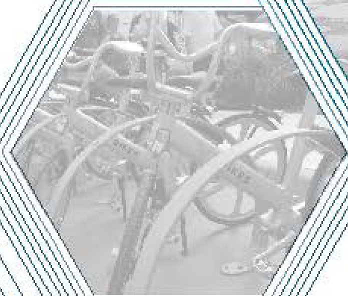
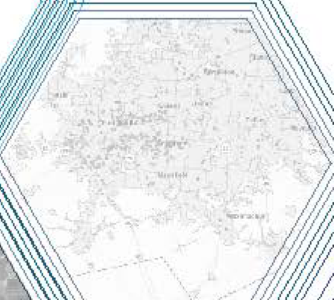



Development of Automated Roadway Lighting Diagnosis Tools for Nighttime Traffic Safety Improvement, Phase II

Zhenyu Wang, Ph.D.
Pei-Sung Lin, Ph.D.
Srinivas Katkoori, Ph.D.
Mingchen Li
Rama Kolla
Runan Yang



FINAL REPORT

Center for Transportation Equity, Decisions & Dollars

Development of Automated Roadway Lighting Diagnosis Tools for Nighttime Traffic Safety Improvement, Phase II

FINAL REPORT

By:

Zhenyu Wang, Ph.D.
Pei-Sung Lin, Ph.D.
Srinivas Katkoori, Ph.D.
Mingchen Li
Rama Kolla
Runan Yang

UNIVERSITY OF SOUTH FLORIDA

Sponsorship:

CTEDD

For:

Center for Transportation, Equity, Decisions and Dollars (CTEDD)
USDOT University Transportation Center
The University of Texas at Arlington
601 W. Nedderman Drive, Suite 103
Arlington, TX 76019-0108
817-272-5138 | C-Tedd@uta.edu

In cooperation with US Department of Transportation
Research and Innovative Technology Administration (RITA)

Acknowledgments

This work was supported by a grant from the Center for Transportation Equity, Decisions, and Dollars (CTEDD) funded by the U.S. Department of Transportation Research and Innovative Technology Administration (OST-R) and housed at The University of Texas at Arlington.

The authors express their deepest appreciation to Peter Hsu and Edith Wong of the Florida Department of Transportation (FDOT) and Emmeth Duran and Sara Beresheim of Johnson, Mirmiran & Thompson, Inc. As stakeholders, they provided great assistance with data collection and valuable comments to improve the tools. Special gratitude is given to the FDOT Research Center for its support in local project matching.

The authors also acknowledge Garrett Speed, Pete Reehling, and Ben Mittler from the University of South Florida (USF) Libraries for their technical support in building the ArcGIS web-GIS platform. Special thanks to USF Graduate Research Assistant Dr. Qianwen Li, who made noble contributions in developing Crash Modification Factors using a case-control study. The authors also thank CUTR faculty, staff, and students, who have willingly helped with this project.

Disclaimer

The contents of this report reflect the views of the authors, who are responsible for the facts and the accuracy of the information presented herein. This document is disseminated under the sponsorship of the U.S. Department of Transportation's University Transportation Centers Program in the interest of information exchange. The Center for Transportation, Equity, Decisions and Dollars (CTEDD), the U.S. Government, and matching sponsors assume no liability for the contents or use thereof.

Technical Report Documentation Page

1. Report No.	**2. Government Accession No.**	**3. Recipient's Catalog No.**

4. Title and Subtitle
Development of Automated Roadway Lighting Diagnosis Tools for Nighttime Traffic Safety Improvement, Phase II

5. Report Date
July 31, 2022

6. Performing Organization Code

7. Author(s)
Zhenyu Wang, Pei-Sung Lin, Srinivas Katkoori, Mingchen Li, Rama Kolla, Runan Yang

8. Performing Organization Report No.

9. Performing Organization Name and Address
Center for Transportation, Equity, Decisions and Dollars (CTEDD)
USDOT University Transportation Center
The University of Texas at Arlington
601 W. Nedderman Drive, Suite 103
Arlington, TX 76019-0108

10. Work Unit No. (TRAIS)

11. Contract or Grant No.

12. Sponsoring Organization Name and Address
U.S. Department of Transportation
Research and Innovative Technology Administration
1200 New Jersey Avenue, SE
Washington, DC 20590

13. Type of Report and Period Covered

14. Sponsoring Agency Code

15. Supplementary Notes

16. Abstract
Roadway lighting is a conventional roadway infrastructure provided to ensure nighttime safety and security for multimodal road users. This Phase II project aimed to enhance the methods and tools developed in Phase I to investigate the impacts of lighting patterns on nighttime pedestrian crashes, address the effectiveness of LED technologies, develop a sliding window algorithm for uniformity diagnosis, and recode the analysis engine to integrate more functions and improve processing speed. The study adopted the matched case-control method, which can address the critical issue in lighting data—the confounding effects between illuminance mean and standard deviation—to investigate the impacts of lighting patterns on nighttime pedestrian crashes. Crash Modification Factors (CMFs) for the mean of horizontal illuminance (representing average lighting level) and the standard deviation of horizontal illuminance (representing uniformity) were developed to quantify the impacts. The study also developed a Safety Performance Function (SPF) for LED technologies based on Florida Department of Transportation (FDOT) District 7 light pole inventory data. The SPF indicates that lighting upgrading projects (HPS to LED) in Florida tend to decrease nighttime crash frequency by 17%. In addition, a sliding window algorithm was developed to diagnose lighting uniformity by scanning the lighting patterns along a segment and calculating the uniformity measures within a limited area covering the driver vision field. Compared to the uniformity for the whole segment, the algorithm can provide more reasonable and detailed diagnosis of lighting uniformity. In addition to the new models, the analysis engine was recoded to include more functions and improve processing speed. The developed methods and tools are being applied in FDOT District 7's district-wide lighting collection and analysis task. The analysis results will provide decision-making support for FDOT District 7 roadway lighting maintenance and nighttime safety management.

17. Key Words
Nighttime safety, roadway lighting pattern, multimodal road users, infrastructure maintenance, big data

18. Distribution Statement

19. Security Classification (of this report)	**20. Security Classification (of this page)**	**21. No. of Pages**	**22. Price**
Unclassified.	Unclassified.	39	

Table of Contents

List of Tables

List of Figures

Abstract

Roadway lighting is a conventional roadway infrastructure to ensure nighttime safety and security for multimodal road users (motorists, pedestrians, cyclists, transit passengers). The Advanced Lighting Measurement System (ALMS) developed by CUTR provides a low-cost and effective solution for collecting high-resolution lighting data for a big-scale roadway network. A previous CTEDD-study (Development of Automated Roadway Lighting Diagnosis Tools for Nighttime Traffic Safety Improvement, Phase I) developed and improved an analysis tool to diagnose lighting patterns and estimate nighttime crash risks based on big lighting data. This Phase II project aimed to enhance the methods and tools developed in Phase I to investigate the impacts of lighting patterns on nighttime pedestrian crashes, address the effectiveness of LED technologies, develop a sliding window algorithm for uniformity diagnosis, and recode the analysis engine to integrate more functions and improving processing speed.

The study adopted the matched case-control method, which can address the critical issue in lighting data—the confounding effects between illuminance mean and standard deviation—to investigate the impacts of lighting patterns on nighttime pedestrian crashes. Crash Modification Factors (CMFs) for the mean of horizontal illuminance (representing average lighting level) and the standard deviation of horizontal illuminance (representing uniformity) were developed to quantify the impacts. The study also developed a Safety Performance Function (SPF) for LED technologies based on Florida Department of Transportation (FDOT) District 7 light pole inventory data. The SPF indicates that lighting upgrading projects (HPS to LED) in Florida tend to decrease nighttime crash frequency by 17%. In addition, a sliding window algorithm was developed to diagnose lighting uniformity by scanning the lighting patterns along a segment and calculating the uniformity measures within a limited area covering driver vision field. Compared to uniformity for the whole segment, the algorithm can provide more reasonable and detailed diagnosis of lighting uniformity. In addition to developing new models, the analysis engine was recoded to include more functions and improve processing speed. The new analysis engine realizes the functions of connecting different data sources, lighting diagnosis, nighttime crash prediction, and geometric and traffic data processing; with the optimized codes, its process time is reduced by 90%.

The developed methods and tools are being applied in FDOT District 7's district-wide lighting collection and analysis task. The analysis results will provide decision-making support for FDOT District 7 roadway lighting maintenance and nighttime safety management.

Chapter 1: Introduction

1.1 Background

Nighttime crashes, particularly those that result in fatalities and injuries, are over-represented on the U.S. highway system. Roadway lighting is a vital countermeasure to increase visibility at night and provides clear safety benefits for multimodal users such as drivers, motorcyclists, pedestrians, bicyclists, and transit-dependents. In 2019–2020, the research team developed a prototype of computer tools in a CTEDD-funded research project titled "Development of Automated Roadway Lighting Diagnosis Tools for Nighttime Traffic Safety Improvement." The computer tools (http://its.cutr.usf.edu/lita), built on the Esri ArcGIS web-GIS platform, provide core functions of data management, data analysis, and data visualization for lighting analysis and safety management, as shown in Figure 1-1.

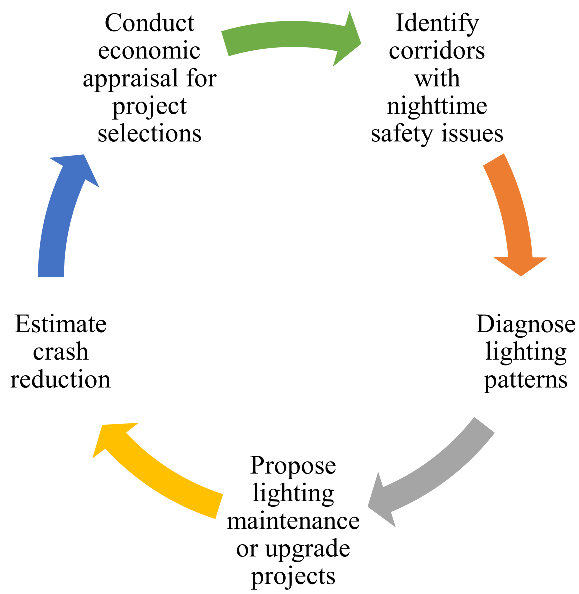


Figure 1-1. Lighting analysis and nighttime safety management

However, the prototype of the computer tools still has some limitations:

- *Safety analysis for vulnerable users* – The prototype is used primarily for vehicular nighttime crash analysis rather than vulnerable users. As nighttime crashes account for almost 70% of pedestrian fatalities (*2*), vulnerable users (pedestrians and bicyclists) are a major concern in nighttime safety management. Limited previous studies (*3, 4*) investigated the impacts of street lighting patterns on nighttime pedestrian/bicyclist crash risk; no implementable Crash Modification Factors (CMFs) of lighting patterns for vulnerable users were identified from these previous studies. It is necessary to develop CMFs for lighting patterns for vulnerable users based on ALMS data and integrate them into the computer tools.

- *Safety analysis for LED lighting* – The prototype does not distinguish LED technology and traditional technologies such as High-Pressure Sodium (HPS) in safety analyses. As more and more road corridors have been upgraded to LED systems in Florida and nationwide recently, engineers and managers need to assess the safety performance of LED technology, which has different vision characteristics from HPS. The SPFs and CMFs developed in the prototype were based primarily on HPS lighting data and cannot capture the safety characteristics of LED lighting. Only one previous study (*5*) explored the impacts of LED upgrade on nighttime crashes. The proposed study needs to develop or calibrate CMFs for LED lighting based on FDOT District LED upgrade projects conducted in the past decade. The enhanced computer tools in Phase II will integrate the CMFs for LED lighting and provide a function to stratify stakeholder needs in assessing the safety performance/benefits of LED lighting projects.
- *Functionality* – The prototype provides an initial function of lighting pattern diagnosis, a simple user interface, and non-optimized geoprocessing codes. It is necessary to enhance these functions to provide an implementable product with full functionality.

1.2 Research Objectives

This project aimed to enhance the prototype of the Automated Roadway Lighting Diagnosis Tools developed in Phase I and produce an implementable system at Technology Readiness Level (TRL) Level 8: Technology Proven in Operational Environment. More specifically, the research objectives are as follows:

- Develop roadway lighting safety analysis methods for pedestrians, who are major concerns in nighttime safety.
- Develop safety analysis methods for LED bulbs that have different photometric performance from traditional lighting technologies.
- Improve the roadway lighting diagnosis algorithms to recognize “unsafe” uniformity patterns more effectively.
- Enhance the functionality of the lighting analysis platform developed in Phase I, including optimal processing speed and include more functions.
- Implement the developed methods and tools for the FDOT District 7 district-wide lighting measurement project.

Chapter 2: Impacts of Lighting Patterns on Nighttime Pedestrian Crashes

2.1 Introduction

Nighttime pedestrian crashes are a major concern in transportation safety management. Fatality Analysis Reporting System (FARS) data indicate that 4,580 pedestrians were killed in dark environments in the U.S. in 2019, accounting for 74% of pedestrian fatalities that year (*2*). Among these, 72% occurred at midblock and 23% were intersection-related. Reduced visibility at night is an inherent factor that increases the risk of vehicle-pedestrian collisions.

Driving is a visual effort, in that drivers continuously scan the surrounding environment to identify potential risks. If an object (e.g., a pedestrian) presents on a route, the driver needs sufficient time to detect the object and take action (e.g., braking and avoidance maneuvers) to avoid a potential collision. Drivers detect pedestrians at night primarily as a result of luminance contrast—the visual (luminance) difference between the pedestrian and the background (*6*). Street lighting is an effective way to increase luminance contrast (visibility) of pedestrians at night and to improve driver detection ability (*7*, *8*). Existing studies have addressed the safety effects of installing street lighting on pedestrian safety. Jensen (*9*) suggested that installing roadway lighting can reduce pedestrian injuries by about 45% when the speed limit exceeds 50 km/h and 12% when the speed limit is less than 50 km/h. Siddiqui et al. (*10*) found that roadway lighting reduced pedestrian crash odds by 42% at midblock locations and 54% at intersections compared to dark conditions with no lighting. Sullivan and Flannagan (*11*) showed that lighting improved pedestrian safety in three crash scenarios—curve, motorway, and corner. Nambisan et al. (*12*) studied the impacts of lighting crosswalks and concluded that lighting enhances pedestrian safety. Mohamed et al. (*13*) found that the probability of fatal pedestrian crashes increased when the roadway was not lighted rather than lighted. Olszewski et al. (*14*) concluded that, compared to daytime, nighttime pedestrian crashes increased 1.95 times with roadway lighting and 4.08 times without roadway lighting at unsignalized crosswalks. Patella et al. (*15*) found that vehicle average speed decreased by 19.3% at crosswalks in illuminated conditions and confirmed the positive effects of roadway lighting on nighttime pedestrian safety.

