced to 26 data points. The WWD events were separated by roadway and year in Table 2. Table 2 shows roadway lengths, number of exits, average main-line traffic volume, and average side street traffic volume at the interchanges. All overlapping between events was removed.

Table 2 data were used to develop Model 1 to predict the outcome of yearly WWD crashes. The assembled data for Model 2 were similar to Table 2 but were broken down to interchange and exit segments.

TABLE 2 WWD Events and Route Characteristics by Route and Year

State Route	Year	Crashes	Citations	911 Calls	Miles	Number of Exits	Mean AADT	Side Mean AADT
SR-821 (HEFT)	2011	2	2	14	47.9	23	96,587	44,713
SR-821 (HEFT)	2012	5	2	10	47.9	23	97,770	44,901
SR-821 (HEFT)	2013	0	1	11	47.9	23	96,296	44,482
SR-821 (HEFT)	2014	2	1	21	47.9	23	104,636	45,832
SR-826 (Palmetto)	2011	1	0	11	24.7	28	167,100	86,632
SR-826 (Palmetto)	2012	1	0	6	24.7	28	165,615	86,996
SR-826 (Palmetto)	2013	2	1	5	24.7	28	164,820	86,185
SR-826 (Palmetto)	2014	2	2	4	24.7	28	168,969	88,800
SR-862 (I-595)	2011	0	0	6	12.9	13	137,927	78,022
SR-862 (I-595)	2012	2	4	4	12.9	13	136,700	78,350
SR-862 (I-595)	2013	1	3	8	12.9	13	136,044	77,620
SR-862 (I-595)	2014	0	3	4	12.9	13	139,469	79,975
SR-869 (Sawgrass)	2011	0	2	4	21.8	13	63,656	57,278
SR-869 (Sawgrass)	2012	1	0	4	21.8	13	64,436	57,519
SR-869 (Sawgrass)	2013	1	0	6	21.8	13	63,465	56,982
SR-869 (Sawgrass)	2014	0	0	8	21.8	13	68,962	58,712
SR-9 and SR-9A (I-95)	2011	1	1	29	42.6	38	221,861	64,645
SR-9 and SR-9A (I-95)	2012	3	2	21	42.6	38	219,888	64,916
SR-9 and SR-9A (I-95)	2013	3	3	19	42.6	38	218,833	64,311
SR-9 and SR-9A (I-95)	2014	3	3	23	42.6	38	224,342	66,263
SR-91 (Turnpike)	2011	1	2	5	29.3	13	87,408	82,126
SR-91 (Turnpike)	2012	1	2	5	29.3	13	88,478	82,470
SR-91 (Turnpike)	2013	1	1	7	29.3	13	87,145	81,702
SR-91 (Turnpike)	2014	0	2	16	29.3	13	94,692	84,181
SR-93 (I-75)	2011	2	1	9	23.4	14	117,603	65,514
SR-93 (I-75)	2012	1	1	4	23.4	14	116,557	65,789
SR-93 (I-75)	2013	0	3	8	23.4	14	115,998	65,176
SR-93 (I-75)	2014	0	1	6	23.4	14	118,918	67,154
Total		36	43	278				

Model 2 had each segment totaled for seven interchange points and overlapped route segments to provide a larger-size data set. For simplicity, these interchanges will be referred to as exits. The Model 2 data setup is similar to that of Model 1, and its method is briefly described later. In attempts to build Model 1, multicollinearity was observed between 911 calls, route miles, number of exits, and mean AADT. Hence, 911 calls were used instead of these route variables.

From Table 2, Model 1 uses yearly WWD citations (noncrashes) and yearly WWD 911 events (noncrashes and noncitations) as the independent variables to predict the yearly outcomes of WWD crashes on routes in the South Florida region. Even though these citations and 911 calls were WWD events, they were noncrash events. Therefore, the purpose of this model is to explore the potential of using noncrash events to predict crash events and to quantify risk assessment. Noncrash WWD events are more common than WWD crashes and provide more insight than would using low-count crash numbers alone.

