Enhancing Rural Roadway Safety through Geospatial Analysis and 2SFCA-Driven Rest Area Serviceability Optimization for Trucks

A Technical Report Submitted to the Rural Safe Efficient Advanced Transportation (R-SEAT) Center and United States Department of Transportation

FINAL REPORT

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DISCLAIMER

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METRIC CONVERSION CHART

When You Know	Multiply by	To Find
Length		
inches (in)	25.4	millimeters (mm)
feet (ft)	0.305	meters (m)
yards (yd)	0.914	meters (m)
miles (mi)	1.61	kilometers (km)
Volume		
fluid ounces (fl oz)	29.57	milliliters (mL)
gallons (gal)	3.785	liters (L)
cubic feet (ft^3)	0.028	meters cubed (m^3)
cubic yards (yd^3)	0.765	meters cubed (m^3)
Area		
square inches (in^2)	645.1	millimeters squared (mm^2)
square feet (ft^2)	0.093	meters squared (m^2)
square yards (yd^2)	0.836	meters squared (m^2)
acres	0.405	hectares (ha)
square miles (mi^2)	2.59	kilometers squared (km^2)

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16. Abstract

This project addresses a critical gap in transportation safety by developing a novel, data-driven framework to assess rural rest area performance in reducing fatigue-related truck crashes along Florida's key freight corridors. Unlike traditional aggregate-level studies, this research introduces a spatially precise approach that individually links each fatigue-related crash to its nearest rest area using crash proximity, severity, and facility characteristics. A novel Deficiency Score (DS) was developed to quantify rest area performance, and negative binomial regression analysis confirmed its significance in predicting crash frequency, offering a valuable decision-support tool to identify high-risk facilities. Complementary crash-level analysis revealed fatigue-related crashes occur more frequently during late-night and early-morning hours and are associated with hazardous crash types such as rear-end and off-road collisions. The findings offer actionable insights for prioritizing rest area improvements, including parking expansion, amenity upgrades, and real-time information systems, to reduce crash risks and enhance freight safety. Although limitations remain, such as assumptions about driver rest area use, underreporting of fatigue, and exclusion of private truck stops, the methodology offers a scalable framework. While applied in Florida, the framework is adaptable for broader use to support safer and more resilient freight corridors.

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EXECUTIVE SUMMARY

This project addresses a critical gap in truck parking and fatigue-related crash research, particularly within rural roadway networks where infrastructure limitations and long driving distances increase driver vulnerability. While urban freight planning has been widely studied, rural freight corridors pose unique safety challenges due to limited truck parking, driver fatigue risks, and impacts on surrounding communities. Focusing on Florida's major freight corridors as a test bed, this project develops an integrated methodology to assess and improve the performance of rest areas in reducing fatigue-related crashes by combining spatial analysis, deficiency scoring, and regression modeling techniques.

The project is structured around two core components, each contributing to a comprehensive understanding of the rest area performance, and roadway safety:

i. **Development and Application of the Deficiency Stops (DS):**
   The project introduces a novel Deficiency Score (DS) metric to quantify rest area performance in mitigating fatigue-related crashes. This score integrates crash severity, proximity, and catchment characteristics to evaluate each facility's contribution to nearby crash risks. For example, an analysis of Florida's Interstate corridors revealed that rest areas with higher DS values were linked to elevated fatigue-related crash frequencies. As such, this metric enables transportation agencies to prioritize rest area upgrades, guide investment decisions, and ultimately enhance safety for truck drivers, rural communities, and all roadway users exposed to fatigue-related crash hazards.

ii. **Identification of Critical Factors and Key Patterns**:
   Through the analysis of over 36,000 truck-involved crashes, including more than 500 fatigue-related incidents, the project also identifies critical spatial, temporal, roadway-related, and driver behavior-related factors linked to fatigue involvement. The assessment reveals key patterns, such as increased crash likelihood during early morning hours and in proximity to certain rest areas. As such, this approach highlights where and when fatigue risks are elevated, enabling targeted safety interventions and rest area improvements to directly address these vulnerabilities.

The project's methodology is designed to assess vulnerability at multiple levels, enabling:

- Identification of truck drivers' vulnerability through analysis of fatigue-related crashes and proximity to rest areas with inadequate facilities.
- Evaluation of risks to other roadway users by analyzing crash types and behaviors that may endanger passenger vehicles and local traffic sharing the roadways with fatigued truck drivers.
- Development of a holistic deficiency scoring framework to prioritize rest area improvements that addresses safety risks across truck drivers, rural populations, and general motorists.

Outcomes and Impacts:

The project supports rural roadway safety planning, offering critical insights into the relationship between rest area facilities and fatigue-related crash risk. By testing and validating the methodology in Florida’s Major Freight Corridors, the project:

- Develops and validates a novel Deficiency Score (DS) to quantify rest area performance in relation to fatigue-related crash occurrence.
- Provides a scalable methodology that can guide transportation agencies in planning rest area enhancements and reducing fatigue-related crash risks.
- Identifies crash-related factors associated with fatigue involvement for truck drivers.
- Investigates how crash frequency near rest areas is influenced by facility characteristics using a novel metric, Deficiency Score (DS).

Alignment with USDOT Priorities:

This project directly supports USDOT priorities by addressing critical gaps at the intersection of rest area infrastructure, truck driver safety, and freight mobility. Fatigue-related crashes pose serious risks not only to truck drivers but also to other roadway users and rural communities. Limited and inadequate rest areas along major freight corridors increase this risk, leading to disruptions in freight movement and jeopardizing roadway safety. By developing a novel methodology to assess rest area performance and its relationship to fatigue-related crashes, this project enables transportation agencies to make data-driven decisions on where to enhance facilities to better serve truck drivers. In doing so, the project contributes to improving safety, ensuring more reliable freight movement, and protecting rural populations who share these corridors. The outcome is a scalable framework that promotes safer and more resilient freight networks, while aligning with USDOT's goals of advancing safety, supporting economic strength through efficient goods movement, and focusing on rural regions.

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Chapter 1 Introduction

Truck driver fatigue poses a persistent and serious challenge to rural highway safety, particularly along major freight corridors where infrastructure limitations and long-distance travel elevate risk levels. The need for constant freight movement, a lack of rest areas, and parking restrictions all contribute to truck drivers becoming more fatigued, which can result in serious collisions, traffic jams, and wider effects on rural communities and other roadway users. In states like Florida, where vital freight corridors act as lifelines for the movement of goods both nationally and regionally, these risks are particularly noticeable.

Traditional studies assessing rest area impacts on fatigue-related crashes often rely on aggregate analyses, overlooking individual crashes and their spatial relationship to specific rest areas. In contrast, this project introduces a data-driven methodology that links each fatigue-related crash to its assigned rest area based on proximity and facility characteristics. Advanced statistical models further assess how rest area features influence crash likelihood.

This project also integrates crash data analysis, spatial proximity modeling, and a novel Deficiency Score (DS)-based framework to develop innovative methodologies for evaluating rest area performance and its relationship to fatigue-related crashes. The research is structured around two key components, each addressing a critical dimension of freight corridor safety and driver vulnerability:

i. **Rest Area Performance Evaluation through Deficiency Score Modeling (Chapter 2):** This study a) develops a novel Deficiency Score (DS) to quantify the safety performance of individual rest areas in mitigating nearby fatigue-related crashes, b) validates the DS using spatial analysis techniques (e.g., Kernel Density Estimation) and statistical models to examine its relationship with crash occurrence, and c) identifies high-risk rest areas with elevated DS values, providing agencies with a decision-support tool for prioritizing rest area improvements and reducing fatigue-related crashes across Florida's freight network.

ii. **Crash-Level Fatigue Risk Assessment and Spatial Linkage (Chapter 3):** This study a) analyzes truck-involved crashes to identify spatial, temporal, roadway-related, and driver behavior-related factors associated with fatigue involvement, b) introduces a crash-to-rest area assignment methodology that links each fatigue-related crash to its nearest rest area using proximity and facility characteristics, and c) develops Florida-specific risk factors to reflect the unique challenges of fatigue-related crashes along major freight corridors, enhancing targeted safety analysis and intervention planning.

By combining crash data analysis, spatial modeling, and advanced statistical methodologies, this project develops a comprehensive framework for assessing rest area performance and mitigating fatigue-related crash risks along major freight corridors. The findings offer actionable insights for transportation planners, safety officials, and freight stakeholders, supporting data-driven decisions to enhance truck driver safety, improve rest area infrastructure, and promote safer and more efficient freight movement through rural regions.

Chapter 2 Evaluating Truck Rest Area Safety Performance Using a Data-Driven Approach to Reduce Fatigue-Related Crashes

2.1 Introduction

Considering their prevalence, severity, and the challenges in prevention, fatigue related crashes are significant concern for roadway safety. In the U.S., fatigue is the reason behind 91,000 reported crashes with 800 fatalities and 50,000 injuries in 2017 (*1*). When the drivers are under fatigue, the driving performance is impaired by diminishing attention and focus, leading to slower reaction time and poor decision-making process (*2*). As a result, they are less likely to engage in preventative actions like brake or swerve, leading to high-speed impacts crashes to be more severe, as shown by other studies (*3*, *4*). Moreover, it is suggested that fatigue related crashes are 50% more likely to result in death or serious injury (*5*). Similarly, one-quarter of fatal and serious collisions is estimated to be under the effect of fatigue (*5*). In addition, these crashes are associated with huge economic impact in the U.S. with approximately \$109 billion annual cost, even the property damage is not considered (*6*).

Sleep deprivation is one of the major reasons for fatigue-related crashes, making it essential for drivers to take regular breaks to rest and refresh themselves on their travel. Rest areas are one of the key facilities that offer this opportunity to drivers by providing them with safe and convenient locations, playing a crucial goal in reducing fatigue-related crashes. There are some contributing factors related to increased rest area service. One of those factors is strategic placement and their spacing. Studies in the Pacific Northwest found mixed impacts of rest area closure on fatigue related crashes, with some locations experiencing higher crash rates during the closures (*5*). The study highlights the importance of operational safe areas. In addition, closely spaced rest areas on highways (i.e., 30 miles apart) can reduce fatigue related crashes significantly (*7*). Furthermore, infrastructure improvements like sufficient parking spaces and amenities are also needed to encourage the drivers to use them (*7*).

Among all drivers, truck drivers are highly susceptible to fatigue since they are driving long hours under monotonous roadway conditions and in strict delivery schedule without having adequate sleep. Considering this, facilities like rest areas become extremely critical. However, some of the rest areas are unable to meet the parking demand of increasing commercial motor vehicle (CMV) traffic, which contributes to the occurrence of crashes. Therefore, it is crucial to assess the safety performance of rest areas with a focus on fatigued truck drivers to identify and diagnose the problematic areas.

To address these challenges, this study aims to assess the safety performance of rest areas in mitigating fatigue-related crashes among truck drivers. To achieve this, a systematic data-driven approach is developed to quantify rest area safety performance, with a particular emphasis on crash severity, proximity, and spatial distribution. By analyzing the underlying spatial dynamics of these crashes, this research develops a novel Deficiency Score (DS) metric and identifies key deficiencies in rest area safety performance, identifying possible targeted interventions. Beyond addressing a critical gap in transportation safety research, this study also provides practical insights for transportation agencies in strategically optimizing the design, placement, and capacity of rural rest areas along the National Highway System.

2.2 Literature Review

Truck drivers face increased crash risk due to multiple factors such as fatigue and increased crash severity in rural areas. Specifically, fatigue-related crashes disproportionally impact truck drivers and fatigue is the most common factor linked to truck collisions after speeding (*8*). As it was indicated by several researchers, almost 20% of truck-involved crashes were due to fatigue or drowsiness, while it is approximately 1-2% for crashing involving all vehicles (*1*, *9–11*). The role of fatigue in increasing the crash severity has been also discussed across multiple studies (*12–17*) .

Some researchers investigated the impact of fatigue on crash severity for different crash configuration and familiarity of the environment by using random parameter ordered logit models. For example, Azimi et al analyzed the severity of large truck rollover crashes in Florida that occurred between 2007 and 2016 and determined fatigue as a significant factor increasing the severe outcomes (*15*). Similarly, Okafor et al. examined large truck crashes in Alabama from 2016 to 2020 to assess the effect of environmental familiarity on crash severity by evaluating different driver centered crash factors (*16*). They reported that fatigue increased the severity in both in-state and out-of-state large truck crashes, with rates of fatigue related crashes resulting in severe injuries in out-of-state (23%) and in-state (21%).

Beyond fatigue, another critical factor elevating crash risks for truck drivers is the higher severity of truck-involved crashes in rural areas. Wei et al. investigated traffic crash severity between urban and rural crashes, using 3,735 crashes between 2017 and 2019. In the study, a binary logit model was developed incorporating 14 different variables related to drivers, driving environments, and other influencing factors (*13*). They showed that traffic crashes involving trucks are 4.6% and 9.8% more likely to be fatal than those without trucks in urban and rural areas, respectively. In addition, fatigue driving was found to have significant relationship with the crash severity with higher marginal contributions in rural areas (5.4%) than in urban areas (3.9%). Similarly, Islam et al. studied single and multi-vehicle large truck at-fault crashes on rural and urban roadways in Alabama by random parameter logit models, identifying fatigue as one of the factors contributing significantly to these crashes in rural areas (*17*).

Literature indicates that most of the fatigue and drowsy driving crashes take place from midnight to early morning (*18*, *19*), when natural alertness of the body is at minimum due to circadian rhythm. In a Federal Motor Carrier Safety Administration (FMCSA) study, it was also suggested that driver alertness was more influenced by the time of the day, rather than duration of driving (*20*). Therefore, drivers were advised to park their car and have a rest if they felt drowsy, especially in that period. However, although rest area services provide this service, there are still challenges in meeting the parking demand.

Understanding the parking needs and preferences of truck drivers is crucial for addressing these challenges effectively. Coleman et al. (*21*) surveyed more than 2,000 truck drivers with different-sized carriers from various U.S. states. Many of the respondents reported that they made the decision on where to park with the reason being meeting their basic needs mostly. Parking facilities that provide food, fuel, restrooms, phone, and showers were preferred where safety and convenience were considered critical. As shown by the study, while private truck stops were preferred over public rest areas, rest areas were chosen over truck stops for quick naps. A major issue highlighted by the survey was the lack of adequate parking facilities, leading to unauthorized parking on ramps and shoulders, where 83% of drivers cited the absence of nearby facilities and 94% reported that there were no available spaces even when rest areas were nearby. The drivers recommended increasing the number of truck parking facilities to mitigate this problem.

Garber et al. (*22*) evaluated the supply and demand characteristics of commercial vehicle parking on I-81 Interstate Highway in Virginia by considering 14 public rest areas and 29 private truck stops. In the study, the amount of parking spaces available in these areas was considered as the parking supply, and demand was defined as the total amount of parking done by truck drivers, including illegal parking, at any given time frame. Their findings indicated that parking demand exceeded the supply by 309 spaces, and this gap was projected to increase significantly if the number of parking spaces remained constant. In terms of the time frame, the period between 9 pm and 6 am was found to be the worst in terms of truck parking space shortage. In addition, based on the interviews conducted with truck drivers, researchers received meaningful details regarding the supply-demand gap of truck parking and how truck drivers select rest areas under those conditions. 95% of truck drivers expressed the inadequacy of long-term truck night parking spaces along I-81 Interstate Highway in Virginia, while 90% indicated they would choose to stop at the next closest stop in case of not finding the spot in the first facility.