Despite these insightful developments, the effects of lighting photometric patterns (i.e., average lighting and lighting uniformity) on nighttime pedestrian crashes remain unclear. Intuitively, drivers can easily detect pedestrians in a bright environment and have more opportunities to avoid collisions. When driving in uneven lighting conditions (i.e., from a dark environment to a bright visual field or vice versa), drivers need additional time to adapt to the new lighting conditions, and their visual functions may be degraded during the adaption, which increases crash risks. A well-designed street lighting pattern (bright and uniform) can increase pedestrian luminance contrast against the roadway surface and aid human eyes in adapting to a changing lighting environment better than headlights alone. Several previous studies have addressed the safety effects of street lighting patterns on vehicle crashes and developed crash modification factors (CMFs) (*16*–*21*). However, little effort has been made to explore the impact of lighting patterns on nighttime pedestrian crashes. Zhou and Hsu (*22*) reported that nighttime pedestrian crash frequency at low lighting level segments was much higher than at high lighting level segments. Wei et al. (*18*) found that horizontal illuminance of 0.9 foot-candle (fc) or higher can reduce the likelihood of fatal and serious pedestrian injury by 10.7% at signalized intersections. Nabavi Niaki et al. (*3*) concluded that nighttime pedestrian crash frequency increased with average lighting conditions and attributed this counterintuitive finding to driver safety compensation in the dark environment and selection bias (traffic agencies tend to improve roadway lighting at sites that experience more crashes).

Two photometric parameters are widely used in the roadway lighting design (*6*). Average horizontal illuminance—the average number of lumens that fall onto a unit of pavement surface either in foot-candle (fc, lumens per ft^2) or lux (lx, lumens per m^2)—measures the average lighting level on a roadway segment. Illuminance ratio—the maximum illuminance divided by the minimum illuminance (max-to-min ratio) or the average illuminance divided by the minimum illuminance (mean-to-min ratio)—represents the uniformity of street lighting patterns along a segment. It has been argued that the ratio-based uniformity measures may not accurately capture the "true" lighting patterns that influence driver vision in large-scale lighting analysis (i.e., roadway corridor) because of the potential issue of spatially-unrelated extreme lighting points (*21*, *23*, *24*). To overcome this disadvantage of ratio-based uniformity criteria, two previous studies (*23*, *24*) adopted the standard deviation of horizontal illuminance as the uniformity measure, arguing that it uses the information of all lighting points and thus prevents the issue of spatially-unrelated extreme lighting points. However, as Yang et al. (*23*) indicated, the standard deviation of illuminance is strongly and positively correlated to the illuminance mean, especially in a low mean range, which may cause a collinearity issue such that the model cannot distinguish the safety effects of the mean and the standard deviation (*25*). This correlation issue is a significant limitation in a previous study conducted by Nabavi Niaki et al. (*3*) that ignored the counteracting effects of the standard deviation of illuminance on the illuminance mean and might lead to the counterintuitive conclusion—a high illuminance mean (accompanying a high standard deviation) is associated with a high pedestrian crash frequency (probably caused by the high standard deviation [poor uniformity]) at intersections.

2.2 Research Objectives

The literature review indicated several research gaps that exist in nighttime pedestrian safety studies—1) due to lack of lighting data, few studies explored the effects of street lighting patterns (brightness and uniformity) on nighttime pedestrian crashes, and no CMFs were developed; 2) counterintuitive findings of the illuminance mean were observed, probably due to ignoring the counteracting effects of the standard deviation of illuminance (*3*); and 3) the safety effects of illuminance patterns for pedestrians on midblock segments that experience a sizable portion of nighttime pedestrian crashes were not well-addressed.

Motivated by these research gaps, this study quantified the safety effects of illuminance photometry on nighttime pedestrian crash frequency at midblock. Matched case-control studies were applied to address the critical issues in previous studies—the confounding effects of the standard deviation of illuminance on illuminance mean and spatially-unrelated extreme values for ratio-based uniformity measures. Based on the modeling results, reliable and implementable

CMFs of lighting photometric criteria (average lighting and lighting uniformity) were developed for nighttime pedestrian crash study and management.

2.3 Methodology

2.3.1 Matched Case-Control Study

The matched case-control method has been used in highway safety to relate risk factors to a specific outcome (i.e., crash occurrence) with confounding effects (*26–29*). Li et al. (*21*) recently adopted the matched case-control method to develop CMFs of lighting photometric criteria for nighttime vehicle crashes. Compared to cross-sectional studies, the matched case-control method is more pertinent for lighting-related crash modeling. First, it is suitable for rare-events modeling (e.g., nighttime pedestrian crashes) and addresses the low mean and aggregation bias issues in the cross-sectional studies (*30*). Second, it effectively eliminates the impacts of confounding variables (i.e., counteracting effects of the standard deviation of illuminance on the mean, and vice versa) because each matched case-control stratum shares the same or similar values of the confounding variables (*31*). Finally, it guarantees a balanced number of cases and controls so the variance in the parameters of interest is reduced and the statistical efficiency of the model estimation is improved (*32*). Motivated by these merits, this study adopted the matched case-control method to fit nighttime pedestrian crashes and lighting data.

Steps for conducting a matched case-control study are as follows:

1. **Define** – Roadway segments with a uniform length are categorized into two groups—1) case, for a roadway segment that experienced at least one nighttime pedestrian crash in the study period, and 2) control, for a roadway segment that did not experience any nighttime pedestrian crashes in the study period.
2. **Match** – A certain number of controls are randomly matched to each case based on the similarity of confounding variables related to both the risk factor of interest (e.g., photometric patterns) and the outcome (i.e., nighttime pedestrian crash). With this matching technique, the biased estimations on the association between the risk factor of interest and the outcome can be avoided by mitigating the disturbance from confounders (*31*). The case-control ratio is determined by the minimum ratio of controls to cases among all cross-classification categories.
3. **Model** – A conditional logistic regression model is developed based on the matched case-control strata. The odds ratio, which represents the change of relative nighttime crash risks due to an alternation of unmatched risk factors (e.g., street lighting photometry), is derived from the fitted model and could be used as the equivalent of a CMF (*27*, *33*).

2.3.2 Conditional Logistic Regression

Conditional logistic regression extends logistic regression by accounting for stratification in matched case-control studies (*34*). Let y_{ij} denote the j^{th} observation (i = 1, 2, ⋯, I) of the i^{th} stratum j (j = 1, 2, ⋯, J). The unconditional likelihood of one observation is

$$\Pr(y_{ij} = 1) = \frac{\exp\left(\alpha_i + \boldsymbol{\beta X_{ij}}\right)}{1 + \exp\left(\alpha_i + \boldsymbol{\beta X_{ij}}\right)} \tag{1}$$

where $\boldsymbol{X_{ij}}$ is a vector of k explanatory variables associating with y_{ij}; $\boldsymbol{\beta}$ is the coefficients corresponding to $\boldsymbol{X_{ij}}$; α_i is the stratum-specific interpretation term reflecting the different combination effects of confounding variables for different strata. Maximum Likelihood Estimation (MLE) based on the unconditional likelihood is invalid and biased, as the number of parameters $(I + k)$ grows with the number of observations (assuming the case-control ratio is fixed).

To eliminate unnecessary parameters (α_i), the conditional likelihood of each stratum i is calculated as:

$$L(Y_i|\boldsymbol{\beta}) = P\left(y_{i1} = 1, y_{ij} = 0 \text{ for } j > 1 \mid \boldsymbol{X_{ij}}, \sum_{j=1}^{J} y_{ij} = 1, \boldsymbol{\beta}\right) = \frac{\exp\left(\boldsymbol{\beta X_{i1}}\right)}{\sum_{j\in J}\exp\left(\boldsymbol{\beta X_{ij}}\right)} \tag{2}$$

where y_{i1} is the case observation of the i^{th} stratum; y_{ij} for $j > 1$ are the matched controls of the i^{th} stratum; $\boldsymbol{X_{i1}}$ is the vector of explanatory variables associating with y_{i1}. As the strata are assumed to be independent of each other, the conditional log-likelihood function $LL(Y|\beta)$ over the population of I strata can be written as (*31*):

$$LL(Y|\boldsymbol{\beta}) = -\sum_{i=1}^{I} \ln\left\{1 + \sum_{j\epsilon J} \exp\left[\boldsymbol{\beta}\left(\boldsymbol{X_{ij}} - \boldsymbol{X_{i1}}\right)\right]\right\} \tag{3}$$

The MLE is used to maximize $LL(Y|\boldsymbol{\beta})$ with respect to $\boldsymbol{\beta}$.

2.3.3 Odds Ratio

The odds ratio indicates the change of relevant risk due to the alternation of an explanatory variable. Based on the definition, the odds ratio is equivalent to the CMF. For a dummy variable, the odds ratio is defined as the ratio of the odds that nighttime crashes occur in the presence of a roadway characteristic k ($x_k = 1$) to the odds that nighttime crashes occur in the absence of that roadway characteristic k ($x_k = 0$), holding other variables constant. The odds ratio for a dummy variable can be written as follows.

$$OR(x_k) = \frac{\dfrac{P(y_{i0} = 1|x_k = 1, \boldsymbol{Z})}{[P(y_{i0} = 0|x_k = 1, \boldsymbol{Z})]}}{\dfrac{P(y_{i0} = 1|x_k = 0, \boldsymbol{Z})}{[P(y_{i0} = 0|x_k = 0, \boldsymbol{Z})]}} = \exp(\beta_k) \tag{4}$$

where $\boldsymbol{Z}$ is the vector of explanatory variables other than x_k; β_k is the estimated parameter for x_k.

2.4 Model Development

2.4.1 Data Collection

Researchers at the Center for Urban Transportation Research (CUTR) at the University of South Florida used the Advanced Lighting Measurement System (ALMS) (*35*) to collect the horizontal illuminance data. This system precisely measures horizontal illuminance and generates two measurement points every 10 ft for each lane. With this system, the CUTR team completed illuminance measurements for more than 300 center miles in Tampa from 2011 to 2014. The data were collected in an entirely dark environment (9:30–11:59 PM) to ensure that no natural light was present. In this study, 440 roadway corridors in urban and/or suburban areas with street lighting data were identified based on the following criteria—1) roadway sections between two successive signalized intersections, 2) equipped with High-Pressure Sodium (HPS) light bulbs, and 3) no upgrades on street lighting in the past several years. A 250-ft buffer was subtracted from the two ends of the roadway corridor to exclude influence from adjacent signalized intersections.

2.4.2 Case and Control Definition

The 440 roadway corridors were separated into small segments with a uniform length. Different segment lengths (600 ft, 800 ft, 1000 ft, 1200 ft, 1400 ft) were tested, and the length of 600 ft was selected, given that it produced the best model results in terms of the variable significance. In total, 1,638 segments were produced.

Nighttime crash data from 2011 to 2014 were matched to roadway segments. A case was defined as a segment that experienced at least one nighttime pedestrian crash, and a control was defined as a segment that did not experience any nighttime pedestrian crashes. The measured lighting data points (horizontal illuminance at foot-candle, HFC) that fall into the same roadway segment were used to calculate the mean and standard deviation. Segments with missing information were screened out, which left 1,234 segments for matching.

2.4.3 Matching

The HFC mean and standard deviation, representing average brightness and uniformity, respectively, are confounders of each other because they are correlated and both related to the outcome (i.e., nighttime crashes) (*21*). As plotted in Figure 2-1, it is clearly observed that the mean and standard deviation of HFC are positively correlated; the correlation becomes more significant as the mean decreases. When the mean is less than 0.7 fc, Pearson's correlation coefficient is as great as 0.86, indicating a strong correlation. This correlation may prevent models to correctly distinguish the safety effects of one criterion from another. Because the impacts of the two photometric measures on crashes are theoretically converse, the positive correlation between them may result in counterintuitive estimations. Therefore, when quantifying the safety effects of one photometric measure, it is necessary to control the impacts of another to develop reliable CMFs. In this study, two models were developed—1) matching the standard deviation to address the impact of the mean on nighttime pedestrian crash occurrence, and 2) matching the mean to address the impact of the standard deviation on nighttime pedestrian crash occurrence.

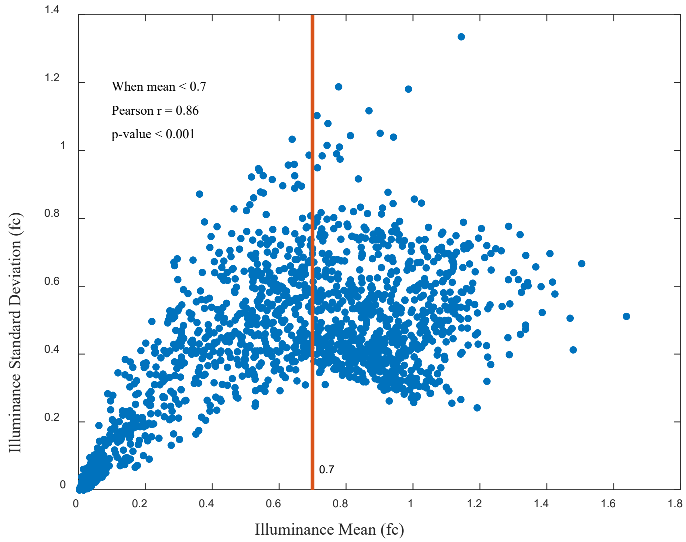


Figure 2-1. Illuminance standard deviation vs. illuminance mean

Annual Average Daily Traffic (AADT), representing traffic exposures, is another confounder commonly matched in case-control studies for vehicle crashes (*21*, *26*, *28*, *29*, *36*, *37*). However, AADT does not present a strong correlation with either the mean (r = 0.29) or standard deviation (r = -0.03). To avoid overmatching, this study treated AADT as an explanatory variable rather than a matching variable.

