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Fast Detection and Prediction of Slippery Roadway Conditions for Enhanced Safety

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16. Abstract
Black ice, a nearly invisible hazard causing over 10% of weather-related crashes in the US, poses significant risks to roadway safety. Current measures like stationary Road Weather Information sensors (mRWIS) and cautionary signs improve awareness, but have limitations. Mobile Advanced Road Weather Information Sensors (MARWIS) offer enhanced, cost-effective, and real-time data collection at highway speed at the network level during and after inclement weather. The project aimed to develop procedures and models for fast detection and prediction of slippery conditions using the data of 51 miles of roadway, including SH-51, SH-177, SH-33, and a county road in Oklahoma. In conjunction with surface characteristics, the project was divided into three major steps on roadway conditions data collection by using MARWIS as measured parameters like ice percentage, water film height, road temperature, humidity, and pavement condition. In the middle, using Pave 3D 8K technology the project captured detailed pavement surface characteristics, and pavement friction by using a Grip Tester. Finally, machine learning methods were used (i.e., regression model, Random Forest, and Gradient Boosting) to analyze the data by modeling ice percentage, water film height, and pavement friction. The models achieved accuracy rates up to 75.8% and highlighted critical factors influencing icy and rainy conditions using the key variables of Mean Profile Depth (MPD), International Roughness Index (IRI), Cross Slope, and Crack Density. These findings enhance proactive safety measures and align with USDOT priorities for road safety.

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FAST DETECTION AND PREDICTION OF SLIPPERY ROADWAY CONDITIONS FOR ENHANCED SAFETY

FINAL REPORT
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SOUTHERN PLAINS
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Executive Summary

Slippery road conditions, particularly black ice and high-water film on roadway surfaces, pose significant hazards to roadway safety, contributing to over 10% of weather-related crashes in the U.S. State Departments of Transportation (DOTs) traditionally rely on fixed Road Weather Information Sensors (RWIS) and static signage, offering limited coverage to address this challenge. Advancements in mobile sensor technology now enable the collection of road condition data at highway speeds, addressing the high costs and limited coverage of fixed RWIS units.

This research project aimed to develop predictive models for identifying and forecasting slippery conditions to enhance highway safety. Comprehensive field data collection was conducted using mobile RWIS sensors and advanced surface characterization instrumentation technologies, including the OSU Pave3D 8K and Grip Tester. With field data collected on four roadway segments in Oklahoma (SH-177, SH-33, N2432 County Road, SH-51), three machine learning based predictive models were developed for predicting ice formation, water film height, and pavement friction.

Key findings:

- Field Data Collection: Mobile RWIS sensors captured road state variables such as water film height, ice percentage, and friction estimates under diverse weather conditions. Surface characteristics influencing slipperiness, including macrotexture, cracking, and rut depth, were measured using advanced tools.
- Predictive Models: Machine learning models, including Random Forest and Gradient Boosting, achieved robust prediction results. Ice percentage, water film height, and friction models demonstrated accuracies of 75.8%, 65.2%, and 71.7%, respectively. Critical parameters identified include Mean Profile Depth (MPD), cross slope, rut depth, and the International Roughness Index (IRI).

Key outcomes:

- ODOT PMS Data Integration: The study highlighted the feasibility of using the Oklahoma DOT (ODOT) Pavement Management System (PMS) database to predict slippery conditions. Six key variables in the PMS database were identified as significant contributors, which could enable the implementation of developed models for the estimation of ice percentage, water film height, and friction. However, some influential variables like RMS and kurtosis are not currently saved in the PMS database.
- Strategic Implications: The developed models support a proactive approach to identifying slippery conditions and offer potential for integration into Maintenance Decision Support Systems (MDSS) to enhance situational awareness during inclement weather and support winter maintenance decision-making.

This research aligns with strategic objectives to improve transportation safety and supports USDOT goals. While the study relied on limited data, the results recommendations include expanding data collection across broader networks, incorporating additional weather variables, and addressing gaps in the PMS database to further improve predictive capabilities.

Chapter 1. Introduction

1.1 Problem Statement

Black ice, a nearly invisible hazard, forms as a translucent layer of frozen glaze resembling dark pavement and wet roads. It primarily emerges on bridges and overpasses before spreading to roadways as temperatures drop. This peril contributes to over 10% of weather-related crashes in the U.S., causing nearly 200,000 annual automobile crashes. It leads to an average of 700 fatalities and over 65,000 injuries yearly due to icy road conditions. Besides, other slippery surface conditions also could play significant roles in roadway safety. Traditionally, state DOTs have relied on fixed Road Weather Information Sensors (RWIS) and cautionary signs such as "Ice May Form on Bridge," along with flashing lights, to notify drivers of adverse road conditions with limited localized coverage.

Additionally, during inclement weather conditions with heavy precipitation, residual water film on roadway surfaces can significantly reduce pavement friction, thereby compromising roadway safety. The height of the water film on the surface also serves as a critical precursor to ice formation on roads. However, the measurement of water film height and the detection of ice on roadway surfaces remain underdeveloped in network-level system surveys.

Recent advancements in weather sensor technology now allow for collecting road conditions and weather data at highway speeds directly from moving vehicles, eliminating the costs and limited coverage associated with installing complete RWIS units. Nonetheless, obtaining real-time road condition data at the network level during and after inclement weather remains not only expensive but also hazardous.

State agencies are mandated to gather pavement surface condition data for asset management purposes. It is acknowledged that road surface characteristics, in conjunction with environmental conditions, can significantly impact ice formation on roadways, although these relationships have not yet been established. Therefore, there exists a critical need to harness existing surface characteristics, pertinent climatic variables, and road geometry datasets to proactively predict slippery conditions.