WWD CRASH RISK MODELS

Model 1. Yearly Route WWD Crash Prediction Model

With the data in Table 2, a GLM was developed to predict the number of crashes on each route per year. The Poisson distribution was used for the dependent variable (number of crashes). The general form of the Poisson regression model is

$$Y_i = E(Y_i) + \varepsilon_i \qquad i = 1, 2, \ldots, n \tag{1}$$

where Y is the nonnegative response variable with mean μ that depends on $p - 1$ predictor variables $X_1, \ldots, X_{P-1}$ in the following fashion:

$$\mu_i = \exp(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots) \tag{2}$$

where μ_i is the mean of Y_i for the ith set of values of predictor variables $X_1, \ldots, X_{P-1}$, and β_s are the regression coefficients.

The WWD yearly crash prediction model developed has the following form:

$$\ln(\mu) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 \tag{3}$$

where

μ = route's yearly WWD crash frequency,
X_1 = log (citation frequency + 0.5), and
X_2 = log (911 frequency).

The citation variable X_1 had 0.5 added to allow values with zeros to be used with the log function transformation.

TABLE 3 Yearly Route WWD Crash Prediction Model: Whole Model Test

Model	–Log Likelihood	L-R X^2	df	Prob. > X^2
Difference	4.13348219	8.267	2	.0160[a]
Full	34.4729646			
Reduced	38.6064468			

NOTE: L-R = likelihood ratio; df = degrees of freedom.
[a]Statistically significant at 95% confidence.

TABLE 4 Yearly Route WWD Crash Prediction Model: Goodness-of-Fit Statistic

Goodness-of-Fit Statistic	X^2	df	Prob. > X^2
Pearson	17.1887	23	.7999
Deviance	20.8076	23	.5928

The function used in this model resembles the following equation:

$$\hat{\mu} = \exp\left(\hat{\beta}_0 + \hat{\beta}_1 X_1 + \hat{\beta}_2 X_2\right) \tag{4}$$

The generalized Poisson regression model equation is

$$\text{response function (yearly crashes)} = \exp\begin{pmatrix} -1.00626 + 0.5216398 \times \log(\text{citation freq.}) \\ + 0.4685037 \times \log(911 \text{ call freq.}) \end{pmatrix} \tag{5}$$

Tables 3 to 5 show the model output; the output indicates that the parameter estimates, log function of citations frequency, and log function of the 911 calls frequency are close to statistical significance (<0.06). For Table 3, the GLM fit is as follows:

- Response: crashes,
- Distribution: Poisson,
- Link: log,
- Estimation method: maximum likelihood, and
- Observations (or sum weights) = 26.

Goodness-of-fit statistics show that the Pearson statistic was 0.7999 and the deviance was 0.5928. The Akaike information criterion (AIC) value was 76.0368. The citations and 911 call coefficients are then used to predict the crash frequency. For Table 5, the GLM fit is as follows:

- Response: crashes segment,
- Distribution: Poisson,

TABLE 5 Yearly Route WWD Crash Prediction Model: Parameter Estimates

Term	Estimate	SE	L-R X^2	Prob. > X^2	Lower CL	Upper CL
Intercept	–1.00626	0.6052875	2.9335268	.0868	–2.24585	0.141091
log(citations)	0.5216398	0.2858482	3.6672383	.0555	–0.01173	1.116788
log(911 calls)	0.4685037	0.2477557	3.5395156	.0599	–0.01981	0.95781

NOTE: CL = confidence limit.