As both the mean and standard deviation are continuous, it is impossible to match them by the exact values. The following procedures were carried out to categorize them into different levels—1) calculate the mean μ and standard deviation σ of the two photometric measures, respectively, and 2) categorize the two photometric measures based on μ and σ. The cutoff values are $-\infty, \mu - 1.5\sigma, \mu - 0.5\sigma, \mu + 0.5\sigma, \mu + 1.5\sigma$ and $+\infty$.

Sample sizes by matched categories are presented in Table 2-1. To keep the number of samples of different categories as high as possible, a case-control matching ratio of 1:6 was used, as it is the minimum in Table 2-1. This makes the analysis power of the case-control study approximately 98% (*30*).

Table 2-1. Matched Categories and Sample Sizes

HFC Mean (fc)										
<0.045		0.045-0.421		0.421-0.797		0.797-1.172		>1.172		**Total**
Case	Control	Case	Control	Case	Control	Case	Control	Case	Control	
6	131	21	237	36	350	36	369	6	42	1234
HFC Standard Deviation (fc)										
<0.069		0.069-0.299		0.299-0.529		0.529-0.760		>0.760		**Total**
Case	Control	Case	Control	Case	Control	Case	Control	Case	Control	
7	162	12	131	37	494	42	298	7	44	1234

2.4.4 Descriptive Statistics

A stratum consists of one case and six randomly-matched controls. A total of 105 strata (105 cases and 630 controls) were identified. Explanatory factors for each segment were converted into dummy variables. Descriptive statistics of explanatory variables are provided in Table 2-2.

Table 2-2. Descriptive Statistics of Explanatory Variables

Variable Description	Mean Model				Standard Deviation Model			
	Case (n = 105)		Control (n = 630)		Case (n = 105)		Control (n = 630)	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
HFC mean < 0.2 fc	0.171	0.379	0.133	0.340	\	\	\	\
0.2 fc ≤ HFC mean ≤ 0.5 fc	0.133	0.342	0.152	0.360	\	\	\	\
0.5 fc < HFC mean ≤ 1.0 fc	0.505	0.502	0.537	0.499				
HFC mean > 1.0 fc	0.192	0.396	0.178	0.383	\	\	\	\
HFC std dev < 0.52 fc	\	\	\	\	0.514	0.502	0.671	0.470
HFC std dev ≥ 0.52 fc	\	\	\	\	0.486	0.502	0.329	0.470
Daytime pedestrian crash occurred	0.191	0.395	0.044	0.206	0.191	0.395	0.037	0.188
Shoulder width < 9 ft	0.581	0.496	0.371	0.484	0.581	0.496	0.346	0.476
Curve presence	0.171	0.379	0.344	0.476	0.171	0.379	0.340	0.474
Access points > 12	0.286	0.454	0.220	0.415	0.286	0.454	0.173	0.379
AADT per lane > 6200	0.600	0.492	0.573	0.495	0.600	0.492	0.613	0.488

2.5 Model Estimation

The software package STATA 16 (*38*) was used to fit the two conditional logistic regression models—mean and standard deviation. The fitted models are presented in Table 2-3 and Table 2-4, respectively. The coefficients, odds ratio (or equivalent to CMF), confidence interval (CI) of OR, and standard error (SE) of OR were reported. All ORs were significant at a confidence level of 95% or higher in the two models.

Table 2-3. Fitted Conditional Logistic Model for HFC Mean

Variable	Coef.	*z*	*p*-value	OR (CMF)	95% CI of OR	SE of OR
HFC mean						
< 0.2 fc				*Baseline*		
[0.2 fc, 0.5 fc]	-1.49	-2.16	0.031	**0.225**	[0.058, 0.870]	0.155
(0.5 fc, 1.0 fc]	-1.67	-2.34	0.020	**0.188**	[0.046, 0.764]	0.134
> 1.0 fc	-1.93	-2.55	0.011	**0.145**	[0.032, 0.640]	0.110
Daytime pedestrian crash occurred	1.31	4.46	0.000	3.719	[2.088, 6.623]	1.095
Shoulder width < 9 ft	0.93	3.58	0.000	2.537	[1.523, 4.225]	0.660
Curve presence	-0.97	-3.10	0.002	0.378	[0.204, 0.699]	0.118
Access points > 12	0.70	2.41	0.016	2.017	[1.141, 3.565]	0.586
AADT per lane > 6,200	0.76	2.80	0.005	2.142	[1.256, 3.652]	0.583
Model Statistics						
Number of observations					735	
Log-likelihood					-172.671	
Pseudo R^2					0.155	

Table 2-4. Fitted Conditional Logistic Model for HFC Standard Deviation

Variable	Coef.	*z*	*p*-value	OR (CMF)	95% CI of OR	SE of OR
HFC standard deviation						
< 0.52 fc				*Baseline*		
≥ 0.52 fc	0.59	2.16	0.031	**1.803**	[1.056, 3.077]	0.492
Daytime pedestrian crash occurred	1.68	4.52	0.000	5.373	[2.591, 11.139]	1.999
Shoulder width < 9 ft	0.84	3.48	0.000	2.320	[1.444, 3.724]	0.560
Curve presence	-0.97	-3.13	0.002	0.378	[0.206, 0.695]	0.117
Access points > 12	0.79	2.74	0.006	2.205	[1.253, 3.878]	0.635
AADT per lane > 6,200	0.59	2.22	0.027	1.795	[1.070, 3.010]	0.474
Model Statistics						
Number of observations					735	
Log-likelihood					-167.414	
Pseudo R^2					0.181	

2.6 Discussion

2.6.1 HFC Mean

The mean of horizontal illuminance represents the average brightness of a roadway segment—the higher the HFC mean, the more visible the pedestrian. Theoretically, an increase in HFC mean should decrease nighttime pedestrian crash risks. The negative coefficients for HFC mean variables in Table 3 support this speculation. To be specific, if the HFC mean of a roadway segment increases from < 0.2 fc to [0.2 fc, 0.5 fc], the relatively nighttime pedestrian crash risk decreases to 0.255 times; if the HFC mean increases from < 0.2 fc to (0.5 fc - 0.1 fc], the relatively nighttime pedestrian crash risk decreases to 0.188 times. Further, if the HFC mean increases from < 0.2 fc to > 1.0 fc, the relatively nighttime pedestrian crash risk decreases to only 0.145 times. By controlling the HFC standard deviation, reductions of nighttime pedestrian crash risks when increasing the HFC mean are significant at a confidence level of 95%.

Results also indicate a non-linear relationship between average lighting level and nighttime pedestrian crash risks. As shown in Figure 2-2, nighttime pedestrian crash risk declines very quickly in a low mean range (crash reduction factor of 0.775 [= 1 – 0.225] for < 0.2 fc → [0.2 fc, 0.5 fc]). With a continuous increase in average lighting level, nighttime pedestrian crash risk gradually decreases, but the reduction amplitude becomes smaller; the crash reduction factors for [0.2 fc, 0.5 fc] → [0.5 fc, 1.0 fc) is 0.164 (= 1 - 0.188/0.225) and for [0.5 fc, 1.0 fc) → > 1.0 fc is 0.229 (=1- 0.145/0.188). This trend also exists in nighttime vehicle crashes (*19*, *21*, *23*).

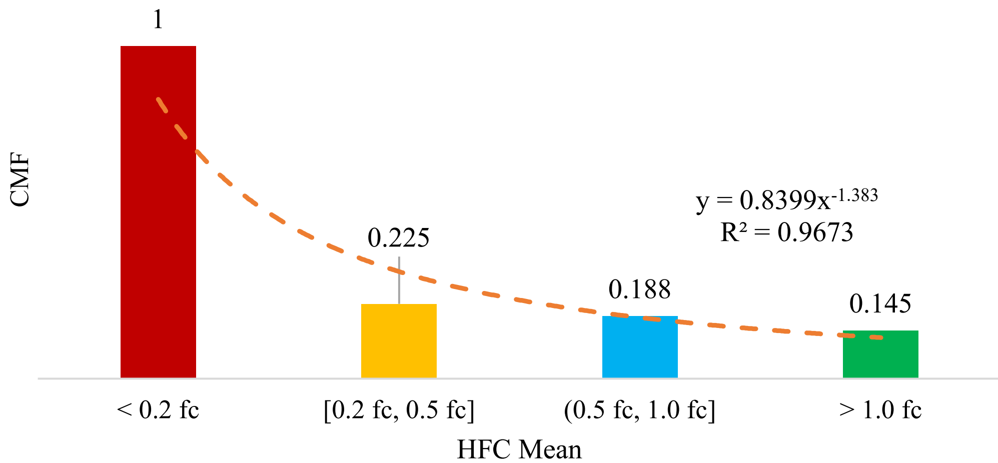
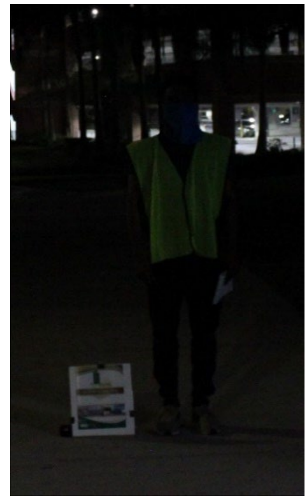


Figure 2-2. Trendline of CMFs of nighttime pedestrian crashes for HFC mean

Visual figures of pedestrians may provide an intuitive understanding of the safety effects of horizontal illuminance on pedestrian visibility. Figure 2-3 represents a series of scenarios in which a pedestrian presents on the roadside with various horizontal illuminance levels. Figure 2-3A represents a fully dark environment (HFC = 0.1 fc); although the pedestrian wears a safety jacket with retroreflective materials, it is still very difficult for a motorist to recognize him from the background, which implies that an extremely dark environment (< 0.2 fc) is very dangerous for pedestrians. Figure 2-3B represents a medium bright environment (HFC = 0.5 fc); human eyes can detect the pedestrian contour in this lighting condition and, compared to the extremely dark environment (Figure 2-3A)**,** motorists have a much longer detection distance so the risk of pedestrian collisions may be greatly reduced. With an increase in lighting conditions to medium-high (HFC = 1.0 fc, Figure 2-3C) and high (HFC = 1.5 fc, Figure 2-3D), pedestrian visibility is better, but the crash risk reduction effects of increasing the HFC from medium to medium-high and from medium-high to high are lower than increasing from fully dark (pedestrian is unseen to motorists) to medium bright (motorist can detect pedestrian contour).

A. HFC = 0.1 fc



B. HFC = 0.5 fc

C. HFC = 1.0 fc

D. HFC = 1.5 fc

Figure 2-3. Visual figures of pedestrians in various lighting conditions

2.6.2 HFC Standard Deviation

The HFC standard deviation is a uniformity measure; compared to ratio-based measures (max-min ratio or mean-min ratio), it can avoid the amplified impacts of extreme lighting points and use the full lighting data information such that it is suitable for describing lighting patterns for a large space (i.e., roadway segments). A high HFC standard deviation, representing a more diverse distribution of lighting level along a roadway segment, theoretically should decrease pedestrian visibility and cause higher crash risks because of the driver's impaired vision and extended reaction time. The association between the HFC standard deviation and nighttime vehicle crashes has been proven in two previous studies (*23*, *24*). By controlling the confounding effects of the HFC mean, this study (Table 2-4) quantified the impact of the HFC standard deviation on nighttime pedestrian crash risks. Given constant other factors (i.e., average lighting level), segments with a diverse lighting pattern (HFC standard deviation ≥ 0.52 fc) experience a nighttime pedestrian crash risk that is 1.802 times as many as those with a uniform lighting pattern (HFC standard deviation < 0.52 fc).

2.6.3 Other Factors

The daytime pedestrian crash indicator (one or more daylight pedestrian crashes occurred at a given segment) was included in both models as an explanatory variable to capture the impacts of risk factors that contributed to both daytime and nighttime pedestrian crashes but not related to street lighting patterns. These factors are usually not included in the crash database, e.g., pedestrian exposure levels. The function of the daytime pedestrian crash indicator is similar to the night-to-day ratio widely used in lighting-safety studies (*17*, *19*, *23, 24*, *39*, *40*). The coefficients of the daytime pedestrian crash indicator in the models suggest a significantly positive relationship between nighttime pedestrian crash occurrence and daytime crash occurrence.

A narrower shoulder width (< 9 ft) was positively related to nighttime pedestrian crash risk in the two models. This finding is consistent with the existing literature (*41*, *42*). Wider shoulders provide more refuge space for pedestrians when they are facing collision risks; meanwhile, wider shoulders usually associate with high-level roadway classification with better safety design standards, such as better sight distance, traffic controls, and geometric features.

Curve presence was significantly and negatively associated with nighttime pedestrian crash risk. Fewer pedestrians cross the road at curves than at straight segments, given that driver sight distance is much shorter at curves. Meanwhile, motorists tend to decrease their speed when operating through curves. Less exposure together with slower vehicle speed contributes to lower nighttime pedestrian crash risk. This finding aligns with existing studies that fewer nighttime pedestrian crashes occur at curves (*11*, *43*).

Access points introduce conflicts between turning vehicles and pedestrians crossing driveways or side streets along a roadway segment. More access points imply higher crash risks for pedestrians. The two models indicate that if a segment has more than 12 access points, the relative risk of nighttime pedestrian crashes increases significantly. With AADT as the measure of vehicle traffic exposure, the two models indicate that if AADT is higher than 6,200 per lane, the relative risk of nighttime pedestrian crashes tends to significantly increase.