Bayraktar et al. (*23*) focused on assessing truck parking adequacy in Florida's public rest areas along the I-10, I-75, and I-95 interstate highways. In the analysis based on truck count data, field observations, and interviews, overutilized facilities during peak hours were identified and categorized as having low, medium, or high level of parking capacity problems. In a follow-up study, researchers (*24*) utilized various database resources, including parking parcels with capacity and raw GPS data records, to identify locations which truck drivers were engaging in unauthorized truck parking close to rest areas and truck stops in Florida. In the analysis conducted at both district and site levels, annual average dwell time, parking spaces per 100,000 truck miles, and daily parking utilization rates for each FDOT (Florida Department of Transportation) District were also calculated. This study provided a detailed picture of truck parking patterns in Florida.

While numerous studies focus on the convenience and logistics of parking, others examine the role of rest areas in reducing fatigue-related crashes, highlighting their role in overall road safety. In their study, Banerjee et al. (*25*) investigated the relationship between fatigue-related crashes and rest area locations. They compared the rate of fatigue and non-fatigue collisions in the proximity of rest areas by employing statistical tests based on two different approaches. In the first approach, they evaluated the 10-mile radius up/downstream of rest areas, while the second approach focused on the distance traveled from these facilities. Findings indicated that collisions resulting from both fatigue and non-fatigue collision dropped downstream of rest areas, followed by a sudden increase of fatigue-related crashes after 30 miles from rest areas. This highlights the critical importance of strategically placed rest areas in reducing fatigue-related incidents and ensuring road safety. McArthur et al. (*26*) provided a similar approach where all various factors like traffic volume and network distance to the nearest rest area. It was suggested that crash frequency decreased when the road segment was closer to the rest area.

In another study, Crizzle et al. (*27*) investigated the fatigue-related truck crashes in the highways of Saskatchewan, Canada, by using the Chi-square test. They found a positive relation between the number of inadequate truck parking spaces and fatigue-related truck crashes. Pigman et al. (*28*) investigated fatigue-related and shoulder-related crashes on the interstate highways, and parkways in Kentucky where utilization of parking spaces in nighttime was found to be much higher than daytime. Crash cluster locations were also found to be directly related to the proximity and usage rate of parking facilities. Bunn et al. (*29*) examined CMV crash data in Kentucky from 2005 to 2014 and identified 7,538 incidents where the driver was at fault, with 284 of these involving driver fatigue. They focused on interstates and parkways that had at least one rest area, weigh station with a rest haven, or truck stop within the KYTC Designated National Truck Network. Their analysis revealed that driver at-fault crashes due to fatigue were almost 2.5 times more likely to happen compared to non-fatigue crashes on roads when the distance to the nearest rest facility from the crash site was between 20 and 40 miles. Furthermore, it was nearly seven times more likely when the rest options were more than 40 miles away.

Given the critical role of rest areas in mitigating driver fatigue, it is essential to develop a structured approach to assess their effectiveness. One way to achieve this is through safety performance indices. Similar efforts have been undertaken in different contexts to create and validate indices. Dou et al. developed an index to monitor the development of Industrial Internet Platform (*30*). To validate the practical applicability of the index and see whether it matches with industry growth patterns, they collected real-world data from 10 major Industrial Internet Platforms and conducted comparative trend analysis with expected industry trends. Wagner et al.(*31*) developed a composite index of national research capacity, that measures a country's capability in producing research by a set of credible indicators. They employed convergent and discriminant validation techniques to verify the index. Besides, to test the predictive power of the index they have employed Bayesian multilevel regression, demonstrating a significant relationship between their index and the Fractional Field-Weighted Citation Impact (FWCI), a widely used measure of scientific impact.

There are also some studies in the transportation domain that develop and validate relevant indices. In one study, the authors developed a Crash Severity Index (CSI) to provide a safety evaluation for work zones (*32*). They have achieved this by applying logistic regression on the crash data which involved fatalities and injuries in Kansas. Their index, CSI, ranging from 0 and 1, represented the possibility of having a fatality in case of a severe crash happening in each work zone. This index was verified by comparing the actual crash result of 355 crashes with the predicted value from CSI index. It was found that 95% of the injury-involved crashes were predicted correctly while approximately 23% of the fatal crashes were detected, raising questions on the accurate performance of the index for fatal crashes. In another study, Gates et al. created a value index for Michigan rest areas, incorporating economic factors (e.g., excess travel time, crash reduction benefit, and tourism impact), and non-economic factors (e.g., site characteristics, truck parking availability, and facility usage). Their index provided a composite score to evaluate rest area safety performance. To validate the index, scaled non-economic scores were compared with the scaled economic scores (*33*). The analysis found a strong correlation between high-value index scores and high-performing rest areas, supporting the validity of the approach. Although the focus was not directly on crash safety, the study was very important as it developed a safety performance index for rest areas.

While previous studies have explored fatigue-related crashes, truck parking challenges, and the impact of rest areas on crash prevention, a structured and quantitative assessment of rest area safety performance remains limited. Many studies have also examined parking demand features of rest areas and their impact on fatigue-related truck crashes, yet a comprehensive evaluation of rest area safety performance in reducing these crashes is lacking. Additionally, existing research mainly focuses on crash frequency and reduction, while overlooking crash severity; however, fatigue has been a well-documented factor in increasing crash severity and fatality risk. Furthermore, the role of rest area placement and safety performance in mitigating these crashes has not been systematically quantified. To bridge these gaps, this study develops a data-driven safety performance metric that evaluates rest areas based on their effectiveness in preventing and reducing the severity of fatigue-related crashes. By introducing a Deficiency Score (DS) metric that accounts for crash severity, proximity, and catchment area, this research provides a methodology that can be used by transportation agencies to identify high-risk rest areas that could lead to prioritizing improvements and enhancing roadway safety.

2.3 Data and Study Area

The State of Florida was chosen as the study area due to its extensive interstate highway network, high levels of commercial truck traffic, and high number of crashes. Key corridors such as I-10, I-75, and I-95 are critical routes for freight movement, making the state an ideal case for evaluating rest area safety performance. Freight Analysis Framework (FAF) roadway network and rest area facilities in Florida were used for this purpose. The study area with the rest area facilities and the National Highway system (including state highways and interstates) can be seen in Figure 2-1 and the list of rest areas with their location and capacity information is provided in Table 2-1.

Table 2-1 General Overview of Florida Rest Areas

Facility ID	# Parking Spots	Highway	Mile Post	Municipality	County
1	60	I-75N	35	Weston	Broward
2	37	I-75N	63	Big Cypress	Collier
3	74	I-75N	131	Fort Myers	Lee
4	32	I-75S	161	Punta Gorda	Charlotte
5	82	I-95S	106	Palm City	Martin
6	60	I-95N	106	Palm City	Martin
7	43	I-95S	133	Fort Pierce	St. Lucie
8	44	I-95N	133	Fort Pierce	St. Lucie
9	16	I-275N	7	Terra Ceia	Manatee
10	14	I-275N	13	St. Petersburg	Pinellas
11	36	I-75N	238	Ochopee	Hillsborough
12	43	I-75S	238	Gulf City	Hillsborough

13	60	I-95N	168	Palm Bay West	Brevard S
14	67	I-95S	168	Grant Valkaria	Brevard S
15	23	I-4E	46	Polk City	Polk
16	23	I-4W	46	Polk City	Polk
17	51	I-75N	278	Wesley Chapel	Pasco
18	51	I-75S	278	Wesley Chapel	Pasco
19	43	I-75N	307	Ridge Manor Est	Sumter
20	33	I-75S	307	Croom	Sumter
21	33	I-95N	225	Mims	Brevard N
22	16	I-4W	94	Wekiva Springs	Seminole
23	35	I-95S	227	Mims	Brevard N
24	17	I-4E	96	Longwood	Seminole
25	43	I-75S	346	Ocala	Marion
26	43	I-75S	346	Ocala	Marion
27	7	I-75N	383	Daysville	Alachua
28	13	I-75S	382	Daysville	Alachua
29	15	I-95N	302	Hastings	St. Johns S
30	16	I-95S	302	Vermont Heights	St. Johns S
31	50	I-75N	413	Ellisville	Columbia
32	50	I-75S	413	Ellisville	Columbia
33	45	I-95N	331	Sampson	St. Johns N
34	45	I-95S	331	Sampson	St. Johns N
35	10	US19/US27	n/a	Perry	Taylor
36	22	I-10E	318	Olustee	Baker
37	25	I-10W	318	Olustee	Baker
38	15	I-10W	295	Wellborn	Hamilton
39	14	I-10E	294	Wellborn	Suwannee
40	26	I-10E	265	Lee	Madison
41	23	I-10W	265	Lee	Madison
42	10	I-10E	234	Aucilla	Jefferson
43	11	I-10W	234	Aucilla	Jefferson
44	19	I-10E	194	Tallahassee	Leon
45	19	I-10W	194	Tallahassee	Leon
46	74	I-10E	31	East Milton	Santa Rosa
47	68	I-10W	31	East Milton	Santa Rosa
48	43	I-10W	162	Hardin Heights	Gadsden
49	17	I-10W	96	Ponce De Leon	Holmes
50	53	I-10E	58	Crestview	Okaloosa
51	53	I-10W	60	Crestview	Okaloosa
52	12	I-10E	133	Jacob	Jackson
53	24	I-10W	133	Cottondale	Jackson

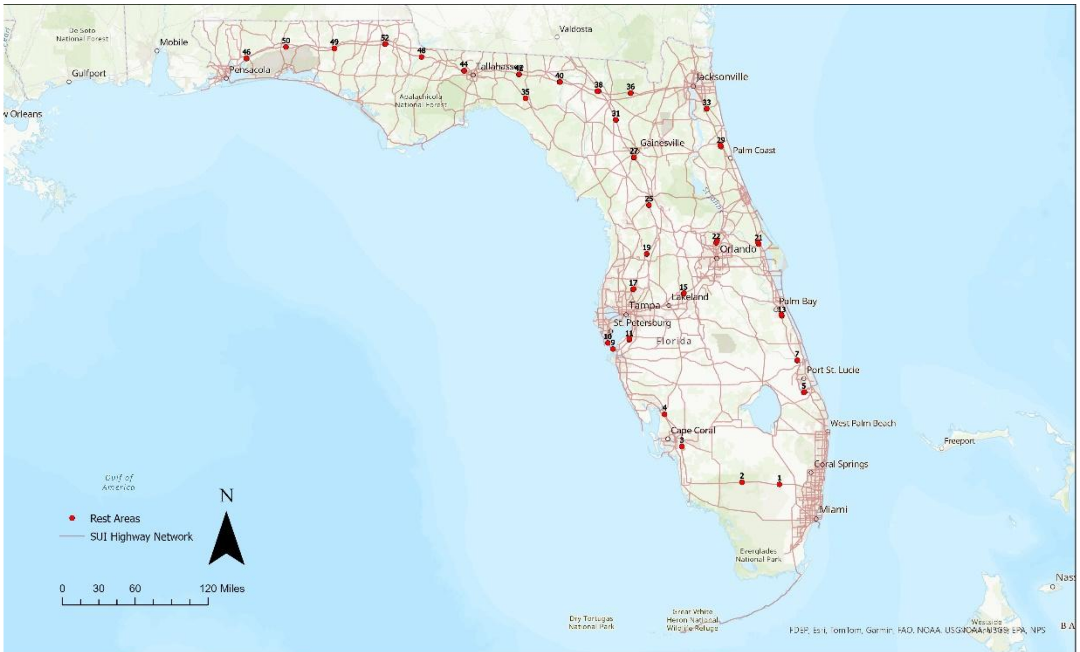

Figure 2-1 Study Area with Rest Area Facilities and National Highway System

In this study, only fatigue-related crashes involving medium or heavy trucks were analyzed. Throughout the remainder of this study, the term "trucks" will refer to exclusively to medium or heavy trucks. Tables 2-2, 2-3, and 2-4 provide the annual distribution of crashes by severity level over the study period where Table 2-2 summarizes all crashes within the study area, Table 2-3 focuses on crashes involving trucks, and Table 2-4 presents statistics specifically for fatigue-related truck-involved crashes. As shown in Table 2-2, there have been almost 1.94 million crashes over five years in the state, with fatal crashes accounting for 1% of all reported incidents. Most crashes (~58%) resulted in no injuries whereas ~38% of crashes involved injuries with varying severity. The highest total crash count was observed in 2021, while 2020 saw a decline, likely due to reduced travel during the Covid-19 pandemic. Studying Table 2-3, we observe that approximately 8.4% of total crashes involve trucks, with the majority (83%) of them being no-injury crashes. While trucks are involved in fewer crashes overall, fatal truck crashes make up a similar proportion (~0.75%) to overall fatal crashes (~0.82%). The number of truck-involved follows a similar pattern with respect to total crashes, showing a decrease in 2020 and a rebound afterward. Referring to Table 2-4, fatigue-related crashes represent a very small percentage of truck-involved crashes (~0.83% of all truck crashes). However, as also discussed in the literature, they are more severe in proportion. In comparison with all truck-involved crashes, the rate of fatal crashes is almost doubled (1.47% vs. 0.75%) and the rate of incapacitating injury crashes is nearly tripled when fatigue is the reason for the truck-involved crashes (5.31% vs.1.82%). The annual distribution of fatigue-related truck-involved crashes remains relatively stable, with minor fluctuations in total numbers.

Table 2-2 All Crash Statistics by Year and Severity Level

Year	Fatal Crashes	Incapacitating Injury Crashes	Other Injury Crashes	Crashes with No Injuries	Total Codable Crashes

2023	3,162	12,456	151,957	227,600	395,175
2022	3,320	12,747	150,375	231,178	397,620
2021	3,454	13,435	150,521	234,130	401,540
2020	3,098	12,462	127,705	198,134	341,399
2019	2,951	14,252	152,768	231,896	401,867
Σ	15,985	65,352	733,326	1,122,938	1,937,601
%	0.82	3.37	37.85	57.96	100

Table 2-3 All Truck-involved Crash Statistics by Year and Severity Level

Year	Fatal Crashes	Incapacitating Injury Crashes	Non-incapacitating Injury Crashes	Possible Injury Crashes	Crashes with No Injuries	Total
2023	240	543	1,885	3,109	28,897	34,674
2022	240	604	1,825	3,141	29,034	34,844
2021	253	611	1,777	3,051	27,300	32,992
2020	254	587	1,530	2,550	22,884	27,805
2019	234	613	1,711	2,867	27,115	32,540
Σ	1,221	2,958	8,728	14,718	135,230	162,855
%	0.75	1.82	5.36	9.04	83.04	100

Table 2-4 Fatigue-related Truck-involved Crash Statistics by Year and Severity Level

Year	Fatal Crashes	Incapacitating Injury Crashes	Non-incapacitating Injury Crashes	Possible Injury Crashes	Crashes with No Injuries	Total
2023	4	14	43	27	173	261
2022	6	13	46	39	175	279
2021	2	20	37	50	201	310
2020	4	13	34	49	137	237
2019	4	12	34	41	178	269
Σ	20	72	194	206	864	1,356
%	1.47	5.31	14.31	15.19	63.72	100

Descriptive statistics provide an overview of crash distribution by severity and vehicle involvement. To further examine trends and patterns over time, a daily time series analysis is conducted for truck-involved crashes. Figure 2-2 presents the daily variation in all truck-involved crashes and those only involving fatigue. As shown in Figure 2-2, majority of truck-involved crashes occur between 7am-4pm, peaking at 12 pm. On the other hand, truck crashes involving fatigue are more common between midnight and early morning (i.e., between 2 am and 8 am), drawing parallels to the timeframe discussed in the literature.

