SYSTEMIC NETWORK-LEVEL APPROACHES FOR IDENTIFYING LOCATIONS WITH HIGH POTENTIAL FOR WET AND HYDROPLANING CRASHES

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Keywords: wet crash, hydroplaning, systemic safety analysis, negative binomial, safety performance function, empirical Bayes, water-film thickness.

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Kenneth X. Velez-Rodriguez

ABSTRACT

Crashes on wet pavements are responsible for 25% of all crashes and 13.5% of fatal crashes in the US (Harwood et al. 1988). This number represents a significant portion of all crashes. Current methods used by the Department of Transportations (DOTs) are based on wet over dry ratios and simplified approaches to estimate hydroplaning speeds. A fraction of all wet crashes is hydroplaning; although they are related, the difference between a "wet crash" and "hydroplaning" is a wet-crash hydrodynamic-based severity scale is less compared to hydroplaning where the driver loses control. This dissertation presents a new conceptual framework design to reduce wet- and hydroplaning-related crashes by identifying locations with a high risk of crashes using systemic, data-driven, risk-based approaches and available data.

The first method is a robust systemic approach to identify areas with a high risk of wet crashes using a negative binomial regression to quantify the relationship between wet to dry ratio (WDR), traffic, and road characteristics. Results indicate that the estimates are more reliable than current methods of WDR used by DOTs. Two significant parameters are grade difference and its absolute value.

The second method is a simplified approach to identify areas with a high risk of wet crashes with only crash counts by applying a spatial multiresolution analysis (SMA). Results indicate that SMA performs better than current hazardous-road segments identification (HRSI) methods based on crash counts by consistently identifying sites during several years for selected 0.1 km sections.
A third method is a novel systemic approach to identify locations with a high risk of hydroplaning through a new risk-measuring parameter named performance margin, which considers road geometry, environmental condition, vehicle characteristics, and operational conditions. The performance margin can replace the traditional parameter of interest of hydroplaning speed. The hydroplaning risk depends on more factors than those identified in previous research that focuses solely on tire inflation pressure, tire footprint area, or wheel load. The braking and tire-tread parameters significantly affected the performance margin. Highway engineers now incorporate an enhanced tool for hydroplaning risk estimation that allows systemic analysis.

Finally, a critical review was conducted to identify existing solutions to reduce the high potential of skidding or hydroplaning on wet pavement. The recommended strategies to help mitigate skidding and hydroplaning are presented to help in the decision process and resource allocation. Geometric design optimization provides a permanent impact on pavement runoff characteristics that reduces the water accumulation and water thickness on the lanes. Road surface modification provides a temporary impact on practical performance and non-engineering measures.
Crashes on wet pavements are responsible for 25% of all crashes and 13.5% of fatal crashes in the US (Harwood et al. 1988). This number represents a significant portion of all crashes. Current procedures used by DOTs to identify locations with a high number of wet crashes and hydroplaning are too simple and might not represent actual risk. A fraction of all wet crashes is hydroplaning, although they are related to the difference between a "wet crash" and "hydroplaning" is a wet crash water-vehicle interaction is less compared to hydroplaning where the driver loses control. This dissertation presents a new procedure to evaluate the road network to identify locations with a high risk of wet crashes and hydroplaning. The risk estimation process uses data collected in the field to determine the risk at a particular location and, depending on the available data a transportation agency uses, will be the approach to apply.

The first statistical method estimates the frequency of wet crashes at a location. This estimate is developed by using a statistical model, negative binomial regression. This model measures the frequency of dry crashes, wet crashes, traffic, and road characteristics to determine the total number of wet crashes at a location. Results indicate that this option is more reliable than the current methods used by DOTs. They divide the number of wet crashes by the number of dry crashes. Two elements identified to influence the results are the difference in road grade and its absolute value.

The second statistical method to estimate wet crashes considers crash counts by applying a statistical process, spatial multiresolution analysis (SMA). Results indicate
that SMA performs better than current processes based only on the crash counts. This option can identify the high-risk location for different years, called consistency. The more consistent the method is, the more accurate is the results.

A third statistical method is a novel way to estimate hydroplaning risk. Hydroplaning risk is currently based on finding the maximum speed before hydroplaning occurs. A vehicle's performance related to the water-film thickness provides an estimation method developed by (Gallaway et al. 1971), which includes rainfall intensities, road characteristics, vehicle characteristics, and operating conditions. The hydroplaning risk depends on more aspects than tire inflation pressure, tire footprint area, or vehicle load on the wheel. The braking and tire tread affect the performance margin. Highway engineers can use this improved hydroplaning risk-estimation tool to analyze the road network.

Finally, a critical review showed the available solutions to reduce the probability of having a wet crash or hydroplaning on wet pavement. The recommended strategies to mitigate wet crashes and hydroplaning provide information to allocate resources based on proven, practical strategies. Road geometry design can be optimized to remove water from the road. This geometry is a permanent modification of pavement characteristics to reduce water accumulation and water thickness on the road. Road surface treatments and non-engineering measures provide temporary measures to improve vehicle performance or driver operation.

DEDICATION

This dissertation is dedicated to my family, friends, and every Puerto Rican considering or pursuing a professional degree. Do not let anything or anyone discourage you from succeeding in life. Everything comes with sacrifice! There might be difficult times during the process when you will think it was not for you; however, getting the degree is not impossible. I encourage you to keep strong, push through, and complete your life goals. Life is too short!
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List of Abbreviations

ADT  Average Daily Traffic
AIC  Akaike's Information Criterion
ASOS  Automated Surface Observing System
CCF  Crash Cost Frequency
CF  Crash Frequency
CFD  Computational Fluid Dynamics
CMF  Crash Modification Factor
CSTI  Center for Sustainable Transportation Infrastructure
DOT  Departments of Transportation
EB  Empirical Bayes
EPDO  Equivalent Property Damage Only
FB  Full Bayes
FI  Frequency Index
GCF  Grade Correction Factor
GLM  Generalized Linear Model
HRSI  Hazardous-road segments Identification
HSIP  Highway Safety Improvement Program
HSM  Highway Safety Manual
KABCO  Injury Scale
KDE  Kernel Density Estimation
MSPE  Mean Squared Prediction Error
NOAA  National Oceanic and Atmospheric Administration
OGFC  Open-Graded Friction Course
PAVDRN  Proposed Design Guidelines for Improving Pavement Surface Drainage
PDO  Property Damage Only
PFC  Permeable Friction Course
PM  Performance Margin
<table>
<thead>
<tr>
<th>Acronym</th>
<th>Full Form</th>
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<tbody>
<tr>
<td>PPR</td>
<td>Puerto Rico Police</td>
</tr>
<tr>
<td>PR</td>
<td>Puerto Rico</td>
</tr>
<tr>
<td>PR-SHSP</td>
<td>Puerto Rico Strategic Highway Safety Plan</td>
</tr>
<tr>
<td>PRDTPW</td>
<td>Puerto Rico Department of Transportation and Public Works</td>
</tr>
<tr>
<td>PRHD</td>
<td>Puerto Rico Health Department</td>
</tr>
<tr>
<td>PRHTA</td>
<td>Puerto Rico Highway and Transportation Authority</td>
</tr>
<tr>
<td>PRTSC</td>
<td>Puerto Rico Traffic Safety Commission</td>
</tr>
<tr>
<td>PURE</td>
<td>Poisson's Unbiased Risk Estimate</td>
</tr>
<tr>
<td>PWAH</td>
<td>Potential Wet Accident Hotspot</td>
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<tr>
<td>Q-Q</td>
<td>Quantile-Quantile</td>
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<tr>
<td>RSCA</td>
<td>Road Segment Consistency Analysis</td>
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<td>RTM</td>
<td>Regression-To-The-Mean</td>
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<tr>
<td>SCT</td>
<td>Segment Consistency Test</td>
</tr>
<tr>
<td>SE</td>
<td>Standard Error</td>
</tr>
<tr>
<td>SHSP</td>
<td>Strategic Highway Safety Plan</td>
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<tr>
<td>SLW</td>
<td>Sliding Window</td>
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<tr>
<td>SMA</td>
<td>Spatial Multiresolution Analysis</td>
</tr>
<tr>
<td>SPA</td>
<td>Spatial Autocorrelation</td>
</tr>
<tr>
<td>SPF</td>
<td>Safety Performance Function</td>
</tr>
<tr>
<td>TASAS</td>
<td>Traffic Accident Surveillance and Analysis System</td>
</tr>
<tr>
<td>USDOT</td>
<td>United Stated Departments of Transportation</td>
</tr>
<tr>
<td>VDOT</td>
<td>Virginia Department of Transportation</td>
</tr>
<tr>
<td>WDR</td>
<td>Wet Over Dry Ration</td>
</tr>
<tr>
<td>WFT</td>
<td>Water-film thickness</td>
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</table>
CHAPTER 1: Introduction

1.1 Background

The US reports that one out of ten fatal crashes is wet-pavement related (NHTSA, 2004). Wet pavements contribute to fatal crashes and overall crashes. Safety highway engineers have researched crashes, but more research is needed to address specific crash types, such as wet crashes. A fraction of all wet crashes is identified as hydroplaning crashes. Although they are related, a "wet crash" is classified as dynamic hydroplaning when lift forces caused by water accumulated in the pavement reduce the tire's contact with the pavement causing the driver to lose control. When a rolling tire encounters a film of water on the roadway, the water is channeled through the tire tread and the pavement surface macrotexture. With increasing vehicle speeds, the ability decreases for the tire-tread pattern and the pavement surface macrotexture to displace water. When the drainage capacity of the tire tread and pavement macrotexture are exceeded, a water wedge begins to build a hydrodynamic force and may provide partial or total lift to the rolling tire, which reduces the available vertical and horizontal forces in some situations (AASHTO 2018). If the reduced tractive forces are lower than those required by the vehicle to complete a specific maneuver safely, the vehicle may lose control and eventually crash. Because of their impact on the fatality rate on roadways, there is a need for data-driven systemic network analysis methodologies to identify locations with a high risk of wet pavement or hydroplaning crashes.

The latest United States federal surface transportation bill, the "America's Transportation Infrastructure Act of 2019," allowed the continuation of the Highway Safety Improvement Program (HSIP) to reduce crashes with fatalities and severe injuries on public roads. The program promotes data-driven decision-making to consider crashes, traffic, and infrastructure-related highway safety features. The HSIP supports States and territories with planning highway safety projects, implementing projects,
evaluating the effectiveness of past projects, and reporting the annual status of implemented efforts (FHWA, 2019).

Any project funded through HSIP must comply with the eligibility criteria to assure project selection has occurred (FHWA, 2019). The four criteria include:

1. Address one of the priorities established in the Strategic Highway Safety Plan (SHSP);
2. Identify projects based on data-driver processes (crash events, crash rate, or other data) using a hotspot analysis or risk-based approach;
3. The project or program must target a safety problem identified from data-driven analysis; and
4. Apply an effective countermeasure to reduce fatalities and serious injuries.

An adequate HSIP is founded on quality data and reliable risk estimates. Engineers analyze available data and provide highway safety improvement recommendations based on a sound statistical approach to identify locations with a high risk. Recent studies demonstrate that a systemic safety approach is more reliable than hot spot analysis because it allows a comprehensive network screening with better estimates of the risk at different locations (Preston et al. 2013, Gross and Harmon 2019).

1.2 Problem Statement

Wet pavements increase the risk of vehicle skidding or hydroplaning, leading to a crash. When analyzing wet pavement crashes, the wet over dry ratio (WDR) has traditionally been the parameter of interest for DOTs to identify locations with a high risk of wet crashes (McGovern et al. 2011). However, proactive systemic statistical methods applied at the network level can provide more appropriate approaches for identifying these critical locations.

In addition, the identification of locations with a high risk for hydroplaning has been based on equations to estimate a hydroplaning speed based on road geometry. For example, the program Proposed Design Guidelines for Improving Pavement Surface
Drainage (PAVDRN) used road surface geometry to compute the water-film thickness (WFT) and hydroplaning speed (Huebner et al. 1997). However, hydroplaning risk also depends on other factors, such as vehicle characteristics and operating conditions. Thus, a systemic methodology based on a multi-disciplinary analysis of the vehicle road interaction would also be beneficial to identify high hydroplane potential locations at the network level.

1.3 Objective

The objective of this dissertation is to help reduce wet- and hydroplaning-related crashes by proposing and testing systemic, data-driven, risk-based approaches for the identification of the road segment with a high risk of wet and hydroplaning crashes. The specific goals to achieve the main objective are the following:

1. Develop a robust, systemic approach to identify areas with a high risk of wet crashes, which can be used to select safety improvements to reduce wet crashes when enough data are available.
2. Propose a simplified approach to identify areas with a high risk of wet crashes with only the crash counts used only when crash data are available.
3. Propose a systemic approach to identify locations with a risk of hydroplaning, which considers road geometry, environmental condition, vehicle characteristics, and operational conditions.
4. Conduct a critical review of existing solutions for sites with a high potential of skidding or hydroplaning on wet pavement.

FIGURE 1-1 summarizes the dissertation through a potential decision-process flow diagram of the applicable methods based on available DOT data. An arrow with "yes" represents the path taken when there is available data, and an arrow with a "no" for data not available. The figure also maps different methods proposed to address the wet pavement and hydroplaning hazardous road segment identification (HRSI) to the manuscripts included in the dissertation.
The DOTs must gather their network data and select the wet or hydroplaning risk approach based on their available data. When there is interest in identifying the risky location with a lower hydrodynamic-based severity, a wet crash approach is more suitable. If a higher hydrodynamic-based severity is of interest, more detailed data are needed to apply the hydroplaning approach. Once risky locations are identified, the
listed countermeasure alternatives serve as guidance for safety improvements. Finally, future work is proposed to complete the risk assessment process.

1.4 Significance

The dissertation proposes a series of innovative approaches to investigate and identify areas of a high risk of wet and/or hydroplaning crashes considering road geometry, surface characteristics, vehicle characteristics, and operational conditions. One advantage of conducting systemic analyses is that DOTs can meet federal requirements for the Highway Safety Improvement Program and identify highway safety improvement projects by considering the crash risk and potential to reduce crashes and the severity of injuries.

The dissertation proposes systemic methodologies for identifying locations with a high risk of wet crashes and illustrates their use in a DOT that collects roadway surface properties and geometric data (Virginia) and another that only has crash data available (Puerto Rico). In both examples, the models showed good performance for identifying safety improvement locations to reduce wet crashes.

Additionally, the dissertation also provides a systemic approach to identify locations with the risk of hydroplaning, which considers significant factors affecting water accumulation and hydroplaning. Finally, solutions to improve safety on sites with a high potential of skidding or hydroplaning are presented to help reduce crashes on wet pavements.

1.5 Overview

The dissertation consists of 7 chapters, including four manuscripts in chapters 3, 4, 5, and 6.

Chapter 1 introduces the wet pavement and hydroplaning contributions to crashes and presents the background, problem statement, objective, and significance of
the work. Chapter 2 contains the literature review on factors contributing to wet and hydroplaning crashes and principal crash and hydroplaning risk analysis methods.

Chapter 3, the first manuscript, presents the proposed method for estimating wet-crash risk using a negative binomial regression and the empirical Bayes analysis. The variables found to be significant to estimate wet crashes are dry crashes, curvature, the number of lanes, ramps, ADT, speed, the difference in grade, absolute value of grade difference, average grade, and urban/rural locations. The proposed approach addressed the zero-crash count problem and provided a new option to estimate wet crashes. This method requires data on the pavement-surface characteristics and road geometry.

Chapter 4, the second manuscript, proposes a simplified methodology for crash HRSI based on the Spatial Multiresolution Analysis (SMA). The paper uses a Segment Consistency Test (SCT) to compare the consistency of the hazardous site identified with different HRSI methods and the mean-squared prediction error (MSPE) to measures the quality of the prediction. This method offers a statistical method that solely uses crash counts.

Chapter 5, the third manuscript, presents a skidding or hydroplaning risk method for systemic analysis. The method generates the road surface using measured field data, estimates the water-film thickness, and calculates a performance margin for each segment using a simplified vehicle-dynamics model. The performance margin can be used to identify areas with high hydroplaning potential.

Chapter 6, the fourth manuscript, presents available mitigation solutions to reduce the potential for wet or hydroplaning crashes. The chapter identifies proven suitable solutions to improve highway safety by mitigating wet pavement and hydroplaning risk.

Chapter 7 summarizes the dissertation, main findings, conclusions, contributions, and recommendations.
References


CHAPTER 2: Literature Review

For years, researchers have studied the factors affecting the probability of crash occurrences. Determining the exact causes of individual crashes is challenging due to limited accessibility to detailed driving data, such as acceleration, braking, and driver response. Researchers have recently focused their studies on understanding the factors that affect the expected number of crashes by considering location type (segments or intersections) and particular periods (weekly, monthly, yearly, multi-year) to find the best cause-effect estimate (Lord and Mannering 2010).

Many factors contribute to crashes, including the human, the vehicle, and road/weather-related factors (FIGURE 2-1). The road environment factor can contribute as much as 28%.

![Contributing Crash Factors](image)

**FIGURE 2-1 Contributing Crash Factors**

Crash reductions are possible by modifying human behavior, roadway weather-related conditions, road and vehicle design, and applying modern technology. Some proven strategies to reduce crashes include designing, planning, and maintaining roads to reduce crash frequency and severities; awareness campaigns to improve driver
behavior; crash reduction policies (text-drive and DUI); enforcement (speed limits, DUI, text-drive); and incorporating technology to alert drivers of potential hazards or adverse weather conditions on the road (NRC 2010).