2.7 Conclusions

This study investigated the safety effects of illuminance photometric criteria (HFC mean as an indicator of average lighting level and HFC standard deviation as an indicator of lighting uniformity) on nighttime pedestrian crash occurrence on roadway segments that were overlooked in previous studies. The matched case-control method successfully decoupled the correlation between the HFC mean and standard deviation, which resulted in counterintuitive findings in previous studies. Significant CMFs were developed to quantify the safety effects of the two photometric criteria. For average lighting level, taking the low HFC mean (<0.2 fc) as the baseline, the CMFs for medium [0.2 fc, 0.5 fc], medium-high (0.5 fc, 1.0 fc], and high (>1.0 fc) illuminance means are 0.225, 0.188, and 0.145, respectively. For lighting uniformity, compared to low HFC standard deviation (<0.52 fc), the CMF for high illuminance standard deviation (≥ 0.52 fc) is 1.803. The CMFs can be used in nighttime pedestrian safety management and street lighting assessment.

Some limitations exist in this study and should be addressed in further studies. First, this study considered horizontal illuminance only. Due to lack of data, vertical illuminance, an important photometric measure related to pedestrian safety (*44*), was not included in the models. The CUTR team is expanding its lighting data collection efforts in Florida. Vertical illuminance data collection will be included in follow-up tasks, and the data will be used to address the safety effects of vertical illuminance for pedestrians in future studies. Second, existing photometric criteria (mean and standard deviation) are not ideal photometric measures and may not perfectly capture the "true" spatial relationship of lighting patterns that influence driver vision (*21*). New photometric measures are needed to encapsulate and fully account for the spatial relationship among lighting data points.

Chapter 3: Safety Effectiveness of LED Lighting Technology

3.1 Introduction

As oil and gas reserves decrease and the demand for energy increases, energy conservation is an urgent priority. The use of energy-efficient technology is necessary in roadway lighting to mitigate the effects of the energy crisis. Light-emitting diodes (LEDs) are fourth-generation light sources developed as an energy-efficient alternative to traditional street lighting, such as high-pressure sodium (HPS). As shown in Figure 3-1, LED street lights are designed to keep streets and roads well-illuminated by directing the output light towards specific locations. By switching to LED streetlights, cities are able to reduce maintenance, energy cost, glare, and loss of light. Although LEDs have a higher installation cost than HPS light sources and generally provide inferior luminous efficacy, continuous development in the capacity of LEDs is anticipated in the near future. Assuming an annual usage of 4,000 hours, the estimated average lifetime of LEDs is 10+ years; metal halide lamps have a shelf life of approximately 5.5 years. LED light sources can be switched on/off immediately, but it takes a long time for metal halide lamps to reach an ideal functioning temperature. Moreover, LEDs will eliminate the problem of hot spots on pavement, as observed with the use of metal halide street lights, because LEDS provide a uniform distribution of light. Table 3-1 summarizes the advantages of LED technologies for roadway illumination.

Figure 3-1. Comparison of HPS (*left*) and LED (*right*) lighting technologies
(Source: ADOT LED Lighting Pilot Study)

Table 3-1. Summary of Advantages and Disadvantages of LED Street Lights

Advantages	
Energy Efficiency	• LEDs can lead to reduction in energy consumption by as much as 80%. • LEDs led to an annual saving of $6 million in energy costs in Toronto • Use of solar-powered LEDs can be an environmentally-friendly illumination solution.
Long Service Life	• Average life of LED street lamps is ~ 50,000 hours, double that of HPS.
Color Quality	• Most LEDs have CCTs often above 5,000K and a cool bluish-white appearance. • LEDs have a range of 85–90 on the color rendering index (CRI). • The white light produced by LEDs can lead to accurate rendering of an object's actual color.
Mesopic Vision	• The higher blue content of the LED light spectrum can render LEDs brighter than conventional light sources at the same lumen output. • The perceived lighting level of LEDs may not be fully represented by the conventional lumen and surface-level foot-candle measurements.
Lack of Warm-up Time	• LEDs can turn on/off instantly to full brightness without re-strike time. • The instant response speed of LEDs can turn on/off LEDs immediately according to environmental changes.
Compact Size	• Due to their compact size, LEDs allow flexibility in their form and design.
Directional Light	• LEDs enable more optical control. • LEDs can be designed to emit light in a specific direction.
Reduced Light Pollution	• LEDs can be designed to focus light on a preferred location. • LEDs can result in less light pollution and light trespass to adjacent areas. • LEDs can reduce over-illumination and glare to improve traffic safety for drivers and pedestrians alike.
Environmental Benefits	• LEDs are free of toxic materials such as mercury. • LEDs are free of heavy metals such as lead. • LEDs do not produce ultraviolet and infrared light.
Dimmable Capabilities	• LEDs provide more advantages in dimming over mercury vapor, metal halide, and HPS lamps.
Breakage and Vibration Resistance	• LEDs do not have a filament, arc tube, or fragile glass components. • LEDs offer a more robust light source and are more resistant to breakage and vibration.
Luminous Efficacy	• The luminous efficacy of LED street lights is not yet superior to conventional street lamps.
Heat Conversion Rate	• LEDs have a higher rate of power-to-heat conversion compared to conventional streetlights. • High-power LED chips generally transform ~ 80% of input power into heat.
Installation Cost	• LEDs currently require significantly higher initial installation costs compared to conventional streetlights. • LEDs currently require higher replacement costs compared to conventional street lights.
Use of LED Array	• The use of LED module arrays has a chance of component failure that increases with the increasing number of LED chips used.

The existing SPFs and CMFs for lighting levels do not distinguish LED technology and traditional technologies such as HPS in safety analyses. As more and more road corridors have been upgraded to LED systems in Florida and nationwide recently, engineers and managers need to assess the safety performance of LED technology that has different vision characteristics from HPS. The SPFs and CMFs developed in the prototype were based primarily on HPS lighting data and cannot capture the safety characteristics of LED lighting. Only one previous study (*5*) explored the impacts of LED upgrade on nighttime crashes. It is needed to develop or calibrate CMFs for LED lighting based on FDOT District LED upgrade projects conducted in the past decade. The enhanced computer tools in Phase II will integrate the CMFs for LED lighting and provide a function to stratify stakeholder needs in assessing the safety performance/benefits of LED lighting projects.

This study focused on the following objectives:

- Address the safety effectiveness of LED lighting technologies to preventing nighttime crashes.
- Evaluate the visibility performance of LED colors in terms of human's detection distance.

3.2 Experiment Design

The research team collected a 2018 inventory of LED lighting poles on major corridors in the Tampa Bay area, as shown in Figure 3-2, from FDOT District 7. The inventory provides the location information and lamp types (HPS, LED, or unknown) for each lighting pole. However, it does not include the starting date of LED poles, and it impossible to identify the before (HPS) and after (LED) periods from the inventory. Thus, this study could not apply the before-after study to compare nighttime crash frequencies before and after upgrading HPS to LED at the same sites. Alternatively, a cross-sectional study, which compares nighttime crash frequencies between two site groups (with and without LEDs) during the same time frame, was used in this study.

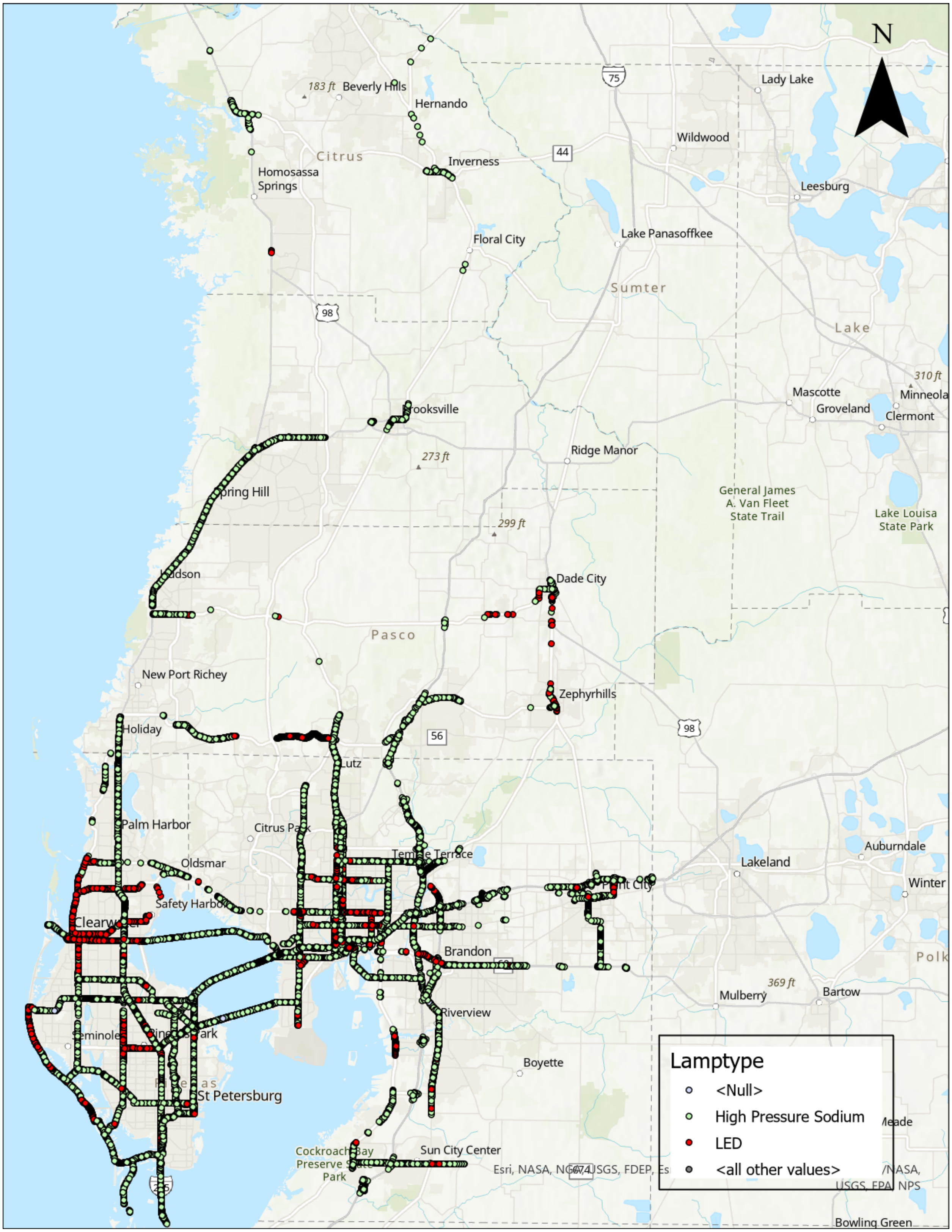


Figure 3-2. LED and HPS lighting poles in Tampa Bay area

3.3 Data Preparation

The procedure for data collection and processing is given in Figure 3-3.

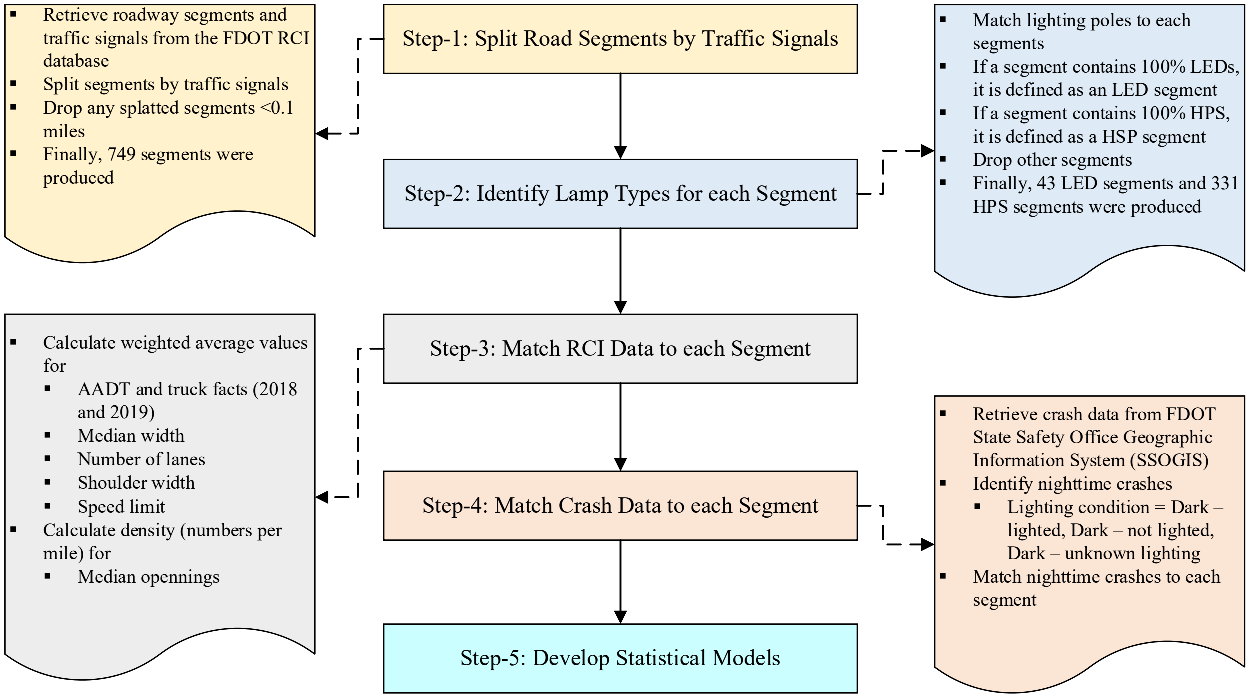


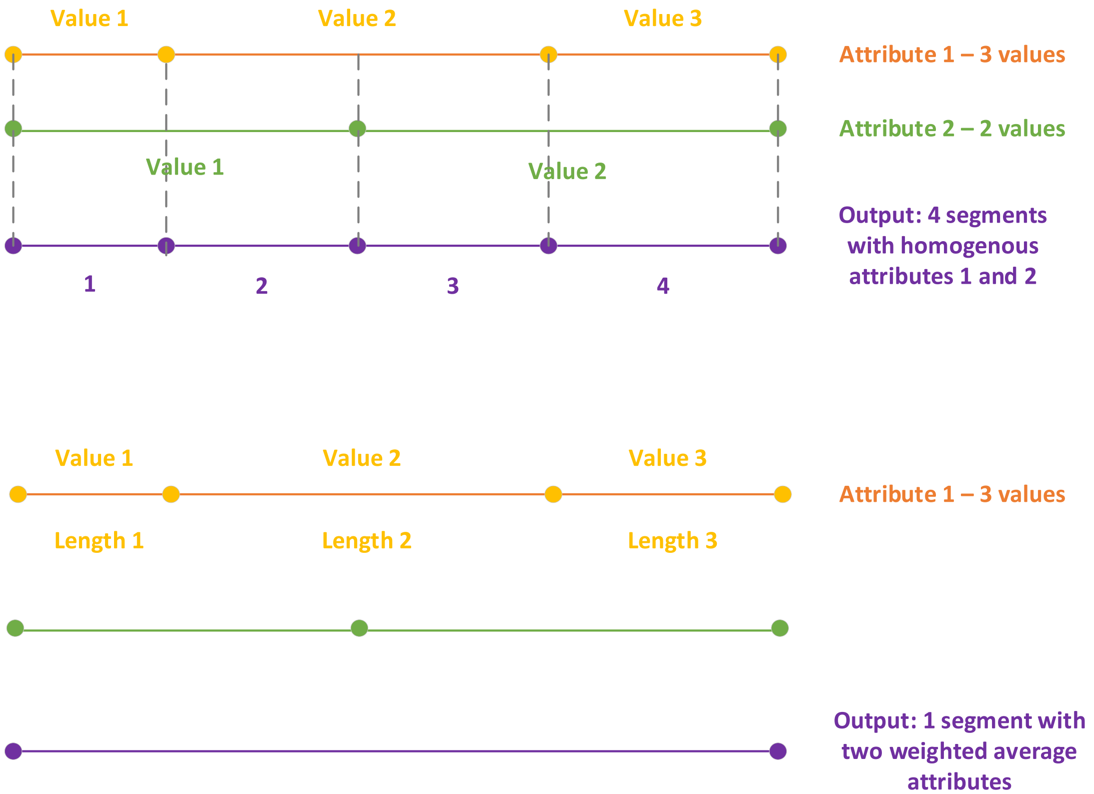
Figure 3-3. Procedure for data collection in LED study