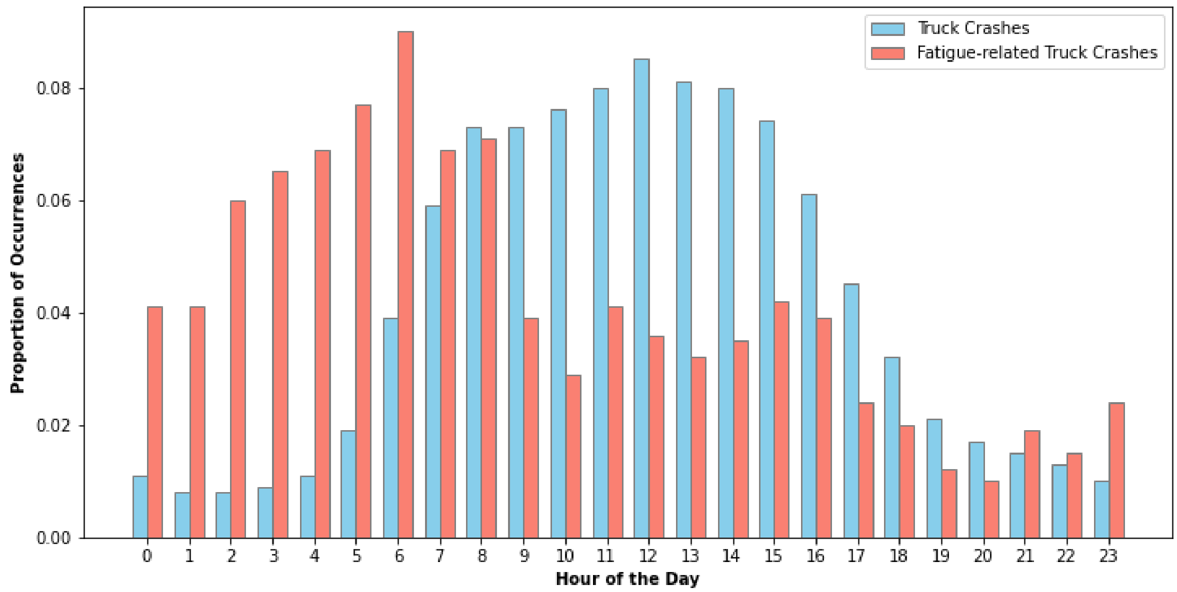

Figure 2-2 Hourly Distribution of Truck and Fatigue-related Truck Crashes

The crash data was obtained from Signal4Analytics (*34*). Over Signal4Analytics, crash information is arranged in distinct sections including crash events and drivers, and a 'unique' crash number is reported for each crash. We used those sections and report numbers to filter fatigue-related crashes involving trucks. The filtration process included three steps. In the first step, we extracted truck related crashes by using the ('is_cmv_involved'==Y) and (('v1_vhcl_bdy_typ_cd' or 'v2_vhcl_bdy_typ_cd') =='Medium/Heavy Trucks') query on "**crash events file**". On the second step, we determined unique report numbers of fatigue related crashes by considering the "condition at time of crash" == "asleep or fatigued" query in the "**driver file**". In the final step, we identified all the fatigue-related crashes involving trucks whose crash number is already received in previous steps.

Crash data utilized in this study includes rural fatigue-related crashes occurring on Florida's highway network between 2019 and 2023, filtered by proximity to FAF roadways and rest areas. The FAF network was chosen due to its comprehensive coverage of truck-relevant routes, ensuring relevance to the study's focus on truck parking needs. Urban crashes were excluded to avoid the effects of urban aggregation, where high crash density in urban areas could bias the assessment of rural rest area safety performance. This decision aligns with the scope of the study, which focuses on rural rest areas serving long-haul truck drivers. The spatial relationship between rest areas (red dots) of the rural fatigue-related crashes (blue dots) can be seen in Figure 2-3.

Mapping the spatial distribution of crashes and rest areas helps us identify where the crash hotspots are and observe the effect of rest areas on these clusters. As seen in Figure 2-3, the selected fatigue-related crashes are heavily accumulated on major corridors such as interstate I-10, I-75 and I-95, with the highest concentration on I-75. It can also be observed that there are a smaller number of crashes in the proximity of rest areas. However, in certain regions, despite the presence of nearby rest areas, crashes still occur frequently, especially on I-75 and I-4. This may be because of those drivers not utilizing the rest area due to scheduling constraints and insufficient parking capacity. In addition, some regions have dense crash concentrations but relatively fewer rest areas, showing the potential need for additional rest areas or alternative truck parking facilities.

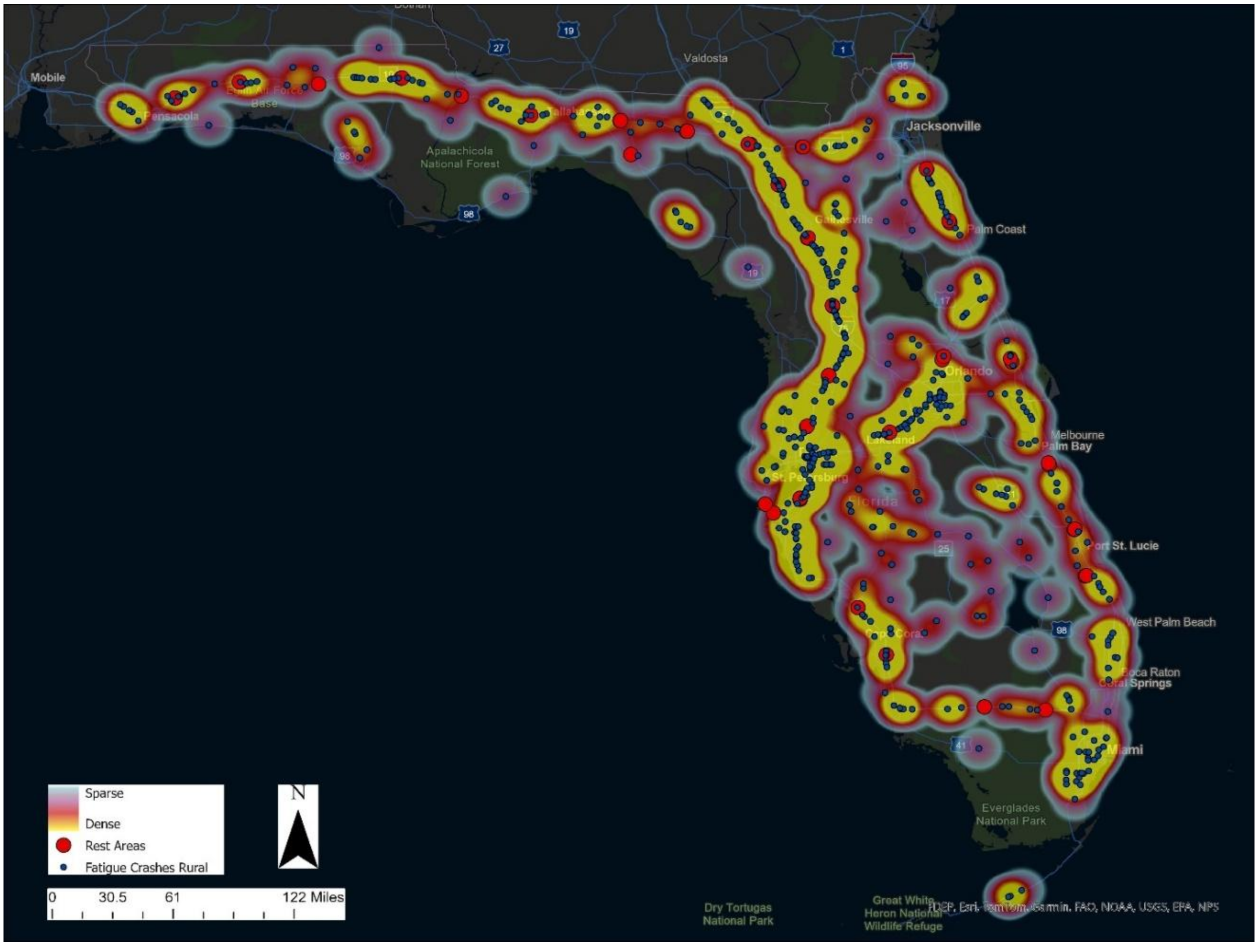

Figure 2-3 Spatial Distribution of Rest Areas and Fatigue-Related Crashes

2.4 Methodology

In this study, a safety performance metric, namely Deficiency Score (DS), is developed with a focus on rest areas on the National Highway system (State Highway, US Highway, Interstates) based on fatigue-related truck-involved crashes. After relevant crash data have been filtered for the analysis, they were assigned to the nearest rest area facility based on trucking network distance from the truck driver to the closest rest area (i.e., using roadways that are not restricted to trucks). Finally, using several attributes related to the rest areas and crashes assigned to the given rest area, the metric is introduced, and each rest area is assessed based on the efficiency of this metric. Our approach, which combines advanced GIS-based spatial analyses with a data-driven scoring metric and incorporates proximity, severity, and catchment area adjustments, provides a novel approach to evaluating and assessing rest area safety performance. The following section describes the selection, assignment, and assessment process and the flowchart of the methodology can be seen in Figure 2-4.

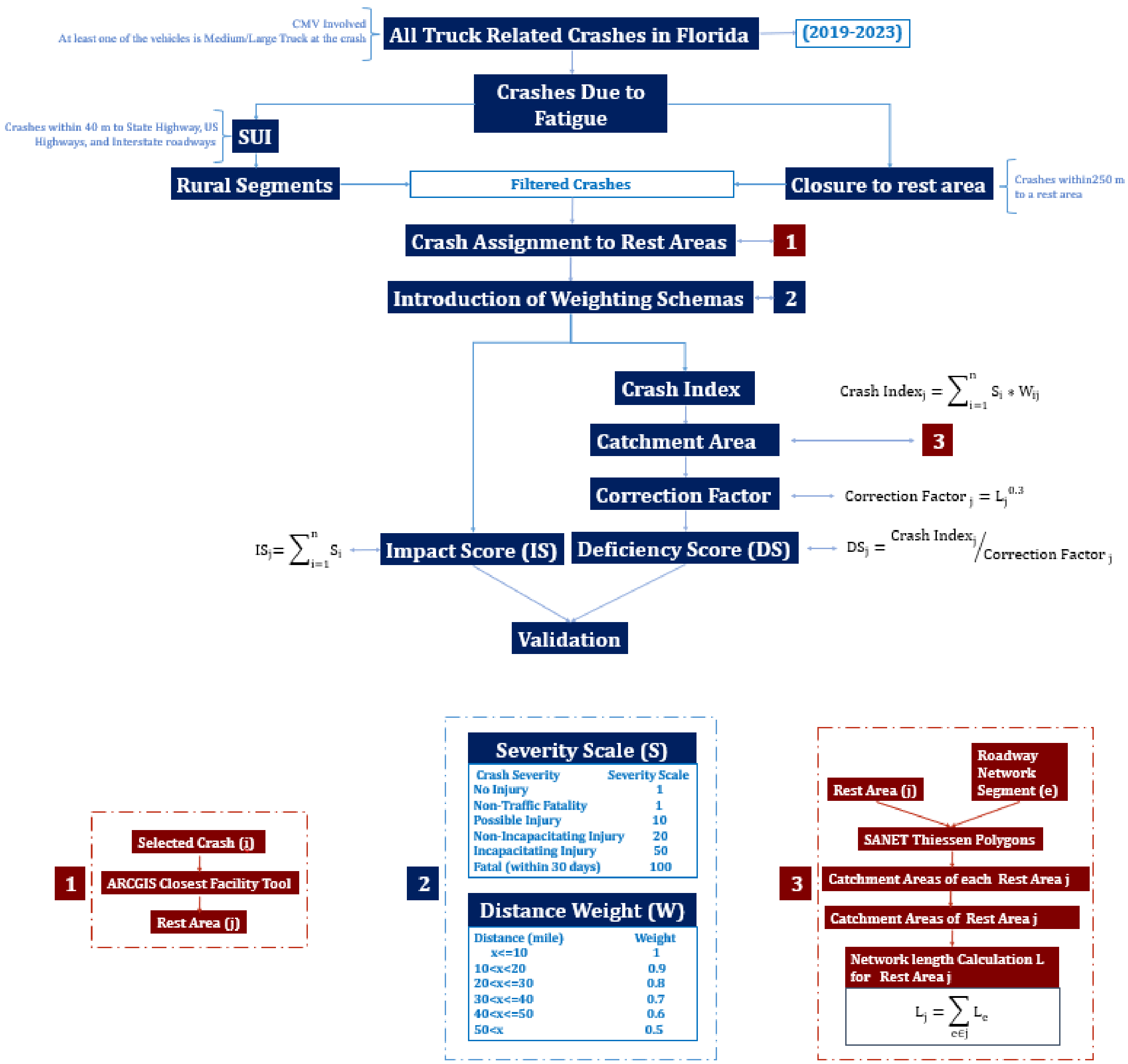

Figure 2-4 Flowchart of the Methodology

2.4.1 Crash Selection Process

In the selection process, the FAF (Freight Analysis Framework) roadway network (*35*) was used to detect state highways and interstate highways. This selected roadway network will be referred to as the 'main highway network' in the rest of the study. This network was used to identify relevant fatigue-related crashes spatially by filtering for those that occur within 40 meters of the network. This distance accounts for the lane widths, and the imprecise recording of some collision locations.

In addition to the main highway network, the point location of rest areas was used to capture the collisions that were outside of the main highway network, but still within the vicinity of the rest area. As some rest areas are quite large, 250 meters have been used to ensure all collisions that are influenced by rest areas are included. Along with the spatial selection, some tabular filtration has been done on the crashes. Initially, all the crashes that occurred in urban areas were excluded. This filtration was performed since the scope of this study is to evaluate rest areas based on their safety performance; however, considering urban crashes may lead to urban aggregation issue that was discussed in NCHRP Report 324 (*36*). At the end of the selection process, 554 fatigue-related truck-involved crashes were chosen for the analysis.

2.4.2 Crash Assignment to Rest Areas

Time constraints (*37*) and hours of service regulations (*38*) may help truck drivers choose rest areas close to their planned route so that they can minimize extra time and detours. This tendency was also observed in the survey done by Garber et al (*22*) where 90% of the drivers would prefer to stop at the next closest facility when there are no parking spaces available in the rest area they arrived first. Our assumption here is that a truck driver with fatigue is trying to go to the nearest rest area (*22*). Therefore, based on this assumption, the closest rest area to the truck driver is assumed to be influencing that crash due to its inability to provide the required service. As such, a deficiency score was added to the corresponding rest area. More details regarding the scoring can be seen in the next subsection. To find the nearest rest area, the Closest Facility tool was utilized in ArcGIS Pro. This tool assigns each incident to the closest facility considering different metrics, such as driving distance, driving time, trucking distance and time, and shows the assigned path from the incident to the facility. In our case, each fatigue-related crash is matched with the closest facility based on trucking distance (*39*).