TABLE 6 Model 1 Yearly Crash Prediction Versus Actual Crashes by Routes

State Route	Year	Citations + 0.5	911 Calls	Model 1 Predicted Crashes	Actual Crashes	Model + Actual = Crash Risk
SR-821(HEFT)	2011	2.5	14	2	2	4
SR-821(HEFT)	2012	2.5	10	1.7	5	6.7
SR-821(HEFT)	2013	1.5	11	1.4	0	1.4
SR-821(HEFT)	2014	1.5	21	1.9	2	3.9
SR-826 (Palmetto)	2011	0.5	11	0.8	1	1.8
SR-826 (Palmetto)	2012	0.5	6	0.6	1	1.6
SR-826 (Palmetto)	2013	1.5	5	1	2	3
SR-826 (Palmetto)	2014	2.5	4	1.1	2	3.1
SR-862 (I-595)	2011	0.5	6	0.6	0	0.6
SR-862 (I-595)	2012	4.5	4	1.5	2	3.5
SR-862 (I-595)	2013	3.5	8	1.9	1	2.9
SR-862 (I-595)	2014	3.5	4	1.3	0	1.3
SR-869 (Sawgrass)	2011	2.5	4	1.1	0	1.1
SR-869 (Sawgrass)	2012	0.5	4	0.5	1	1.5
SR-869 (Sawgrass)	2013	0.5	6	0.6	1	1.6
SR-869 (Sawgrass)	2014	0.5	8	0.7	0	0.7
SR-9 (I-95)	2011	1.5	29	2.2	1	3.2
SR-9 (I-95)	2012	2.5	21	2.5	3	5.5
SR-9 (I-95)	2013	3.5	19	2.8	3	5.8
SR-9 (I-95)	2014	3.5	23	3.1	3	6.1
SR-91 (Turnpike)	2011	2.5	5	1.3	1	2.3
SR-91 (Turnpike)	2012	2.5	5	1.3	1	2.3
SR-91 (Turnpike)	2013	1.5	7	1.1	1	2.1
SR-91 (Turnpike)	2014	2.5	16	—	0	—
SR-93 (I-75)	2011	1.5	9	1.3	2	3.3
SR-93 (I-75)	2012	1.5	4	0.9	1	1.9
SR-93 (I-75)	2013	3.5	8	—	0	—
SR-93 (I-75)	2014	1.5	6	1	0	1
Total		61	278	40	36	

NOTE: — = not predicted.

- Link: log,
- Estimation method: maximum likelihood, and
- Observations (or sum weights) = 104.

Table 6 shows the Model 1 yearly crash prediction versus actual crash values. The model does not produce whole numbers, but these numbers are within the range of the actual crash observations. Model 1 shows that WWD citations (noncrashes) and WWD 911 calls (noncrashes and noncitations) have a positive influence in the prediction of WWD crashes. The WWD crash predictions are added to the actual crash values to see the yearly crash risk value, which is scaled in WWD crash magnitude to include the effect of citations and 911 data along with crashes in the analysis.

SR-9 (I-95) and SR-821 (HEFT) have the highest WWD crash risk values through the years and also high numbers of citations and 911 calls.

Model 2. 4-Year Segment WWD Crash Prediction Model

The second model used additional variables to predict WWD crashes for a 4-year period in segments of each limited access route. Seven exit (interchange) segments along the routes were totaled and accumulated by the WWD data events. Distances varied and the count of interchanges was typically seven exits. Figure 2 demonstrates the data preparation process for Model 2. Segments were overlapped to create additional data points for building the model.

In Figure 2, Segment 1 of SR-821 was totaled for the first seven exits (interchanges) as found in the Florida DOT interchange report (*11*). The numbers in the rectangular boxes represent the exit sequence. From Exit 0 to 11, there were three WWD crashes in these 4 years, and they are shown as stars. In the same segment, there was 1 WWD citation shown as a square, and 10 WWD 911 calls shown as circles. The mean AADT along this segment's main line was calculated along with the "at street AADT" for each interchange junction. The counts of each interchange and the segment length were noted. Next, the interchanges were divided by interchange type per mile. From Figure 2, the second segment accounted for was from Exit 1 to Exit 12. The same counts and data were acquired as with the first segment. In statistical terms, this process is referred to as "aggregation." With this process, it was possible to obtain 104 rows of data, which allowed additional data points to be used in Model 2. As explained earlier, seven interchange segments were used because the choice of seven produced a cumulative average count of three WWD crashes during the 4 years. The reason 4 years was used to build Model 2 is the lack of WWD crashes. Model 2 has the advantage of creating additional data points through overlapping segments in the 4 years of crash data.