Data Sources

Three data sources were used in this study. The inventory of FDOT D7 lighting poles in 2018 was provided by FDOT District 7 and included locations and lamp types of street lighting poles. The traffic and geometric information were retrieved from the FDOT Roadway Characteristics Inventory (RCI) database, and historical crash data were obtained from the FDOT State Safety Office Geographic Information System (SSOGIS).

RCI Data Matching Method

RCI data (traffic and geometries) were matched to each segment. For statistical modeling, the *Highway Safety Manual* (*45*) advises that segments need to be divided into homogenous sections in which roadway characteristics are similar. However, homogenous segmentation may result in very short segments and lead to a zero-inflated issue (*46*). To avoid this, the research team adopted the aggregation method (aggregating roadway characteristics for a long segment). The two methods are explained in Figure 3-4. In addition, any segments shorter than 0.1 miles were removed from the dataset to avoid bias estimation (*47*).



$$\text{Weighted Average Attribute} = \frac{\text{Value}_i \times \text{Length}_i}{\text{Length}_i}$$

Figure 3-4. RCI data matching methods

Analysis Time Frame

The inventory of lighting poles does not include information on activation date for LED lighting poles; the only information is LED poles in activated status in 2018. To minimize identification errors for lamp types, the analysis time frame was adopted as two years—2018 and 2019. It is assumed that FDOT did not change the lamp types (LED and HPS) in those two years. Nighttime crash frequencies were counted for the two years for each segment, and traffic information (AADT and truck percentage) were matched by the two years for each segment; their yearly weighted averages were calculated using the method described in Figure 3-4.

A final dataset containing 418 segments was produced for statistical modeling. The descriptive statistics of the dataset are shown in Table 3-2.

.

Table 3-2. Descriptive Statistics of Collected Data for LED Study (obs = 418)

Variable	Mean	Std	Min	Max
Nighttime crashes, 2018 and 2019	14.978	16.036	0	151
LED segment (1 = yes, 0 = no)	0.103	0.304	0	1
Segment length (mi)	0.611	0.693	0.1	5.575
Yearly weighted average AADT, 2018 and 2019	76520.09	38633.34	1300	273200
Yearly weighted average truck factor, 2018 and 2020	9.096	4.550	3.2	27.7
Weighted lane width (ft)	11.778	0.781	10	16
Weighted lane width (ft)	23.944	13.257	0	117.727
Weighted speed limit (mph)	45.136	6.265	30	62
Density of unsignalized intersections	10.638	7.472	0	43.716

3.4 Model Development

Nighttime crashes are a typical count data with overdispersion (variance > mean). The negative binomial (NB) model was used to account for over-dispersion in count data. The model can be written as (*48*):

$$\Pr(y_i) = \frac{\Gamma\big((1+\alpha)+y_i\big)}{\Gamma(1/\alpha)y_i!}\left(\frac{1/\alpha}{(1/\alpha)+\lambda_i}\right)^{1/\alpha}\left(\frac{\lambda_i}{(1/\alpha)+\lambda_i}\right)^{y_i} \tag{5}$$

where $\Pr(y_i)$ is the probability of segment i having y_i crashes occurring per a given period (e.g., one year); $\Gamma(\cdot)$ is a gamma function; λ_i is the expected number of crashes per period at segment i as a function of explanatory variables; α is the over-dispersion parameter. The log-linear form of λ_i can be expressed as

$$\lambda_i = E\lfloor y_i \rfloor = EXP(X_i\beta + \varepsilon_i) \tag{6}$$

where $EXP(\varepsilon_i)$ represents a Gamma-distributed disturbance term with mean 1 and variance α. X_i denotes the vector of explanatory variables; and β is the vector of coefficients.

CMF is the comparison of crash frequencies with and without a trament. For a binary variable (x_k:1 – with treatment, 0 – without treatment), its CMF can be written as:

$$CMF = \frac{Crashes\ with\ Treatment}{Crashes\ without\ Tratement} = \frac{e^{\beta_k \cdot 1 + \sum \boldsymbol{\beta_i} \cdot \boldsymbol{X_i}}}{e^{\beta_k \cdot 0 + \sum \boldsymbol{\beta_i} \cdot \boldsymbol{X_i}}} = e^{\beta_k}$$

(7)

where β_k is the coefficient for x_k; $\boldsymbol{x_i}$ and $\boldsymbol{\beta_i}$ are other independent variables and associated coefficients, assuming they are constant over sites.

The statistical package STATA 16 was used to estimate the NB model for nighttime crashes. A step-wise method was used to select independent variables. Any variables with a significance higher than 90% were included in the model. The fitted model is shown in Table 3-3.

Table 3-3. Fitted Negative Binominal Model for LED Study

	Coefficient	S.E.	z-statistics	*p*-value	[95% conf. interval]	
Constant	-5.904	0.633	-9.32	0	-7.145	-4.662
Logarithm of yearly weighted average AADT	0.777	0.056	13.77	0	0.666	0.887
Logarithm of segment length	0.546	0.044	12.41	0	0.460	0.632
Density of unsignalized intersections	0.026	0.005	5.1	0	0.016	0.036
LED corridor indicator (1 = LED, 0 = HPS)	-0.191	0.115	-1.66	0.098	-0.417	0.035
alpha (overdispersion factor)	0.394	0.034			0.333	0.467
Model Statistics						
Number of observations	416					
Log likelihood	-1418.768					
Pseudo R^2	0.0837					
Degree of freedom	6					
AIC	2849.536					
BIC	2873.72					

3.5 Conclusions

The sign of LED segment indicator is a negative value and significant at a confidence level of 91%. It can be concluded that, compared to HPS, LED tends to decrease nighttime crash frequency on a roadway segment. The CMF for LED is derived from Eq. 7 as

$$CMF = e^{-0.191} = 0.83$$

If the lighting system on a roadway segment is upgraded from HPS to LED, nighttime crash frequency is more likely to be reduced by 17% (=1-0.83*100%). This result indicates that LED not only introduces economic benefits (i.e., long service life and energy saving) but also brings safety benefits. The safety benefits of LED lighting is evidenced by its better performance for driver vision; the higher blue content of the LED light spectrum can render LEDs brighter than conventional light sources at the same lumen output.

This study did not include lighting pattern parameters (i.e., horizontal illuminance) due to the absence of lighting data on the study corridors in 2018. Thus, comparison of LED and HPS could not exclude the influence from different lighting patterns. The CMF can explain the benefits of upgrading projects in FDOT District 7, but it may be biased to interpret the safety improvement from HPS to LED with the same lighting photometric patterns (i.e., same lighting level or same uniformity). A future study will collect enough data to address this issue.

Chapter 4: Upgrading Lighting Uniformity Diagnosis Algorithm

4.1 Problem Statement

Uniformity is a measurement of how equally light is distributed on a road. A good uniformity design improves both visibility and visual comfort for drivers (*6*). Many transportation agencies have adopted two illuminance ratios—max-min ratio (MMR) and average-min ratio (AMR)—to measure roadway lighting uniformity:

$$\mathrm{MMR} = \frac{\mathrm{HFC_{Max}}}{\mathrm{HFC_{min}}} \qquad \mathrm{AMR} = \frac{\mathrm{HFC_{Avg}}}{\mathrm{HFC_{min}}} \tag{5}$$

FDOT's *Florida Design Manual* establishes a requirement of 4:1 or lower uniformity ratio for AMR and 10:1 or lower uniformity ratio for MMR, as shown in Table 4-1.

Table 4-1. FDOT Conventional Roadway Lighting Requirements

Road Classification	Illumination Level Average Initial HFC	Uniformity Ratios	
		Avg/ Min	***Max/Min***
Interstates, Expressways, Freeways, Major Arterials	1.5	4:1 or less	10:1 or less
All other roadways	1.0	4:1 or less	10:1 or less
Pedestrian ways and bicycle lanes	2.5	4:1 or less	10:1 or less

In practice, simply calculating the MMR and AMR for a whole segment may introduce extremely high ratio values and may not accurately capture the "true" pattern features influencing driver vision on a roadway corridor. For example, as shown in Figure 4-1, the uniformity for the whole roadway segment is the ratio of the maximum value (1.5 fc) over the minimum value (0.1 fc), equal to 15. The maximum illuminance point, however, is far from the minimum illuminance point. The change from minimum illuminance to maximum illuminance does not influence driver vision; the true pattern that deteriorates the vision is the change from a low-lit zone (0.1 fc) to a high-lit zone (0.9 fc) in successive subsections along the travel route.

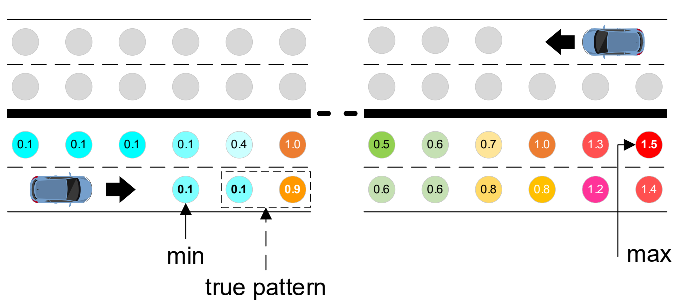


Figure 4-1. Example of ratio-based uniformity calculation for a whole roadway segment

4.2 Sliding Window Algorithm

This study developed an sliding window diagnosis algorithm to better address the uniformity pattern along a corridor. When driving along a road segment, a driver needs to continuously scan the front to detect any potential risk. The field of driver vision is a function of travel speed, as shown in Figure 4-2.

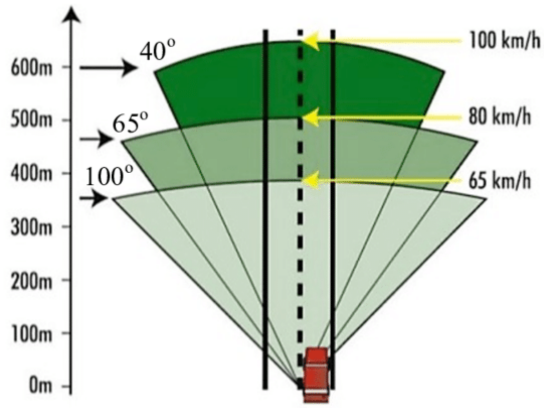


Figure 4-2. Field vision and speed *(49)*

In night driving, driver vision is influenced by the lighting pattern within the field of vision rather than the whole segment. Thus, the calculation of uniformity should be applied on a window that covers the field of vision rather than the whole segment.

Figure 4-3 shows the concept of the sliding window algorithm, which creates a series of windows along a road segment from the beginning of segment to the end of segment in small steps. The windows, which are a rectangle with parameterized dimension (length and width), represent the fields that influence driver vision at each moment when driving on the segment. The uniformity measures, MMR and AMR, are calculated for each window. The windows may be overlapped, as the move step is usually smaller than the window length. The uniformity measures for the overlapped area adopt the "worst case"—the maximum uniformity measures of the overlapped windows.

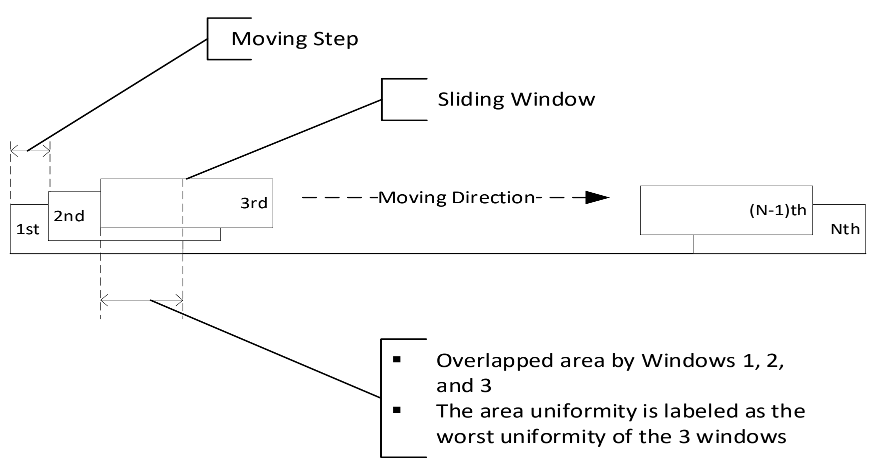


Figure 4-3. Concept of sliding window algorithm for uniformity diagnosis

Finally, the areas with an issued uniformity (does not satisfy the DOT standards) are labeled. Percentage of issued uniformity, weighted average uniformity, and worst uniformity performance are calculated for each section.