2.4.3 Deficiency Score (DS) Metric Development

In this process, rest areas are evaluated heuristically based on their safety performance in mitigating crashes, which is their expected functionality. In this practical approach, if the expected result is achieved (i.e., mission is completed), the rest area is considered to be performing well and close to the ideal condition, indicating low deficiency. Conversely, if the rest area fails to meet the mission, it will have a high deficiency from the ideal conditions. Additionally, it is assumed that rest areas have a catchment area, which is incorporated into the safety performance evaluation. The expected missions from rest areas can be adjusted, and scoring can be performed accordingly. All details regarding the expected missions and steps to create this deficiency score are discussed below.

The frequency and impact of fatigue-related crashes are expected to be minimized for a rest area along the network. Therefore, for each crash that happened, a deficiency score (DS) is added. While adding the DS, some factors have been considered, one of which is proximity. Numerous researchers concluded that fatigue-related truck-involved crashes are not common in the vicinity of rest areas. As the distance increases from the rest area along the network, the chances of fatigue-related crashes are more expected (*26*, *29*, *40*).Therefore, in light of these findings, we have added proximity as an evaluation factor. To simulate the effect of proximity, a weighting factor is introduced. In this weighting system, a rest area is penalized more for a crash that occurs nearby than a crash that happens farther away. The introduced weighting scheme is shown (Table 2-5). In addition to proximity, severity of crashes is also taken into consideration. To simulate the effect of severity, each crash is categorized using KABCO scale (*41–44*). Since the KABCO scale is often utilized due to its alignment with the costs and risks associated for each severity level, we employed it as scale factor for the crash severity. As shown in Table 2-5, to reflect on the increasing societal and economic impacts of injuries and fatalities, fatal and incapacitating injuries are heavily punished on the severity scale.

Table 2-5 Weighting Scheme for Distance and Crash Severity

Distance Weight (W)	Distance x (mile)	Severity Scale (S)	Crash Severity
1	x <= 10	1	No Injury
0.9	10 < x <= 20	1	Non-Traffic Fatality
0.8	20 < x < =30	10	Possible Injury
0.7	20 < x < =30	20	Non-Incapacitating Injury
0.6	40 < x <=50	50	Incapacitating Injury
0.5	50< x	100	Fatal (within 30 days)

By using these weights, a crash index metric was obtained for each rest area, as shown in Equation 1:

$$Crash\ Index_{\ j} = \sum_{i=1}^{n} S_i * W_{ij} \qquad (1)$$

where j represents rest areas while i portrays each crash, and n is the total number of crashes assigned to rest area j. For each crash i, the severity index S_i is multiplied by W_{ij} and cumulatively added to the crash index (CI) for rest area j. For example, if a crash occurs 15 miles far away from a rest area with a severity level of "Non-Incapacitating Injury", the CI can be calculated as follows: CI = (Distance Weight of 0.9) × (Severity Weight of 20) = 18.

2.4.4 Catchment Area Adjustment

After calculating the rest area CI values, a correction is needed for the catchment area. As discussed previously, every rest area has a catchment along the network. If the spacing between the rest areas is higher, we should be expecting more crashes as discussed by several researchers (*40*). In addition, due to geographical constraints, this score may be needed. For instance, the catchment area of the rest facility located in Southeast Florida (indicated by blue rectangle in Figure 2-5) is very large since there is no other rest area facility in the southern direction. The correction factor used for this reason is shown below in Equation 2 and Equation 3:

$$Correction\ Factor_{\ j} = L_j^{\ 0.3} \qquad (2)$$

$$Deficiency\ Score_{\ j} = {}^{Crash\ Index_{\ j}}\!\Big/_{Correction\ Factor_{\ j}} \qquad (3)$$

where L_j is sum of length in catchment area for the rest area j and shows the total network line in miles and 0.3 is selected based on empirical testing. It should be noted that this layer is obtained by using SANET Thiessen Polygons in SANET tool (*45*) based on roadway network lengths, not planar distance lengths. The concept of Thiessen polygons, also known as Voronoi diagrams, plays a critical role in this process. Thiessen polygons provide a spatial partitioning method that divides a plane into regions based on the proximity to a specific set of points. Each region, or Thiessen polygon, contains all locations that are closer to its defining point than to any other point. This method ensures that each area is uniquely associated with the nearest point, making it a powerful tool for spatial analysis. Using Thiessen polygons, possible overlaps are avoided while determining catchment areas.

The correction factor is developed to account for large catchment areas, which may inherently experience more crashes due to greater roadway coverage. However, at the same time, the correction should not punish rest areas with smaller catchment area just because they have low network coverage. By considering those conditions, correction factors are introduced. Developed deficiency scores represent the deficiency of rest area along the given network. Low values of this score means that the rest area performs sufficiently to decrease the impact of fatigue-related crashes; however, high values indicate that the area is not working effectively. This analysis can give important hints to the authorities while assessing the rest areas' deficiencies, and it can be compared with other rest areas in the system to quantify the deficiency. Basically, the obtained index tells the user how far away the given rest area is from an idealized one.

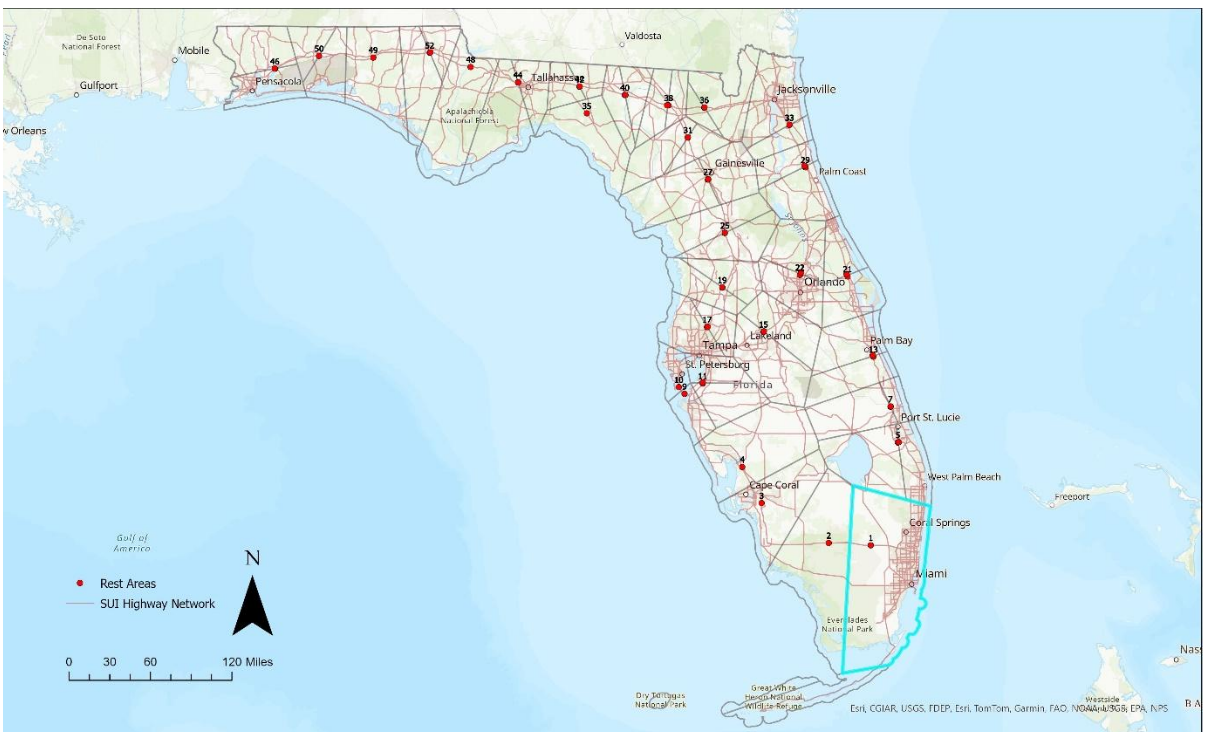

Figure 2-5 Catchment Areas of each Rest Area Facility

2.4.5 Impact Score (IS) Calculations

In this section, a new score metric, namely Impact Score (IS), is derived to verify the reliability of Deficiency Score. In this score, we used the severity scale that we developed earlier to assign the cost of crashes to the corresponding rest areas. The derivation of this score is shown in Equation 4:

$$IS_j = \sum_{i=1}^{n} S_i \qquad (4)$$

As seen in Equation 4, this score shows us the impact of the crashes for rest area *j* by considering every crash in the catchment area and calculating the cumulative severity scale of them. In Table 2-6, Impact Score (IS) of fatigue-related truck-involved crashes and other critical information related to the distance and frequency of crashes have been presented. This table provides key information related to the impact of each rest area on fatigue related crashes although there is no information regarding the severity and proximity of crashes.

Looking at the crash number alone does not give the full picture to assess the safety performance. To illustrate using Table 2-6 and Table 2-7, in Rest Area 1, the IS was 381 for 43 crashes and mean crash distance was 47.04 miles, whereas in Rest Area 44, there have been only 6 crashes, and it had an IS of 120 with a mean crash distance of 9.87 miles. This implies that more crashes might have occurred in closer proximity with higher severity in Rest Area 44. This clearly indicates that neither impact score nor crash frequency is enough to assess which rest area is performing worse since there are conflicting factors. On the other hand, based on the proposed data driven Deficiency Score (DS), evaluation process becomes easier. That is, DS can incorporate key indices related to the crash frequency, severity, and distance Therefore, we need DS to assess the overall deficiency of each facility. In Table 2-7, DS and IS can be compared.

As discussed before, IS is derived to validate DS values. Similar to the other rest area study (*33*), this validation process is done by scaling both scores and comparing the rank of each facility based on that. In Table 2-8, facilities are ranked from the highest to the lowest DS. The validation of the score based on this comparison will be discussed in the "Discussion and Results" section.

Table 2-6 Obtained Results After the Spatial Analysis

Facility ID	Impact Score	Mean Fatigue Crash Distance (mile)	Median Fatigue Crash Distance (mile)	Maximum Fatigue Crash Distance (mile)	Minimum Fatigue Crash Distance (mile)	# Truck-involved Fatigue Crashes
1	381	47.04	43.6	126.67	7.87	43
2	123	23.77	24.39	50.23	8.39	5
3	255	25.38	24.48	58.3	0.53	25
4	186	31.29	35.92	63.09	4.13	13
5	54	45.45	51.36	65.33	8.21	5
6	61	31.39	36.54	50.66	4.5	15
7	152	38.75	42.64	52.71	14.73	8
8	62	22.28	22.63	41.88	2.2	6
9	205	22.21	21.26	40.93	5.03	20
10	12	17.59	18.86	21.11	12.79	3
11	1	2.51	2.51	2.51	2.51	1
12	266	17.79	17.11	48.9	3.06	31
13	42	10.81	12.07	14.82	4.3	4
14	42	20.51	17.61	28.98	14.13	5
15	118	17.57	10.75	54.5	2.12	13

16	344	19.5	16.5	64.43	4.41	40
17	14	14.56	12.51	25.42	3.83	5
18	360	19.02	20.15	28.96	3.88	40
19	164	13.58	15.16	23.03	2.81	11
20	37	12.48	14.37	17.4	5.16	9
21	135	19.32	20.46	27.09	8.33	8
22	54	22.08	23.58	35.04	7.06	5
23	143	33.32	35.55	46.46	1.85	7
24	227	22.04	23.67	32.62	8.81	24
25	190	9.64	7.27	24.96	0	14
26	30	11.29	11.75	21.52	0.57	12
27	226	15.37	11.85	37.84	1.52	13
28	64	14.61	13.81	26.9	3.67	17
29	111	23.37	30.34	36.47	7.83	7
30	143	13.36	11.58	33.31	2.35	7
31	20	15.43	15.43	15.43	15.43	1
32	108	9.26	8.77	23.79	0.03	15
33	41	11.79	13.49	26.65	0.85	13
34	25	46.74	47.61	54.73	24.73	7
35	24	34.84	39.05	47.28	4.38	6
36	51	5.62	5.62	11.23	0	2
37	104	26.46	23.73	36.68	18.77	9
38	91	11.24	10.87	12.89	10.34	4
39	15	17.25	21.51	24.01	0.28	6
40	8	21.63	24.78	32.49	9.5	8
41	10	27.41	27.41	27.41	27.41	1
42	93	13.33	13.75	22.86	6.02	6
43	2	10.4	10.4	11.97	8.83	2
44	92	9.87	11.24	18.26	0	6
45	43	19.11	14.47	53.52	5.33	6
46	36	19.05	22.65	28.02	2.13	8
47	2	16.4	16.4	27.99	4.81	2
48	73	13.86	17.07	25.22	1.6	5
49	74	23.08	18.88	42.48	6.63	8
50	120	20.07	20.97	28.24	11	3
51	81	9.63	8.24	18.97	3.05	4
52	98	19.22	19.04	49.5	1.41	12
53	122	10.1	10.46	17.15	2.34	4

Table 2-7 Final Scores for Each Facility

Facility ID	# Truck-involved Fatigue Crashes	Crash Index	Length (Mile)	Deficiency Score	Impact Score
1	43	295.8	1603.07	32.32	381
2	5	102.2	194.35	21.03	123
3	25	184.5	351.11	31.8	255
4	13	147.6	262.51	27.76	186
5	5	27.6	346.03	4.78	54
6	15	39.4	447.36	6.31	61
7	8	100.5	342.72	17.45	152
8	6	46.6	59.66	13.67	62
9	20	174.2	487.44	27.21	205
10	3	10.7	264.69	2.01	12
11	1	1	3.55	0.68	1
12	31	237.5	142.08	53.69	266
13	4	39.9	20.01	16.24	42
14	5	35.7	234.56	6.94	42
15	13	80.7	267.05	15.1	118
16	40	246.1	451.4	39.33	344
17	5	12.6	570.66	1.88	14
18	40	304.8	56.69	90.77	360
19	11	143.9	212.43	28.83	164
20	9	36.4	116.93	8.72	37
21	8	108.5	238.02	21.01	135
22	5	48.3	750.65	6.63	54
23	7	92	180.37	19.36	143
24	24	187.2	288.55	34.22	227
25	14	188.5	87.14	49.35	190
26	12	26.4	375.79	4.46	30
27	13	210.3	447.09	33.71	226
28	17	58.8	83.84	15.57	64
29	7	88.7	220.61	17.57	111
30	7	131.7	229.48	25.78	143
31	1	18	202.02	3.66	20
32	15	106.4	133.4	24.51	108
33	13	37.3	25.07	14.19	41
34	7	14.9	727.21	2.06	25
35	6	15.9	165.88	3.43	24

36	2	46	41.33	15.06	51
37	9	82.2	150.35	18.27	104
38	4	81.9	108.79	20.06	91
39	6	14.2	163.03	3.08	15
40	8	6.7	188.19	1.39	8
41	1	8	14.72	3.57	10
42	6	81.9	94.4	20.93	93
43	2	1.9	70.87	0.53	2
44	6	90.8	71.71	25.2	92
45	6	32.7	423.44	5.33	43
46	8	31	457.46	4.93	36
47	2	1.8	19.33	0.74	2
48	5	68.8	167.37	14.81	73
49	8	57.4	152.2	12.71	74
50	3	97	169.72	20.79	120
51	4	74	105.71	18.28	81
52	12	77	280.59	14.19	98
53	4	110	481.79	17.24	122