It is common knowledge that crash risk is affected by road geometry. However, more research is needed to identify which parameters can be modified to reduce the crash frequency-severity and improve road safety (Persaud 1991, Shankar et al. 1995). Once high-risk locations are identified, it is essential to make drivers aware of potential road hazards and geometrical deficiencies. Static signs are quick and economic countermeasures; other alternatives are dynamic signs or smartphone apps (Dingus et al. 1998). When treating unsafe highways, attention should be given to road geometry events such as sharp curves, steep slopes, and high-speed segments. For example, locations with a sharp turn tend to have higher crash rates.

2.1 Crash Analysis Methods

Identifying the factors contributing to a crash is the initial step of crash analysis. Statistical methods are used to consider the factors contributing to the crash risk by quantifying the relationship between the contributing factors and potential risk. Crash estimation methods have evolved with newer technology, sophisticated statistical methods, and road safety thinking paradigm shifts. The following sections present an overview of crash and hydroplaning analysis methods that highway engineers have used to model and understand crash risk.

2.1.1 Crash Frequency

The Highway Safety Manual (HSM) defines observed crash frequency as "the number of crashes occurring at a particular site, facility, or network in a one-year period." Crash rates are the average crash frequency during a period per exposure during that same period. The crash frequency and crash rates are traditional descriptive parameters used to rank sites based on total crashes, crash type, or severity, and they are also used to estimate and evaluate the effectiveness of treatments. Locations with high crash rates or rates above a defined threshold are evaluated for potential
treatments to reduce crashes. Detailed analyses also include finding crash trends and patterns over time.

The recent three-years of crash data are often used because more crash counts improve the estimate's reliability and recent data represents current road conditions. The expected average crash-frequency estimates the $n$ years and does not account for year variations due to changes in road conditions (Herbel et al. 2010).

Several estimation methods have been developed to determine the average crash frequency. A commonly applied method assumes a similar crash frequency for all periods. Using all year counts reduces the standard error ($SE$) of the estimate; however, the quality of the estimate will not always be better than the expected number of wet crashes with more years of crash counts (Herbel et al. 2010).

Other commonly used crash frequency methods are: (1) estimating without assuming similar crash frequency in all periods, (2) estimating average crash frequency using the longer crash record history, (3) estimating average crash frequency based on historical data of similar roadways or facilities, and (4) estimating average crash frequency based on historical data of the roadway or facilities and similar roadways and facilities (Herbel et al. 2010).

The crash data has limitations since crashes are random events and change over time at any given location. Some limitations include: (1) natural variability in crash frequency, (2) regression-to-the-mean (RTM), (3) variations in roadway characteristics, and (4) conflict between crash frequency variability and changing site conditions (NRC 2010). To account for crash data limitations, more sophisticated statistical techniques are needed.

2.1.2 Regression Models

Regression analysis is a statistical procedure used to estimate the relationship between a dependent variable and one or more independent variables. Numerous studies have applied different statistical methods to estimate crashes. Research on crashes indicates that conventional linear regression models cannot adequately model
crash data, which are random, discreet, non-negative, and intermittent (Jovanis and Chang 1986, Joshua and Garber 1990, Jones et al. 1991, Miaou and Lum 1993).

Regression models in highway safety engineering are referred to as Safety Performance Functions (SPF). The main benefit of applying advanced statistical methods is that they account for most limitations, including crash variability, bias, RTM bias, error, omitted variables, and unobserved heterogeneity. Regressions also offer adequate crash estimation for new, existing, and modified existing road conditions of similar sites. A model with good reliability depends mainly on a good fit and calibration to local settings. Better crash estimates can be obtained by modeling historical crash data and the particular characteristics of different sites (AASHTO 2010).

Crashes are counts of events, and to model them adequately, it is necessary to use a count-data model. Count-data models are used for non-negative integers and to denote frequency during a specific period. Several count-data models are available, and each method has advantages and disadvantages (Basu and Saha 2017). Some examples of the methods that have been applied include:

- Poisson regression
- Negative binomial/Poisson-gamma regression
- Poisson-lognormal regression
- Zero-inflated Poisson and negative binomial regression

These regression equations will relate crashes with diverse roadway characteristics (Srinivasan and Bauer 2013).

The most broadly used models to predict rare events such as crashes are the Poisson and negative binomial regressions. However, Poisson is limited to crash data where the variance is equal to the mean. This constraint makes the Poisson model less appropriate for crashes overly-dispersed relative to the mean because they overstate or understate the likelihood of the crash (Miaou and Lum 1993). Typically, crashes are over-dispersed, which means that the variance of crash frequency is higher than the mean. Not accounting for over-dispersion results in bias model coefficients and
erroneous standard error; thus, the regression will produce an under-estimation or over-estimation of crashes.

The Poisson regression model considers the number of crashes per year at a location. It models the probability of site characteristics $i$ having $y_i$ crashes per year and can be expressed as:

$$P(y_i) = \frac{\exp(-\lambda_i) \times \lambda_i^{y_i}}{y_i!}$$  \hspace{1cm} \text{Eq. 2-1}

where, $\lambda_i$ is Poisson parameter for location $i$ and is equal to the $i$'s estimated number of crashes in a year $E(y_i)$. Poisson models estimate the expected number of crashes as a function of the road characteristics, meaning that $\lambda_i = f(\beta X_i)$, where $f$ is the function, $\beta$ is the estimable parameter or coefficient, and $X_i$ is the explanatory variable. The Poisson model is most commonly expressed as:

$$\lambda_i = \exp(\beta X_i) \text{ or } \ln(\lambda_i) = \beta X_i$$  \hspace{1cm} \text{Eq. 2-2}

The Poisson model, also known as the log-linear model, is popular for having constraints to positive values of the response. The resulting equation is a linear combination of predictors. The parameters for the generalized linear model (GLM) are estimated by maximum likelihood.

One of the Poisson distribution limitations is that the model forces the mean and variance to be equal; however, crash data often has a larger variance than the mean. This variation in crash data typically results in over-dispersion (Lord and Miranda-Moreno 2008). A suitable alternative to account for over-dispersion is the negative binomial regression model.

Negative binomial regression can be considered a special case of the Poisson distribution. The main difference to the Poisson is that a new term is added to account for over-dispersion by accommodating excess variation separately from the mean (Miaou and Lum 1993, Shankar et al. 1995). It is expressed as:
\[
\lambda_i = f(\beta X_i) \times \exp(\varepsilon_i)
\]

Eq. 2-3

where,

\[\varepsilon_i = \text{the gamma-distributed disturbance.}\]

Poisson-lognormal is a recently used alternative method to the negative binomial (Poisson-gamma). These models are similar; however, the distribution used for the \(\exp(\varepsilon_i)\) term is changed in the Poisson-lognormal from gamma to lognormal. The lognormal distribution provides greater flexibility than the gamma distribution because Poisson-lognormal does not have a closed form, but it cannot handle under-dispersion and can be unfavorably influenced by small sample size and low sample mean (Aguero-Valverde and Jovanis 2008, Lord and Park 2008).

Zero-inflated Poisson and negative binomial is a two-step modeling process. Zero-inflated models can manage data with significant amounts of zeros or more than the expected number of zeros. The zero-inflated models are sometimes applied when traditional count models cannot handle excess zero density. The zero-inflated model manages the excess zeros by establishing a splitting system to model locations without crashes versus locations with a higher potential for crashes. Zero-inflated models are used frequently to develop SPF (Shankar et al., 1997). However, the model can be limited for a long-term mean equal to zero, causing inappropriate reflection of crash-data generation and theoretical inconsistencies.

2.2 Wet Crashes Studies

In 1988, (Harwood et al. 1988) found that about 25% of all crashes and 13.5% of fatal crashes in the US occurred on wet pavement surfaces. The rate of fatal crashes on wet pavements is from 3.9 to 4.5 times the rate of fatal crashes on dry pavements (Smith and Larson 2011).

(McGovern et al. 2011) found that low friction is a significant factor in wet crashes with some estimates suggesting that a reduction of 70% in wet crashes is possible by improving friction. Friction is essential in weaving sections where the crash ratio increases by 77% in wet conditions (Wang et al. 2015). Some of the associated
factors contributing to this are the changes in acceleration, deceleration, switching lanes, and the complexity of maneuvering with traffic. Researchers suggest that high friction surface treatments could help reduce high wet-crash counts at weaving sections. Some researchers suggest that a Permeable Friction Course (PFC) could reduce wet crashes (Nicholls 1997, Nicholls and Daines 1997, Kandhal 2002, Flintsch 2004, McGhee et al. 2009). However, other studies suggest insufficient evidence for that claim (Elvik and Greibe 2005, Buddhavarapu et al. 2015).

(McGovern et al. 2011) studied the strategies different states have used to identify sections with high potential for skidding crashes. Below is a summary of the methodology seven states used to identify locations with wet crashes.

- Caltrans uses locations with three or more wet crashes in one year (6 for two years and 9 for three years) coupled with a significance test to identify locations of high wet-weather crashes. The analysis is based on a 0.2-mile window moving at 0.02-mile intervals. The significance test is based on traffic, length of time, length of section, and average wet-crash count. The average wet-crash ratio is 
  \( \frac{0.3(1-wt\%) + 3.2(R_E)}{1 + 2.2(wt\%)} \), where \( wt\% \) is the percentage of wet time and \( R_E \) is the base rate or average daily traffic (ADT) factor to total ADT, both of which can be obtained from the Traffic Accident Surveillance and Analysis System (TASAS) tables.

- Florida identifies wet-weather crash locations in two ways: (1) those with four or more wet-weather crashes with 25% or more wet-weather crashes, and (2) those with 50% or more wet-weather crashes. The analysis is performed with a 0.3-mile sliding window (SLW) at 0.1-mile increments.

- Michigan determines wet-weather crash locations based on friction testing with the locked-wheel ribbed tire.

- New York identifies wet-weather crash locations based on the total number of wet crashes and the proportion of wet crashes. The minimum total number of wet crashes is 6 for rural areas and 10 for urban areas, and the proportion of wet crashes is 35%.
• Virginia uses a potential wet-accident hotspot (PWAH) approach with crashes recorded at 0.1-mile intervals. A location is classed as PWAH when there are at least three wet-weather crashes separated by less than 0.2 miles, and the proportion of wet-weather collisions is at least 20% higher than the proportion for all roads in the area.

• New Jersey incorporates crash severity into the identification of wet-weather crash locations.

• Although not using a wet-weather crash location, Kentucky uses a roadway departure safety implementation plan.

(Larson et al. 2008) used linear regression to model the WDR as a function of several parameters. The authors were not successful in identifying the relationships between the different variables (most importantly friction) and WDR, which was perhaps due to missing essential variables in the model. (Carriquiry and Pawlovich 2004) applied Poisson regression to wet crashes as a function of several variables, including friction and road geometry. The approach did not consider data overdispersion (negative binomial model) or dry crashes in modeling the WDR.

2.3 Hydroplaning

This section provides an overview of the concept of hydroplaning and the different elements contributing to hydroplaning on wet pavement.

Hydroplaning, or aquaplaning as commonly known in Europe and Asia, occurs when a layer of water forms in front of the tire and interferes with the interaction of the asphalt and tire, causing the vehicle to lose direct physical contact with the road. FIGURE 2-2 illustrates the interaction of water on a road with a tire, especially with a layer of water. A thick layer of water forces the tire to lose contact and results in hydroplaning (Glennon 2006).
There are three types of hydroplaning: viscous, dynamic, and reverted rubber (FIGURE 2-3). Dynamic hydroplaning is usually a thick layer of water forcing the tire off the pavement, with the vehicle losing traction and the ability to brake. Viscous hydroplaning is when a thin layer of water accumulates on the pavement's surface, causing the tires to run over the water. Reverted rubber is when the tires are locked and water under the tire becomes steam (Aarons 2010).

Since water can be assumed to be incompressible, water pressure in front of the tire forces the vehicle tires away from the pavement surface. Hydroplaning occurs when the water film reaches a thickness that does not allow the tire's grooves to disperse the water out at a fast enough rate so that a water wedge begins to build a hydrodynamic force to provide partial or total lift to the rolling tire, which reduces the available vertical
and horizontal forces. If the reduced tractive forces are lower than those required by the vehicle to complete a specific maneuver safely, the vehicle may lose control (hydroplane) and eventually crash.

2.4 Factors Contributing to Skidding or Hydroplaning on Wet Pavements

Hydroplaning was of great concern in the late 1980s due to the increased number of wet crashes after speed limits were increased nationwide from 55 mph to 65 mph on rural interstates (Johnson 1980). Today, the speed limit on interstates fluctuates from 55 mph to 85 mph, depending on functional classification and state law. Studies reveal that hydroplaning potential increases when driving speeds are higher than 45 mph and water-film thickness is 1/10 inch or more for an extension of 30 feet or more (Al-Ahad Ekram and Kane 2018). Hydroplaning crashes are more likely to occur with a thick water layer on pavement and in severe weather conditions (Khattak et al. 1998).

The basic principles for skidding and hydroplaning are tire-pavement contact zone, water-film zone, and fluid drag forces (Huebner et al. 1986). The tire-pavement contact zone is where friction contributes to skid resistance in the area where the tire is in contact with the pavement. When tire-pavement contact is reduced, normal contact and horizontal traction forces are reduced, affecting the skid resistance (Fwa and Ong 2008).

The four main components contributing to hydroplaning are roadway, weather, driver, and vehicle. Multiple factors affect or increase the potential to crash by skidding or hydroplaning. TABLE 2-1 summarizes the different factors contributing to skidding and hydroplaning and the major impacts of each.
### TABLE 2-1 Hydroplaning or Skidding Contributing Factors

<table>
<thead>
<tr>
<th>Num.</th>
<th>Factor</th>
<th>Main impacts</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Speed</td>
<td>Skid resistance (friction coefficient)</td>
<td>(Allbert 1968)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(Ong and Fwa 2007)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Tire-pavement contact zone</td>
<td>(Fwa and Ong 2008)</td>
</tr>
<tr>
<td>2</td>
<td>Braking</td>
<td>Friction forces needed</td>
<td>(Srirangam et al. 2013)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(Kummer 1968)</td>
</tr>
<tr>
<td>3</td>
<td>Steering</td>
<td>Slip ratio and yaw angle</td>
<td>(Srirangam et al. 2013)</td>
</tr>
<tr>
<td>4</td>
<td>Pavement</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4.1</td>
<td>Macrotecture</td>
<td>Drainability</td>
<td>(Flintsch et al. 2003)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Pavement friction</td>
<td>(Flintsch et al. 2003)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(Kandhal 2002)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Friction (hysteresis)</td>
<td>(Flintsch et al. 2003)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Tire-pavement contact</td>
<td>(Flintsch et al. 2003)</td>
</tr>
<tr>
<td>4.2</td>
<td>Pavement Microtexture</td>
<td>Friction (adhesion)</td>
<td>(Ong et al. 2005)</td>
</tr>
<tr>
<td>4.3</td>
<td>Rutting</td>
<td>Braking distance</td>
<td>(Fwa et al. 2012)</td>
</tr>
<tr>
<td>4.4</td>
<td>Pavement Width (Number of lanes)</td>
<td>Hydroplaning crash rates</td>
<td>(Gunaratne et al. 2012)</td>
</tr>
<tr>
<td>5</td>
<td>Road characteristics and geometric design</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5.1</td>
<td>Cross-slope</td>
<td>Water accumulation and drainability</td>
<td>(Gunaratne et al. 2012)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(Kandhal 2002)</td>
</tr>
<tr>
<td>5.2</td>
<td>Grade</td>
<td>Water accumulation and drainability</td>
<td>(Gunaratne et al. 2012)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Sags and zero-grade</td>
<td>(Mounce and Bartoskewitz 1993)</td>
</tr>
<tr>
<td>5.3</td>
<td>Super-elevation</td>
<td>Water accumulation and drainability</td>
<td>(Kandhal 2002)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(Mounce and Bartoskewitz 1993)</td>
</tr>
<tr>
<td>6</td>
<td>Weather (rainfall)</td>
<td>Driver risk perception</td>
<td>(Mondal et al. 2011)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Crash rate</td>
<td>(Mondal et al. 2011)</td>
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<tr>
<td></td>
<td></td>
<td>Visibility</td>
<td>(Jung et al. 2014)</td>
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<tr>
<td></td>
<td></td>
<td>Water-film thickness</td>
<td>(Charbeneau et al. 2008)</td>
</tr>
<tr>
<td>7</td>
<td>Vehicle type</td>
<td>Tire design</td>
<td>(Sakai et al. 1978)</td>
</tr>
<tr>
<td>8</td>
<td>Tire characteristics</td>
<td>Hydrodynamic pressure</td>
<td>(Allbert 1968)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Tread wear</td>
<td>(DeVinney 1968)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Hydroplaning speed</td>
<td>(Khattak et al. 1998)</td>
</tr>
<tr>
<td>9</td>
<td>Urban/rural location</td>
<td>Wet crash and hydroplaning crash rate</td>
<td>(NHTSA, 2014)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(Rakauskas et al. 2009)</td>
</tr>
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</table>

*Speed.* (Allbert 1968) developed a predictive model to prove that the tire and wet pavement friction decreases with higher speeds because displacing the water is difficult. (Ong and Fwa 2007) found that the hydroplaning speed increases with wheel load and
tire inflation pressure, decreasing with the water-film thickness (WFT). Hydroplaning speeds are affected primarily by tire inflation pressure, secondly by WFT, and thirdly is less influenced by the wheel load. (Fwa and Ong 2008) found that increasing wheel-sliding speed reduces the wheel and pavement contact zone. This reduction is due to a higher fluid-flow speed that causes water uplift force where the fluid interacts with the tire wall. The contact-zone reduction continues until reaching zero contact, and the fluid-uplifting force equals the wheel's load. This condition results in hydroplaning.