The detailed algorithm is described in Figure 4-4 and Figure 4-5. The terms used in the algorithm are as follows:

- **Window** – a rectangle covers a driver's vision field when driving; the window is the unit for uniformity calculation, and the window dimension can be configured:
  - *Length* – determined by stopping sight distance, which is a function of speed; 600 ft is default value.
  - *Width* – for undivided roads, width suggested to cover all through lanes or, otherwise, through lanes on one side.
- **Moving step** – distance between two adjacent windows, representing the uniformity scan resolution; a smaller moving step may introduce additional processing time; the default value is 100 ft.
- **Slice** – area overlapped by sliding windows; its uniformity is labeled by the worst uniformity measure of the overlapped windows.
- **Section** – aggregation of neighboring slices that have similar uniformity; length of section should satisfy minimum length; final statistics calculated based on sections.

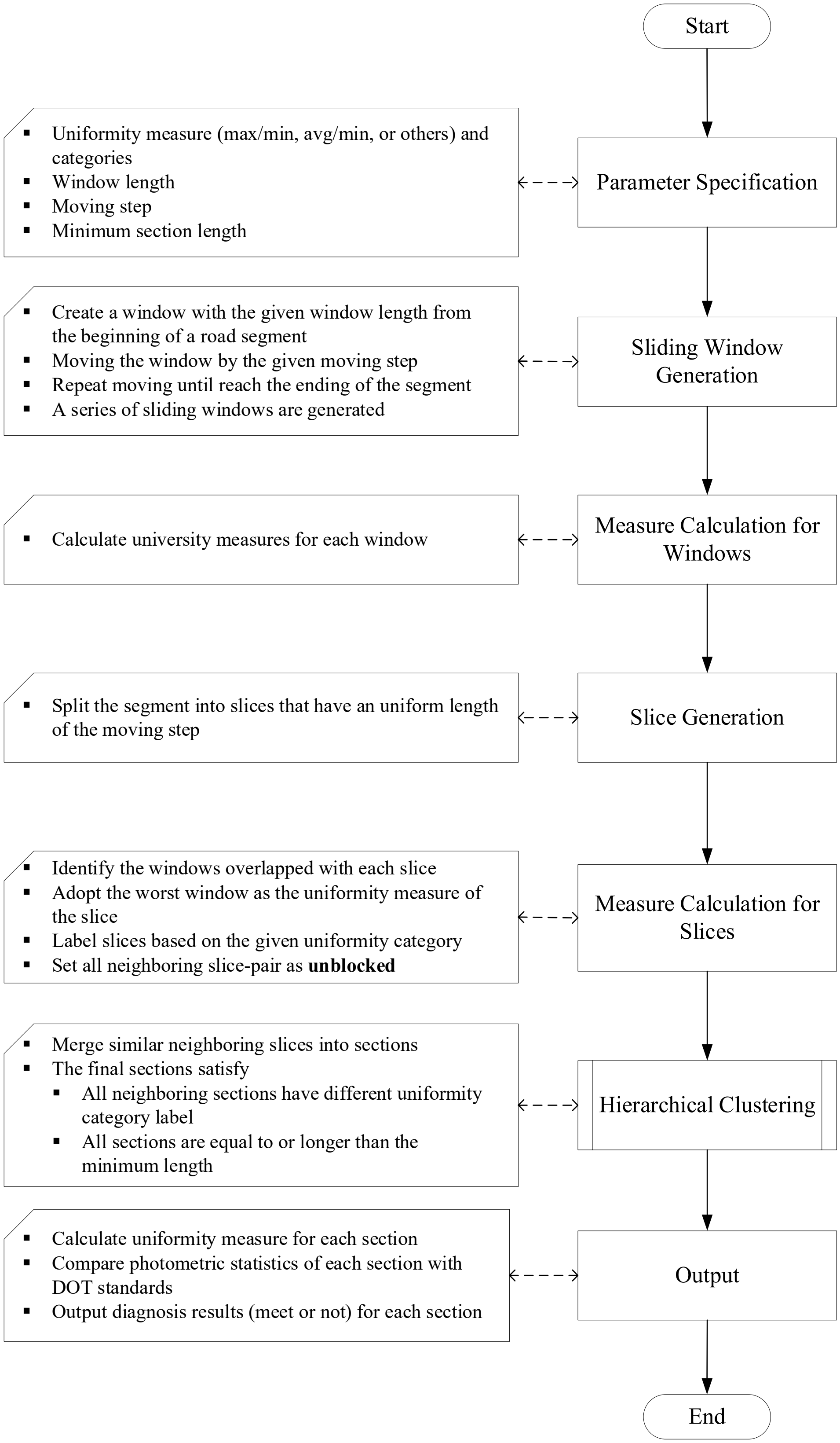


Figure 4-4. Sliding window algorithm for uniformity diagnosis

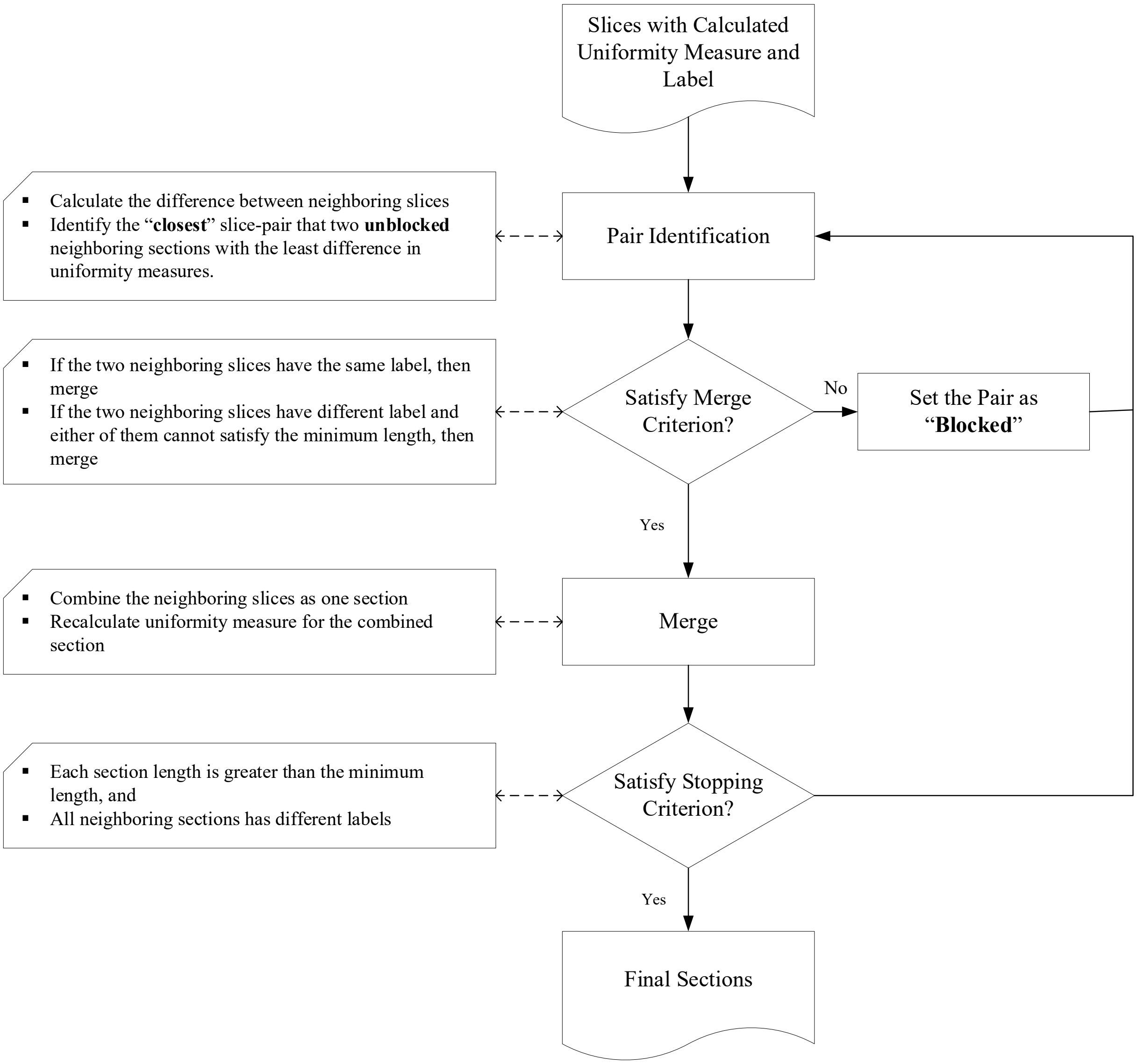


Figure 4-5. Hierarchical clustering for slice merging

4.3 Example of Sliding Window Algorithm

Lighting data were collected on a 0.5-mile segment (College Ave between US-41 and 7th St SE, Ruskin, FL). The segment layout and lighting data are shown in Figure 4-6. Lighting statistics are shown in Table 4-2.

Figure 4-6. Lighting data for 0.5-mile segment

Table 4-2. Horizontal Illuminance Statistics for Whole Segment, College Avenue in Ruskin, FL

LT Points	Average	Max	Min	MMR	AMR
1,106	0.56 fc	2.21 fc	0.1 fc	22.1	5.6

This study applied the sliding window diagnosis algorithm using the following parameters:

- **Uniformity measure**: MMR (max-min ratio)
- **Window Length**: 600 ft (0.114 mi)
- **Window Width**: all through lanes on both sides
- **Moving Step**: 100 ft (0.019 mi)
- **Minimum Length of Final Sections**: 0.1 mi
- **Uniformity Categories** (category for demonstration only):
  - 1 – MMR ≤ 10 (meets FDOT standard)
  - 2 – 10<MMR≤20 (does not meet FDOT standard)
  - 3 – 20<MMR≤30 (significantly does not meet FDOT standard)
  - 4 – MMR> 30 (extremely does not meet FDOT standard)

Step 1: Generate windows and calculate MMR. A series of window was created along the segment in a moving step of 0.114 miles. MMR was calculated for each window. The sliding windows and uniformity measures are shown in Table 4-3.

Table 4-3. Sliding Windows and Uniformity Measures

Window	BMP	EMP	Average	Max	Min	MMR
1	0	0.114	0.55	1.69	0.13	12.97
2	0.019	0.133	0.56	1.69	0.17	9.94
3	0.038	0.152	0.59	1.69	0.17	9.94
4	0.057	0.17	0.51	1.62	0.14	11.36
5	0.076	0.189	0.45	1.62	0.13	12.27
6	0.095	0.208	0.41	1.34	0.13	10.14
7	0.114	0.227	0.50	1.81	0.13	13.68
8	0.133	0.246	0.60	1.94	0.13	14.65
9	0.152	0.265	0.58	1.94	0.13	14.65
10	0.17	0.284	0.58	1.94	0.13	14.65
11	0.189	0.303	0.60	1.94	0.13	14.42
12	0.208	0.322	0.70	2.21	0.10	21.39
13	0.227	0.341	0.65	2.21	0.10	21.39
14	0.246	0.36	0.57	2.21	0.10	21.39
15	0.265	0.379	0.53	2.21	0.10	21.39
16	0.284	0.398	0.51	2.21	0.10	21.39
17	0.303	0.417	0.59	2.21	0.10	21.39
18	0.322	0.436	0.57	1.72	0.10	16.64
19	0.341	0.455	0.59	1.72	0.12	14.05
20	0.36	0.473	0.63	1.72	0.12	14.05
21	0.379	0.492	0.61	1.72	0.13	13.66
22	0.386	0.5	0.62	1.72	0.14	12.60

Step 2: Generate slices. A slice represents a small area in which multiple windows are overlapped; the slice length is the moving step (0.019 miles). For example, Slice 4 (0.057 – 0.076) is the overlapping area for Window 1 (0 – 0.114), Window 2 (0.019 – 0.133), Window 3 (0.038 – 0.152), and Window 4 (0.057 – 0.17). As Window 1 has the worst uniformity (MMR = 12.97), the uniformity for Slice 4 is labeled as 12.97. The slices and associated uniformity measures are given in Table 4-4.

Table 4-4. Slice Generation

Slice	BMP	EMP	MMR
1	0	0.019	12.97
2	0.019	0.038	12.97
3	0.038	0.057	12.97
4	0.057	0.076	12.97
5	0.076	0.095	12.97
6	0.095	0.114	12.97
7	0.114	0.133	13.68
8	0.133	0.152	14.65
9	0.152	0.17	14.65
10	0.17	0.189	14.65
11	0.189	0.208	14.65
12	0.208	0.227	21.39
13	0.227	0.246	21.39
14	0.246	0.265	21.39
15	0.265	0.284	21.39
16	0.284	0.303	21.39
17	0.303	0.322	21.39
18	0.322	0.341	21.39
19	0.341	0.36	21.39
20	0.36	0.379	21.39
21	0.379	0.398	21.39
22	0.398	0.417	21.39
23	0.417	0.436	16.64
24	0.436	0.455	14.05
25	0.455	0.473	14.05
26	0.473	0.492	13.66
27	0.492	0.5	12.60

Step 2: Merge slices. Table 4-5 shows the sections that merge neighboring slices with the same MMR values. The MMR category is assigned to each section. Compared to the MMR for the whole segment (MMR=22.1), the sliding window algorithm gives more detailed information on the uniformity pattern. Table 4-5 indicates that uniformity of all sections does not meet the FDOT standard; however, Section 4 (0.208-0.417) has the worst uniformity (MMR=21.39). The weighted average MMR for this segment is calculated as

$$Weighted\ Average\ MMR = \frac{\sum MMR_i \times Length_i}{\sum Length_i} = 17.01$$

The diagnosis results are displayed in Figure 4-7.