Table 2-8 Ranked Deficiency Scores of Facilities From the Worst to the Best

Facility ID	Deficiency Score	Scaled Deficiency Score	Deficiency Rank	Impact Score	Scaled Impact Score	Impact Rank
18	90.77	1.00	1	360	0.95	2
12	53.69	0.59	2	266	0.70	4
25	49.35	0.54	3	190	0.50	9
16	39.33	0.43	4	344	0.90	3
24	34.22	0.38	5	227	0.60	6
27	33.71	0.37	6	226	0.59	7
1	32.32	0.36	7	381	1.00	1
3	31.8	0.35	8	255	0.67	5
19	28.83	0.32	9	164	0.43	11
4	27.76	0.31	10	186	0.49	10
9	27.21	0.30	11	205	0.54	8
30	25.78	0.28	12	143	0.38	13
44	25.2	0.28	13	92	0.24	25
32	24.51	0.27	14	108	0.28	21
2	21.03	0.23	15	123	0.32	16
21	21.01	0.23	16	135	0.35	15
42	20.93	0.23	16	93	0.24	24

50	20.79	0.23	18	120	0.32	18
38	20.06	0.22	19	91	0.24	26
23	19.36	0.21	20	143	0.38	13
37	18.27	0.20	21	104	0.27	22
51	18.28	0.20	21	81	0.21	27
29	17.57	0.19	23	111	0.29	20
7	17.45	0.19	24	152	0.40	12
53	17.24	0.19	25	122	0.32	17
13	16.24	0.18	26	42	0.11	37
28	15.57	0.17	27	64	0.17	30
15	15.1	0.17	28	118	0.31	19
36	15.06	0.17	28	51	0.13	35
48	14.81	0.16	30	73	0.19	29
33	14.19	0.16	31	41	0.11	39
52	14.19	0.16	31	98	0.26	23
8	13.67	0.15	33	62	0.16	31
49	12.71	0.14	34	74	0.19	28
20	8.72	0.10	35	37	0.10	40
14	6.94	0.08	36	42	0.11	37
22	6.63	0.07	37	54	0.14	33
6	6.31	0.07	38	61	0.16	32
45	5.33	0.06	39	43	0.11	36
46	4.93	0.05	40	36	0.09	41
5	4.78	0.05	41	54	0.14	33
26	4.46	0.05	42	30	0.08	42
31	3.66	0.04	43	20	0.05	45
41	3.57	0.04	44	10	0.03	49
35	3.43	0.04	45	24	0.06	44
39	3.08	0.03	46	15	0.04	46
34	2.06	0.02	47	25	0.07	43
10	2.01	0.02	48	12	0.03	48
17	1.88	0.02	49	14	0.04	47
40	1.39	0.02	50	8	0.02	50
47	0.74	0.01	51	2	0.01	51
11	0.68	0.01	52	1	0.00	53
43	0.53	0.01	53	2	0.01	51

2.5 Discussion and Results

In line with findings from earlier research, the data demonstrates that fatigue-related truck-involved crashes typically have higher crash severity rates and happen most frequently between midnight and early morning. This highlights the vital role that rest areas can play in providing safe stopping places for tired drivers and supports the well-established link between fatigue, circadian cycles, and collision risk.

As seen in Table 2-8, rest areas which have high deficiency rank also have high impact rank, indicating a strong correlation between rest area deficiencies and their overall impact on crash frequency and severity. To verify the DS further, scaled DS was regressed with scaled IS in Figure 2-6 where the results are promising with a R^2 value of 0.75. For better safety performance, the model can be adjusted by different weights, severity and correction functions, possibly based on information obtained by state agencies.

In Figure 2-7, catchment areas were categorized by the DS of the respective rest area and overlaid by crash hotspots, which were drawn by considering network distance KDE estimation. It should be noted that although the term "catchment area" was used in the entire research, it is indeed a roadway segment; however, just for visual purposes and to illustrate the value of the findings, planar-based catchment area was added to the map visually. Here, as urban crashes are filtered out, DS in rest areas that are near to urban regions have low value. Figure 2-7 enables us to verify the proposed DS score spatially. It highlights regions where high DS values coincide with dense crash hotspots, as discussed in Figure 2-3. For example, Along I-75, there are 2 rest areas with the highest DS, with Facility IDs 18 and 12, over the study area. As discussed before, the same region is known for frequent fatigue-related truck-involved crashes near the rest area. In addition, Southeast Florida region exhibited one of the highest DS values due to limited alternative facilities and a high frequency of fatigue-related crashes. On the contrary, the regions with sparse crash density, such as areas near to Rest area 35 and 40, are associated with low deficiency rank.

As rest areas serve the catchment area, this score can also be related to the catchment area itself. With this logic, it can also be used while finalizing the site selection process. Among the candidate sites, the location that is inside of the catchment area that has the highest score can be chosen, if the total mile of the particular area is also high.

The primary objective of the development of the DS is to identify and prioritize rest areas that require improvements to mitigate fatigue-related crashes, thereby enhancing overall highway safety. By using maps like Figure 2-7, the traffic authorities can pinpoint problematic areas that need immediate intervention. Rest areas with high DS values should be prioritized for targeted interventions, such as expanding parking capacity, improving amenities, or enhancing lighting and signage. The DS metric can serve as a decision-support tool in planning the location of new rest areas to address gaps in service coverage. Collaborative efforts with private truck stop operators could also provide additional parking options and alleviate pressure on public rest areas. Additionally, the methodology proposed in this study can be adapted for use in other regions to guide national-level rest area planning initiatives.

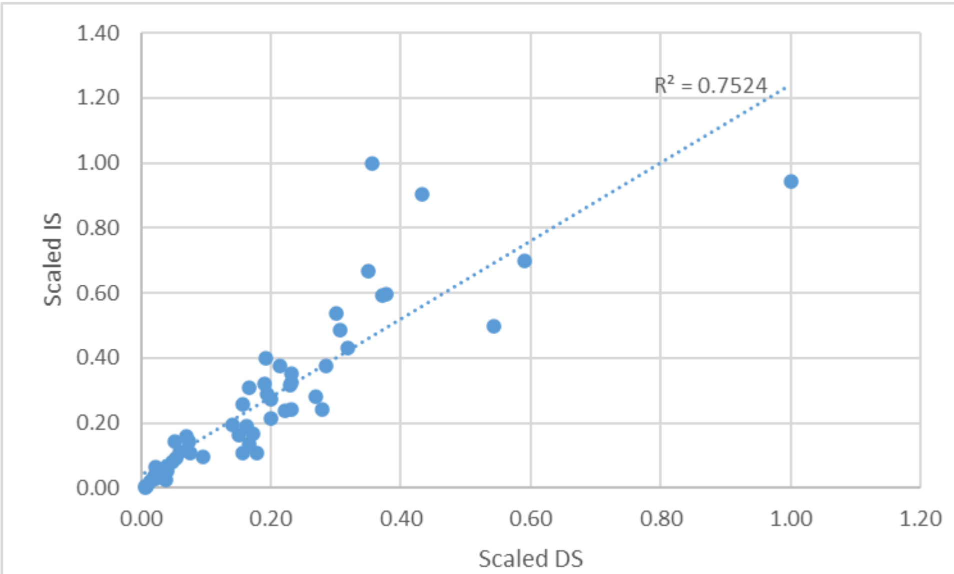

Figure 2-6 Comparison of IS and DS

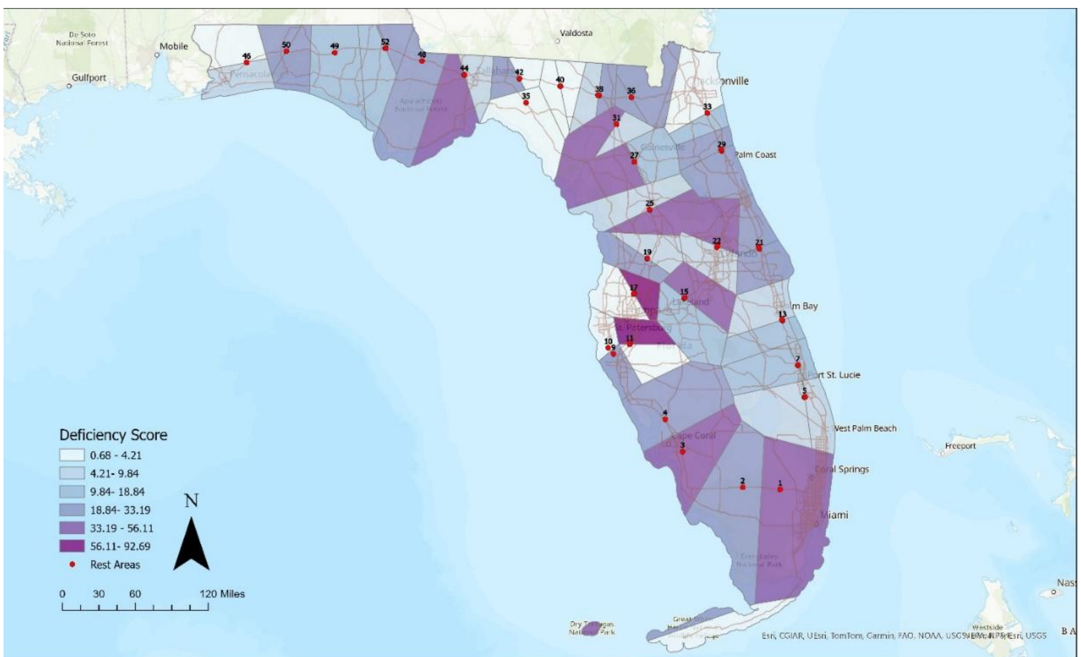

Figure 2-7 DS of Rest Areas in Florida

2.6 Conclusions

To meet the projected increase in truck traffic without compromising on traffic safety, it is crucial for decision makers to assess and improve the safety performance of parking facilities, especially rest areas. As such, in this study, a data-driven safety performance metric in rural rest areas to assess their adequacy. The developed safety performance metric, namely Deficiency Score (DS), offers a systematic approach to evaluate the safety performance of rest areas, considering factors such as proximity to crashes, and severity of crashes. This metric can be utilized for identifying high-risk rest areas and guiding targeted safety interventions, which account for crash severity, proximity, and catchment area. It has been determined that certain rest areas, particularly those with high traffic volumes and limited parking capacity, have significantly higher Deficiency Scores, highlighting the urgent need for infrastructure improvements. Conversely, rest areas located closer to crash-prone segments with lower crash severity demonstrated lower DS values, suggesting higher safety performance. By identifying deficiencies and providing actionable insights, this research provides valuable insights to improving roadway safety and optimizing the placement and functionality of rest areas. Based on the proposed systematic and scalable approach to assess the rest area safety performance, our findings emphasize the need for targeted improvements and strategic planning to address the challenges posed by rising truck traffic. The proposed DS metric offers transportation agencies a powerful tool to prioritize investments in rest area improvements and guide the planning of new facilities.

While this study provides a comprehensive framework for evaluating the safety performance of rest areas in mitigating fatigue-related crashes, several limitations should be acknowledged. First, the analysis relies on crash data coding accuracy, particularly for fatigue-related crashes. Underreporting of drowsiness and fatigue as contributing factors in crashes is a common issue (*46*), which may lead to an underestimation of the true extent of fatigue-related incidents. Second, the methodology assumes that drivers always choose the nearest rest area, which may not reflect real-world behavior influenced by factors such as facility amenities, parking availability, or driver preferences. Additionally, the exclusion of private truck stops due to data unavailability limits the scope of the analysis since these facilities also play a significant role in providing rest opportunities for truck drivers. Another limitation is the use of proximity and severity weights in the Deficiency Score calculation, which were derived based on literature and empirical testing; however, this approach could benefit from refinement through more extensive field validation or stakeholder input. The correction factor applied to account for variations in catchment area size assumes a linear relationship between roadway length and crash likelihood, which may not fully capture the complexities of crash dynamics in larger areas. For future work, incorporating real-time truck parking data and utilization rates could enhance the reliability of the findings. Additionally, integrating private truck stops into the analysis and exploring multi-modal factors, such as driver surveys or behavior modeling, could provide a more holistic view of rest area safety performance. Finally, expanding the study to other regions or incorporating advanced machine learning techniques could help generalize the findings and improve the predictive capabilities of the Deficiency Score.

Chapter 3 Evaluating Rest Area Accessibility and Fatigue-Related Truck Crashes Using a Two-Stage Analytical Framework

3.1 Introduction

Fatigue remains one of the leading contributors to crash risk in commercial motor vehicle operations, particularly among long-haul truck drivers. Fatigued driving impairs critical cognitive and motor functions, slows reaction time, and reduces situational awareness, which substantially increases the risk of collision. The severity of fatigue-related crashes is often elevated, especially in crash types such as single-vehicle, off-road, and rollover incidents, which tend to result in higher rates of injury and fatality. These patterns are amplified during nighttime hours when drivers' natural circadian rhythms reduce alertness. In parallel, the role of rest area accessibility has gained attention as a preventive strategy for fatigue-related incidents. Prior studies have demonstrated a spatial association between the availability of rest facilities and crash risk, showing that crash frequency tends to rise as the distance from rest areas increases. However, many of these studies have focused narrowly on rest area placement without considering the broader roadway context or the performance of these facilities in terms of actual crash reduction. Moreover, while logistic regression and count models have been used to assess crash risk and frequency, limited research has integrated these methods to investigate fatigue-related crashes specifically, especially in connection with rest area infrastructure.

The State of Florida presents a compelling case for such an investigation. As a major freight corridor with extensive interstate highways and a high volume of truck activity, the state also suffers from well-documented truck parking shortages. National surveys conducted by the Federal Highway Administration and commercial driver organizations such as OOIDA and ATA have consistently ranked Florida among the states with the most critical truck parking deficits (*47*). This shortage not only limits drivers' ability to take breaks but may also lead to risky behavior such as parking in unauthorized or unsafe locations or continuing to drive while fatigued.

Motivated by this, the current study develops and applies a two-stage analytical framework to evaluate the relationship between rest area accessibility and fatigue-related truck crashes. The first stage uses a case-control design with bootstrapped logistic regression to identify crash- and environment-related factors significantly associated with fatigue involvement. The second stage applies a negative binomial model to examine how crash frequency near rest areas is influenced by exposure, facility characteristics, and a Deficiency Score (DS) metric, which integrates crash severity and spatial proximity. By combining individual crash-level analysis with rest area-level performance metrics, this study aims to offer a comprehensive understanding of how rest infrastructure impacts fatigue-related safety outcomes along Florida's freight corridors.

3.2 Literature Review

Fatigue leads to impaired cognitive and motor functions, including slower reaction times, reduced situational awareness, delayed braking or steering responses and lack of avoidance maneuvers (*48–50*). Presumably because of those factors, it has been consistently associated with increased crash severity(*12–17*). Certain types of crashes, such as single-vehicle, run-off-road, and rollover crashes, are more prevalent when drivers are fatigued (*51–53*). These crash types also tend to result in more severe outcomes under fatigue. For instance, fatigue significantly elevates the injury severity of single-vehicle (*52*, *53*), run-off-road (*52*), and rollover crashes (*15*, *52*, *54*) , suggesting a compounded risk where both crash type and driver state interact to produce more dangerous consequences.