With the prepared data points, the GLM 2 WWD crash prediction model was developed with the following form:

$$\ln(\mu) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 \qquad (6)$$

where μ_i is the mean of Y_i for the ith set of values of the predictor variables $X_1, \ldots, X_{P-1}$, and β_s are the regression coefficients.

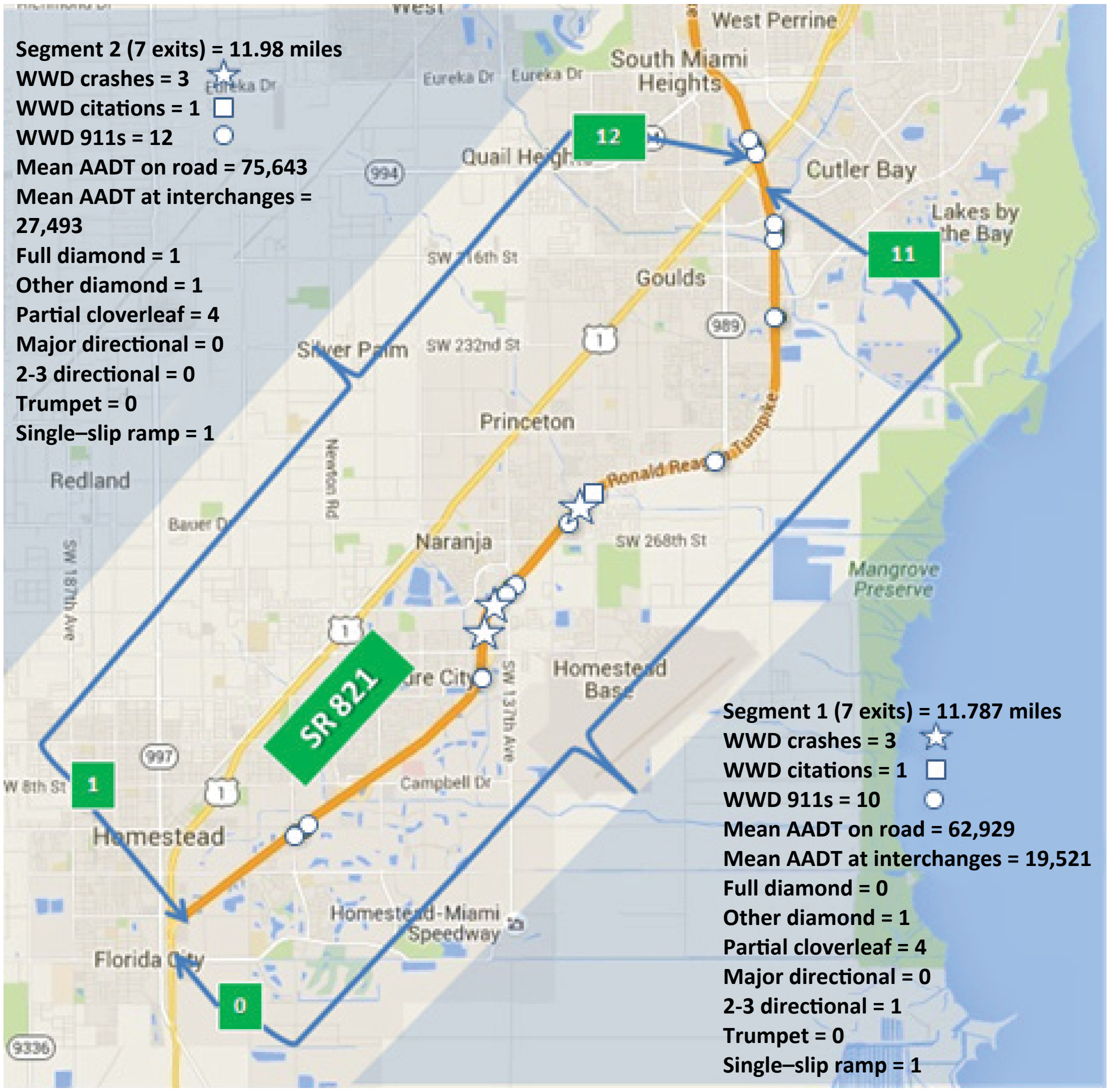


FIGURE 2 Segmenting route for building Model 2.