Table 4-5. Merge Slices by Value to Sections

Section	BMP	EMP	MMR	Category
1	0	0.114	12.97	2
2	0.114	0.133	13.68	2
3	0.133	0.208	14.65	2
4	0.208	0.417	21.39	3
5	0.417	0.436	16.64	2
6	0.436	0.473	14.05	2
7	0.473	0.492	13.66	2
8	0.492	0.5	12.60	2

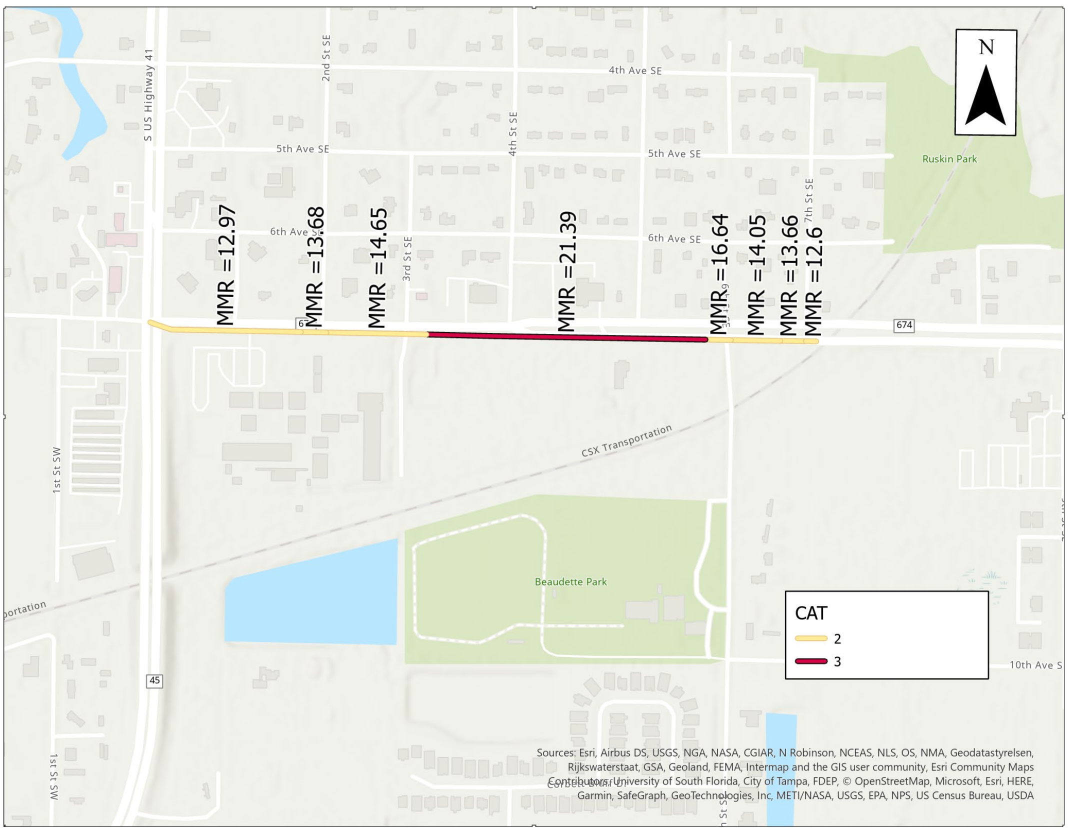


Figure 4-7. Display of uniformity diagnosis results

Step 3: Hierarchical Clustering (Optional). The sections can be clustered based on the uniformity category. For example, Sections 1, 2, and 3 in Table 4-5 have the same category (Category 2) and can be merged into one section. Sections 5–8 in 4-4 also have the same category (Category 2). However, the total length of the four sections is 0.083 miles, less than the minimum length for the final sections (0.1 miles). Thus, the four sections were combined with Section 4 in Table 4-5. The final sections are shown in Table 4-6.

Table 4-6. Slice Merge by Category using Hierarchical Clustering

Section	BMP	EMP	Length	Category
1	0	0.208	0.208	2
2	0.208	0.5	0.292	3

Chapter 5: Software Development

The computer tools developed in Phase I were built on an Esri Web-GIS platform and a map was integrated for data visualization, such as roadway inventory, heatmaps, analysis results, and figures. Based on the prototype developed in Phase I, this study recoded the analysis engine to integrate the uniformity of a diagnosis algorithm developed in this study and to optimize the speed of the existing algorithms. The analysis engine is coded as a pure Python package and can run as a stand-alone application or a Python toolbox in ArcGIS Pro. The system architecture of analysis engine is shown in Figure 5-1.

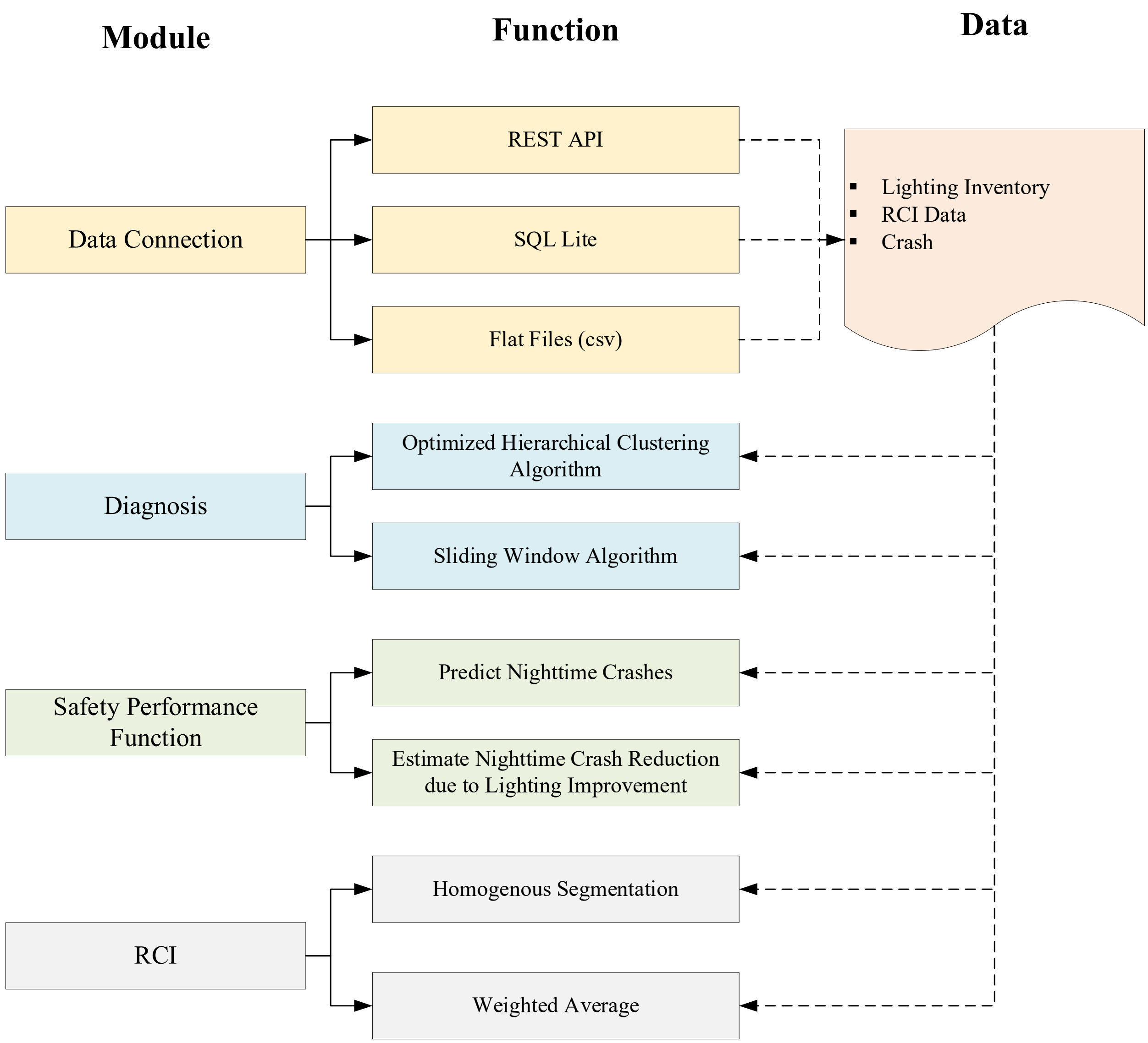


Figure 5-1. System architecture of analysis engine

The major modules include:

- **Data Connection** – provides a logic layer to separate analysis functions from data sources. The module can access lighting data, roadway characteristics inventory (RCI) data, and crash data from different sources, such as web service (REST API), local database (SQLLite), or flat text files. The retrieved data will be provided to other modules.
- **Diagnosis** – provides two major diagnosis functions—(1) hierarchical clustering algorithm for lighting level diagnosis, and (2) sliding window algorithm for uniformity diagnosis.
- **Safety Performance Function (SPF)** – predicts nighttime crashes based on lighting data, geometries, and traffic data for a segment; can also estimate the benefits (crash reduction) due to a lighting improvement.
- **RCI** – processes geometry and traffic data obtained from the FDOT RCI database for SPFs; provides two major functions—s: (1) homogenous segmentation and (2) weighted average. The detailed information of the two functions is given in Figure 3-4.

The study optimized the algorithms to improve the running speed. Figure 5-2 shows the comparison of applying the hierarchical clustering diagnosis algorithm on the same segment before and after optimization. With the optimization, the running time is reduced from 504 seconds to 53 seconds. The optimized algorithm can be used on a big-scale network.

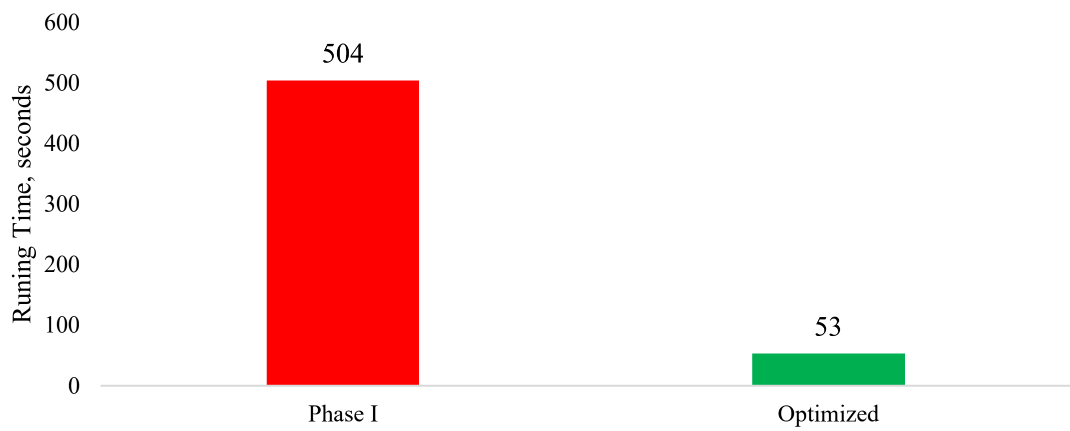


Figure 5-2. Comparison of running time for applying hierarchical clustering diagnosis on Rickenbacker Drive, Ruskin, FL

Chapter 6: Summary and Conclusions

6.1 Summary and Conclusions

Roadway lighting is a conventional roadway infrastructure to ensure nighttime safety and security for multimodal road users (motorists, pedestrians, cyclists, transit passengers). To cost-effectively maintain a roadway lighting system, key tasks in infrastructure management include periodically measuring roadway lighting levels, diagnosing lighting performance based on collected data, and providing decision-making support for maintenance and improvement.

The ALMS developed by CUTR provides a low-cost and time-effective solution for collecting high-resolution lighting data for a big-scale roadway network. A previous CTEDD-study, "Development of Automated Roadway Lighting Diagnosis Tools for Nighttime Traffic Safety Improvement, Phase I," developed improved an analysis tool to diagnosis lighting patterns and predict nighttime crash risks based on the big lighting data. This Phase II study enhanced the tool in terms of investigating the impacts of lighting patterns on nighttime pedestrian crashes, addressing the effectiveness of LED technologies, developing a sliding window algorithm for uniformity diagnosis, and recoding the analysis engine to integrate more functions and improving processing speed.

Major conclusions from this study include the following:

- Both the mean of horizontal illuminance (representing average lighting level) and the standard deviation of horizontal illuminance (representing uniformity) significantly impact nighttime pedestrian crashes on roadway segments. For average lighting level, taking the low HFC mean (<0.2 fc) as the baseline, the CMFs for medium [0.2 fc, 0.5 fc], medium-high (0.5 fc, 1.0 fc], and high (>1.0 fc) illuminance means are 0.225, 0.188, and 0.145, respectively. For lighting uniformity, compared to low HFC standard deviation (<0.52 fc), the CMF for high illuminance standard deviation (≥ 0.52 fc) is 1.803.
- Upgrading the conventional lighting system (HPS technologies) to LED lighting tends to decrease nighttime crash frequency. The CMF for LED lighting upgrading is 0.83, which can be used to evaluate the benefits of roadway lighting upgrading projects in Florida.
- Ratio-based uniformity measures (max-min ratio, average-min ratio) for the whole segment may introduce extremely high values and cannot capture the true lighting pattern influencing driver vision. The sliding window algorithm scans the lighting patterns along a segment and calculates the uniformity measures within a limited area covering a driver's vision field. The algorithm can provide more reasonable and detailed diagnosis of lighting uniformity.
- The recoded analysis engine contains more functions and greatly improves processing speed. The engine can be executed as a stand-alone application or can be integrated into ArcGIS Pro or the Web-GIS tool developed in Phase I. The improved processing speed allows applying the analysis to a big-scale roadway network.

6.2 Implementation

The CUTR team is working with FDOT District 7 to collect and analyze lighting data on District-wide state roads under contract FDOT BDV25 762-30. As shown in Figure 6-1, the identified corridor segments within the district include:

- 171 State Road segments with streetlights
- 412 total centerline mileage is **412** miles
- The total lane mileage is **1,926** miles.