By influencing driver alertness and workload, environmental factors play a significant role in fatigue-related truck crashes. Road geometry may impact the condition of driver; steep grades and sharp curves necessitate constant braking and steering, increasing cognitive load, while long, smooth expressways produce monotony and increase drowsiness. Due to poor tire traction, slippery surfaces and wet pavement require slower speeds and more sustained attention, which lengthens travel times and increases mental strain. Bad weather, like fog or rain, makes it harder to see and makes drivers pay closer attention. Road characteristics, weather, and surface condition all work together to either reduce alertness or increase driving strain, which raises the risk of fatigue-related collisions (*51*).

In addition to environmental stressors, temporal factors such as time of day and work schedules further compound driver fatigue risk. During the late-night to early-morning hours, when circadian rhythms reduce alertness, fatigue related crash risk is increased (*19*, *50*). Besides to time of the day, driver working conditions, such as driving hours, total working hours and working schedule influence fatigue related to truck crashes. Using K-means clustering and logistic regression to analyze driver logs of 878 commercial truck drivers, Chen and Xie found that certain work schedules involving irregular and extended working hours, such as extended on-duty hours in early morning and late afternoon, are associated with increased crash risk (*55*). In addition, while focused on transit bus operators, Mitoi et al. offer valuable parallels in how extended duty hours and early start times elevate fatigue-related crash risk—patterns similarly observed in truck drivers (*56*). All these studies show importance of sufficient rest to decrease fatigue related crashes.

Building on the critical role of sufficient rest in preventing fatigue-related crashes, spatial access to rest facilities also emerges as a key factor. Several studies have demonstrated that the distance to the nearest rest area significantly influences the likelihood of fatigue-induced incidents. The significance of timely access to rest is demonstrated by (*25*) et al.'s finding that crash risk, both fatigue-related and non-fatigue-related, decreased on the downstream of rest areas but sharply increased once drivers had traveled more than 30 miles beyond them. In a similar study, McArthur et al. (*26*) demonstrated that crash frequency decreased as one got closer to rest areas, with more incidents noted as one got farther away. Bunn et al.'s analysis of crash data from Kentucky further supported this spatial pattern, showing that fatigue-related crashes were almost 2.5 times more likely to occur when rest facilities were 20–40 miles away and nearly seven times more likely to occur when they were more than 40 miles away (*29*).

Statistical modeling techniques have been used to assess potential risks of fatigue-related crashes by considering various characteristics related to roadways, environment, driver, and the crash. The authors conducted case-control study by taking crashes resulted in fatigue as a case and all other crashes as a control. After applying chi-square test to determine significant crash related factors, they used stepwise logistic regression to estimate the likelihood of fatigue involvement under specific crash conditions (*29*, *51*). In addition, Islam investigates factors influencing driver injury severity in single large-truck crashes by considering both fatigue and non-fatigue crashes between 2011 and 2019 in Florida using random parameter logit models. The paper compares injury outcomes between fatigue-related and non-fatigue-related crashes and highlights some key distinctions between fatigue and non-fatigue scenarios. For example, the presented analysis reveals that in rollover crashes, truck drivers involved in fatigue-related incidents were 2.5 times more likely to sustain severe injuries compared to those in non-fatigue-related rollovers (*54*).

A significant methodological challenge in modeling fatigue-related truck crashes is the imbalance between fatigue-involved and non-fatigue-involved crash records. As these crashes typically represent a small portion of total crashes, rare event bias is created in standard logistic regression estimates (*57*). To address this problem different strategies have been implemented, including under sampling (*58*), over sampling (*58*, *59*), bootstrapping (*60*) and variations of SMOTE (*58*, *59*, *61*, *62*) (Synthetic Minority Over-sampling Technique). While prior studies have explored class imbalance in crash classification and separately modeled crash frequencies, few have combined these approaches within the specific context of fatigue-related truck crashes and rest area accessibility. This study addresses that gap by implementing a two-stage framework: 1) applying bootstrapped logistic regression to examine the distinguishing characteristics of fatigue versus non-fatigue truck-involved crashes, and 2), employing negative binomial regression to model the frequency of fatigue-related crashes in relation to rest area accessibility and facility attributes. This integrated approach enables a more comprehensive understanding of both the individual-level risk factors and corridor-level safety performance.

3.3 Data and Study Area

The State of Florida was selected as the study region due to its extensive freight corridors and the high volume of commercial truck traffic. Moreover, Florida faces notable challenges related to truck parking shortages. In a national survey conducted by the Federal Highway Administration to assess current truck parking capacity and adequacy of rest area facilities, the state is associated with serious truck parking problems. These significant truck parking shortages have also been cited by 35% of Owner Operator Independent Drivers Association (OODIA) and 32% of American Trucking Associations (ATA) drivers. In addition, when the truck parking supply is compared with truck activity indicators like vehicle miles traveled (VMT), Florida ranks among the states with the lowest number of spaces relative to VHT mileage (*47*).

For the roadway network, Freight Analysis Framework (FAF) was utilized. Over this network all the road segments that are considered on the State Highway, US Highway, and Interstate were selected. Rest areas along the selected roadway network are shown in Figure 1, while the attributes related to the rest areas can be seen in Table 3-1. These characteristics include several important variables created for the analysis, such as the Mean Truck Flow, Length, and Deficiency Score (DS), which are explained below.

To measure each rest area's safety performance in reducing fatigue-related collisions, the Deficiency Score (DS) was created based on two primary factors: crash severity, and crash proximity. Firstly, each crash assigned to a rest area is weighted according to its severity using a KABCO-derived severity scale, where crashes resulting in more serious outcomes were assigned higher scores. Secondly, proximity, measured using truck-accessible network distance, was incorporated into the weighting process for each crash. For the crashes occurring closer to the rest area, higher weights were assigned to the crashes to reflect their stronger spatial association with the facility. For each rest area, we found a combined score by cumulatively adding up weighted crashes based on these factors. This combined score was later normalized by the total network length within the facility's catchment area, creating the DS score. The catchment area represents the segment of the highway network that each rest area is most likely to serve, ensuring that facilities with larger coverage are not unfairly penalized. Here, “Catchment Length” reflects the total roadway mileage within each rest area's catchment zone whereas “Min Fatigue Distance” indicates the smallest distance between a fatigue-related crash and its assigned rest area. Additionally, “Mean Truck Flow” is obtained by taking the mean value of the road segments that are covered by the given rest area facility by using “Total Truck Flows” for the baseline year 2022. This was made possible through utilizing the Freight Analysis Framework (FAF) network.

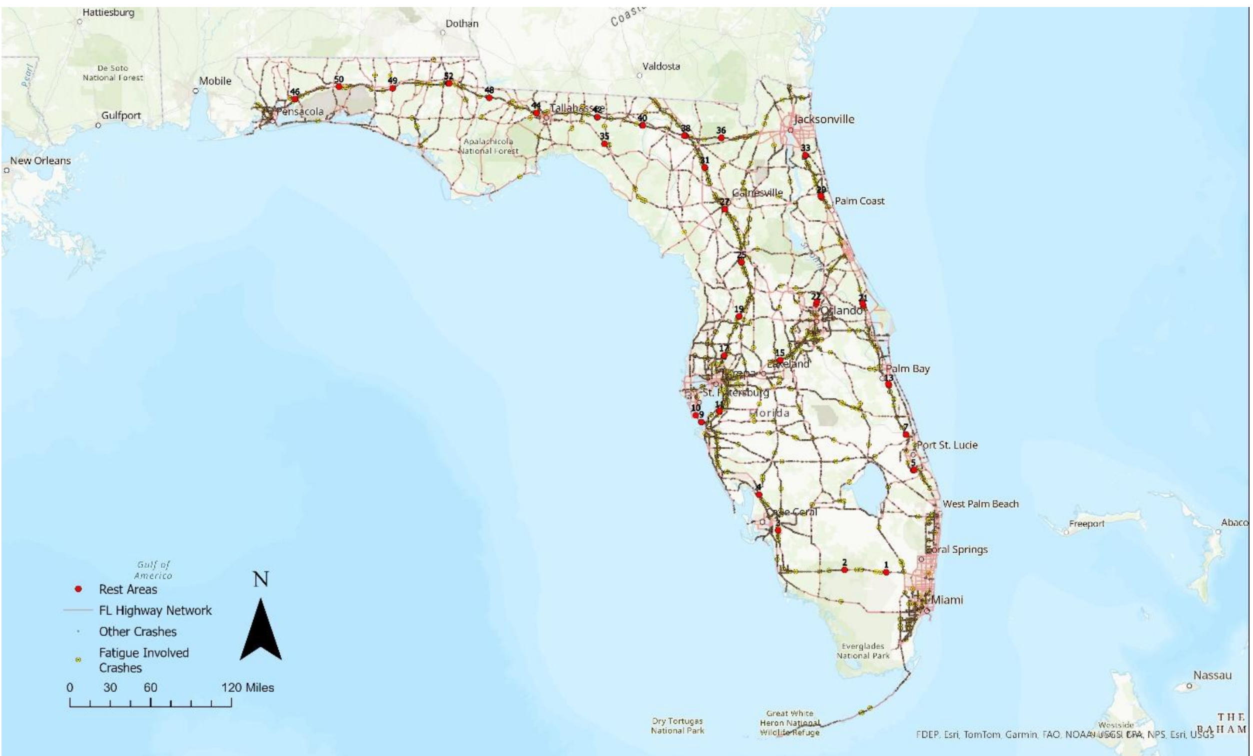

Figure 3-1 Location of Rest Areas Along Florida’s Major Freight Corridors

Crashes between 2019 and 2023 that involve medium or heavy truck were selected from Signal4Analytics (*34*) by querying body type (medium/heavy truck) and commercial vehicle involvement indicators. In the rest of the study, the term ‘truck’ will correspond to the medium or heavy trucks. Urban crashes were excluded to avoid the confounding effects of dense urban traffic patterns. Crashes were spatially filtered to occur within 40 meters of designated route network, accounting for mapping inaccuracies and the spatial extent of rest areas. Fatigue-related crashes were determined from the driver condition field (asleep or fatigued). By those selection criteria, 36,277 non-fatigue- and 554 fatigue-related truck crashes were selected.

Table 3-1 Descriptive Statistics of Rest Area Attributes and Fatigue-Related Crash Frequency by Highway

ID	Fatigue Crashes	Number of Parking Stops	Deficiency Score	Catchment Length (Mile)	Min Fatigue Distance (Mile)	Highway	Mean Truck Flow
1	43	60	32.32	1,603.07	7.87	I-75N	548.10
2	5	37	21.03	194.35	8.39	I-75N	389.15
3	25	74	31.8	351.11	0.53	I-75N	361.37
4	13	32	27.76	262.51	4.13	I-75S	406.70
5	5	82	4.78	346.03	8.21	I-95S	387.24
6	15	60	6.31	447.36	4.5	I-95N	499.02
7	8	43	17.45	342.72	14.73	I-95S	804.94
8	6	44	13.67	59.66	2.2	I-95N	1,746.96
9	20	16	27.21	487.44	5.03	I-275N	352.18
10	3	14	2.01	264.69	12.79	I-275N	1,521.32
11	1	36	0.68	3.55	2.51	I-75N	582.18
12	31	43	53.69	142.08	3.06	I-75S	307.25
13	4	60	16.24	20.01	4.3	I-95N	1,590.63
14	5	67	6.94	234.56	14.13	I-95S	1,170.73
15	13	23	15.1	267.05	2.12	I-4E	319.29
16	40	23	39.33	451.4	4.41	I-4W	364.74
17	5	51	1.88	570.66	3.83	I-75N	479.29
18	40	51	90.77	56.69	3.88	I-75S	656.86
19	11	43	28.83	212.43	2.81	I-75N	556.71
20	9	33	8.72	116.93	5.16	I-75S	856.72
21	8	33	21.01	238.02	8.33	I-95N	623.20
22	5	16	6.63	750.65	7.06	I-4W	299.30
23	7	35	19.36	180.37	1.85	I-95S	1,191.36
24	24	17	34.22	288.55	8.81	I-4E	631.79
25	14	43	49.35	87.14	0	I-75S	3,328.30
26	12	43	4.46	375.79	0.57	I-75S	1,130.38
27	13	7	33.71	447.09	1.52	I-75N	1,215.77
28	17	13	15.57	83.84	3.67	I-75S	2,345.19
29	7	15	17.57	220.61	7.83	I-95N	1,343.62
30	7	16	25.78	229.48	2.35	I-95S	897.49
31	1	50	3.66	202.02	15.43	I-75N	1,530.37
32	15	50	24.51	133.4	0.03	I-75S	1,432.61
33	13	45	14.19	25.07	0.85	I-95N	1,601.77
34	7	45	2.06	727.21	24.73	I-95S	653.83
35	6	10	3.43	165.88	4.38	US19/US27	1,890.74
36	2	22	15.06	41.33	0	I-10E	977.07
37	9	25	18.27	150.35	18.77	I-10W	875.72
38	4	15	20.06	108.79	10.34	I-10W	1,386.83

39	6	14	3.08	163.03	0.28	I-10E	1,237.49
40	8	26	1.39	188.19	9.5	I-10E	933.81
41	1	23	3.57	14.72	27.41	I-10W	2,005.89
42	6	10	20.93	94.4	6.02	I-10E	2,768.90
43	2	11	0.53	70.87	8.83	I-10W	2,025.11
44	6	19	25.2	71.71	0	I-10E	2,660.05
45	6	19	5.33	423.44	5.33	I-10W	1,220.09
46	8	74	4.93	457.46	2.13	I-10E	877.97
47	2	68	0.74	19.33	4.81	I-10W	3,015.55
48	5	43	14.81	167.37	1.6	I-10W	2,377.65
49	8	17	12.71	152.2	6.63	I-10W	1,833.45
50	3	53	20.79	169.72	11	I-10E	1,024.87
51	4	53	18.28	105.71	3.05	I-10W	1,213.23
52	12	12	14.19	280.59	1.41	I-10E	1,394.28
53	4	24	17.24	481.79	2.34	I-10W	867.87

3.4 Methodology

In this part of the study, we utilized a case-control design to investigate the variables that are associated with fatigue-related crashes. The outcome of interest was the presence or the absence of fatigue at the truck-related crash. Cases were identified as truck crashes in which the driver was under the influence of fatigue or sleepiness (Fatigue=1) in the moment of the crash, while controls were defined as crashes resulted by any other human-related factor other than fatigue or sleepiness (Fatigue=0). The following variables were examined in the analysis:

- Distance to the closest rest area (mile) (Less than 10, 10-20, 20-30, 30-40, 40-50, More than 50)
- Type of Shoulder (Paved, Unpaved)
- Road Type (State Road, US Route, Interstate, Others)
- Time Zone (Fatigue Zone: 2 am - 7.59 am, Normal Zone: Other hours)
- Crash Type (Angle, Head on, Left turn, Right turn, Rear end, Off Road, Rollover, Sideswipe, The rest)
- Crash Severity (No injury, Injury, Serious Injury, Fatality)
- Weather Condition (Clear, Cloudy, Rain, Fog / Smog / Smoke, The rest)
- Road Surface Condition (Dry, Wet, The rest)
- Aggressive Driving (Y/N)
- Alcohol Related (Y/N)
- Drug Related (Y/ N)
- Lane Departure Related (Y/ N)
- Speeding Related (Y/N)
- Intersection Related (Y/N)

The main goal of the study was to test the relationship between fatigue-related crashes and distance to the closest rest area, creating the exposure variable in the analysis as the distance from the truck driver involved in the crash to the closest rest area facility. Using ArcGIS Service

Area Layer, the distance from the truck to the nearest rest area was categorized in 6 groups: less than 10 miles, 10-20 miles, 20-30 miles, 30-40 miles, 40-50 miles, and more than 50 miles. In addition, roadway type was assigned to each crash by taking their spatial join with the roadway segment they are closest to.