**Breaking.** (Srirangam et al. 2013) found that friction forces declined when the slip ratio is increased. Under the hydroplaning condition, braking and direction control are almost null. (Kummer 1968) studied wet pavements with a thin WFT, indicating that the contact between the tire and the surface remains while braking through the water. Holmes' (1970) study found that in pure braking, when plotting braking-force coefficient vs. wheel-slip ratio, the braking-force coefficient increases to a peak of 7%-25% and then decreases with wheel-slip increases until reaching the lock-wheel condition.

**Steering.** (Srirangam et al. 2013) developed three-dimensional models and found that the higher the slip ratio and yaw angle with rolling tires, the higher is the hydroplaning risk.

**Pavement Surface properties**

**Macrotexture.** Macrotexture is the large-scale texture of the pavement aggregate. The wavelength ranges from 0.5 to 50 mm. A good macrotexture can help reduce hydroplaning potential because it helps drain the water from the tire-pavement interface and improves the tire-pavement contact. Materials such as open-graded friction course (OGFC) are pavement with a porous structure that improves drainability, provides better friction, reduces hydroplaning, reduces splash, and minimizes traffic noise (Kandhal 2002, Flintsch et al. 2003).

**Microtexture.** Microtexture is the small-scale texture of the pavement aggregate. The wavelength and amplitude range from 0.001 to 0.5 mm. Studies have demonstrated that appropriate microtexture results in higher friction during dry and wet conditions (Ong et al. 2005).
**Rutting.** Rutting is significant distress in asphalt pavements. The DOT’s primary concern is when pavements are wet because rutting causes water accumulation and impacts braking, leading to skidding or hydroplaning (Fwa et al. 2012).

**Pavement Width (Number of Lanes).** (Gunaratne et al. 2012) studied hydroplaning in a multi-lane facility, finding that the additional lanes generated increased hydroplaning crashes. This study used crash data from the Florida DOT’s database and the PAVDRN software to predict water accumulation (Huebner et al. 1997, Gunaratne et al. 2012).

**Road Characteristics and Geometric Design**

**Cross-slope.** Locations with zero cross-slope have a higher accumulation of water. Higher cross-slope forces water to run off the pavement to decrease water film thickness. Studies show that changing the cross slope from 1/16 to 1/4 in/ft can help reduce water depth up to 62% (Kandhal 2002, Gunaratne et al. 2012).

**Grade.** Analysis of crash data has identified that sections with downhill longitudinal grades are less safe, especially for wet pavement. Inadequate grade can increase water accumulation and increase the wet-crash rate.

**Super-elevation and transitions.** Super-elevation is the road feature that helps control centrifugal forces to keep the vehicle on the road and provide adequate traveling speeds. Super-elevation transitions provide the change in cross-slope to accommodate for higher speeds and improved water drainage. However, transition sections may result in higher water accumulation (Kandhal 2002). These locations have grades that change from a typical crown to a super-elevation creating a zone where the surface is flat. This flat spot is a critical location, especially when there is no or slight longitudinal grade because it prompts water ponding (Mounce and Bartoskewitz 1993).

**Weather (Rainfall).** In general, rainfall increases crash rates. Some studies have found that the wet crash rate is double the dry rate (Mondal et al. 2011). Rain affects drivers by producing a higher risk perception; adverse weather affects drivers' visibility (Jung et al. 2014). Rainfall is measured in intervals of precipitation. Researchers have found that
the highest rates of crashes typically are found when rainfall is greater than 0.2 to 0.6 in (5 to 15 mm), followed by greater than 0.08 to 0.2 (2 to 5 mm). Thinner water-film thickness may produce more crashes than the thicker water-film thickness (Charbeneau et al. 2008).

**Vehicle Type.** There are several vehicle types, including motorcycles, cars (hatchback, sedan, SUV), trucks, buses, and tractor-trailers. Each vehicle type varies in size, structure, purpose, and safety features. Modern vehicles provide safety features that help avoid or reduce the severity of hydroplaning crashes. Radial tires have increased resistance to hydroplaning (Sakai et al. 1978).

**Tire.** Hydrodynamic pressures result from tire contact with water film accumulated on the pavement. As the vehicle tire tread forces incline over the water’s surface, a change in momentum causes an upward thrust on the tire tread. Low tire tread provides low braking coefficients and increases the potential of skidding or hydroplaning crashes. Tire inflation pressure is also essential because higher tire pressure results in higher hydroplaning speeds.

**Urban/Rural location.** The crash rate varies in location because population density, driving behaviors, and risk vary between rural and urban areas. NHTSA studies on rural vs. urban show that, during 2004-2013, fatal crashes were higher in rural areas compared to urban locations (MHTSA, 2014). The driver attitude on rural roads is to engage in riskier behaviors than drivers in urban areas. Wet crashes and hydroplaning crashes should follow a similar tendency, depending on the crash location (Rakauskas et al. 2009).

From all the factors discussed, pavement and roadway geometry are two elements that DOTs can improve to ensure increased safety levels to prevent hydroplaning. Critical roadway elements contributing to water accumulation include vertical curves, sags, horizontal curves, and rutting. Specific factors increasing the hydroplaning potential include (1) high-grade draining downhill (sags), (2) little or no cross slope, (3) wide pavements, (4) roadway curve transitions, (5) road rutting, (6)
water dammed along the shoulder, and (7) water flows in sheets across the road (Balmer and Gallaway 1983).

2.5 Summary of Literature Review

- The main factors contributing to all crashes are human, vehicle, roadway, and weather-related.

- Cash frequency and crash rates have traditionally been used to rank high-risk locations. However, this method is impacted by crash data randomness and variability over time. Thus, advanced regression models are preferred to estimate crashes because they account for over-dispersion results in bias-model coefficients, under-estimation, and/or over-estimation of crashes.

- Wet crashes contribute to about 25% of all crashes and 13.5% of all fatalities in the US. Wet over dry crash ratio has traditionally been the preferred parameter of interest by DOTs.

- Hydroplaning is affected by the existence of water on the road. The factors affecting vehicle performance are speed, braking, steering, pavement, road characteristics, weather, vehicle type, tire characteristics, and urban/rural locations.

- This chapter presented the literature review to support the development of this dissertation. The following three chapters present the general framework implemented to develop this study.

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CHAPTER 3: An Enhanced Methodology for the Identification of Locations with a High Risk of Wet Crashes

3.1 Abstract

This chapter presents the first approach to estimate wet-crash risk when there is a crash, road characteristics, and traffic data available. About 18% of crashes on Virginia’s interstates from 2014 to 2016 were reported to be wet crashes. Although extensive research on crashes has been conducted, limited attention has been devoted to the prediction of wet crashes. The ratio of wet over dry crashes (wet over dry ratio, [WDR]) has traditionally been the parameter of interest. In this chapter, negative binomial regression is used to quantify the relationship between WDR and traffic and road parameters. One issue with the WDR is the handling of sites with zero dry crash counts. This was addressed by numerically replacing the zeros with 0.5 or by using an empirical Bayes estimate of the expected number of dry crashes instead of the dry crash counts. The empirical Bayes approach resulted in a better model fit as measured using Akaike’s Information Criterion. The negative binomial model developed for wet crashes was used to identify parameters that affect the pavement water film thickness and the expected number of wet crashes. The approach identified the longitudinal grade difference as an important parameter.

1 This manuscript has been published by the Transportation Research Record: Journal of the Transportation Research Board and co-authors include: Samer W. Katicha, Gerardo W. Flintsch
3.2 Introduction

3.2.1 Background

Each year worldwide, about 1.2 million people die, and 50 million are injured in vehicle crashes (Mondal et al. 2008). The primary factors contributing to crashes are human-, vehicle-, and roadway/weather-related. Fatal crashes on wet pavement represent between 11.2% and 13.8% of crashes in the US reported since the year 2000 (NHTSA, 2004). In Virginia, 18% of crashes reported on interstates from 2014 to 2016 were wet crashes. Although extensive research on crashes has been conducted, limited attention has been devoted to the study of wet crashes, which is discussed in the literature review. Most approaches aimed at reducing wet crashes rely on a simple analysis of wet over dry ratio (WDR) without evaluating the parameters that affect the WDR (refer to AASHTO Pavement Design Guide).

3.2.2 Problem Statement

Research has been performed to understand factors contributing to crashes. However, there is a need to understand better the factors affecting wet-crash rates. In wet-crash analysis, WDR has traditionally been the parameter of interest. In that respect, locations with high WDR are selected for improvement. This is usually done heuristically, and a more sound statistical method is needed.

3.2.3 Objective

This research will develop a statistically-sound model to quantify the relationship between WDR and traffic and road parameters. This was achieved by developing a model using negative binomial regression and identifying parameters that affect wet crashes using interstate crash data from Virginia.

3.3 Factors Contributing to Crashes

Determining the exact causes of individual crashes has been challenging due to limited accessibility to detailed driving data (i.e., acceleration, braking, driver response) (Victor et al. 2015). Instead, researchers have focused on understanding the factors that affect the expected number of crashes (Mountain et al. 1998, Shankar et al. 1998, Lord and
Persaud 2000, Lord and Mannering 2010). The factors contributing to crashes are divided into human-, vehicle-, and roadway/weather-related. Human factors include driver age, skills, experience, and mental abilities and can be the primary cause of all crashes. Vehicle design, malfunction, or maintenance have been estimated to be the main factors in about 3% of crashes. Roadway/weather factors, such as road geometry, traffic, weather, and visibility, have also been estimated to be the main factors in about 3% of crashes. About 37% of crashes have various combinations of these three factors (Treat et al. 1979, NRC 2010). Road geometry, such as sharp curves, steep slopes, multiple lanes, high speeds, and other features, strongly correlates with crash frequency. For example, locations with a sharp turn tend to have a higher crash rate. It is essential to identify which parameters have the most significant effect on crash frequency to design effective treatments and improve road safety (Persaud 1991, Shankar et al. 1995).

3.4 Wet Crash Studies

In 1988, Harwood et al. (1988) found that about 25% of all crashes in the US and 13.5% of fatal crashes occurred on wet pavement surfaces. The rate of fatal crashes on wet pavements is between 3.9 to 4.5 times the rate of fatal crashes on dry pavements (Smith and Larson 2011).

McGovern et al. (2011) found that low friction is a significant factor in wet crashes, with some estimates suggesting that an accident reduction of 70% in wet crashes is possible by improving friction. Friction is essential for weaving sections, where the crash ratio could increase by 77% in wet conditions (Wang et al. 2015). Some of the associated factors contributing to this are acceleration, deceleration, switching lanes, and complexity of maneuvering with traffic. Wang et al. (2015) suggest that high friction surface treatments could solve high wet crashes at weaving sections. Some researchers suggest that a permeable friction course (PFC) can reduce wet crashes (Nicholls 1997, Nicholls and Daines 1997, Kandhal 2002, Flintsch 2004, McGhee et al. 2009, Wang et al. 2015). However, some studies argue that there is insufficient evidence for that claim (Elvik and Greibe 2005, Buddhavarapu et al. 2015).
States have applied different methods to identify locations with many wet crashes. Caltran uses locations with three or more wet crashes during a 1-year period (six for two years and nine for three years), coupled with a significance test to identify locations of high wet-weather crashes. The analysis is based on a 0.2-mile window moving at 0.02-mile intervals. The significance test is based on traffic, length of time, length of section, and average wet crash. The average wet crash is the ratio of the average daily traffic (ADT) factor to total ADT, both of which can be obtained from Traffic Accident Surveillance and Analysis System (TASAS) tables. Florida identifies wet-weather crash locations in two ways: (1) those with four or more wet-weather crashes with 25% or more wet-weather crashes, and (2) those with 50% or more wet-weather crashes. The analysis is performed with a 0.3-mile sliding window at 0.1-mile increments.

Michigan determines wet-weather crash locations based on friction testing with a locked-wheel ribbed tire. New York identifies wet-weather crash locations based on the total number of wet crashes and the proportion of wet crashes. The minimum total number of wet crashes is six for rural areas and ten for urban areas, and the proportion of wet crashes is 35%. Virginia uses the potential wet accident hotspot (PWAH) approach with crashes recorded at 0.1-mile intervals. When there are at least three wet-weather crashes separated by less than 0.2 miles and the proportion of wet-weather collisions is at least 20% higher than the proportion for all roads in the area, the location is classed PWAH. New Jersey incorporates crash severity into identifying wet-weather crash locations, while Kentucky, although not using wet-weather crash locations to identify the risk of wet crashes, uses a roadway departure safety implementation plan.

Larson et al. (2008) used linear regression to model the WDR as a function of several parameters. The authors were not successful in identifying the relationships between the different variables (most notably, friction) and WDR, which was perhaps due to missing essential variables in the model. Cenek et al. (2004) applied Poisson regression to wet crashes as a function of many variables, including friction and road geometry. The approach did not consider data overdispersion (negative binomial model) and dry crashes to model the WDR.
The literature review shows that the analysis of WDR is still primarily performed based on the crash counts or using simple linear regression. This chapter applies negative binomial regression with the empirical Bayes approach to estimate WDR. One particular aspect of the modeling is how to handle the dry crashes in the negative binomial regression. Two approaches are used. The first approach uses the dry-crash counts as a variable in the negative binomial regression. This leads to problems at the locations where zero dry crashes are recorded. Zero dry-crash counts were replaced with a numerical value of 0.5. The second approach uses the expected number of crashes estimated using an empirical Bayes approach based on a dry-crash negative binomial regression model. This approach does not suffer from zero crash counts and results in a better model.

3.5 Data Sources

The Virginia interstate network contains a total of 23,953 0.1-mile segments. FIGURE 3-1 shows 14 variables collected and considered in the model. The Virginia Department of Transportation (VDOT) provided the statewide roadway data. The National Oceanic and Atmospheric Administration (NOAA) and Automated Surface Observing System (ASOS) by Iowa State University – Environmental Mesonet provided precipitation data. Because the collected variables were in tables and shapefiles, each variable was aggregated to each 0.1 miles using ArcGIS.

FIGURE 3-1 Variables Studied.

FIGURE 3-2 shows two histograms with the crash-frequency distribution for the years 2014–2016. On the left are wet-crash counts for every 0.1-mile section, ranging from 0 to 31 crashes per section. On the right are the dry crashes, ranging from 0 to 76.
Most sections have one or two wet crashes, typically with one vehicle involved. About 75% of the road sections have no crashes reported. When analyzing dry crashes, most sections have reported between one and three crashes. About 43% of the road sections have no crashes reported.

The right side of FIGURE 3-3 presents a histogram of the frequency distribution of the ADT. After applying the high traffic volume minimum threshold criteria to Virginia interstates, these can be classified as having a 3% low, 4% medium, and 93% high traffic. This indicates that, on average, most roads have high traffic. The histogram on the left shows the grade difference of the vertical curves for each 0.1-mile interstate section. Grade values range from −11% to 10%. About 43% of sections have a 0% grade difference (which most likely represent a flat surface or sag/crest location). The remaining 57% have some uphill or downhill grade.
3.6 Regression Model Selection

The models often used for crashes are count-data models. Some count-data models applied to crash-frequency analysis are Poisson, negative binomial/Poisson-gamma, Poisson-lognormal, zero-inflated Poisson, and negative binomial (Miaou 1994, Lord et al. 2007, Aguero-Valverde and Jovanis 2009). The negative binomial model is the most commonly used model for crash analysis. It accounts for over-dispersion, is easy to understand, and is simple to apply (Lord and Mannering 2010).

The pairwise Pearson correlation between the variables considered was calculated to measure the strength of the linear association among the different variables in the model. FIGURE 3-4 illustrates the pairwise correlation of the variables. There is a high positive correlation between average daily traffic (ADT), number of lanes, and ADT with the empirical Bayes-method dry crashes.

![FIGURE 3-4 Pearson Correlation.](image)
The quantity we are trying to estimate is the WDR. Poisson or negative binomial regression rates are handled using simple algebra to change the problem into a count problem. Suppose we want to model the WDR as a function of other variables as follows:

$$WDR = \frac{\text{Wet Crashes}}{\text{Dry Crashes}} = \exp\left(\sum_{i=0}^{N} \beta_i X_i\right) \times \varepsilon$$  \hspace{1cm} \text{Eq. 3-1}

Here, \(\varepsilon\) is a gamma-distributed error term with a mean equal to one. Dry crashes can be seen as an exposure variable, and multiplying both sides of the equation by that exposure, we obtain:

$$\text{Wet Crashes} = \exp\left(\sum_{i=0}^{N} \beta_i X_i\right) \times \text{Dry Crashes} \times \varepsilon$$  \hspace{1cm} \text{Eq. 3-2}

$$\text{Wet Crashes} = \exp\left(\sum_{i=0}^{N} \beta_i X_i + \ln(\text{Dry Crashes})\right) \times \varepsilon$$  \hspace{1cm} \text{Eq. 3-3}

With this, we can see that \(\ln(\text{Dry Crashes})\) can be treated as an offset variable in the negative binomial regression model. We can generalize the WDR by dividing the wet crashes by a power of the dry crashes as follows:

$$WDR = \frac{\text{Wet Crashes}}{\text{Dry Crashes}^\alpha}$$  \hspace{1cm} \text{Eq. 3-4}

In this case, the model becomes:

$$\text{Wet Crashes} = \exp\left(\sum_{i=0}^{N} \beta_i X_i + \alpha \ln(\text{Dry Crashes})\right) \times \varepsilon$$  \hspace{1cm} \text{Eq. 3-5}

To obtain the value of \(\alpha\), \(\ln(\text{Dry Crashes})\) is treated as a regression variable similar to the other \(X_i\) variables. A significant issue with using the dry-crash counts in the modeling is that many sections have a recorded dry-crash count of zero for which the
logarithm is not defined. We followed two strategies to address the issue. In the first strategy, we replaced the zeros with a numerical value of 0.5, for which the logarithm is defined (we also tried 0.1 and found no difference in the result). In the second strategy, we estimated the expected number of dry crashes using the empirical Bayes method and estimated the variable Dry Crashes. Although requiring more computation, this second strategy resulted in a better model fit as measured using Akaike's information criterion (AIC).