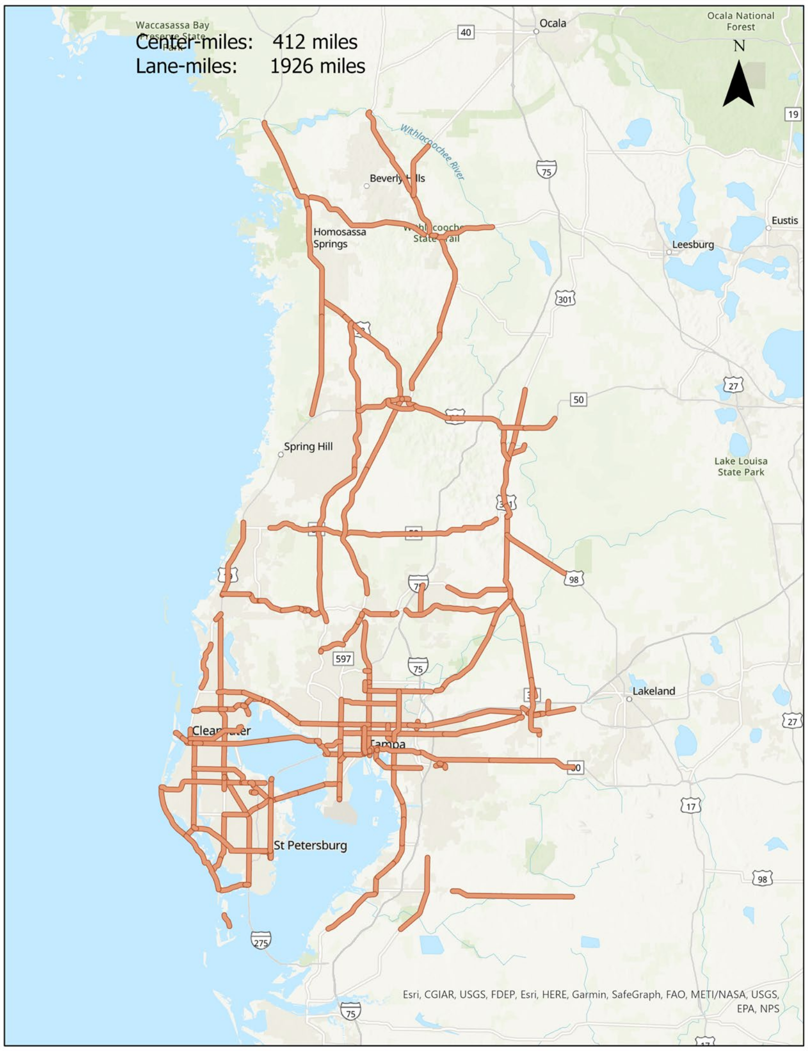


Figure 6-1. FDOT District 7 district-wide lighting data collection and analysis

The analysis methods and engine developed in this study will be used to analyze the district-wide lighting data and provide decision-making support to FDOT for their roadway lighting management and maintenance.

References

1. Johnson, M., A. Fabregas, Z. Wang, S. Katkoori, and P.-S. S. P.-S. Lin. Embedded System Design of an Advanced Illumination Measurement System for Highways. 2014.

2. NHTSA. Fatality Analysis Reporting System. http://www-fars.nhtsa.dot.gov/QueryTool/QuerySection/Report.aspx. Accessed Jul. 7, 2021.

3. Nabavi Niaki, M. S., T. Fu, N. Saunier, L. F. Miranda-Moreno, L. Amador, and J.-F. Bruneau. Road Lighting Effects on Bicycle and Pedestrian Accident Frequency: Case Study in Montreal, Quebec, Canada. *Transportation Research Record*, Vol. 2555, No. 1, 2016, pp. 86–94.

4. Zhou, H., and P. Hsu. Effects of Roadway Lighting Level on the Pedestrian Safety. In *ICCTP 2009: Critical Issues In Transportation Systems Planning, Development, and Management*, pp. 1–9.

5. Srinivasan, R., D. Carter, S. Smith, and B. Lan. Safety Evaluation of Converting Traffic Signals from Incandescent to Led Bulbs. *Transportation research record*, Vol. 2398, No. 1, 2013, pp. 9–18.

6. FHWA. *FHWA Lighting Handbook*. Washington, DC, 2012.

7. Gibbons, R. B., C. J. Edwards, B. M. Williams, and C. K. Andersen. *Informational Report on Lighting Design for Midblock Crosswalks*. United States. Federal Highway Administration, 2008.

8. Thomas, L., L. Sandt, C. Zegeer, W. Kumfer, K. Lang, B. Lan, Z. Horowitz, A. Butsick, J. Toole, and R. J. Schneider. *Systemic Pedestrian Safety Analysis*. 2018.

9. Jensen, S. Pedestrian Safety in Denmark. *Transportation Research Record*, Vol. 1674, No. 1, 1999, pp. 61–69.

10. Siddiqui, N. A., X. Chu, and M. Guttenplan. Crossing Locations, Light Conditions, and Pedestrian Injury Severity. *Transportation research record*, Vol. 1982, No. 1, 2006, pp. 141–149.

11. Sullivan, J. M., and M. J. Flannagan. Determining the Potential Safety Benefit of Improved Lighting in Three Pedestrian Crash Scenarios. *Accident Analysis & Prevention*, Vol. 39, No. 3, 2007, pp. 638–647.

12. Nambisan, S. S., S. S. Pulugurtha, V. Vasudevan, M. R. Dangeti, and V. Virupaksha. Effectiveness of Automatic Pedestrian Detection Device and Smart Lighting for Pedestrian Safety. *Transportation research record*, Vol. 2140, No. 1, 2009, pp. 27–34.

13. Mohamed, M. G., N. Saunier, L. F. Miranda-Moreno, and S. V Ukkusuri. A Clustering Regression Approach: A Comprehensive Injury Severity Analysis of Pedestrian–Vehicle Crashes in New York, US and Montreal, Canada. *Safety science*, Vol. 54, 2013, pp. 27–37.

14. Olszewski, P., P. Szagała, M. Wolański, and A. Zielińska. Pedestrian Fatality Risk in

Accidents at Unsignalized Zebra Crosswalks in Poland. *Accident Analysis & Prevention*, Vol. 84, 2015, pp. 83–91.

15. Patella, S. M., S. Sportiello, S. Carrese, F. Bella, and F. Asdrubali. The Effect of a LED Lighting Crosswalk on Pedestrian Safety: Some Experimental Results. *Safety*, Vol. 6, No. 2, 2020, p. 20.

16. Box, P. C. Effect of Lighting Reduction on an Urban Major Route. *Traffic engineering*, Vol. 46, No. 10, 1976, pp. 26–27.

17. Scott, P. P. *The Relationship between Road Lighting Quality and Accident Frequency*. 1980.

18. Wei, F., Z. Wang, P.-S. Lin, P. Hsu, S. Ozkul, J. Jackman, and M. Bato. Safety Effects of Street Illuminance at Urban Signalized Intersections in Florida. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2555, No. 1, 2016, pp. 95–102. https://doi.org/10.3141/2555-13.

19. Wang, Z., P.-S. Lin, Y. Chen, P. P. Hsu, S. Ozkul, and M. Bato. Safety Effects of Street Illuminance on Roadway Segments in Florida. 2017.

20. Bhagavathula, R., R. B. Gibbons, and C. J. Edwards. Relationship Between Roadway Illuminance Level and Nighttime Rural Intersection Safety. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2485, 2015, pp. 8–15. https://doi.org/10.3141/2485-02.

21. Li, Q., Z. Wang, M. Li, R. Yang, P.-S. Lin, and X. Li. Development of Crash Modification Factors for Roadway Illuminance: A Matched Case-Control Study. *Accident Analysis & Prevention*, Vol. 159, 2021, p. 106279.

22. Zhou, H., F. Pirinccioglu, and P. Hsu. A New Roadway Lighting Measurement System. *Transportation research part C: emerging technologies*, Vol. 17, No. 3, 2009, pp. 274–284.

23. Yang, R., Z. Wang, P.-S. Lin, X. Li, Y. Chen, P. P. Hsu, and A. Henry. Safety Effects of Street Lighting on Roadway Segments: Development of a Crash Modification Function. *Traffic Injury Prevention*, Vol. 0, No. 0, 2019, pp. 1–7. https://doi.org/10.1080/15389588.2019.1573317.

24. Zhao, J., H. Zhou, and P. Hsu. Correlating the Safety Performance of Urban Arterials with Lighting. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2482, 2015, pp. 126–132. https://doi.org/10.3141/2482-16.

25. Dormann, C. F., J. Elith, S. Bacher, C. Buchmann, G. Carl, G. Carré, J. R. G. Marquéz, B. Gruber, B. Lafourcade, and P. J. Leitão. Collinearity: A Review of Methods to Deal with It and a Simulation Study Evaluating Their Performance. *Ecography*, Vol. 36, No. 1, 2013, pp. 27–46.

26. Gross, F., and P. P. Jovanis. Estimation of the Safety Effectiveness of Lane and Shoulder Width: Case-Control Approach. *Journal of transportation engineering*, Vol. 133, No. 6, 2007, pp. 362–369.

27. Xin, C., Z. Wang, C. Lee, P.-S. Lin, T. Chen, R. Guo, and Q. Lu. Development of Crash Modification Factors of Horizontal Curve Design Features for Single-Motorcycle Crashes on Rural Two-Lane Highways: A Matched Case-Control Study. *Accident Analysis & Prevention*, Vol. 123, 2019, pp. 51–59.

28. Gross, F., and E. T. Donnell. Case–Control and Cross-Sectional Methods for Estimating Crash Modification Factors: Comparisons from Roadway Lighting and Lane and Shoulder Width Safety Effect Studies. *Journal of safety research*, Vol. 42, No. 2, 2011, pp. 117–129.

29. Gross, F. Case–Control Analysis in Highway Safety: Accounting for Sites with Multiple Crashes. *Accident Analysis & Prevention*, Vol. 61, 2013, pp. 87–96.

30. Woodward, M. *Epidemiology: Study Design and Data Analysis*. CRC press, London, 2013.

31. Schlesselman, J. J. *Case-Control Studies: Design, Conduct, Analysis*. Oxford university press, 1982.

32. Sahai, H., and A. Khurshid. *Statistics in Epidemiology: Methods, Techniques and Applications*. CRC press, 1995.

33. Gross, F., B. Persaud, and C. Lyon. *A Guide to Developing Quality Crash Modification Factors*. 2010.

34. Breslow, N. E., N. E. Day, K. T. Halvorsen, R. L. Prentice, and C. Sabai. Estimation of Multiple Relative Risk Functions in Matched Case-Control Studies. *American Journal of Epidemiology*, Vol. 108, No. 4, 1978, pp. 299–307.

35. CUTR. Advanced Lighting Measuremetn System. http://its.cutr.usf.edu/alms/.

36. Abdel-Aty, M., N. Uddin, A. Pande, F. Abdalla, and L. Hsia. Predicting Freeway Crashes from Loop Detector Data by Matched Case-Control Logistic Regression. *Transportation Research Record: Journal of the Transportation Research Board*, No. 1897, 2004, pp. 88–95.

37. Davis, G. A., S. Davuluri, and J. Pei. Speed as a Risk Factor in Serious Run-off-Road Crashes: Bayesian Case-Control Analysis with Case Speed Uncertainty. *Journal of Transportation and Statistics*, Vol. 9, No. 1, 2006, p. 17.

38. Stata.com. Clogit — Conditional (Fixed-Effects) Logistic Regression. https://www.stata.com/manuals13/rclogit.pdf.

39. Box, P. C. Relationship between Illumination and Freeway Accidents. *Illuminating Engineering*, Vol. 66, No. 5, 1971, pp. 365–393.

40. Keck, M. E. A New Visibility Criteria for Roadway Lighting. *Journal of the Illuminating Engineering Society*, Vol. 30, No. 1, 2001, pp. 84–89.

41. Abdel-Rahim, A., and J. Sonnen. *Potential Safety Effects of Lane Width and Shoulder Width on Two-Lane Rural State Highways in Idaho*. Idaho. Transportation Dept., 2012.

42. Anoop, P. A., T. B. Aswathy, K. B. Rachana, V. Chandran, and B. Paul. Analysis of

Pedestrian Risk Exposure in Thrissur City. *International research journal of engineering and technology*, Vol. 3, No. 4, 2016, pp. 2468–2471.

43. Chen, Z., and W. D. Fan. A Multinomial Logit Model of Pedestrian-Vehicle Crash Severity in North Carolina. *International journal of transportation science and technology*, Vol. 8, No. 1, 2019, pp. 43–52.

44. AASHTO. *Roadway Lighting Design Guide*. American Association of State Highway and Transportation Officials, Washington, DC, 2011.

45. AASHTO. *Highway Safety Manual*. Washington, D.C., 2010.

46. Srinivasan, R., and K. M. Bauer. *Safety Performance Function Development Guide: Developing Jurisdiction-Specific SPFs*. United States. Federal Highway Administration. Office of Safety, 2013.

47. Srinivasan, R., D. Carter, and K. Bauer. Safety Performance Function Decision Guide: SPF Calibration vs SPF Development. *Federal Highway Administration–Office of Safety Report*, 2013.

48. Washington, S. P., M. G. Karlaftis, and F. Mannering. *Statistical and Econometric Methods for Transportation Data Analysis*. CRC press, 2010.

49. Marsh, B., B. Lautner, L. Fournier, J. Klang, P. Anelli, W.-E. Kang, U. Brumec, and K. Cota. The Role of Road Engineering in Combatting Driver Distraction and Fatigue Road Safety Risks. 2017.

CENTER FOR TRANSPORTATION EQUITY, DECISIONS & DOLLARS

The **Center for Transportation, Equity, Decisions and Dollars (CTEDD)** is a USDOT University Transportation Center, leading **transportation policy research** that aids in **decision making** and **improves economic development** through **more efficient, and cost-effective use of existing transportation systems,** and offers **better access to jobs and opportunities.** We are leading a larger consortium of universities focused on **providing outreach** and **research to policy makers**, through **innovative methods** and **educating future leaders of the transportation field.**

UNIVERSITY OF TEXAS ARLINGTON

CAL POLY SAN LUIS OBISPO

Georgia Tech

USF UNIVERSITY OF SOUTH FLORIDA

WISCONSIN UNIVERSITY OF WISCONSIN–MADISON

C-TEDD@UTA.EDU | CTEDD.UTA.EDU | @UTACTEDD | @C__TEDD | @ CENTER FOR TRANSPORTATION, EQUITY, DECISIONS AND DOLLARS | 817.272.5138