Model 2 predicts 4-year WWD crash totals for seven-exit (or interchange) segments and has the following form:

$$\mu = \exp(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5) \tag{7}$$

where

μ = route's 4-year, seven-exit segment WWD crash frequency;
X_1 = log(citation segment + 0.5);
X_2 = log(911 segment);
X_3 = AADT at interchange at road;
X_4 = major directional/mi; and
X_5 = 2- to 3-leg directional/mi.

The function used in this paper resembles the following equation:

$$\hat{\mu} = \exp\left(\hat{\beta}_0 + \hat{\beta}_1 X_1 + \hat{\beta}_2 X_2 + \hat{\beta}_3 X_3 + \hat{\beta}_4 X_4 + \hat{\beta}_5 X_5\right) \tag{8}$$

Tables 7 to 9 show the model output for GLM 2 (*16*). All five parameters were found to be significant at a probability < .05. The

TABLE 7 Four-Year Seven-Exit Segment WWD Crash Prediction Model: Whole Model Test

Model	–Log Likelihood	L-R X^2	df	Prob. > X^2
Difference	13.3951012	26.7902	5	<.0001[a]
Full	147.84815			
Reduced	161.243251			

[a]Statistically significant at 95% confidence.

TABLE 8 Four-Year Seven-Exit Segment WWD Crash Prediction Model Goodness-of-Fit Test

Goodness-of-Fit Statistic	X^2	df	Prob. > X^2
Pearson	46.4284	98	1.0000
Deviance	62.1589	98	.9982

TABLE 9 Four-Year Seven-Exit Segment WWD Crash Prediction Model: Parameter Estimates

Term	Estimate	SE	L-R X^2	Prob. > X^2	Lower CL	Upper CL
Intercept	–0.453523	0.6637065	0.4694407	.4932	–1.765694	0.8379689
log(citations segment)	–0.302024	0.1056948	8.1826754	.0042[a]	–0.509627	–0.095082
log(911 segment)	0.5865768	0.2500182	5.5383635	.0186[a]	0.0978654	1.0784743
AADT at interchange at road	–1.062e–5	3.4461e–6	10.817973	.0010[a]	–1.766e–5	–4.131e–6
Major directional/mile	1.4755753	0.4467142	9.7543736	.0018[a]	0.5700224	2.3268435
2- to 3-leg directional/mile	2.4113643	0.7666669	9.0738177	.0026[a]	0.8671313	3.8784806

[a]Statistically significant at 95% confidence.

goodness-of-fit statistics for the Pearson statistic were 1.0000 and the deviance was 0.9982. The AIC value was 308.5623; it was the lowest AIC in comparison with all other GLM attempts. Equation 9 predicts the expected 4-year crash values and can be used to apply crash risk along interchange corridors.

$$\text{response function}\,(\text{4-year crashes per 7-exit segment})$$

$$= \exp\left(\begin{array}{l} -0.453523 + \left(-0.302024 \times \log(\text{citation segment})\right) \\ + \left(0.5865768 \times \log(911\ \text{segment})\right) \\ + \left((-1.062\text{e}-5) \times \text{AADT at interchange at road}\right) \\ + \left(1.4755753 \times \dfrac{\text{major directional}}{\text{mi}}\right) \\ + \left(2.4113643 \times \left(\dfrac{\text{2- to 3-leg directional}}{\text{mi}}\right)\right) \end{array}\right) \tag{9}$$

MODEL 2 PREDICTION, MICROSCOPIC WWD RISK VALUE, AND RANKING OF ROUTE SEGMENTS

Table 10 shows the actual WWD crash counts for route segments between seven exits. The WWD crash prediction values are shown in the third column from the right. The predicted values match the actual number of crashes. The second column from the right shows the WWD risk values created by adding the actual crash values and the WWD crash predictions. The WWD crash prediction allows for citations and 911 calls to be converted to crash units and then added to actual crash values to create this WWD risk value. The WWD risk value represents a holistic and robust approach, which pulls in more than just WWD crashes when the WWD is ranked and assessed.