The empirical Bayes estimate of dry crashes can be expressed as:

$$D_{EB} = W(D_{counts}) + (1 - W)D_{model}$$  \hspace{1cm} \text{Eq. 3-6}

When the empirical Bayes estimate of dry crashes is integrated into the wet crash model, it can be expressed as:

$$Wet\ Crash = \exp \left[ \beta_1 \ln(ADT) + \beta_2 \ln(D_{EB}) + \left[ \sum_{i=0}^{N} \alpha_i X_i \right] \right]$$  \hspace{1cm} \text{Eq. 3-7}

$$Wet\ Crash = \exp \left[ \beta_1 \ln(ADT) + \beta_2 \ln(W(D_{counts}) + (1 - W) \exp[\alpha_1 \ln(ADT)]) + \left[ \sum_{i=0}^{N} \alpha_i X_i \right] \right]$$  \hspace{1cm} \text{Eq. 3-8}

### 3.6.1 Model Summary

A forward and backward stepwise procedure was used to select the essential variables in the model. Three different models were built. The first model relates the wet crashes with the other variables without considering dry crashes. The second model is similar to the first and adds the dry-crash counts as a regression variable with counts equal to zero replaced by 0.5. The third model is similar to the second except that the empirical Bayes estimate of the expected number of dry crashes is used instead of the dry-crash count.
The resulting AICs were 34,097; 33,314; and 32,940 for the first, second, and third models. The third model with dry-crash empirical Bayes was the best fit model. TABLE 3-1 summarizes the details of the three models' estimated parameter, standard error, z-value, p-value, and level of significance. Each box in the table contains three lines. The first line is for model 1, the second for model 2, and the third for model 3. Each parameter has a p-value less than 0.05, which indicates that the parameter is significant. The overdispersion parameters (\( \phi \)) indicate the amount of overdispersion in the negative binomial regression model, which are 0.9902, 0.6536, and 0.6344 for the respective models. The standard error (SE) is the asymptotic standard error of the regression coefficients, which estimates the precision of the regression coefficient. The SEs are 0.0395, 0.0736, and 0.0772 for the respective models.

The three models studied provide the same response but have different variables and functions. Different models show different resulting coefficients, which is normal. In the third model, the ADT coefficient is negative, suggesting that wet crashes decrease with an increasing ADT. However, ADT is included in multiple parts of the model.

A couple of significant variables in the model are the grade difference and its absolute value. These two variables are important because they relate to the water-film thickness accumulation when it is raining. Therefore, they can link wet-crash risk and water-film thickness. This is further discussed in the grade correction factor (GCF) section.
TABLE 3-1  Model Parameter Results Summary.

| Dependent Parameter | Estimate Coefficient | Std. Error | z-value | Pr(>|z|) | Signif. Codes |
|----------------------|-----------------------|------------|---------|----------|--------------|
| \(X_0\) Intercept  \(\beta_0\) | -6.1577 | 0.5348 | -11.514 | < 2e-16 | 0.001, 0.001, 0.05 |
| \(X_1\) Dry Crash Counts  \(\beta_1\) | 0.0866 | 0.0028 | 31.340 | < 2e-16 | N/A, 0.001, N/A |
| \(X_2\) Dry Crash Empirical Bayes  \(\beta_2\) | 0.8067 | 0.0235 | 34.298 | < 2e-16 | N/A, N/A, 0.001 |
| \(X_3\) Curvature  \(\beta_3\) | 0.0244 | 0.0244 | 10.955 | < 2e-16 | <0.0001, <0.0001, <0.0001 |
| \(X_4\) 2 Lanes  \(\beta_4\) | 0.4654 | 0.3424 | 1.359 | 0.1741 | 0.1, 0.1, 0.1 |
| \(X_5\) 3 Lanes  \(\beta_5\) | 0.739 | 0.3349 | 2.195 | 0.0282 | 0.01, 0.01, 0.1 |
| \(X_6\) 4 Lanes  \(\beta_6\) | 0.7731 | 0.3300 | 1.233 | 0.1107 | 0.01, 0.01, 0.1 |
| \(X_7\) 5 Lanes  \(\beta_7\) | 0.7533 | 0.3358 | 0.841 | 0.4006 | 0.1, 0.1, 0.1 |
| \(X_8\) 6 Lanes  \(\beta_8\) | 0.9871 | 0.4019 | 2.536 | 0.0112 | 0.01, 0.01, 0.1 |
| \(X_9\) Ramps  \(B_9\) | 0.5881 | 0.0294 | 19.994 | < 2e-16 | <0.0001, <0.0001, 4.23e-08 |
| \(X_{10}\) ADT  \(B_{10}\) | 0.5462 | 0.0286 | 19.088 | < 2e-16 | <0.0001, <0.0001, <0.0001 |
| \(X_{11}\) Speed  \(B_{11}\) | -0.0288 | -0.0031 | -2.923 | 0.0035 | 0.0001, 1.45e-06, <0.0001 |
| \(X_{12}\) Diff. in Grade  \(B_{12}\) | 0.0166 | 0.0063 | 2.63 | 0.0085 | 0.0001, 0.0001, 8.31e-07 |
| \(X_{13}\) | 0.2599 | 0.0373 | 6.969 | 3.19e-12 | <0.0001, <0.0001, <0.0001 |
| \(X_{14}\) Average Grade  \(B_{14}\) | -0.4050 | -0.0091 | -4.469 | 7.86e-06 | <0.0001, <0.0001, 0.001 |
| \(X_{15}\) Urban/Rural  \(B_{15}\) | 0.2599 | 0.0373 | 6.969 | 3.19e-12 | <0.0001, <0.0001, <0.0001 |

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A quartile-quartile (Q-Q) plot was created to verify the distribution of the model residuals. The Q-Q plot denotes a quantile-quantile plot, representing a probability plot that compares the quantiles of two distributions by plotting their quantiles against each other. Quantiles are the limits, or cutting points, to divide the distribution into four equal parts. The general quantiles are represented by lower (25%), middle (50%), and high (75%). Q-Q plots are generated for determining the quantiles. The points represented on the X-axis are the quantiles of the first distribution (predicted wet crashes). The Y-axis shows the quantiles of the second distribution (observed wet crashes). R software defines quantiles by the percentage of data points under a value of 30%.

The continuous line is a parametric curve or interval for each quantile. The closer the points are to the line indicates that the quantiles of each point are approximately equal. In other words, the closer to the line, the better the prediction. R produces a 45-degree reference line. If the observed and predicted values follow the same distribution, they should be closer to the line; the further away from the line, the greater the chance they have different distributions.

FIGURE 3-5 shows the Q-Q Plot for the negative binomial distribution. Note in the plot that the model's residuals follow a negative binomial distribution with few high outliers. The figure's right end increases, representing a gap in the density of values with peaks or extreme cases.
FIGURE 3-6 shows the observation, model estimation, and empirical Bayes estimation of wet crashes on Virginia interstate highways from 2014–2016. On the $X$-axis are the cumulative mileposts of the 0.1-mile road segments. The light blue lines represent the observed wet crashes. The red line is the estimated wet-crash rate obtained from the negative binomial model. The green line is the estimated wet-crash rate corrected using the empirical Bayes method. After comparing the regression model coefficients to the observed values, it was noted that the estimation follows the same pattern as the observed values. However, some high peaks are outliers and affect the estimate. The empirical Bayes method was applied to improve the results. This correction results in better estimates taken from averaging the observations and the regression model estimates.
FIGURE 3-6  Wet Crashes 2014–2016 on Interstates Observed, Estimated, and Empirical Bayes.

3.7  Example Application

According to the FHWA Highway Safety Improvement Program, a crash modification factor (CMF) measures the safety effectiveness of a particular treatment or design element (Herbel et al. 2010). It is also a factor applied in the calculation to predict crashes when applying a countermeasure in a specific location. To obtain a CMF, data from a before-and-after treatment are needed. Since obtaining a CMF from a regression
model is not feasible, exploratory research was started to identify alternatives to produce a CMF.

The grade is one of the most critical factors in the regression model. Adjusting the grade could be considered a highway treatment to reduce wet crashes. Similar to the CMF, a grade correction factor (GCF) presents the sum of crests and sags to adjust the model for these types of vertical curves, denoted in Eq. 3-9. The absolute value of the grade represents the crest difference. The change in grade represents the sag difference.

\[
\text{GCF} = e^{\beta_1 (X_{\text{grade difference}})} + \beta_1 (X_{\text{grade difference}})
\]

Eq. 3-9

where,

\[ \beta_1 = \text{grade difference values}. \]

FIGURE 3-7 presents the grade difference over the GCF. When the grade difference goes from negative to zero, it is represented by crests and flat surfaces, as illustrated in FIGURE 3-8. Crests tend to drain water due to the grade forcing water to move downward. Flat surfaces also drain water when cross-sloped grades are not zero. Sags tend to accumulate water because the runoff water will drain from the crest to the sag. The GCF reflects where grade differences are positive values and where wet-crash rates increase.

In theory, the GCF can serve as a CMF. Nonetheless, this is a new approach. Its effectiveness has not been studied, nor has it been validated with field data. Applying the GCF to the presented wet-crash model could negatively affect the regression parameters and the overall wet crash estimation. Further research is required before it is implemented.
3.8 Conclusions

This chapter proposed a statistically sound approach to quantify the relationship between WDR and traffic and road parameters. The negative binomial regression model using the empirical Bayes estimate of the dry crashes as a variable produced better estimates of wet crashes than the methods currently used by departments of transportation (DOTs). A detailed analysis of the model revealed that the critical variables to estimate wet crashes are dry crashes empirical Bayes, curvature, number of lanes, ramps, ADT, speed, the difference in grade, absolute value of the difference in grade, average grade, and urban/rural locations.
As an example of the application of the model, the research investigated the effect of grade on wet crashes and found that the grade difference and its absolute value are significant. The proposed approach can be used to enhance the understanding of wet crashes and will be helpful for DOTs to improve and update the safety improvement programs.

References


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CHAPTER 4: New Crash Hazardous Segments Identification Method: Puerto Rico Total Crashes and Wet Crashes Application

4.1 Abstract

This paper presents a novel approach to estimate wet-crash risk when only crash data is available. The crash hazardous-road segments identification (HRSI) process, also known as "hotspot" identification, is a standard practice in most US departments of transportation. Numerous HRSI methods have been presented in the literature, from simple to sophisticated. While simple methods may not consistently identify the highest risk locations, more sophisticated methods typically require more data and resources. Puerto Rico's situation is particularly challenging because resources and available data are limited. This paper proposes a new systemic method that identifies high-crash risk locations using only the crash data. The assessment considers total crashes and wet crashes in Puerto Rico from 2014-2015. The method applies spatial multiresolution analysis (SMA), a geospatial approach that allows a variable bandwidth on each road segment and calculates the optimal bandwidth. Using the SMA to estimate crash risk minimized the unbiased estimate of the mean square error from the actual crash risk. The site consistency analysis results indicate that the proposed method is more consistent at predicting fatal, injury, and property-damage-only crash counts than the current methodology. Applying the proposed method will provide a more accurate systemic approach to identifying high-risk locations, effectively identifying potential problems and appropriate countermeasures. This method is also valid for other jurisdictions.

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2 This manuscript has been submitted for publication to the Transportation Research Record: Journal of the Transportation Research Board and co-authors include: Samer W. Katicha, Gerardo W. Flintsch
4.2 Introduction

The Commonwealth of Puerto Rico (PR) is an unincorporated territory of the US that participates in different federal grant programs. On July 30, 2019, the US Congress approved "America's Transportation Infrastructure Act of 2019" to authorize $287 billion to be available to states and territories under the Highway Trust Fund from 2021 to 2025. In addition, $249 billion was granted for highway formula programs. Section 1128 authorizes a funding increase for the "Territorial and Puerto Rico Highway Program," which provides Puerto Rico (PR) a total of $841 million (Environment and Public Works 2020).

The highway safety improvement program (HSIP) is a core federal-aid program designed to significantly reduce fatalities and serious injuries on public roads. The program requires each state to develop a Strategic Highway Safety Plan (SHSP) using a data-driven approach to improve highway safety on all public roads, focusing on performance (FHWA, 2019). States and territories, including Puerto Rico, must comply with these federal regulations to be granted HSIP funds.

The hazardous-road segments identification (HRSI) process, also known as "hotspots," "blackspots," or "high risk" identification, has become the standard practice in most departments of transportation (DOTs) in the United States (Elvik 2007, Park et al. 2014, Jia et al. 2018, Ghadi and Török 2019, Cheng et al. 2020, Lee et al. 2020) and is the subject of ongoing research. The most well-known HRSI methods are crash frequency (CF), equivalent property-damage only (EPDO) crash frequency, crash rate (CR), empirical Bayes (EB) estimate of total-crash frequency, and geospatial methods such as the local spatial autocorrelation method and kernel density estimation (KDE) (Lord and Park 2008, Huang et al. 2009, Montella 2010, Park et al. 2014, Yu et al. 2014).

The EB method and the geospatial methods are more effective than the traditional methods based on the crash count, which do not account for the randomness of crashes and traffic volume and produce systemic regression-to-mean (RTM) bias (Lakshmi et al., Hauer 1997, Cheng and Washington 2005, Brijs et al. 2007, Elvik 2008, Loo et al. 2011,
This leads to inaccurate estimates of actual crash risk and erroneously identifies hazardous locations with low volume and few crashes.

Due to limited resources and data, PR's current HRSI approach is based on the ranking of crash frequency and crash costs using crash-count data. Because simple crash count methods are not a reliable measure of crash risk, we show in this research that the HRSI approach used by PR can be improved (Montella 2010). We present a spatial multiresolution analysis (SMA) to obtain a more reliable estimate of the crash risk (expected number of crashes) at each road section to improve the reliability of PR's HRSI approach (Katicha and Flintsch 2018, Katicha et al. 2020). We apply the approach to total crashes (wet and dry) and wet crashes only, contributing 15% of the fatalities on primary roads (PRTSC, 2020).

4.3 Objective

The objective of the paper is to propose a new systemic method to reliably identify high crash-risk locations with the current data parameters, namely just the crash counts used by Puerto Rico. This was achieved by using the SMA method to estimate the crash risk for every 0.1-km road section and using the crash risk instead of the crash count in the HRSI approach currently implemented by PR.

4.4 Background

This section presents the background on the methods used for the crash data analysis and the current procedure for HSRI used by PR.

4.4.1 Common HRSI Methodologies

Methods Based on Crash Count

Many methods have been proposed for HRSI, from simple crash counts to more sophisticated statistical models. US federal law requires state DOTs to implement data-driven highway safety management processes to identify HRSI, which has made HRSI a
standard practice in the United States (NRC 2010, Congress 2015). HRSI aims to identify locations with higher crash risk than other locations and patterns and contributing factors for the high-crash risk and candidate countermeasures to reduce crash risk. Performing an HRSI with unreliable methods results in suboptimal identification of risky locations, inefficient use of resources, and unsuccessful crash reduction (Montella 2010).

Crash frequency (CF) is one of the first and simpler methods to conduct an HRSI analysis. It is based on crash counts as shown follows:

\[
CF_i = \frac{N_i}{L_i Y_i}
\]  

Eq. 4- 1

where,

\( CF_i \) = crash frequency at section \( i \) (crashes per length-year)
\( N_i \) = total number of crashes recorded in \( Y_i \) years at section \( i \)
\( L_i \) = length of section \( i \)
\( Y_i \) = number of years used for the analysis at section \( i \)

In the CF approach to HRSI, a proportion \( \alpha \) (e.g., 0.05 for 5%) of the total number of sections is selected. The proportion of the sections with the highest calculated \( CF_i \) are identified as "hotspots." The main drawback of the CF approach is that crashes are random, and crash counts are not a reliable indicator of the crash risk. Therefore, the CF approach often results in many false positives (wrongly identified hotspots) and false negatives (missed hotspots).

Equivalent property-damage only (EPDO) crash frequency is an alternative method where weights are assigned to the severity of crashes (based on the KABCO scale). It is based on weighing the crashes by their impact on cost as follows:
\[
    \text{EPDO}_i = \frac{KABCO \text{ Crash Cost}_i}{PDO \text{ Crash Cost}_i} \tag{Eq. 4-2}
\]

where,

\( \text{EPDO}_i \) = equivalent property-damage only at section \( i \)

\( KABCO \text{ Crash Cost}_i \) = injury-scale crash costs at section \( i \)

\( PDO \text{ Crash Cost}_i \) = property-damage only (PDO) crash costs of section \( i \)

EPDO works by summarizing the crash cost, severity, and frequency of crashes in a specific location. The weight considered is crash costs. A typical example of EPDO uses the USDOT national average costs of a crash: fatal $4,002,800; injury $89,200; and PDO $7,400 (NRC 2010, Harmon et al. 2018). All crashes are converted to PDO by dividing the crash cost by the PDO cost. In other words, the fatal crash weight is 541, the injury weight is 12, and the PDO weight is 1. The strength of this method is its simplicity and that it considers crash severity. Limitations of the method include that the data does not follow a Poisson or negative binomial distribution after applying the weights, complicating the analysis, and the method does not account for RTM bias or traffic (Washington et al. 2014). In addition, the largest weight is applied to crash fatality counts, which have the lowest numbers and are therefore the least accurate estimate of the crash risk of any category.