Logistic regression is used to predict the likelihood that an event will occur given the information at hand. When the dependent variable is binary, logit regression is an appropriate regression model (*63*). The multiple logistic regression model in python statsmodel package was implemented to assess the relationship between the occurrence of fatigue-related crashes and selected independent variables. The odds ratio (OR) was used as the primary effect measure. The dependent variable was assigned a value of 1 if the crash was fatigue-related, and 0 if the crash occurred without fatigue involvement.

In order to estimate the coefficients of the predictor variables of the logit model, we maximized the following log-likelihood function:

$$\ln L(\delta\beta) = \sum_{i=1}^{n} \{Y_i * \ln [\psi(X_i\beta)] + (1 - Y_i) * \ln[1 - \psi(X_i\beta)]\}$$

where Y_i is the binary outcome variable (0 or 1) representing the occurrence of a fatigue-related truck crash, X_i is the row vector containing the predictor values for observation i, β is the vector of coefficients for the predictors, n is the total number of observations, and $\psi(Xi\beta)$ denotes the predicted probability of the outcome. In this study, the outcome variable Y_i is equal to 1 if the crash is fatigue-related, or 0 if it is caused by another factor.

Logistic regression was chosen over machine learning classifiers like Random Forest or XGBoost for a couple of reasons. The first reason is the easier interpretation of logistic regression as a causal model, allowing policymakers to get practical insights easier. Secondly, logistic regression is less prone to overfitting while complex machine learning classifiers can capture the noise easier. Finally, considering the hypothesis driven nature of the study, logistic regression is better fit than exploratory machine learning classifier models such as random forest or XGBOOST.

Three logistic regression models were developed. In the first model, the association between fatigue involvement and distance category to the rest area investigated. In the second model, the effect of roadway on fatigue involvement was assessed. The final model evaluated the relationship between crash severity levels and the probability of fatigue to be the outcome.

To preserve the interpretability and statistical integrity of categorical variables in the model, we applied **grouped forward stepwise selection**, where all dummy variables corresponding to a single categorical factor (e.g., crash type) were added to the logistic regression model as a unit. This approach prevents the misrepresentation of partially included categorical variables, which can lead to biased coefficient estimates and misinterpretation, as mentioned in regression modelling literature (*64–66*).

The Chi square test was conducted to test the association between independent factors and crash outcome. Considering class imbalance, bivariate analysis was applied 1,000 times for the bootstrap samples generated by the strategy above. Variables that have 80% of the time a level of significance less than 0.1 were included in the logistic regression model. In logistic regression models, the dataset was bootstrapped and for each bootstrap sample stepwise logistic regression was carried out. For each resample, we tracked the selected variables and how often they are selected. When a variable is selected, their coefficients were recorded, and they were used to report median, and confidence interval ORs. Furthermore, how often the selected variable was significant ($p < 0.05$) was also recorded. Similar to the bivariate analysis, dataset was resampled 1,000 times.

In the second part of the study, a negative binomial regression model was developed using the variables presented in Table 3-1 to examine how rest area accessibility and infrastructure characteristics relate to the frequency of fatigue-related truck-involved crashes.

3.5 Results and Discussion

Table 3-2 presents the rates of each variable for the case and controls. Based on the proportion, fatigue related crashes were seen more frequently on Interstates, at night hours (2:00 am-7:59 am). Related to the crash type off road, rear end and rollover crashes were more common than the cases, with higher rates of injury and serious injury.

Table 3-2 Distribution of Spatial, Temporal, Roadway, Crash, and Driver Behavior Characteristics by Fatigue Involvement

Characteristic	Cases (n=554) (Fatigue=1)	Controls (n=36,277) (Fatigue=0)
Crash Location and Time Characteristics		
Distance to the closest rest area (mile)		
Less than 10	168 (30.3%)	8,023 (22.1%)
10-20	163 (29.4%)	11,297 (31.1%)
20 - 30	109 (19.7%)	7,909 (21.8%)
30 - 40	51 (9.2%)	4,501 (12.4%)
40 - 50	45 (8.1%)	3,326 (9.2%)
More than 50	18 (3.2%)	1,221 (3.4%)
Time Zone		
2:00 am - 7:59 am	328 (59.2%)	10,178 (28.1%)
Other Times	226 (40.8%)	26,099 (71.9%)
Roadway and Environmental Conditions		
Type of Shoulder		
Paved	475 (85.7%)	29,596 (81.6%)
Unpaved	79 (14.3%)	6,681 (18.4%)
Road Type		
Interstates	284 (51.3%)	11,142 (30.7%)
State Highway	134 (24.2%)	11,456 (31.6%)
US Highway	101 (18.2%)	9,439 (26.0%)

Others	35 (6.3%)	4,240 (11.7%)
Weather Condition		
Clear	416 (75.1%)	27,390 (75.5%)
Cloudy	104 (18.8%)	5,678 (15.7%)
Rain	18 (3.2%)	2,817 (7.8%)
Fog, Smog, Smoke	15 (2.7%)	332 (0.9%)
The Rest	1 (0.2%)	60 (0.2%)
Road Surface Condition		
Dry	503 (90.8%)	31,770 (87.6%)
Wet	50 (9.0%)	4,424 (12.2%)
The Rest	1 (0.2%)	83 (0.2%)
Crash Characteristics		
Crash Type		
Angle	5 (0.9%)	1,056 (2.9%)
Head On	12 (2.2%)	357 (1.0%)
Left Turn	7 (1.3%)	2542 (7%)
Off Road	62 (11.2%)	2,075 (5.7%)
Rear End	258 (46.6%)	10,976 (30.3%)
Rollover	26 (4.7%)	784 (2.2%)
Sideswipe	144 (26.0%)	10,875 (30.0%)
The Rest	40 (7.2%)	7,612 (21.0%)
Crash Severity		
No Injury	345 (62.3%)	27,133 (74.8%)
Injury	163 (29.4%)	7,209 (19.9%)
Serious Injury	35 (6.3%)	1,308 (3.6%)
Fatality	11 (2.0%)	627 (1.7%)
Lane Departure Related		
N	240 (43.3%)	19,526 (53.8%)
Y	314 (56.7%)	16,751 (46.2%)
Intersection Related		
N	492 (88.8%)	28,735 (79.2%)
Y	62 (11.2%)	7,542 (20.8%)
Driver Behavior Factors		
Aggressive Driving		
N	548 (98.9%)	35,356 (97.5%)
Y	6 (1.1%)	921 (2.5%)
Alcohol Related		
N	551 (99.5%)	35,819 (98.7%)
Y	3 (0.5%)	458 (1.3%)
Drug Related		

N	548 (98.9%)	35,968 (99.1%)
Y	6 (1.1%)	309 (0.9%)
Speeding Related		
N	549 (99.1%)	35,687 (98.4%)
Y	5 (0.9%)	590 (1.6%)

In the final dataset, there were 544 cases where the crash happened because of driver fatigue and in 36,277 of the crashes another factor was the reason. To get the full picture related to the significance, the results of the bootstrapped samples should be assessed. Table 3-3 highlights the proportion of times where there is a significant difference between the cases and controls in 1,000 iterations. For roadway type, time zone, crash type, crash severity, weather condition and on lane departure-related and intersection-related crashes, most of the time (over 98%), significant statistic differences were observed between cases and controls. For other variables, including, type of shoulder, road surface condition, aggressive driving, alcohol, drug and speed related indicators, the proportion significance was not enough to consider those variables in the next step. The distance to the closest rest area variable was almost 80% of the time significant. Due to the interest between the rest areas and fatigue-related crashes, this variable was also added to the logistic regression analysis.

Table 3-3 Bootstrap Analysis of Bivariate Associations: Proportion of Significant Differences Between Fatigue and Non-Fatigue Crashes

Variable	% Proportion (p<0.1)
Distance to the closest rest area (mile)	79.1
Time Zone	100
Type of Shoulder	57.1
Road Type	100
Weather Condition	98.9
Road Surface Condition	31.7
Crash Type	100
Crash Severity	100
Lane Departure Related	99
Intersection Related	100
Aggressive Driving	42.6
Alcohol Related	17.6
Drug Related	0.8
Speeding Related	12.2

The result of the first regression model, where the distance to the rest area was considered as an exposure variable, is displayed in Table 3-4. Contrary to expectations, the results suggest that as the distance from the driver to the rest area increased, less fatigue-related crashes happened. This phenomenon could happen due to various reasons. The first reason might be the problems related to the temporal utilization of rest areas and associated capacity problems of rest areas in Florida. Fatigue-related crashes are expected to happen at night hours (Median OR = 3.34). In the literature, the same frame is known for the time when it is harder to find parking space. On top of that utilization pattern, there are already parking shortages in Florida, both verified by driver surveys and parking indicators like total parking space per 100 K daily truck VMT(*47*), and it will probably get worse during night. The fatigued drivers are challenged by finding a parking spot at the worst time for themselves. Secondly, there are complex roadway segments near some rest areas, such as additional diverging and merging lanes, leading to the dangerous interaction between high-speed traffic and slower exiting/entering vehicles. Those areas require slow decision time and high lane control. However, for a truck driver, it gets harder to manage all those interactions, especially when they are under the influence of fatigue.

Considering those problems related to rest area utilization and increasing fatigue at night hours, various strategies can be applied. One of the strategies might be to expand truck parking capacity by dynamic parking management systems so that drivers can reserve their spot in advance and plan their trip accordingly (*67*). Based on the demand partnership between private stops, weight station and public rest areas can be developed (*68*). In addition, using reservations, policymakers can keep track of the demand and for those segments with consistently high demands the drivers who could not reserve their spots can be channelized into safe parking areas, including industrial parks, and intermodal terminals, especially for nighttime hours. Another strategy can focus on balancing hourly demand by offering incentives like discounts on private truck route services for off demand hours or promoting flexible delivery windows (*69*), to flatten the peak that occurs at night hours (*70*).

Table 3-4 Bootstrapped Logistic Regression Model 1: Effect of Distance to Rest Area and Crash Characteristics on Fatigue Crash Likelihood

Variable	Selection %	Median OR	OR 2.5%	OR 97.5%	Significant ($p<0.05$) %
Distance to the closest rest area (mile) (Base: Less than 10)					
10 - 20	100.00	0.72	0.55	0.90	43.20
20 - 30	100.00	0.69	0.51	0.91	45.40
30 - 40	100.00	0.59	0.42	0.84	60.10
40 - 50	100.00	0.69	0.49	1.02	21.60
More than 50	100.00	0.73	0.44	1.44	4.80
Crash Type (Base: Others)					
Angle	100.00	1.57	0.82	3.35	2.80
Head On	100.00	6.30	2.90	21.13	98.30
Off Road	100.00	5.50	3.54	9.08	100.00
Rear End	100.00	6.27	4.71	8.38	100.00
Rollover	100.00	5.42	3.13	11.63	100.00
Sideswipe	100.00	2.25	1.68	3.04	98.30
Left & Right Turn	100.00	0.81	0.50	1.31	0.10
Time Zone (Base: Other Times)					
2:00 am - 8:59 am	100.00	3.34	2.70	4.28	100.00
Weather Condition (Base: Clear)					
Cloudy	99.30	1.18	0.92	1.55	6.80

Fog, Smog, Smoke	99.30	2.11	0.88	12.12	15.10
Rain	99.30	0.34	0.24	0.49	97.80
Lane Departure Related (Base: N)					
Y	96.30	1.87	1.40	2.55	90.00
Intersection Related (Base: N)					
Y	20.90	0.68	0.54	0.73	7.60

Table 3-5 presents the results of the second logistic regression model, which examines the relationship between roadway type and the likelihood of fatigue-related truck crashes. The findings indicate that, compared to U.S. Highways, both State Highways and Interstates are associated with a higher probability of fatigue involvement. This pattern is consistent with the results of the first model and aligns with expectations, as most rest areas in Florida are located along Interstates, which also serve as primary freight corridors with higher volumes of commercial truck traffic. However, despite the strategic placement of rest areas along these routes, the presence of such facilities did not significantly reduce the odds of fatigue-related crashes in the first model. This counter-intuitive finding may point to deeper systemic issues, such as rest area capacity limitations, mismatches between facility locations and driver demand, or insufficient availability of overnight truck parking. Previous research showed that drivers often struggle to find safe and legal parking, particularly during nighttime hours when fatigue risk peaks. As a result, drivers may be forced to continue driving while fatigued or park in unauthorized locations, reducing the intended safety benefits of nearby rest areas. Additionally, the assumption that proximity to a rest area equates to its effective use may not hold in practice. Factors such as real-time parking availability, driver preferences, or awareness of facility locations can influence actual usage. Therefore, even though Interstates are more likely to have rest areas, these facilities may not be functioning at their full potential in preventing fatigue-related crashes. This finding underscores the need for more nuanced measures of rest area effectiveness, such as utilization data or service quality indicators, rather than relying solely on geographic proximity.

Table 3-5 Bootstrapped Logistic Regression Model 2: Effect of Road Type and Crash Characteristics on Fatigue Crash Likelihood

Variable	Selection %	Median OR	OR 2.5%	OR 97.5%	Significant (p<0.05) %
Road Type (Base: US Highway)					
State Highway	100	1.056	0.808	1.399	0.9
Interstates	100	2.015	1.559	2.701	99.7
Others	100	0.802	0.579	1.148	3
Time Zone (Base: Other Times)					
2:00 am - 8:59 am	100	3.355	2.665	4.275	100
Crash Type (Base: Others)					
Angle	100	1.723	0.945	3.963	6.3
Head On	100	7.292	3.053	23.864	99.1
Off Road	100	5.304	3.447	8.653	100
Rear End	100	5.751	4.206	7.689	100

Rollover	100	5.691	3.139	12.436	100
Sideswipe	100	2.078	1.517	2.894	93.4
Left & Right Turn	100	0.907	0.562	1.494	0
Weather Condition (Base: Clear)					
Cloudy	98.8	1.164	0.904	1.479	4.2
Fog, Smog, Smoke	98.8	1.972	0.813	11.452	10.2
Rain	98.8	0.319	0.222	0.467	98
Lane Departure Related (Base: N)					
Y	93.9	1.698	1.344	2.35	81
Intersection Related (Base: N)					
Y	8	1.482	0.721	1.751	1.6

The results of the third logistic regression model, which considers crash severity as the exposure variable, are presented in Table 3-6. As anticipated, fatigue-related crashes were associated with more severe outcomes compared to crashes attributed to other contributing factors. Specifically, the odds of a crash resulting in an injury or serious injury were notably higher when fatigue was involved, as indicated by the elevated median odds ratios and statistically significant results. These findings are consistent with prior studies that have demonstrated the heightened risk of injury severity when drivers experience diminished alertness or delayed reaction times due to fatigue. Interestingly, the pattern was less pronounced in the case of fatal crashes. Although the odds ratio was greater than 1, suggesting a potential association between fatigue and fatality, the low statistical significance indicates limited reliability of this result. This may be due to the relatively small number of fatal cases in the dataset, which limits the power of the model to detect significant effects. Additionally, fatalities can result from a wide range of complex crash dynamics, some of which may not be directly attributable to fatigue alone. The overall findings reinforce the notion that fatigue not only increases crash risk but also contributes to more serious crash outcomes. This underscores the critical need for proactive fatigue management strategies, especially in high-speed, long-haul freight environments where injury severity tends to be elevated. Future studies could benefit from larger samples of fatal crashes or linkage with hospital and emergency response data to further explore the connection between fatigue and fatal injury outcomes.