The highest WWD risk value of 9.9 is shown for SR-821 (HEFT) between Exits 23 and 34. SR-821 was ranked in various segments as first, third, fourth, and fifth for WWD risk value. SR-9 (I-95) ranked second between Exits 0 and 4AB. For most of these segments, the WWD crashes predicted from Model 2 and the actual WWD crash counts matched closely.

Figure 3 shows the predicted crashes from Model 2 for two routes with high risk values as shown in Table 10: SR-821 (HEFT) and SR-9 (I-95). Figure 3 shows more details than Table 10 by indicating the risk for each individual segment of these two WWD hot routes.

Figure 3*a* shows that SR-821 (HEFT) has the highest risk value of WWD crashes at the seven-interchange segment between Exits 23 and 34, with a total risk value of 9.9 (actual crashes + predicted crashes). Overall, SR-821 from Exit 20 to Exit 39 has a risk value of about 6. Figure 3*b* shows that SR-9 (I-95) has its highest risk value of 8.9 WWD crashes between Exits 0 and 4AB. Overall, SR-9 hot spots are shown to be between Exits 0 and 6B and from Exit 7 to Exit 14.

SUMMARY AND CONCLUSIONS

While most previous studies focused on WWD crashes to develop countermeasures, the combined risk of WWD citations and 911 calls was overlooked. This paper builds on previous work pioneered by the authors in which WWD crashes were linked with noncrash WWD events, including citations and 911 calls. These noncrash events occur more frequently, and these data are widely available.

The major objectives of this paper are to develop new models for predicting WWD crashes on Interstates and toll roads and apply them to corridors in South Florida. To construct these new models, WWD data sets for crashes, citations, and 911 calls were gathered for 4 years from 2011 to 2014 in Broward and Miami–Dade Counties. Model 1 targeted the prediction of WWD crashes per year along an entire route in the region. It showed that citations and 911 calls in combination had a positive effect on the WWD yearly crash prediction values. Model 2 showed that the number of major directional interchanges per mile and the number of 2- to 3-leg directional interchanges per mile have a significant and positive effect on WWD crash prediction for 4 years in the segment. In Model 2, the 911 calls had a positive and significant effect on WWD crash prediction.

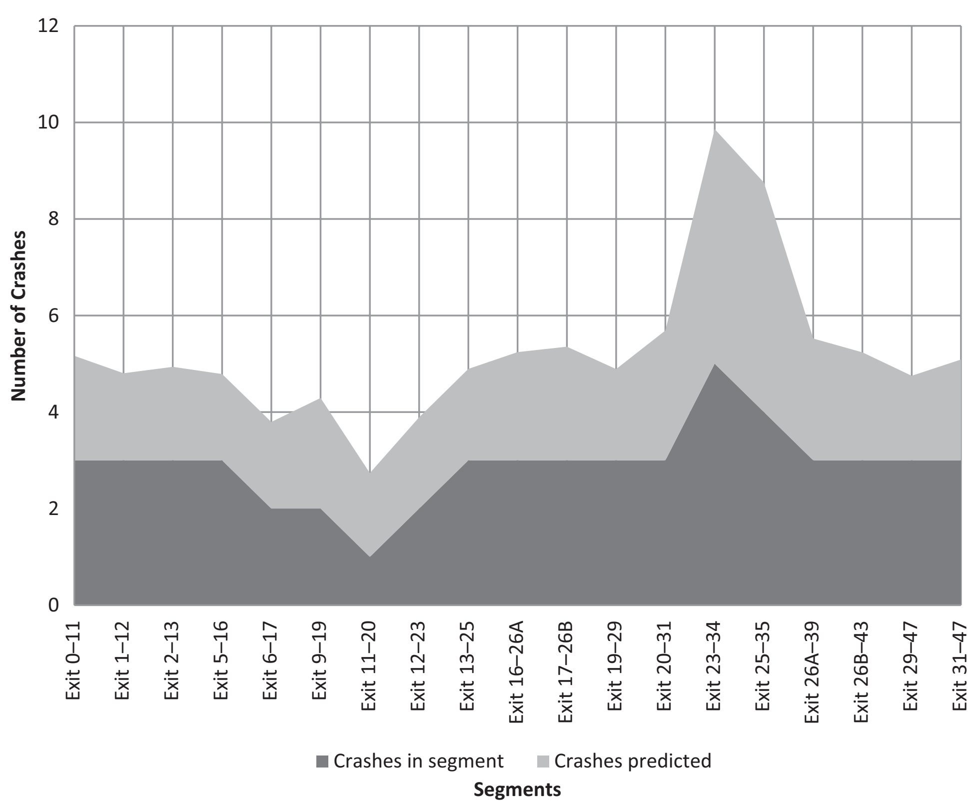
Model 2 can be applied to determine the location of WWD hot spot segments. Crash prediction values for the segments were added to the actual crash values to provide crash risk values. SR-9 (I-95) and SR-821 (HEFT) had high rankings relative to WWD crash risk. Crash risk values in order of magnitude showed that SR-821 (HEFT) has the highest risk value between Exits 23 and 34. Overall, SR-821 from Exit 20 to Exit 39 has high risk values. In addition, SR-9 (I-95) has its highest risk value between Exits 0 and 4AB. Overall, SR-9 hot spots are shown to be from Exit 0 to Exit 6B and from Exit 7 to Exit 14.