Crash rate (CR) is another method used to normalize crash frequency for exposure. It is based on the crash counts as follows:

\[
    R_i = \frac{N_i}{MVM_i} \tag{Eq. 4-3}
\]

where,

\( CR_i \) = crash rate at section \( i \)

\( N_i \) = number of crashes in the year of study at section \( i \)

\( MVM_i \) = million vehicle miles at section \( i \)
The traditional exposure measure used is the traffic volume calculated as follows:

\[ MVM = \frac{AADT \times \text{segment length} \times 365 \times \text{num. of yr.}}{1,000,000} \quad \text{Eq. 4-4} \]

The main benefit of the CR method is its simple application and that it can be adjusted to account for severity by considering EPDO (MNDOT, 2015). The use of CR has been a long-standing practice for several states; nonetheless, there are significant limitations to the method. CR assumes a linear relationship for crash counts and traffic volume; this relationship is nonlinear and varies with facility type and geographical location (Hauer 1995, Qin et al. 2005). Applying this method will produce a systematic RTM bias in the results and may erroneously identify hazardous locations with low volume and few crashes (Hamidi et al. 2010).

**Methods Based on Regression Modeling**

The EB and full Bayes (FB) methods are the most commonly used methods for crash data analysis (Hauer et al. 2002, Elvik 2008, Persaud et al. 2010, Mannering and Bhat 2014). The EB method is often used with the safety performance function (SPF). The Highway Safety Manual (HSM; AASHTO 2010, page G-13) defines an SPF as "... an equation used to estimate or predict the expected average crash frequency per year at a location as a function of traffic volume and in some cases roadway or intersection characteristics (e.g., number of lanes, traffic control, or type of median)." SPFs are typically created by using a negative binomial regression. This assumes that the crash risk (expected average crash frequency per year), \( \lambda \), for sections with similar features is related to those attributes in the following way:

\[ \lambda = \exp \left( \sum_{j=1}^{k} \beta_j X_i \right) \times \varepsilon = \mu \times \varepsilon \quad \text{Eq. 4-5} \]
\[
\mu = \exp \left( \sum_{j=1}^{k} \beta_j X_i \right) \quad \text{Eq. 4-6}
\]

where,
- \(k\) = number of characteristics considered in the model (including intercept)
- \(X_j\) = \(j^\text{th}\) characteristic
- \(\beta_j\) = regression coefficient for the \(j^\text{th}\) characteristic
- \(\varepsilon\) = error terms assumed to be gamma distributed with a mean of 1

Although the regression model includes road-section characteristics, adding an error term accounts for other factors contributing to the crash risk not included in the regression but effectively represented by a gamma distribution. As a result, various crash risks will exist for road sections with identical characteristics in the regression model. The crash counts are assumed to follow a Poisson distribution, as follows:

\[
Y \sim P(Y = Z \mid \lambda) = \frac{\lambda^Z e^\lambda}{Z!} \quad \text{Eq. 4-7}
\]

where,
- \(Y\) = crash count
- \(P(Y = Z \mid \lambda)\) = the probability of \(Y\) taking the value \(Z\) given that the crash risk is \(\lambda\)

The crash counts \(Y\) are used in negative binomial regression to estimate \(\mu\) and the variance of \(\varepsilon\) stated in terms of the overdispersion. Overdispersion is related to the gamma distribution's variance and the model error's variance as follows:

\[
\sigma^2_{\text{Gamma}} = \phi \mu^2 \quad \text{Eq. 4-8}
\]

\[
\sigma^2_{\text{Model Error}} = \mu + \phi \mu^2 \quad \text{Eq. 4-9}
\]
The estimated regression parameters, \( \beta_j \), allow us to derive an estimate \( \hat{\mu} \) for \( \mu \), and \( \sigma^2 \) can be inferred from the residuals allowing to estimate the overdispersion \( \phi \). The EB technique is used to calculate crash risk as a weighted average of the regression model and crash counts, as shown below:

\[
\hat{\lambda} = \left( 1 - \frac{\hat{\beta} \hat{\mu}}{1 + \hat{\beta} \hat{\mu}} \right) \hat{\mu} + \frac{\hat{\theta} \hat{\mu}}{1 + \hat{\theta} \hat{\mu}} Y
\]

**Eq. 4-10**

The hat above the parameters is used to emphasize that the values used are estimated from the data.

Although the EB method has been commonly used for HRSI, sometimes it can become challenging and expensive for DOTs to collect the necessary data to implement a strong SPF (Hauer et al. 2002). The EB has traditionally been used to address regression to the mean bias for estimating the crash risk at homogeneous road segments and identifying hazardous-road segments (Lee et al. 2019).

**Methods Based on Geospatial Analysis**

The accessibility of geographic information systems has allowed researchers to use geolocation analysis to account for the effects of spatial autocorrelation in crash analysis in general and HRSI analysis in particular (McMahon 1999, Depue 2003, Xie and Yan 2008, Anderson 2009, Songchitruksa and Zeng 2010, Loo et al. 2011, Truong and Somenahalli 2011). The use of spatial methods and their good performance is reinforced by findings that spatial variation in crash data can account for 59% to 88% of the heterogeneous crash variation even when other explanatory variables are taken into account (Aguero-Valverde and Jovanis 2008, El-Basyouny and Sayed 2009, Barua et al. 2016).

Kernel Density Estimation (KDE) is the most popular and extensively studied spatial method in crash data analysis. The method estimates the crash risk at a specific location as a weighted average of the observed crashes at locations within a specified
distance from the location of interest. The weights are calculated from a kernel function, with the Gaussian kernel being one of the most popular. In some cases, authors have found that KDE performs just as well as the EB method, and Yu et al. (Yu et al. 2014) have suggested that the KDE is similar to a simplified version of the EB method below.

\[
f_n(x) = \frac{1}{nb} \sum_{i=1}^{n} K \left( \frac{d_i}{b} \right)
\]

Eq. 4-11

where,

- \( f_n(x) \) = density estimate at spatial unit \( x \)
- \( b \) = predefined bandwidth
- \( n \) = number of crashes near location \( x \) within a radius \( h \)
- \( K \) = predefined kernel density function used to measure distance decay effect
- \( d_i \) = distance between spatial unit \( x \) and spatial unit where the \( i^{th} \) crash is located

FIGURE 4-1 shows a graphical representation of how the KDE works. The first step is to plot the crash points, apply the kernel function to each data point, and combine the KDE functions. The kernel choice does not significantly affect the KDE results and the most crucial parameter is the kernel bandwidth. The kernel bandwidth determines the smoothing of KDE. An optimal bandwidth needs to provide a good balance between smoothing random fluctuations due to the random nature of crashes while simultaneously not overly smoothing actual spatial variation in the crash risk.

Although the choice of bandwidth is critical to the performance of KDE, no simple solution has been proposed to determine optimal bandwidth. KDE has traditionally been used in road safety to identify spatial patterns of crashes and HRSI (Anderson 2009, Kuo et al. 2011, Blazquez and Celis 2013).
The Spatial Multiresolution Analysis (SMA) is an alternative geospatial analysis that behaves like a KDE with the additional benefit of allowing a variable bandwidth on each road segment and calculating the optimal bandwidth (Flahaut 2004). Optimizing the bandwidth helps to minimize the unbiased estimate of the mean square error from the actual crash risk (Katicha et al. 2020).

The SMA works like a moving window where a road section \( y_i \) considers the crashes in the neighboring section \( y_{i+1} \). The sections are then combined to create the sliding window \( s_i = y_i + y_{i+1} \). The moving average is given by \( \frac{s_i}{2} = \frac{y_i + y_{i+1}}{2} \).

A crash count difference is calculated from two adjacent sections \( d_i = y_i - y_{i+1}, \)
\( d_{i+2} = y_{i+2} - y_{i+3}, \)
\( d_{i+4} = y_{i+4} - y_{i+5}, \)
\( \ldots \). Then, using the sums and differences, the crash count is recalculated as follows: \( y_i = (s_i + d_i)/2 \) and \( y_{i+1} = (s_i - d_i)/2 \). More than one neighboring section can be added by applying the same concept.

When the crash risks at a section \( \lambda_i \) and neighbor section \( \lambda_{i+1} \) are similar, this means that the sections have similar characteristics; we can assume they are approximately homogeneous, \( \lambda_i \approx \lambda_{i+1} \). Homogeneous sections can be combined to reduce crash-count variability. Non-homogeneous sections should remain separated.

The actual risk \( \lambda_y \) of a road section is unknown. However, a small value of the absolute difference \( |d_i| \) indicates that the sections have similar risks, so these sections can be
combined. High absolute differences indicate that the risk is different and that the
sections can be kept separated.

A threshold \( t \) is needed to distinguish small from large \( d_i \) values. Values where \( d_i = 0 \) will adopt the window of the combined sections \( y_{i+1} \), while the other will maintain
the original section, \( y_i \). The combined sections can then be reanalyzed by combining
other neighboring sections and calculating \( 2s_i = s_i + s_{i+2} \) and \( ds_i = s_i - s_{i+2} \). A new \( t \) is
obtained and reevaluated.

Reliable results are obtained with an optimum threshold \( t \). Because the crash
risk is known, the SMA optimizes \( t \) by applying Poisson's unbiased risk estimate (PURE).
PURE provides an unbiased estimate of the mean square error based on the data and
calculates the differences for any aggregation length. The following equation expresses
PURE:

\[
PURE(\theta) = \| \theta(d, s, \theta) \|^2_2 + \| s \|_1 + 2d^T \theta(d, s, \theta) - (d + s)^T \theta(d - 1, s - 1, \theta) + (s - d)^T \theta(d + 1, s - 1, \theta)
\]

Eq. 4-12

where, \( d \) and \( s \) are the difference and sum vectors, and \( \theta \) is the previously mentioned
threshold. The threshold \( \theta \) is related to the thresholding function as follows: \( \theta \) is a
function of \( d \) and \( s \), and the threshold \( \theta \) is a function of \( \varphi(d, s, \theta) \). \( \varphi(d, s, \theta) = \varphi(d, s, \theta) - d \), where \( \varphi(d, s, \theta) \). PURE is determined for a series of thresholds \( \theta \), and the one
with the lowest PURE is chosen as the ideal threshold.

Discussion

Each of the commonly used HRSI methods has its benefits and disadvantages.
According to the HSM, the crash-count methods presented are recommended for
network screening, and DOTs can apply them to justify countermeasure projects and
investments when only crash data is available (AASHTO 2010). However, these methods
are highly limited by not accounting for RTM bias, potentially leading to erroneous
inferences. Although sophisticated statistical methods provide a more reliable result, the most significant constraint is the availability of the data. A significant benefit of spatial analysis for HRSI is that it requires little data and processing time. Generally, a method that accounts for RTM bias and adequately estimates the crash frequency or crash severity will provide a greater confidence level to estimate high-risk locations more accurately.

4.4.2 Current Hot Spot Estimation Method Used in PR

The Puerto Rico Strategic Highway Safety Plan (PR-SHSP) 2014-2018 was announced in 2014 by the Department of Transportation and Public Works (PRDTPW) and the Puerto Rico Highway and Transportation Authority (PRHTA). This was part of the safety planning efforts developed in collaboration with other agencies and stakeholders and approved in July 2014. This plan was developed by the CSA Group Puerto Rico (private firm) in collaboration with the Puerto Rico Traffic Safety Commission (PRTSC), the Puerto Rico Police (PPR), the Puerto Rico Health Department (PRHD), and the PRHTA. A vital element of the SHSP 2014-2018 is establishing the areas of emphasis for road safety (Colucci et al. 2016).

PRHTA recognizes the importance of accurately identifying and treating HRSI, and reducing high risk as a priority in the safety assessment process. The initial approach was to develop a local SPF or adapt the HSM models to PR. However, neither was possible due to the limited data available. The data required to develop a strong SPF are traffic volume, road characteristics, and regulatory information. PR has insufficient funding to maintain the extensive paved-road network and has limited up-to-date data for traffic and road characteristics. Nonetheless, crash data are available for all state roads and some local routes, including details of the number of crashes, crash severity, location (partially available), and nature of the crash. Furthermore, continued efforts to improve the crash database have led to the recent digitalization of the Puerto Rico Traffic Crash Report (form PPR621.4).
The PRHTA has used HSM as a reference for identifying high-risk locations. The HSM guidelines have been partially implemented and the KABCO injury classification has not yet been implemented in PR. Thus, the traffic data are not reliable. This situation has led to a methodology for identifying high-crash locations using the crash-cost factor (CCF) and frequency index (FI). This method sets priorities by combining the number of crashes, severity cost, and road classification into a ranking value.

The HRSI is divided into three different types of analysis: (1) hotspots, which are defined as 500-meter road segments; (2) hot intersections, which have two or more highway crossings; and (3) hot corridors, which are highway segments three or more kilometers in length (as shown in FIGURE 4-2). Each analysis considers different segment lengths.

![FIGURE 4-2 Types of Location Analysis Considered in PR.](image)

There are a series of steps to complete the current HRSI analysis used in PR. The first step is to generate a list of total crashes within the network by location type to separate intersections, corridors, and hot spots. The list is subdivided by road classification (primary roads, secondary roads, and tertiary roads).

Then, the average total number of crashes in the network is calculated. This adds the crash number in all 0.5-km or 3-km road sections under analysis and divides it by the number of sections. It can be expressed as:
Avg. Total Number of Crashes

\[
\text{Avg. Total Number of Crashes} = \frac{\sum_{i=0}^{n} \text{Total Crashes by Section}}{\text{Number of Sections}}
\]

This average is used to calculate the FI. The FI, sometimes called crash rate, is one of the two parameters considered for ranking sections. The FI allows locations with a higher crash rate than the average to be identified. FI is expressed as:

\[
FI = \frac{\text{Total Crashes by Section}}{\text{Avg. Total Number of Crashes}}
\]

The CCF is the second parameter considered in the ranking. Each crash is given a cost that is related to severity. PR crash data currently do not provide KABCO metrics to define different injury levels. However, the crash costs were taken from federal guidelines and were assumed to be the same locally: $4,002,800 for fatal crashes, $89,200 for injury crashes, and $7,400 for PDO (PRHTA, 2019). The CCF adds all the crashes by severity and multiplies them by the federal guideline cost. This can be expressed as:

\[
CCF = (\text{Fatal Crashes} \times \text{Cost of Fatal Crashes}) + (\text{Injury Crashes} \times \text{Cost of Injury Crashes}) + (\text{PDO Crashes} \times \text{Cost of PDO Crashes})
\]

An adjustment of FI and CCF is performed to account for the variations in the length of segments. The CCF and FI values are divided by the length of the segments, taking the costs and frequency of equal lengths of 1 km. The CCF/km ranking and FI/km ranking of each section are added to obtain the combined ranking of each section, with sections having a higher ranking deemed more risky. However, this approach relies on the crash counts, which are known to provide unreliable results. Therefore, this paper proposes using the crash risk calculated using the SMA method instead of crash counts to provide a more reliable estimate of hazardous crash locations.
4.5 Methodology

This section presents the data sources, compares the new proposed approach to improve the HRSI process, and the available methods to compare the performance of the current HSRI method with the proposed method based on the SMA approach.

4.5.1 Data Sources

The data used for this research are the PR crash data and the PR roadbase map. The crash data consider the number of crashes from 2014–2015. The base map was provided by the Third Mission Institute - Carlos Albizu University and the PRTSC and was the version last updated in June 2019. The total number of 0.1-km sections is 6,600 primary; 15,030 secondary; and 37,110 tertiary. TABLE 4-1 presents a crash data summary by road classification and year and the evaluated road lengths in kilometers. The crash data evaluated considered only state routes with kilometer markers.

<table>
<thead>
<tr>
<th>TABLE 4-1 Crash Data Summary.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Total</td>
</tr>
<tr>
<td>SR Primary</td>
</tr>
<tr>
<td>SR Secondary</td>
</tr>
<tr>
<td>SR Tertiary</td>
</tr>
</tbody>
</table>

4.5.2 Proposed Model

The currently used method identifies high-risk segments using crash-risk estimates based on crash severity. The new method proposed for PR consists of improving the current HRSI ranking method by employing the SMA methodology. The SMA method theoretically outperforms crash-risk estimates based on crash counts (Katicha et al. 2020). However, using SMA directly with total crashes does not represent the actual risk because it does not account for crash severity. Therefore, the approach takes the current PR crash count ranking methodology and replaces them with estimates of the fatal, injury, and PDO crashes determined using the SMA method.
4.5.3 Model Evaluation

The benefits of adopting the SMA method were evaluated with a segment consistency test to determine if the same risky locations are identified in each method using data from different years. Then a mean-square prediction error test was performed to identify how well the SMA method predicts crashes.

Road Segment Consistency Test

In 2008, Cheng and Washington introduced the highway segment consistency test (SCT), which compares site consistency with different HRSI methods (Cheng and Washington 2008). The test compares the sum of observed crashes at $n\alpha$ high-risk sites of one year to the next year $i + 1$ by applying a HRSI method $j(i)$, which is greater than the sum of another HRSI method $j$.

$$SCT = \sum_{k=n-n\alpha}^{n} C_{k,method=j(i),i+1} > \sum_{k=n-n\alpha}^{n} C_{k,method\neq j,i+1}$$  \text{Eq. 4-16}

where,

- $SCT$ = Segment Consistency Test
- $n$ = total road sections
- $C$ = crash count for ranked location $k$
- $\alpha$ = threshold (%) of top risky locations to identify
- $j$ = HRSI method
- $i$ = year of observation

SCT quantifies the performance of different HRSI methods, where a road segment is identified as risky for two years consecutively, and no treatment has been applied. In other words, SCT checks if a road section is in the top-ranked list of high-risk locations in year one and year two while no modifications have been made to the road.
**Mean Squared Prediction Error**

The mean-squared prediction error (MSPE) provides a measurement of the quality of the prediction. MSPE measures the distance between the predictor estimated value and the actual value. Therefore, we can define MSPE as the expected value of the squared distance between the risk estimate values $g_{y+1}(x_i)$ and the crash counts $g_y(x_i)$.

\[
MSPE(L) = E \left[ \sum_{i=1}^{n} (g_y(x_i) - g_{y+1}(x_i))^2 \right] \tag{Eq. 4-17}
\]

where,

- $L$ = projection matrix $L$
- $E$ = expected value
- $g_y(x_i)$ = counts or risk for road section $i$ at year $y$

The objective of risk prediction is to predict the values of a time series with the least possible error. Therefore, an optimal prediction results in the minimum MSPE (Pindyck 1991).