Table 3-6 Bootstrapped Logistic Regression Model 3: Effect of Crash Severity and Crash Characteristics on Fatigue Crash Likelihood

Variable	Selection %	Median OR	OR 2.5%	OR 97.5%	Significant (p< 0.05) %
Crash Severity (Base: No Injury)					
Injury	100.00	1.51	1.17	1.91	76.80
Serious Injury	100.00	1.94	1.17	3.75	49.20
Fatality	100.00	1.22	0.60	3.39	1.40
Time Zone (Base: Other Times)					
2:00 am - 8:59 am	100.00	3.38	2.65	4.37	100.00
Crash Type (Base: Others)					
Angle	100.00	1.40	0.75	3.03	1.20

Head On	100.00	4.76	2.13	18.58	87.40
Off Road	100.00	5.20	3.48	8.51	100.00
Rear End	100.00	6.04	4.45	7.94	100.00
Rollover	100.00	4.42	2.48	9.53	99.10
Sideswipe	100.00	2.39	1.70	3.28	98.80
Left & Right Turn	100.00	0.74	0.45	1.24	0.50
Weather Condition (Base: Clear)					
Cloudy	99.00	1.17	0.92	1.52	5.10
Fog, Smog, Smoke	99.00	2.24	0.89	12.41	19.00
Rain	98.60	0.35	0.25	0.50	96.90
Lane Departure Related (Base: N)					
Y	95.20	1.83	1.39	2.48	88.40
Intersection Related (Base: N)					
Y	25.00	0.67	0.54	0.73	9.60

Fatigue-related crashes show distinct patterns across environmental and crash-type variables, particularly during nighttime hours. Over nighttime (2:00 am–8:59 am), they are expected to happen more frequently, as suggested by the high median odds ratios (ORs) and significance rates. Particular crash types (e.g., head-on, off-road, rear-end, rollover, and sideswipe) are highly associated with fatigue-related crashes (with high significance rates and elevated ORs). To minimize the crash severity, shoulder rumble strips and roadside barriers could be installed, with a particular focus on segments prone to truck rollover crashes (*71*). Compared to clear weather conditions, rainy weather is observed to decrease the likelihood of fatigue-related crashes (with high significance). Considering its low selection rates, there appears to be no practical association between fatigue- and intersection-related crashes. On the other hand, crashes involving lane departure are found to increase the likelihood of a crash being fatigue related. To further quantify these associations and assess the influence of multiple variables simultaneously, negative binomial regression model was employed. The results of this analysis are discussed below.

The regression results in Table 3-7 offer a number of notable insights into the variables affecting the frequency of fatigue-related truck crashes close to rest areas. The Deficiency Score is the only statistically significant predictor among the variables included based on a 95% confidence level, suggesting that a higher number of fatigue-related crashes is linked to higher deficiency levels, which reflect a combination of severe and proximate crashes. This demonstrates the Deficiency Score's value as a useful indicator for assessing rest area safety performance. However, categorical highway indicators like I-75 and I-95 do not show significant differences from the reference group, indicating that crash frequency is not highly correlated with particular highway segments after controlling for other factors. Similarly, variables such as “Parking Stops”, “log-transformed Truck Flow”, “Catchment Length”, and “Minimum Distance” to the crash site do not show statistical significance, though” Length” presents a marginal trend. One likely reason is that these features, while important, may not directly impact fatigue-related crashes on their own. For example, “Parking Stops” indicate the facility capacity but not the availability of parking when drivers need it most. Similarly, “Truck Flow” and “Length” both reflect exposure but not the immediate conditions that lead to fatigue. Additionally, much of the variation related to corridor differences may already be captured by the Deficiency Score, which integrates crash severity and spatial distribution. These results suggest that while structural and exposure factors matter, they may not fully explain fatigue-related crash patterns without also considering crash history and driver behavior.

Table 3-7 Negative Binomial Regression Results: Predicting Fatigue-Related Crash Frequency Near Rest Areas (@95% confidence level)

	Coef	std err	z	P>|z|	[0.025	0.975]
Intercept	2.2158	2.376	0.933	0.351	-2.441	6.872
Highway (I-275)	0.161	0.848	0.19	0.849	-1.501	1.823
Highway (I-4)	0.4904	0.715	0.686	0.493	-0.912	1.892
Highway (I-4)	0.2688	0.443	0.607	0.544	-0.6	1.137
Highway (I-95)	0.3179	0.435	0.73	0.465	-0.535	1.171
Highway (US19/US27)	0.2839	1.13	0.251	0.802	-1.931	2.499
Number of Parking Stops	-0.0033	0.009	-0.363	0.716	-0.021	0.015
Deficiency Score	0.0263	0.01	2.574	0.01	0.006	0.046
Log of Mean Daily Truck Flow	-0.1051	0.305	-0.344	0.731	-0.703	0.493
Catchment Length (Miles)	0.001	0.001	1.582	0.114	0	0.002
Min Fatigue Crash Distance (Miles)	-0.0323	0.028	-1.152	0.249	-0.087	0.023

In order to evaluate the model's performance across highway corridors, actual and predicted crash counts for each group were compared. The model exhibits good matches with observed frequencies, as shown in Figure 3-2, especially for major corridors like I-75, I-95, and I-10. The model appears to adequately capture the overall distribution of fatigue-related crashes across corridors, as the predictions closely match the actual values with only slight deviations. This supports the model’s utility for corridor-level assessment and indicates its reliability in identifying high-risk segments for targeted safety improvements.

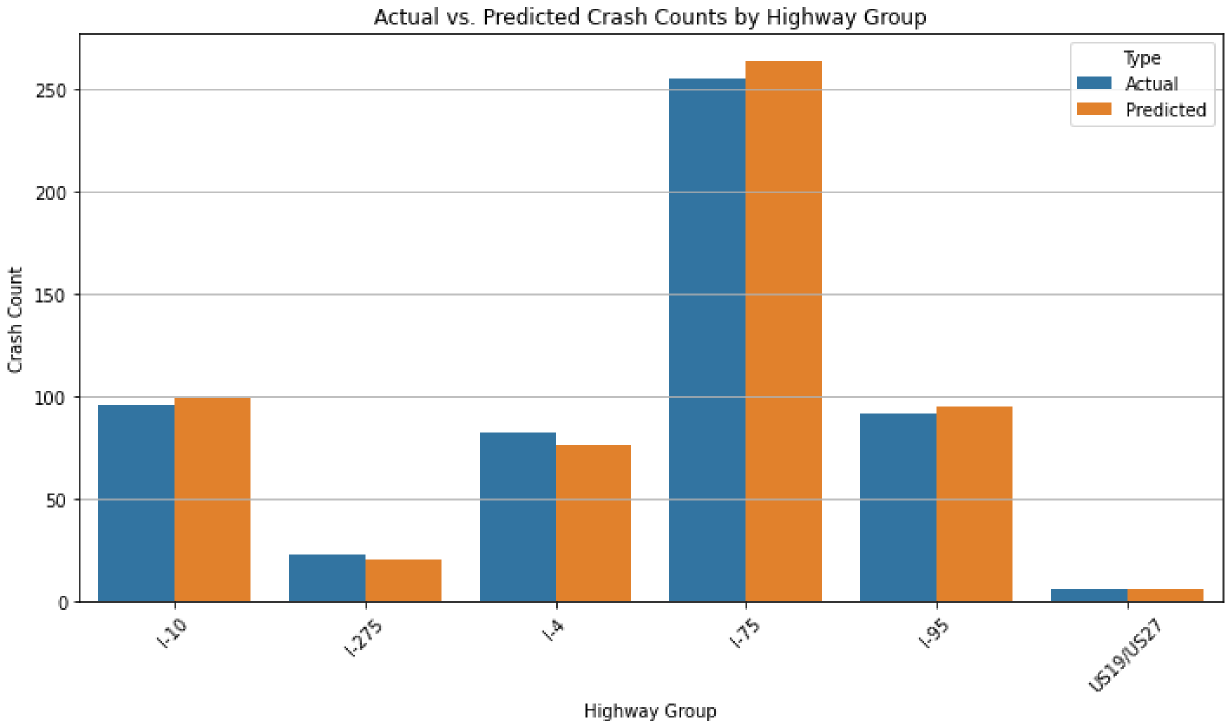

Figure 3-2 Actual vs. Predicted Crash Counts by Highway Group

3.6 Conclusions

This study evaluated the connection between truck crashes caused by fatigue and rest area accessibility along Florida's freight corridors using a two-stage analytical framework. In order to determine crash and environmental factors that were significantly linked to fatigue involvement, the first section of the analysis used a case-control approach with bootstrapped logistic regression. In order to examine crash frequencies at the rest area level, the second section used a negative binomial regression model that included variables like “Mean Truck Flow”, “Catchment Length”, and “Deficiency Score”.

The case-control analysis was successful in identifying crash patterns that were specific to fatigue. It showed that crashes involving fatigue were much more likely to happen at night, on interstates, and in rollovers, off-road, and rear-end configurations. Crucially, one of the main contributing factors was lane departure. However, considering the small percentage of crashes involving fatigue compared to the total dataset, the logistic regression analysis also encountered the typical problem of class imbalance. In order to address this, bootstrapping was used, which preserved the minority class's entire structure while enhancing model stability. However, because fatigue involvement is frequently not reported in crash reports, the method is still susceptible to underreporting, which could skew the results.

In the second part, the negative binomial model provided insight into how rest area infrastructure and spatial exposure contribute to crash frequency. The only statistically significant predictor was the Deficiency Score at the 95% confidence level, a composite measure that combines crash severity, proximity, and spatial distribution. This demonstrates its worth as a performance metric for the safety of rest areas. Furthermore, the DS calculation's assumptions—such as that drivers always use the closest rest area—might not accurately represent how parking availability, amenities, and driver preferences affect actual behavior.

Taken together, the two methods offer complementary perspectives: the case-control design identifies risk factors at the individual crash level, while the count-based model evaluates rest area performance and exposure. Both approaches demonstrate strong potential but also face limitations related to data completeness (e.g., underreporting of fatigue), behavioral assumptions, and corridor-specific influences. Future studies could strengthen this framework by integrating behavioral data, differentiating between rest area types, and incorporating real-time parking utilization metrics. Enhancing the model with such inputs would not only improve its predictive power but also provide transportation agencies with more actionable insights for fatigue mitigation and rest area planning.

The findings of this study carry meaningful policy implications for transportation agencies such as the Florida Department of Transportation (FDOT). The proposed Deficiency Score offers a practical and data-driven approach to evaluating rest area performance, capturing both the severity and spatial proximity of fatigue-related crashes. By integrating this metric into rest area planning and investment strategies, agencies can more effectively identify high-risk corridors where targeted interventions, such as expanding parking capacity, improving amenities, or deploying real-time availability systems, may have the greatest impact on fatigue mitigation. The analysis highlights that fatigue-related crashes are disproportionately concentrated during late-night to early-morning hours, particularly between 2:00 a.m. and 8:59 a.m., when driver alertness is naturally reduced. These crashes are also more likely to involve hazardous configurations such as rear-end, off-road, and rollover incidents, indicating a clear link between fatigue and diminished vehicle control or delayed response times. Moreover, among all the examined factors, the Deficiency Score proved to be the most reliable predictor of crash frequency near rest areas, underscoring its utility as a rest area safety indicator and a prioritization tool for future safety improvements. Despite these insights, the study assumes that drivers consistently use the nearest rest area when fatigued, which may not accurately reflect real-world behavior. Decisions about where to stop can be influenced by a variety of factors, including parking availability, facility amenities, driver familiarity, and route planning preferences. Acknowledging this behavioral complexity, future research should aim to incorporate empirical driver behavior data—such as GPS tracking, survey responses, or real-time parking usage—to better capture actual rest area utilization patterns. Doing so would further enhance the robustness of the Deficiency Score and improve its application for transportation planning and fatigue-related crash prevention.

Chapter 4 Conclusions

This project addressed a critical gap in transportation safety by developing a novel and data-driven framework for assessing the performance of rural rest areas in reducing fatigue-related crashes, particularly along Florida's vital freight corridors. Unlike traditional studies that rely on aggregate-level analyses, this research introduced a methodology that links each fatigue-related crash individually to its closest rest area using spatial proximity, crash characteristics, and facility attributes. This individualized approach enabled a more precise understanding of how rest area availability and design affect fatigue-related crash risk.

Our analysis revealed key fatigue crash patterns, notably their increased frequency during late-night and early-morning hours and a higher likelihood of involving hazardous crash types such as rear-end and off-road collisions. The Deficiency Score emerged as a statistically significant predictor of crash frequency near rest areas, demonstrating its value as a rest area safety performance metric. High-DS rest areas were identified as high-risk locations, offering actionable guidance for agencies seeking to prioritize rest area improvements.

The results demonstrate that this integrated methodology can provide transportation agencies with critical insights for enhancing highway safety. Decision-makers can use the Deficiency Score to identify underperforming rest areas and inform investments in infrastructure upgrades, including parking expansions, amenity improvements, and real-time parking information systems. Additionally, freight stakeholders and roadway planners can leverage these findings to better understand how rest area inadequacy influences crash risks, helping to ensure safer and more efficient freight movement through rural corridors.

Despite the promising results, there are several limitations that need to be mentioned. One challenge is the assumption that drivers use the nearest rest area, which may not always reflect real-world behavior influenced by parking availability, amenities, and personal preferences. Additionally, underreporting of fatigue in crash data remains a persistent issue that may bias analysis results. The exclusion of private truck stops from the study limits the comprehensiveness of the assessment, as these facilities also play a vital role in offering rest opportunities to drivers.

To address these limitations, future research should incorporate behavioral datasets, origin and destination of drivers, driver surveys, and real-time parking utilization rates, to better capture rest area usage patterns. Its generalizability and usefulness would be further increased by extending the analysis to private truck stops and implementing the methodology in other areas. Additionally, improving the Deficiency Score computation through stakeholder input and field validation may increase its predictive accuracy and applicability to various road conditions.

This study highlights the importance of statistical and spatial analysis in transportation safety planning, showing how they can enhance rest area performance evaluation and lower crashes caused by fatigue. By advancing these methodologies, stakeholders can develop more effective strategies for mitigating truck driver fatigue, improving rural highway safety, and fostering resilient freight corridors that protect both drivers and local communities.

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