With new countermeasure technologies and the risk of WWD continuing to pose a serious threat to the public, it is important to find ways to reduce that risk. Reduction can be achieved by targeting WWD hot spots for countermeasure implementation. Identifying these hot spots at the microscopic level can be a challenge because it is difficult to know where the wrong-way drivers come from in many cases. Since WWD crashes are rare, it is difficult to predict them on the basis of crash data only. The application of this type of microscopic model will allow transportation agencies to focus on the most dangerous WWD corridor segments for prioritizing their countermeasures implementation while keeping their costs within budget and simultaneously saving lives.

The authors recommend further WWD prediction research for additional urbanized regions inside and outside Florida. With the use of the various data sources (911 calls and citations), it is important to be capable of geolocating these events. The challenge comes with the market basket analysis and removing the overlapping events. The ability to access 4 years of data, if not more, would benefit others who might attempt to similarly predict between WWD crashes and noncrash events. The authors are currently exploring

TABLE 10 Model 2 WWD Crash Prediction (4 Years) Versus Actual (4 Years) and Risk Ranking

State Route	Exit Start	Exit End	2011–2014 Actual Crashes	Model 2 Predicted Crashes	Combined WWD Risk Value	Risk Value Rank
SR-821(HEFT)	0	11	3	2.2	5.2	4
SR-821(HEFT)	11	20	1	1.7	2.7	21
SR-821(HEFT)	20	31	3	2.7	5.7	3
SR-821(HEFT)	23	34	5	4.9	9.9	1
SR-821(HEFT)	31	47	3	2.1	5.1	5
SR-826 (Palmetto)	US-1, SR-5	SW 8 Street	3	1.9	4.9	7
SR-826 (Palmetto)	SW 8 Street	SR-948	0	0.9	0.9	30
SR-826 (Palmetto)	SR-948	NW 67 Avenue	2	2.1	4.1	13
SR-826 (Palmetto)	NW 67 Avenue	NW 17 Avenue	1	1.1	2.1	28
SR-862 (I-595)	0	5	1	1.6	2.6	22
SR-862 (I-595)	1B	7	3	1.7	4.7	9
SR-862 (I-595)	3	10AB	3	1.8	4.8	8
SR-862 (I-595)	5	13	2	2.7	4.7	9
SR-869 (Sawgrass)	0	11	1	1.6	2.6	22
SR-869 (Sawgrass)	1B	15	2	2.1	4.1	13
SR-869 (Sawgrass)	5	20	2	1.5	3.5	17
SR-869 (Sawgrass)	11	22	1	1.4	2.4	25
SR-9 (I-95)	0	4AB	4	4.9	8.9	2
SR-9 (I-95)	4AB	9	1	2.2	3.2	19
SR-9 (I-95)	10A	18	3	1.7	4.7	9
SR-9 (I-95)	19	25	2	1.4	3.4	18
SR-9 (I-95)	25	33AB	1	1.2	2.2	27
SR-91 (Turnpike)	0	49	1	1.4	2.4	25
SR-91 (Turnpike)	4X	58	0	1.6	1.6	29
SR-91 (Turnpike)	49	67	1	1.5	2.5	24
SR-91 (Turnpike)	54	71	2	1.2	3.2	19
SR-93 (I-75)	0	9AB	2	2.2	4.2	12
SR-93 (I-75)	1	13AB	3	2.1	5.1	5
SR-93 (I-75)	4	15	2	2	4	15
SR-93 (I-75)	5	19	2	2	4	15
Total			60	59.4		