### 4.6 Results

#### 4.6.1 Estimated Crash Risk with the SMA Method

FIGURE 4-3 presents a linear spatial representation of the crash counts along highway PR-2 for 2014. Note that 2015 crash data show the same trend. Typical spatial features can be noted for this road. A high number of crashes are found in the main cities or towns, with fewer crashes in more rural areas. Along PR-2, urbanized and congested areas are located in San Juan, Arecibo, Aguadilla, Mayagüez, and Ponce. Locations with fewer crashes are generally less-congested rural areas and longer road segments with homogeneous crash risk sections. A particular case of confounding factors was noted in the typically dryer south of the island near Ponce, where lower than average wet crash counts are found probably due to less rainfall.
FIGURE 4-3 Crash Count on PR-2 for Year 2014.

FIGURE 4-4 through FIGURE 4-6 presents the SMA method's application to PR-2 for the three crash types: total crashes, PDO, and fatalities. These figures show the cumulative kilometer-post sections every 0.1 km (x-axis), the crash counts in light blue, and the crash-risk estimate in red (y-axis).

FIGURE 4-4(a) shows that the total crash-risk estimates are similar to the crash counts for high crash frequency locations. FIGURE 4-4(b) shows details of a subsection with few crash frequencies. Similarly, FIGURE 4-5 shows the results for PDO crashes; it can be observed that the trends are similar to those for total crashes. The proposed method consistently reflects a good representation of the crash counts through crash-risk locations with low-crash and high-crashes.

FIGURE 4-6 shows the fatal crash count on all roads and the corresponding estimated fatal crash risk. Among all crash categories, fatal crashes, because they are rare, best illustrate the inadequacy of crash counts. Most sections have a count of zero; however, we know that the risk on those sections is not zero.
FIGURE 4-4 Total Crash Counts and SMA Risk Estimates of PR-2 for 2014.
FIGURE 4-5 PDO Crash Counts and SMA Risk Estimates of PR-2 for 2014.
Furthermore, the crash counts at most of the locations that recorded a fatal crash significantly overestimate the crash risk. The red line shows how the SMA method seems to estimate the crash risk for high and low numbers of crashes.

The MSPE of the crash count and crash-risk estimated by SMA are summarized in TABLE 4-2. The analysis was performed for all roads (primary, secondary, and tertiary), segmented every 0.1 km. Subcategories considered total crashes, fatalities, injuries, and PDO. The risk improvement is calculated as $|\text{Count} - \text{Risk}|/((\text{Count} + \text{Risk})/2)$. The outcome of this test indicates that the crash-risk estimate provides an overall lower MSPE for the different analyses compared to crash counts. Fatalities have a substantially higher risk improvement compared to other crash severities.
TABLE 4-2 Summary of MSPE.

<table>
<thead>
<tr>
<th></th>
<th>MSPE</th>
<th>Count</th>
<th>Risk</th>
<th>Risk Improvement</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Total</td>
<td>2.348</td>
<td>1.993</td>
<td>16%</td>
</tr>
<tr>
<td></td>
<td>Fatality</td>
<td>0.006</td>
<td>0.003</td>
<td>59%</td>
</tr>
<tr>
<td></td>
<td>Injury</td>
<td>0.361</td>
<td>0.234</td>
<td>43%</td>
</tr>
<tr>
<td></td>
<td>PDO</td>
<td>1.686</td>
<td>1.419</td>
<td>17%</td>
</tr>
<tr>
<td>Primary</td>
<td>Total</td>
<td>7.419</td>
<td>6.884</td>
<td>7%</td>
</tr>
<tr>
<td></td>
<td>Fatality</td>
<td>0.016</td>
<td>0.009</td>
<td>60%</td>
</tr>
<tr>
<td></td>
<td>Injury</td>
<td>0.975</td>
<td>0.694</td>
<td>34%</td>
</tr>
<tr>
<td></td>
<td>PDO</td>
<td>5.295</td>
<td>4.874</td>
<td>8%</td>
</tr>
<tr>
<td>Secondary</td>
<td>Total</td>
<td>2.237</td>
<td>1.791</td>
<td>22%</td>
</tr>
<tr>
<td></td>
<td>Fatality</td>
<td>0.008</td>
<td>0.005</td>
<td>45%</td>
</tr>
<tr>
<td></td>
<td>Injury</td>
<td>0.388</td>
<td>0.247</td>
<td>44%</td>
</tr>
<tr>
<td></td>
<td>PDO</td>
<td>1.610</td>
<td>1.265</td>
<td>24%</td>
</tr>
<tr>
<td>Tertiary</td>
<td>Total</td>
<td>0.685</td>
<td>0.459</td>
<td>40%</td>
</tr>
<tr>
<td></td>
<td>Fatality</td>
<td>0.003</td>
<td>0.001</td>
<td>78%</td>
</tr>
<tr>
<td></td>
<td>Injury</td>
<td>0.145</td>
<td>0.082</td>
<td>56%</td>
</tr>
<tr>
<td></td>
<td>PDO</td>
<td>0.519</td>
<td>0.344</td>
<td>41%</td>
</tr>
</tbody>
</table>

4.6.2 Comparison of Proposed Method with PR’s Current HRSI Approach

An RSCA was used to compare the current HRSI method used in PR with the alternative model to consistently identify the top locations with a high number of crash counts or high risk in consecutive years. This assessment considers the PR crash data from 2014-2015. Analysis at the 0.1-km level was used to maintain high data resolution, and the road network was broken down by functional classification.

The analysis compared the agreement between the sections selected in the top 1%, 2%, 5%, or 10% of the risk for both years. The baseline was the current methods and the alternative replacing PDO, injury, and fatal crash counts with PDO, injury, and fatal crash risk estimates using the SMA method.

TABLE 4-3 shows the HRSI consistency results for the current and proposed total crashes and wet crashes. Considering an arbitrarily selected 70% consistency threshold, the current method is more consistent for identifying HRSI for primary routes for all
crashes and wet crashes. For all crashes, an outstanding 99% consistency was found for primary roads for the top 10%. A 72% consistency was found for primary roads for the top 5%. Overall, the least consistency was found for secondary and tertiary roads with less than 40%. Looking at wet crashes, the consistency test for the current method shows no values greater than 66%.

The crash risk columns show the site consistency results of the proposed method, where crash-risk estimates replace crash counts. Compared to the current method, it represents an overall improvement for most percentiles and road classifications. The alternative crash-risk estimate shows a significant improvement in consistently identifying high-risk locations for all road classifications compared to the current method.

<table>
<thead>
<tr>
<th></th>
<th>All Crashes</th>
<th>Wet Crashes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crash Count</td>
<td>Crash Risk</td>
<td>Difference</td>
</tr>
<tr>
<td>Top 1%</td>
<td>46%</td>
<td>59%</td>
</tr>
<tr>
<td>Top 2%</td>
<td>46%</td>
<td>66%</td>
</tr>
<tr>
<td>Top 5%</td>
<td>41%</td>
<td>71%</td>
</tr>
<tr>
<td>Top 10%</td>
<td>47%</td>
<td>74%</td>
</tr>
<tr>
<td>Top 1%</td>
<td>52%</td>
<td>69%</td>
</tr>
<tr>
<td>Top 2%</td>
<td>57%</td>
<td>77%</td>
</tr>
<tr>
<td>Top 5%</td>
<td>72%</td>
<td>88%</td>
</tr>
<tr>
<td>Top 10%</td>
<td>99%</td>
<td>99%</td>
</tr>
<tr>
<td>Top 1%</td>
<td>33%</td>
<td>41%</td>
</tr>
<tr>
<td>Top 2%</td>
<td>35%</td>
<td>53%</td>
</tr>
<tr>
<td>Top 5%</td>
<td>35%</td>
<td>64%</td>
</tr>
<tr>
<td>Top 10%</td>
<td>38%</td>
<td>65%</td>
</tr>
<tr>
<td>Top 1%</td>
<td>21%</td>
<td>41%</td>
</tr>
<tr>
<td>Top 2%</td>
<td>18%</td>
<td>46%</td>
</tr>
<tr>
<td>Top 5%</td>
<td>23%</td>
<td>56%</td>
</tr>
<tr>
<td>Top 10%</td>
<td>29%</td>
<td>64%</td>
</tr>
</tbody>
</table>

**TABLE 4-3 Consistency Results for Total and Wet Crashes.**

4.7 Discussion

The proposed method is relatively easy to implement. Only total crash counts by severity are needed for the desired segment length (e.g., 0.1 km). One data set of crash
severity is placed in the SMA Excel spreadsheet calculator, and the risk is obtained in seconds. The process is then repeated for other severities. This risk is then placed in another spreadsheet that calculates the crash-frequency ranking and the crash-cost frequency ranking, then combines these two into a final ranking of crash risk by priority.

The results presented showed that the method works for all crashes and wet crashes. However, the approach can potentially be replicated for any areas or categories, such as aggressive driver, alcohol-related, roadway departure, vulnerable users, or high-risk rural road. Applying the proposed method to other crash programs is essential to validate the method’s reliability with RSCA and MSPE analysis.

Furthermore, assessing different crash-contributing circumstances could help DOTs reevaluate particular areas because the proposed improved risk estimate can provide more reliable risk estimates. Efforts could possibly be refocused based on HRSI to provide a greater impact and significance. The drawback of the SMA method is soft thresholding for the PURE calculation because it reduces differences by a value equal to the threshold. Even when soft thresholding is not desired for significant differences, the literature demonstrates that it is better than hard thresholding. This method provides a more reliable, comprehensive, and strategic approach than other crash-count methods (Katicha et al. 2020).

### 4.8 Conclusion

This manuscript proposes a new systemic, data-based approach to identify hazardous-road segments by estimating the total crash and wet-crash risk for agencies with limited or no road geometry and/or friction data. Spatial multiresolution analysis was used to estimate crash risk and more consistently identify sites over several years than the current HRSI method. Considering the limited resources and data availability, the proposed method provides a viable and enhanced practice to identify high-risk locations in Puerto Rico. The proposed method can screen the network and identify high-risk locations, which may warrant a detailed safety analysis to identify potential problems and applicable countermeasures. This method is applicable for other jurisdictions.
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CHAPTER 5: Methodology for the Identification of Locations with High Potential Hydroplaning at Network Level

5.1 Abstract

This paper proposes an approach to estimate hydroplaning risk using road and pavement characteristics data. The hydroplaning phenomenon has traditionally been studied by estimating the hydroplaning speed as a function of the tire inflation pressure. Later, the footprint aspect ratio also played an important role. Recent efforts to find a comprehensive approach resulted in a computational fluid dynamics method. In combination with the Gallaway water-film thickness estimation method, the fluid dynamics method can provide a reliable estimate of a vehicle's performance, given specified rainfall intensity, road characteristics, vehicle characteristics, and operating conditions. The objective of this research is to present a new method to identify locations with a risk of potential skidding or hydroplaning at the network level. The assessments consist of understanding how each parameter affects the resulting performance measure, replicating real-life road conditions, applying the method to a network section, and presenting strategies that can help decision-making. Applying the proposed method can allow DOT to identify the high-risk locations more accurately, which will help maximize resources and reduce potential crash risk.
5.2 Introduction

5.2.1 Background

In the U.S., nearly 32,000 people die each year and 1.6 million people are injured in crashes (National Highway Traffic Safety Administration 2018). The Federal Highway Administration (FHWA) has reported that 12% of all fatal crashes in the U.S. are wet pavement related, 21% of all crashes reported are related to wet pavement, of which 46% occur during rain events (FHWA, 2020). Statistics on hydroplaning-related crashes are not always available and often, these types of crashes are classified as wet pavement-related crashes. In addition, there is still an ongoing debate as some researchers suggest that all wet crashes are a type of hydroplaning (Moore 1967). Other researchers suggest that most wet crashes are not caused by hydroplaning because hydroplaning is a rare event that depends on many factors (Mounce and Bartoskewitz 1993). Knowing the definition of hydroplaning is essential to understand the differences.

Hydroplaning is the physical phenomenon where the tire is separated from the pavement surface, which is caused by a layer of water. Hydroplaning is divided into three categories: viscous hydroplaning, dynamic hydroplaning, and tread rubber reversion hydroplaning. Highway engineers focus on viscous and dynamic hydroplaning, which impacts the performance of the vehicle. Viscous hydroplaning occurs at low speed, on pavements with low or no microtexture and a thin water film of about 0.001 in (0.025 mm) thick. Having a low microtexture prevents the water from penetrating the pavement, which does not allow to drain the pavement surface and prevents the water from escaping from the tire footprint area (Charbeneau et al. 2008). Dynamic hydroplaning results from a vehicle traveling at high speeds and experiences high hydrodynamic forces that separate one or more tires from the pavement when the water film is about 0.1 in (2.54 mm) thick. Most references agree that dynamic hydroplaning is critical because the driver loses total traction and vehicle control (Moore 1967, Gallaway et al. 1979, Mounce and Bartoskewitz 1993).
The work discussed in this paper builds on past research on hydroplaning speed and risk modeling (Gallaway et al. 1971, Enustum 1976, Black Jr and Jackson 2000, Gunaratne et al. 2012, Yassin et al. 2013, Jayasooriya and Gunaratne 2014, Al-Ahad Ekram and Kane 2018). It proposes a proactive systemic approach to assess hydroplaning potential at the network level. NCHRP Project 15-55 Guidance to Predict and Mitigate Dynamic Hydroplaning Potential has produced a new definition of hydroplaning, as well as a practical tool to assess hydroplaning risk on selected road segments. However, there is a need for a network-level scanning method that identifies locations with a high risk of hydroplaning potential on wet pavements.

5.2.2 Objective

The paper presents an approach to identify locations with a risk of potential hydroplaning at the network level. The approach expands the results of NCHRP Project 15-55 by applying the models developed to the systemic analysis of in-service roads. The method is demonstrated on a section of interstate highway using road surface characteristics collected by the Center for Sustainable Transportation (CSTI) of the Virginia Tech Transportation Institute (VTTI).

5.3 Background

5.3.1 Factors Contributing to Hydroplaning

To adequately address hydroplaning problems is essential to understand the different factors that contribute to this phenomenon. This section presents the significant contributing factors and how they affect water accumulation and driving vehicle performance.

The fundamental issue of the hydroplaning phenomenon is the loss of traction due to the accumulation of water on the pavement surface. However, vehicle performance depends on several factors that affect the interaction between the tires and the pavement. These are the same that affect friction and traction, and include road characteristics (grade, cross-slope, and curvature, macrotexture and roughness), water-
film thickness, vehicle characteristics (type, weight and tire type and condition), and operating conditions (speed, braking, and deceleration/acceleration) (Wallman and Åström 2001, Wilson and Dunn 2005, Kang et al. 2019).

**Road Characteristics**

Road geometric design is important to reduce hydroplaning. A good geometrical design accounts for adequate drainage, allows fast water to flow off the pavement surface and reduces water accumulation. For example, the cross-slope affects water accumulation; thus, providing appropriated cross-slope drainage can improve driver safety by reducing the hydroplaning potential. AASHTO recommends using cross-slopes between 1.5%-2% for single-lane roads and a maximum of 4% for multi-lane roads where intense rains are expected. According to Gallaway et al. (1979), a 2% or higher cross-slope for a typical 3-lane road (10.97 m or 36 ft wide) considering a rainfall intensity of 13 mm/hr should not experience hydroplaning.

Gallaway et al. (1979) demonstrated that steep grades increase the surface runoff drainage flow-path length. Highway design requires a delicate balance. According to Luo et al. (2016), high longitudinal and cross slopes reduce the wheel load of cars traveling perpendicular to the pavement surface, increasing the danger of hydroplaning. American Association of State Highway and Transportation Officials (2018) recommends that a minimum of 0.35% is needed to provide surface drainage.

Road curvature is an important factor that affects hydroplaning potential. During highway design, special attention is needed to provide adequate superelevation in the presence of high curvatures, especially on multi-lane facilities. Locations with a large radius of curvatures tend to accumulate more water, except where design accounts for superelevation equal or greater to the tangential cross-slope (Khan et al. 1994).

Road surface texture is another critical parameter. Pavement texture is divided into four components: microtexture, macrotexture, megatexture, and
unevenness/roughness. Each texture wavelength has a positive and negative impact on the vehicle-pavement interaction. For example, lower microtexture provides better tire-road friction but increases tire wear.

Macrotecture is the coarse-scale texture of the pavement surface. The macrotecture affects the hysteresis grip component of the friction and produces significant noise at wavelengths of 5 mm or higher (Haider et al. 2014). Higher macrotecture allows water to penetrate through larger cavities, which reduced the water-film thickness and helps drain the contact patch between the tire and the pavement. A reduction of the water film results in a reduction of the hydroplaning potential.

Roughness or unevenness is the large-scale texture of the pavement surface, which relates to the ride quality. It affects the tire-pavement contact and adhesion, rolling resistance, rider comfort, and vehicle wear (Panagouli and Kokkalis 1998, Kotek and Kováč 2015).

**Annual Average Rainfall Intensity**

The annual average rainfall intensity can be estimated using different sources. For example, the National Oceanic and Atmospheric Administration (NOAA) provides access to Atlas 14. Atlas 14 is a tool that provides rainfall frequency estimates with a 90% confidence interval by analyzing all available precipitation data. Weather data are very sensitive to time and locations, making it challenging to obtain very accurate results. There could potentially be a discrepancy in rainfall volumes estimates at boundary zones (National Oceanic and Atmospheric Administration 2017). Because NOAA has consistently been the most reliable governmental weather information source in the U.S., data are considered trustworthy and valid for use. Data are available for U.S. states and territories.

Alternatively, in Virginia, the Virginia Stormwater Management Handbook uses the U.S. Weather Bureau Intensity-Duration-Frequency (I-D-F) curves to develop the
local design guidelines. Appendix 4D suggests that Virginia’s maximum rainfall intensity for designing stormwater management is 90 mm/hr (3.5 in/hr) for 100-year design (Virginia Department of Conservation Recreation 1999). Therefore, this paper used a conservative 100 mm/hr maximum rainfall intensity for design purposes.

**Water-film thickness**

Research has demonstrated that one of the main factors that increase the hydroplaning potential is the water-film thickness (WFT) on a pavement surface (Yassin 2019). FIGURE 5-1 illustrates the different elements that compose the WFT. The total flow thickness is found by combing the WFT and the mean texture depth (MTD). WFT is the depth from the highest point of the water film to the highest point of the MTD. Other factors affecting the total flow thickness are texture, slope, and section length, which will be discussed later in the paper.

![FIGURE 5-1 Water Film and Pavement Texture Components.](image)

Rainfall intensity also affects water surface flow and increases the water-film thickness. Therefore, a higher hydroplaning potential is expected during high rainfall intensities.
For nearly 60 years, researchers have attempted to estimate the water-film thickness (WFT) on roads (Dreher and Horne 1963). Two general types of models can be used to predict water-film thickness: (1) empirical models based on empirical data and (2) analytical models.

Gallaway et al. (1971) studied the expected water-film thickness by replicating road surfaces with nine different pavement types at various rainfall intensities, length of pavement surface, texture, and cross-slopes. Several WFT measurements were taken along the surface section samples with 28' x 4' dimensions. The best-fitted regression model was the result and is presented as follows:

\[
WFT = 3.38 \times 10^{-3} (T)^{0.11} (D)^{0.43} (I)^{0.59} \left( \frac{1}{S_f} \right)^{0.42} - T
\]

where,

\[
WFT = \text{average water-film thickness estimate (in.)}
\]

\[
T = \text{average pavement texture depth (in)}
\]

\[
D = \text{pavement drainage length (ft)}
\]

\[
I = \text{rainfall intensity (in/hr)}
\]

\[
S_f = \text{cross-slope of composite slope (ft/ft)}
\]

\[
S_f = \left( S_{cs} + S_g \right)^{\frac{1}{2}}
\]

where,

\[
S_{cs} = \text{cross-slope of pavement surface}
\]

\[
S_g = \text{grade of pavement surface}
\]

The NCHRP 1-29 project PAVDRN computer software used a similar single dimension steady-state form of the kinematic wave to estimate the water film thickness. The study included Manning’s n as a function of Reynold’s number.
Different transportation authorities have used equations similar to Gallaway's in the U.S., Australia, New Zealand, and U.K. (Chesterton et al. 2006).

**Vehicle Characteristics and Operating Conditions**

Vehicle operating parameters, tire properties, and vehicle operation factors also contribute to hydroplaning. However, some of these parameters are not fully controllable by state agencies, as they are dependent on the driver's driving skills, vehicle type, and maintenance. The vehicle characteristics and driver's behavior are also important in estimating hydroplaning potential. Hydroplaning speed is dependent on the WFT, vehicle, and tire characteristics. Vehicle weight will define the uplifting force needed for hydroplaning (Cho et al. 2006). A heavy vehicle can handle thicker WFT than a lighter vehicle. Thus, lighter vehicles can hydroplane at lower speeds. Studies have demonstrated that higher tire pressure results in less contact area with the pavement, which results in a concentration of the vehicle weight and higher hydroplaning speeds (Metz 2011). Tire tread pattern and depth affect the evacuation of the water out of the contact area. A deeper tread will pump water out of the contact area better (Horne and Joyner 1966).

### 5.3.2 Estimation of Hydroplaning Potential

Since the 1920s, hydroplaning has been a topic of research to address hydroplaning risk and road safety. Many studies have modeled the relationship between hydroplaning speed and tires and pavement surface elements. Most studies that address these aspects have been experimental in nature (Wambold et al. 1986).

**Hydroplaning Speed Empirical Equations**

In 1963, NASA presented a study on hydroplaning, where the hydroplaning speed was related to the tire pressure.

\[
v_p = 6.36\sqrt{p}
\]

Eq. 5-3
where,

\[ v_p = \text{hydroplaning speed (km/h)} \]

\[ p = \text{tire inflation pressure (kPa)} \]

The study used aircraft and automobiles on smooth pavement with an average water-film thickness (WFT) of 0.3 in (7.62 mm). Smooth and ribbed tires were considered. This study set the foundations for much research and, to this day, serves as a key reference (Dreher and Horne 1963).

Most research since then has used empirical methods to address hydroplaning potential. During the late 1960s, several analytical models were presented (Martin 1966, Eshel 1967, Henry et al. 1968). These models failed to correctly describe tire deformation and turbulent fluid flow before and during hydroplaning. Browne et al. (1972) used a 2D finite element and assumed a laminar flow, but the results were not comparable to the NASA equation. Grogger and Weiss (1996) present a computational fluid dynamic model to estimate the shape of the water around a vehicle tire by considering a turbulent non-compressive fluid flowing. This method was limited by not considering tire deformation.

PAVDRN defined the critical hydroplaning speed based only on WFT values as given by the following equation.

\[ v_p = 26.04(WFT)^{-0.259} \]  \[ \text{Eq. 5-4} \]

where,

\[ v_p = \text{hydroplaning speed (km/h)} \]

WFT = water-film thickness (mm), calculated with Gallaway Equation Eq. 5-1.

The software predicts the WFT along a line where the maximum flow happens and estimates hydroplaning potential along the flow path. If the design speed exceeds the hydroplaning speed for this maximum WFT, the software recommends countermeasures (Anderson et al. 1998).
Fwa and Ong (2008) proposed an improved analytical model to simulate hydroplaning risk and reduce skid resistance on wet pavements using a 3D finite element model. They concluded that the NASA equation is a specific case of generic solution that applies to a wide range of tire-footprint aspect ratios.

Jayasooriya and Gunaratne (2014) used the simulations developed by Ong and Fwa (2007) and fitted an empirical equation. The resulting model was:

$$v_p = WL^{0.2}p^{0.5}\left(\frac{0.82}{WFT^{0.06}} + 0.49\right)$$

Eq. 5-5

where,

- $v_p$ = hydroplaning speed (km/h)
- WL = wheel load (N)
- $p$ = tire inflation pressure (kPa)
- WFT = water-film thickness (mm) at the end of the pavement surface

**Mechanistic Approach**

*NCHRP Project 15-55* combined advanced water accumulation and vehicle response models into a research-grade *Integrated Hydroplaning Model* to estimate hydroplaning potential. The model evaluates vehicle handling in terms of operating characteristics (Kang et al. 2019).

A 3-D Computational Fluid Dynamics (CFD) model was developed to predict water accumulation on multi-lane highways using ANSYS Fluent software. The model solves the Reynolds-Averaged Navier-Stokes (RANS) equations representing the conservation of mass and momentum using a two-fluid Eulerian model. The model was developed and verified using experimental results from previous studies on very simple geometries and validated through a sensitivity analysis of the water-film thickness (WFT) produced on road segments with complex geometric characteristics.
The effect of water accumulation on the vehicle response was modeled by combining vehicle dynamics, tire, and hydraulic submodels using modeling and simulation tools available on the market. The simulations estimate the influence of the WFT on the vehicle's handling capability and assess the hydroplaning capacity for different operating conditions. The models evaluated the braking and maneuvering ability of three vehicle types (sedan, hatchback, and SUV) considering the road characteristics (grade, cross-slope, and curvature), water-film thickness estimates, vehicle characteristics, and operating conditions (tire condition, speed, and braking).

The study introduced a new definition of hydroplaning potential based on the concept of performance capabilities of the vehicle for varying conditions, as shown in FIGURE 5-2. This definition requires an understanding of both the current performance requirements and the limits with a given level of water on the road. The upper limit of the vehicle capacity is given by the Performance Envelope (PE), which is determined by road geometry and effective friction, which considers the vehicle dynamic and road surface properties. After supplying the required performance for specific operating conditions, the remaining available performance capability is the Performance Margin (PM). PM is determined using equation 5-6. The braking-acceleration component is on the x-axis and the cornering component is on the y-axis. The maximum braking is $\mu_x + \tan \theta_s$, while the maximum lateral acceleration is $\mu_y + \tan \theta_b$.

$$PM = \min \left[ \sqrt{(A_{Brk}^* - A_{Brk})^2 + (A_y^* - A_y)^2} \right], \forall A_x^*, A_y^*$$

Eq. 5-6

where,

$A_{Brk}, A_y = \text{required acceleration components for a given operating condition}$

$A_{Brk}^*, A_y^* = \text{available acceleration components}$
The implementation of the NCHRP 15-55 assessment approach is supported by the development of a software tool that estimates the PM for different conditions using simplified relationships. FIGURE 5-3 shows the main screen of the original Hydroplaning Potential Assessment Tool where a typical predefined road-surface cloud point is imported. Then manual entries of road characteristics, rain intensity, and vehicle characteristics are used to calculate the water-film thickness (WFT) and the performance margin (PM). This tool allows assessing hydroplaning potential at a specific location. However, DOTs may also want to assess the hydroplaning potential of the road network.
5.4 Methodology

The models developed under NCHRP 15-55 are used to develop a systemic network-level analysis for in-service roads. A road surface analysis subroutine was developed to use the road geometrical measurements collected on-site by a typical inertial unit for pavement evaluation to generate a grid representing the pavement surface. The surface grid is then used to estimate water accumulation. The Hydroplaning Risk Assessment Tool was modified systemically to estimate hydroplaning potential along a road segment. To verify the model, a sensitivity analysis was performed considering typical characteristics found on highway sections. After the hydroplaning model was verified, its practicality was tested in a case study that generated a systemic hydroplaning-potential analysis for a section of Virginia Interstate highway. Results from this analysis allowed the identification of high-risk locations.
5.4.1 Data Sources

The sensitivity analysis used synthetic data. The case study considered road geometry and pavement characteristics data collected with the Sideway-force Coefficient Routine Investigation Machine (SCRIM). This data was provided by the Virginia Department of Transportation (VDOT).

5.4.2 Road Surface Generation

The expanded tool generates a representation of the road surface based on parameters measured by pavement evaluation equipment or from data available in DOT databases: grade (%), cross-slope (%), and the number of lanes to produce a road surface XYZ point cloud. The lane width default calculation has been set to 3.65-m lane width. The input distance measurements (e.g., 10 m, 20 m, 30 m) are adjusted to have a grid of 1-meter (e.g., 1 m, 2 m, 3 m) and will be referred to as stations. The lane width, grade, and cross-slopes are then interpolated with a function to match each station.

A centerline elevation function was created to calculate each centerline station elevation by assuming inputs where: $d$ is the section distance or station of row $i$ for the matrix, $w$ is the width $j$ for the matrix, and $G$ is the centerline longitudinal slope at each station $d$, and elevation at station $d(1) = 0$. The number of rows and columns is defined by the $d$ and $w$ sizes, and these are validated. The centerline elevation is computed using equations 5-7:

$$M_0(i) = M_0(i - 1) + [d(i) - d(i - 1)] \left( \frac{G(i - 1)}{100} \right)$$

Eq. 5-7

where,

- $M_0$ = initial matrix
- $d(i)$ = station $i$ evaluated (m)
- $d(i - 1)$ = one station before the station $i$ evaluated (m)
- $\frac{G(i - 1)}{100}$ = grade percentage before the station $i$ evaluated and converted to m/m
With the initial centerline elevation, then the final matrix calculations can be performed. A loop of the final matrix \( M_f \) function calculates the elevation for all remaining stations with respect to the centerline and the corresponding interpolated widths. The final matrix elevation function is expressed as:

\[
M_f = M_0 + w(j) * \frac{CS}{100}
\]

Eq. 5-8

where,

- \( M_0 \) = initial matrix
- \( w(j) \) = width \( j \) evaluated (m)
- \( \frac{CS}{100} \) = cross-slope percentage evaluated and converted to m/m

The final matrix is then converted to an XYZ table that allows the creation of a point cloud. Finally, a grid data surface function generates the pavement surface, taking the XYZ cloud points as coordinates and elevations. FIGURE 5-4 show an example of a section of a corridor simulated.

FIGURE 5-4 Example of Road Surface Simulation Results.
5.4.3 Systematic Hydroplaning Potential Analysis

The analysis uses an expanded version of the simplified hydroplaning potential assessment tool to perform a network-level hydroplaning potential assessment of a road corridor or continuous road sections. This is achieved by automatically taking the continuous field measurements to generate a road-surface cloud point and then estimating the WFT and performance margin using a 30-m sliding window.

The process starts by generating a table with the data of the continuous road sections to be analyzed. The field measurements needed are distance along the section analyzed (m), grade (%), cross-slope (%), number of lanes, MPD (mm), and curvature (1/m) to compute the radius of curvature (m). Once the file is loaded with the "Load Geometry" button, the code initiates by segmenting the data in 30-meters intervals. A higher resolution is set to 1-meter, and the input parameter of the SCRIM is interpolated (e.g., grade, cross-slope, MPD) to match the new resolution. The road surface is computed as discussed in section 5.4.2, and results are stored in a matrix. All matrices are combined and displayed in the surface plot. Water flowlines are computed at a 0.2 mm resolution.

The second step is to define rain intensity and to calculate the WFT with the Gallaway Eq. 5-1 and to apply the diffusion methodology presented in NCHRP 15-55 for each water-flowline section along the route and stored in a matrix $XY{i}$. A final WFT is selected from the array $i$ with the maximum WFT. All sections are then combined to generate the water distribution plot, and the maximum WFT for each array is combined in a list to plot the WFT for each road section. Finally, the performance margin is calculated from Eq. 5-6, which incorporates all the computational fluid dynamics models for the different vehicle characteristics and operating conditions. Each road section evaluated will have a PM and is presented in a continuous section. FIGURE 5-5 represents the modified version analysis tool.
5.5 Model Verification Through Sensitivity Analysis

A sensitivity analysis was performed to verify the model. The analysis quantifies how the independent input variables (curve, grade, and slope) affect the performance
margin output on a uniformly-sloped highway section. A baseline condition typical for each variable was defined for this sensitivity analysis as presented in TABLE 5-1.

<table>
<thead>
<tr>
<th>Groups</th>
<th>Variables</th>
<th>Baseline Value</th>
<th>Range</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>Road Characteristics</td>
<td>Mean Profile Depth (MPD)</td>
<td>0.5</td>
<td>0 -to- 1</td>
<td>mm</td>
</tr>
<tr>
<td></td>
<td>Roughness</td>
<td>Flat</td>
<td>Flat, IOS A, B, C</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>Cross-Slope (CS)</td>
<td>2</td>
<td>0 -to- 5</td>
<td>%</td>
</tr>
<tr>
<td></td>
<td>Radius of Curvature (R)</td>
<td>500</td>
<td>250 -to- 2000</td>
<td>m</td>
</tr>
<tr>
<td>Vehicle Characteristics</td>
<td>Vehicle Type</td>
<td>Sedan</td>
<td>Sedan, SUV, Hatchback</td>
<td>-</td>
</tr>
<tr>
<td>and Operating Condition</td>
<td>Tire Tread</td>
<td>Bald</td>
<td>Bald or New</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>Braking (B)</td>
<td>0</td>
<td>0 -to- 0.5</td>
<td>G</td>
</tr>
<tr>
<td></td>
<td>Speed (S)</td>
<td>105</td>
<td>45 -to- 105</td>
<td>km/h</td>
</tr>
<tr>
<td>Water</td>
<td>Rainfall</td>
<td>60</td>
<td>0 -to- 100</td>
<td>mm/h</td>
</tr>
</tbody>
</table>

FIGURE 5-7 summarizes the sensitivity analysis results comparing variations for each road parameter with respect to the baseline condition in FIGURE 5-7(a). Each plot represents one different variable assessed from the hydroplaning model and shows the relationship between the WFT and the Performance Margin (PM). A performance margin (PM) below or equal to 0 represents a potentially unsafe condition with high potential for hydroplaning as the required traction exceeds the available performance.

All the trends are as expected. FIGURE 5-7(b) shows that the PM tends to increase with higher MPD. As expected, a better MPD reduces water accumulation. FIGURE 5-7(c) shows that the pavement roughness, as defined in ISO 8608 standard classification system (Agostinacchio et al. 2014), does not significantly impact the PM. FIGURE 5-7(d) shows that PM tends to increase when the cross-slope, with lower CS resulting in lower PM because of the higher water accumulation.
FIGURE 5-6 Sensitivity Analysis with Respect to Road Characteristics.

FIGURE 5-8 illustrates the effect of the vehicle characteristics and operating conditions. As expected, the SUV with a bald tire is the most critical vehicle; it has the lowest PM and highest hydroplaning potential. Braking harder tends to significantly reduce the PM as some of the available grip is used in the braking. Similarly, the PM also decreases at higher speeds.
5.6 Case Study

This section illustrates the practicality of the tool by estimating the hydroplaning potential along a sample corridor. The network analysis considers the measured road surface characteristic (mean profile depth, cross-slope, grade, and curvature) on a section of Interstate highway in Virginia, and critical vehicle characteristics and operating conditions: SUV, bold tire, 0.4 g braking, and 120 kph speed. The tool computed the water-film thickness (WFT) and the corridor's performance margin (PM). The rainfall intensity was set at 60 mm/hr.
The data was collected every 100 mm interval and the case study evaluated a 3-km road section. FIGURE 5-8 shows details of the geometrical characteristics for the interstate segment under study. The light gray lines represent the radius of curvature in meters. Sharper curves are found at the beginning of the corridor where the radius of curvature is less than 2,000 m, which also explains the high cross-slopes of -5% to -7% shown with the orange line—the MPD, given by the green line, typical range from 0.8 mm to 1.2 mm. However, a low texture section is found at the beginning of the segment. The yellow line shows the grade, and all sections have a positive value ranging from 2% to 4%, representing an uphill soft, vertical curve. A sag is located between progressives 250 m and 2000 m.