(a)

FIGURE 3 Crashes per segment and crash prediction combined crash risk values for (*a*) SR-821 (HEFT).

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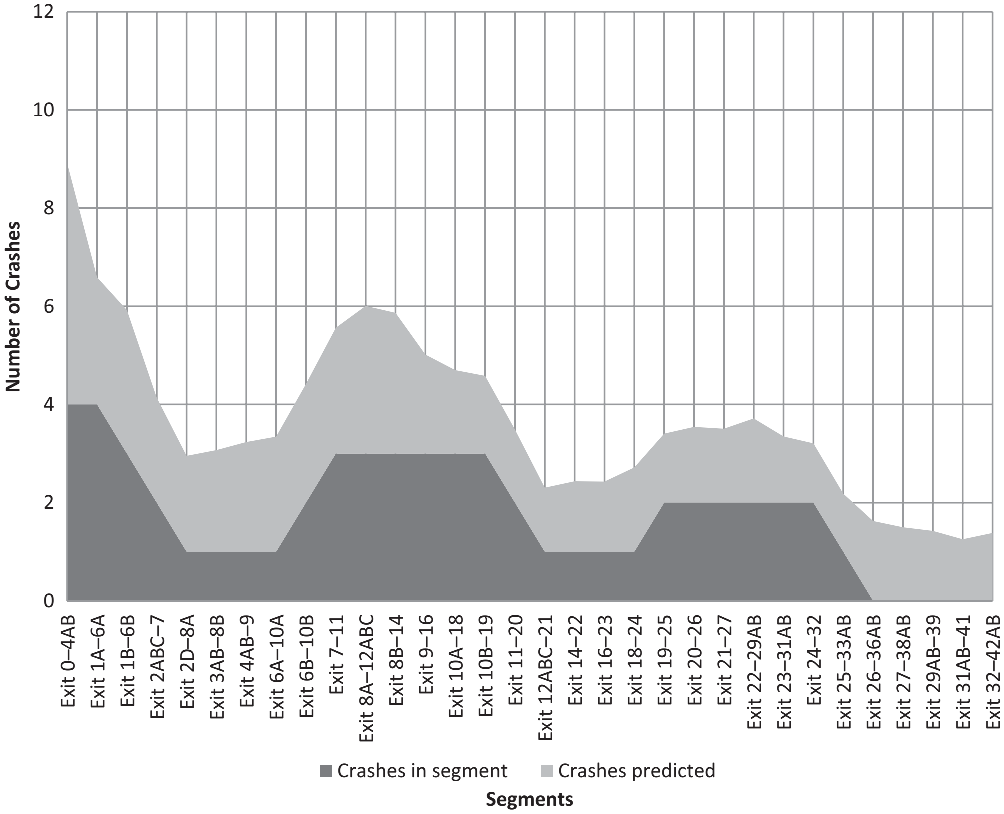

(b)

FIGURE 3 *(continued)* **Crashes per segment and crash prediction combined crash risk values for (*b*) SR-9 (I-95).**

new models to include the Orlando metro area, which contains Osceola, Orange, and Seminole Counties.

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