![Figure 5-8](image)

**FIGURE 5-8** Virginia Corridor Geometrical and Pavement Characteristics.

FIGURE 5-9 shows the results of the potential hydroplaning assessment for the corridor. The PM result for each section is represented with a black dashed line; an illustrative threshold for critically low PM was set at 0.1 and shown by a red line. An orange line gives a threshold for medium PM of 0.12 and the WFT is represented with the light blue line.
The figure shows a 60 mm per hour rainfall rate; a few localized sections have a relatively low PM. The WFT tends to be between 0.4 and 1.2 mm. However, the first 500 meters show a lower WFT due to a crest area and cross-slopes greater than 4%. A total of 60-meters indicates a medium risk of hydroplaning and should be evaluated further.

5.7 Discussion on Potential Implementation

The presented hydroplaning potential analysis tool is easy to implement after selecting the vehicle operating conditions and defining the critical threshold. The biggest challenge is data acquisition. However, more states already collect road geometry and pavement surface characteristics data. Once the data are collected and verified, they can be analyzed using the tool. The road surface is generated automatically, and the water-film thickness and performance margin are calculated for a given rainfall intensity. Thus, the proposed approach and tool can be used to identify locations with high hydroplaning potential. DOTs should consider the inclusion of this methodology in their safety programs. Working together with the pavement resurfacing and/or hydroplaning prevention programs can help maximize resources and increase the significance and impact of the improvement efforts. For a successful implementation, the DOT may define PM thresholds that account for local conditions.
5.8 Conclusions

This paper expanded the results of NCHRP 15-55 to propose a systemic, data-driven approach to identify locations with high hydroplaning potential at the network or corridor level. The approach considers different factors affecting the vehicle-tire-pavement interaction under wet weather conditions to estimate the hydroplaning potential. The hydroplaning potential is estimated based on the available performance margin (PM) for a standard vehicle and operating conditions along a road segment. The PM profile can be used to pinpoint areas with potentially high hydroplaning potential that can be further evaluated in a detailed, project-level safety analysis.

The sensitivity analysis showed that some of the vehicle characteristics and operation conditions, e.g., braking and tire tread, significantly affect the performance margin and thus should be selected carefully. The practicality of the approach was illustrated with a case study. Further development and implementation of the proposed approach will require defining appropriate PM investigation thresholds.

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CHAPTER 6: Wet Crash and Hydroplaning Mitigation Solutions

In this chapter presents a critical review of existing solutions for sites with high hydroplaning potential, including estimated cost, potential drawbacks (if any), and estimated benefits.

Since several mitigation strategies are often available to improve the safety performance of road sections identified to have a potentially high potential for hydroplaning, identifying specific countermeasures would require a project-level assessment. However, this chapter intends to present available options that could assist in the decision process and investment allocation. A fundamental part of the assessment is optimizing the geometric design and pavement surface characteristics to reduce the accumulation and thickness of water in the road lanes while considering comfort, safety, and drainage.

It is important to note that while geometric modification provides a relatively permanent impact on pavement runoff characteristics, road surface modifications often provide only a temporary impact that begins to diminish immediately after construction and that may need periodic retreatment for effective performance. Other non-engineering measures can also help and are mentioned in this chapter for completeness.

6.1 Highway Engineering

When geometric problems that facilitate water ponding are identified, certain measures need to be taken. Examples include insufficient cross slope in a transition from a tangent to a horizontal curve (or vice versa), poor drainage in very wide pavement sections (three or more lanes), and rutted asphalt pavement surfaces. NCHRP 1-29 conducted a survey of highway agencies and identified a portfolio of measures for improving surface drainage that was classified into three broad groups:

1. Optimization of geometric design parameters such as cross slope;

2. Road Surface Improvements, such as the use of milling and grooving; and
3. Improving the drainage through the use of internally draining wearing courses and/or installing drainage appurtenances reduces the distance that water must travel (flow path).

The following sections investigate these strategies.

6.1.1 Optimization of the Road Geometric Design

Geometric design improvements are very important, especially at the highway design phase, and the AASHTO Policy on Geometric Design of Highways and Streets manual mentions hydroplaning as an important consideration (American Association of State Highway and Transportation Officials 2018). However, geometric design improvements are usually expensive once the road has been constructed and they are only considered as a last recourse as a mitigation strategy. Therefore, designs must be checked for areas of potential high hydroplaning risk at the design phase. These include areas of high water accumulation but also areas where deficient features may negatively impact vehicle performance (e.g., deficient super-elevation or incorrect cross slope). The elements that should be considered include the following:

- **Sags and vertical alignment.** Vertical curves are the link between segments with constant grades. Adequately designed crests or sags provide safe transitioning curves for drivers by considering the minimum required sight distance needed for passing other drivers and stopping when there is an object ahead.

  To minimize sight distance problems, the K-value controls the rate of vertical curvatures, which is the length of the curve (L) per percent algebraic difference in intersecting grades (A), expressed by the equation \( K = \frac{L}{A} \). The suggested K-values for sag and crest are less than or equal to 167 ft., with a minimum 0.3% grade (American Association of State Highway and Transportation Officials 2018).

- **Cross slope and super-elevation.** Cross slope is important to facilitate the drainage of the water to the sides of the road. Super-elevation is determined by climate, terrain, type of area, and slow-moving vehicles. Special attention should be taken
in the transition areas (runoff) that are located ahead of the super-elevation. The reason for this is that there is a greater chance of having water accumulation due to the transition from a normal crown to an inverted crown that results in flat areas.

In general, drainage can be improved by increasing grade and cross slopes. This provides faster and more efficient removal of water from the pavement. However, in some designs, a greater longitudinal slope can increase the drainage path and increase water accumulation impacting the hydroplaning potential. Adjusting the road configuration can also shorten the traveling distance of the water (Anderson et al. 1998).

6.1.2 Road Surface Improvements

Designing a new road surface is easier than modifying the geometry of existing roads. Improving the road surface is the alternative for some existing roads. Examples of intervention treatments for correcting geometric design or pavement deterioration problems (e.g., rutting), include the following:

- **Milling** (cold planing, asphalt milling, or profiling) of asphalt pavements is widely used to remove existing pavement to the desired depth (e.g., to fix specific problems such as rutting, where water can accumulate and cause hydroplaning), to restore the pavement surface to a specified grade and/or cross slope, and to help improve the rideability of an existing surface. It can be applied at the small scale (hotspots) or large scale (road corridors).

  This procedure is typically applied for leveling the road geometry or repairing damaged pavement, but it also restores drainage flow, is environmentally friendly, and is relatively low cost compared to other procedures (Epps 1990).

- **Diamond grinding** of concrete pavement produces a similar effect to milling in asphalt pavements. Diamond grinding is a technique to improve pavement irregularities, such as faulting, curling, roughness, and warping of the slabs, by
using a diamond saw blades that are closely spaced and gently abrade the top surface of the concrete. It is used mainly to provide a smoother ride but can also result in noise reduction, better friction, and lower hydroplaning potential.

- **Cutting of grooves** across the entire width of the lane to help channel the water from the traveling lanes of the pavement can also help reduce hydroplaning potential. In the U.S., grooving is applied mostly to Portland cement concrete surfaces to create channels that drain the water out of the surface. In other countries, grooves are also used on asphalt surfaces; however, the grooves’ effectiveness decreases rapidly with traffic. To enhance its effectiveness, grooves should be applied parallel to water flow. For the best result, grooves should be parallel to the slope of the pavement. The grooves are typically 0.25 in. deep, 0.125 inches wide, and 0.75 inches separate (Hoerner et al. 2003).

Laboratory studies indicate that grooves are more effective at channelizing rain falling in the upstream flow path than the downstream path since water is carried in the grooves (Anderson et al. 1998). Furthermore, some limited empirical evidence has suggested that any type of texture would increase the contact between the tire and the pavement on wet pavements and thus, enhance the handling capabilities and available grip (e.g., Flintsch et al. (2010)).

- **Overlay and cross-section overbuild for asphalt pavement**, preferably after a milling operation, to even the surface and allow good bonding of the new layer, and correct any cross slope problems that might be present. The paving is then completed with an even depth on the entire depth of the overlay.

Overlays are used mainly as a rehabilitation or preservation treatment, but they can also help provide adequate drainage. The overlay design can improve slope and crown to allow runoff water to drain to the shoulders, into a ditch, and out from the surface. Cross slope overbuild is usually applied after milling to correct the slope and even the surface.
6.1.3 Drainage Improvements

The portfolio of mitigation strategies also includes measures focusing on reducing water accumulation through the use of permeable pavements and the installation of drainage appurtenances.

- **Permeable wearing courses** are becoming more popular, especially in states that do not have severe winters. Although both permeable and concrete pavement surfaces have been used in parking lots and streets, only porous or permeable asphalt layers are commonly used in roadways. The primary benefit of these permeable surfaces is the potential to reduce WFT because the water can flow through the layer (Noyce et al. 2005), which reduces the hydroplaning potential. In the U.S., porous hot mix asphalt contains 10% to 13% air voids and a maximum depth of 19 mm.

The European mixes usually consist of 20% air voids and a thicker depth of 25 mm. In general, it provides greater texture and more internal drainage (Balmer and Gallaway 1983, Chaithoo and Allopi 2012). Locations with porous pavement were found to reduce wet crashes by 20% in fatal and injury crashes in Europe (Hein and Croteau 2004).

- **Inlets.** An alternative to solving the problem of water ponding and sheet flooding on multilane facilities is installing inlets between lanes. While fewer lanes allow water to travel shorter distances and exit the pavement surface faster, multilane facilities account for higher water paths and higher WFT. Increasing the slopes will drain the water faster; however, when suggested slopes cannot provide adequate drainage for safe roads, installing inlets can be an alternative to improve road drainage when constructing new roads.

However, construction of any form of inlet within the traveled way is almost invariably problematic because all inlets require periodic maintenance and lane closures.
6.2 Enforcement and Traffic Control

Although outside the scope of the study, if potential hydroplaning problems requiring some type of construction solution are identified, temporary signs alerting drivers to reduce speed or that the pavement is slippery when wet can be put in place as soon as possible. This will also help to provide a safer work zone for the construction crews when the repair operations begin. The use of variable speed limits based on changing weather conditions may also be appropriate.

6.3 Advice and Education

Another critical element in the development of hydroplaning mitigation is drivers’ understanding of the phenomenon and their reaction to the conditions in which hydroplaning may occur. The development and use of the Hydroplaning Potential Assessment Tool developed can give a better fundamental understanding of hydroplaning, allowing this phenomenon to be better described to the driving public.

Simulation results can be used to demonstrate to drivers the importance of maintaining the tread depth on their tires while also educating them about the effects of steering and braking commands in wet conditions. With a better understanding of hydroplaning and a sound fundamental model, the differences and similarities between driving on flooded pavements and ice/snow can be conveyed to the driving public. Specifically, drivers can be instructed about how to adapt their driving strategy on wet pavement based on how they should adapt their driving to ice/snow.

On a larger scale, this information should be shared with tire and vehicle manufacturers to aid them in product design. Since tire tread has a major impact on hydroplaning potential, vehicle manufacturers may be able to refine Electronic Stability Control protocols based on the results of this study.

References


CHAPTER 7: Conclusions and Recommendations

7.1 Dissertation Summary

This dissertation focuses on helping reduce wet and hydroplaning crashes through systemic, data-driven, risk-based approaches to enhance the identification of road segments with a high risk of wet and/or hydroplaning crashes. FIGURE 1-1 summarized the analysis approaches proposed and provided guidelines on how to select which one to use based on the available data.

The first approach consists of a robust approach to identify locations with high wet crash potential when substantial road characteristic data is available. The method estimates wet crashes by considering dry and wet crash counts, traffic, and road characteristics. The second approach provides a simplified approach that uses only crash counts to identify areas of high risk of crashes. This approach provides a simpler way to identify areas of crash risk that can be used by jurisdictions with limited resources and available data. The third approach allows to identify locations with high hydroplaning potential, considering road geometry, environmental condition, vehicle characteristics, and operational conditions. This approach estimates the hydroplaning potential based on the performance of a selected vehicle under simulated operational conditions. Finally, the dissertation identifies available solutions to mitigate risk for locations with a high potential of skidding and/or hydroplaning on wet pavement.

7.2 Discussion

The presented methods are used to perform a systemic network-level screening of the wet pavement risk. The first step is to gather the network data, identify available variables, and process the data to match the presented resolution to clearly represent the appropriate results. Once the data is collected and verified, the data can be saved in a spreadsheet that can then be loaded into the different tools. The next step is to decide if performing a wet crash analysis or hydroplaning. To implement the SPF the data needed are grade, speed, ramp, urban, lanes, ADT, dry and wet crashes. When only wet
crashes and/or injury scale is available, then the SMA method is possible to use. To implement the hydroplaning risk method the data needed is mean profile depth, grade, cross-slope, curvature, speed, lanes. After the high-risk segments have been identified, manuscript 4 provides a comprehensive summary of the proven effective countermeasure alternatives available for use. DOTs should consider the inclusion of this methodology in their safety programs, and develop the final list of project selection in collaboration with the pavement management, awareness campaign, law enforcement, and pertinent stakeholders to align state and federal programs to maximize resources.

7.3 Conclusions

The dissertation proposed a conceptual framework that provides a decision tree to perform systemic, data-driven, risk-based identification of the road segment with a high risk of wet and hydroplaning crashes. Different methods were developed to estimate the risk of wet and hydroplaning crashes, which depend on numerous parameters such as road, traffic, weather, vehicle, and operating conditions. The proposed methods can be used to screen to identify high-risk locations, which may warrant a detailed safety analysis to identify potential problems and applicable countermeasures. The various methods are demonstrated by applying them to jurisdictions with a different scope depending on the available data and the interest in hydrodynamic severity interest level.

The main conclusions include the following;

1. A statistical model that incorporates negative binomial regression and empirical Bayes produced better estimates of wet crashes than the currently used by departments of transportation when detailed data are available. This was demonstrated by analyzing the interstate system in Virginia. The proposed approach can be used to enhance the understanding of wet crashes and can help DOTs improve and update the safety improvements programs.

2. The Spatial Multiresolution Analysis method can help identify locations with a high risk of crashes with limited or no road geometry and/or friction data. The
approach provides better crash-risk estimates for DOTs that consider crash counts directly as a measure of risk, overcoming data and resources limitations. The method proved to be more robust than the currently used hazardous road segment identification when applied to the main network in Puerto Rico.

3. A systemic approach to identify locations with a high hydroplaning potential that considers the different factors affecting the interaction between the vehicle and the pavement under wet weather conditions can help reduce hydroplaning-related crashes. The method computes the available performance margin (PM) for a standard vehicle and maneuvers along a road segment. The PM profile can be used to pinpoint areas with potentially high hydroplaning potential that can be further evaluated in a detailed, project-level safety analysis.

This dissertation has provided a more complete understanding of the factors that contributed to wet and hydroplaning crashes, and effective methods are now available for DOTs to enhance their highway safety programs to achieve the main goal of reducing road crashes and severities.

7.4 Contribution

Every year DOTs collect crash data, and FHWA requirements for data-driven analysis have pushed more agencies to collect more data. The use of significant data and valid statistical methods for systemic safety analysis have become the new norm around the world. Substantial research has demonstrated that applying adequate statistical methods can help in effectively identifying the risk on highways. The main scientific contributions of this dissertation are three reliable statistical methods proposed to estimate wet crashes and hydroplaning potential. The first method solves the problem of having zero crash counts when computing the wet-to-dry ratio (WDR) and presents a new alternative that accounts for dry and wet crashes. The second method provides an innovative statistical solution with reliable crash estimates based solely on crash counts consideration. The third method redefines hydroplaning potential based on the performance margin.
Additionally, this dissertation presents a practical engineering framework to identify locations with high-risk wet and hydroplaning crashes based on the jurisdiction's needs and available recourses. Another engineering contribution is bringing a new strategy of accounting for WDR by adding the empirical Bayes estimate of dry crashes as a parameter in the regression model. An alternate wet crash estimation methodology that accounts for spatial correlation on crash counts provides reliable estimates for jurisdictions with data limitations. The dissertation also advances the understanding of the hydroplaning phenomenon by showcasing the effects of each contributing parameter on the hydroplaning potential estimates. The hydroplaning analysis tool can help engineers evaluate network performance at a corridor and network level.

7.5 Recommendations for Future Work

The recommendations of prospective research to complement and enrich this dissertation involves the following:

- The scope of the dissertation was limited to proposing methodologies to enhance safety analysis, considering wet crash and hydroplaning risk. Further expansion to the methods can include a detailed evaluation of confounding factors such as areas with different levels of rainfall or available aggregates.

- Mitigation solutions for areas with high wet and hydroplaning potential were presented in this dissertation. However, analysis is needed to identify the specific countermeasure alternatives to implement based on the local conditions. Therefore, there is a need for recommendations and tools to identify the most suitable countermeasures. For example, a benefit-cost analysis could help identify which treatment can provide the most benefit at the lowest cost to adequately justify the resources needed.

- Tools that help align strategic planning and investment priorities, based on all program goals, available resources, and timelines could also result in significant benefits. This will enhance DOTs planning and maximize return on investment.
A potential enhancement to the proposed hydroplaning methodology could include incorporating LiDar technology into the WFT estimation process. LiDar data produces a real-life surface cloud point which is a more accurate representation of the actual roads.