1.2. Research Approaches

The objective of this project is to develop procedures and models for fast detection and prediction of slippery conditions for enhanced highway safety. This project involved comprehensive field data collection on specific roadway segments before, during, and after inclement weather. We utilized mobile RWIS sensors to detect slippery conditions and the OSU Pave3D 8K to gather data on roadway surface characteristics and geometry. The primary goal was to develop predictive models that could anticipate slippery road conditions in different weather scenarios. These prediction models could then be applied to identify potential slippery areas across Oklahoma, using the annual pavement management system (PMS) datasets collected by the Oklahoma Department of Transportation (ODOT). The anticipated outcomes of this project aligned with the SPTC's strategic objectives, aiming to “make our transportation system safer for all people and advance a future without transportation-related serious injuries and fatalities”, and supported the USDOT's goals.

The research team accomplished the project objectives by breaking down the research into the following four major work activities:

Field roadway weather data collection using Mobile Advanced RWIS (MARWIS) technology to rapidly measure surface states, including temperature, dew point, humidity, road state (dry, wet, icy, etc.), presence of chemicals, water film depth, ice percentage, and friction estimates. We conducted field data collection on selected testing sites under normal traffic conditions by considering various surface characteristics, both before, during, and after inclement weather events.

Field assessment of road surface characteristics used the Grip Tester at OSU for friction measurements and the Pave3D 8K technology for pavement surface characteristics acquisition under dry conditions. The surface characteristics could influence the ice-forming mechanisms, the skid resistance levels and roadway slipperiness.

Slippery condition prediction models’ development was accomplished by leveraging roadway weather data collected from MARWIS, pavement surface characteristics data collected from Pave3D 8K, and surface friction data from Grip Tester. Slippery conditions predictive models were developed using machine learning methods to forecast road conditions during rainy or icy days.

Discussions were held regarding the implementation of predictive models for slippery condition warning using the ODOT PMS database. This integration could help identify potential locations with slippery conditions to assist in enhancing situational awareness and supporting road maintenance operations.

1.3 Report Outline

To attain the goal of research, this report is presented below in the following chapters:

- Chapter 1 introduces the problem statement, research objective, research approaches, and report outline.

- Chapter 2 presents a literature review and includes utilization and various road information sensors, the relevant methodologies for roadway slippery condition detection and monitoring, and the use of MARWIS data for winter maintenance decision support at state DOTs in the United States.

- Chapter 3 summarizes the field data collection and processing, including the use of MARWIS during and after inclement weather, as well as roadway condition data using Pave3D 8K and Grip Tester. The weather and road surface characteristics data were processed and summarized.

- Chapter 4 details the development of predictive models for slippery roadway conditions, including ice percentage, water film height, and pavement friction, utilizing machine learning techniques. In addition, the chapter explored how data from the ODOT PMS database can be integrated into these models to forecast slippery roadway conditions effectively.

Chapter 2. Literature Review

This chapter presents a comprehensive literature review on weather-related road safety, fast detection, and prediction of slippery roads with its contributing factors, and statistics on crashes caused by slippery roads. It also extended to current technologies for detecting slippery roads, accuracy, and limitations of current technologies.

2.1 Weather-Related Roadway Safety

Adverse weather conditions can significantly impact traffic mobility and safety, as they can create hazardous driving conditions and increase the risk of crashes. For example, snow and high wind speeds could increase the probability of single-truck crashes, while rain has the largest effect on single-car crashes. Especially at higher speed limits and in rear-end crashes, sun glare prompts multi-car crashes. So, understanding the impact of inclement weather reduces weather-based crashes, and allocates substantial significance to winter maintenance operation (WRM) to improve mobility and public traffic safety. Snow and ice reduce pavement friction and vehicle maneuverability, causing slower speeds, reducing roadway capacity, and increasing crash risk.

Extensive research has been conducted on traffic crashes correlated with winter precipitation events. Winter weather conditions in the US pose a hazard to motorists, one-half of fatalities occur in snow, while 75% occur in ongoing snowfall, 41% happen near the onset of freezing precipitation, 42% of fatalities occur before the crash, more than 25 percent primary visibility reduction, eventually resulting in approximately 1000 fatalities annually on U.S. roadways (Tobin et al., 2022). This number is greater when all other weather-related fatalities are combined. Among the various forms of hazardous weather for motorists, winter precipitation is correlated with a heightened risk of vehicular collisions and injuries and increasing precipitation rates augment collision frequencies (Qiu and Nixon, 2008; Strong et al., 2010; Theofilatos and Yannis, 2014). Meteorological conditions have a direct impact on road safety, thus monitoring weather and its impact on road conditions can save lives, and winter maintenance services.

2.2 Slippery Roadway Conditions

Slippery roads occur when friction is reduced due to factors like rain, snow, ice, black ice, or oil spills. The conditions reduce tire traction, making it difficult for vehicles to maintain control, and significantly increase the risk of crashes. Slippery roadways can result from various weather conditions, road surface conditions, or the presence of substances such as ice, snow, or water on the road. Quick identification and accurate prediction of slippery conditions are crucial for authorities and drivers to implement appropriate measures, prevent crashes, and ensure road safety.

When the temperature drops below the freezing point, ice is formed, causing water on the road surface to freeze. It can be extremely slippery and make the road very hazardous, especially when it is not visible to drivers. Snow creates a slippery surface, which is formed when water vapor in the atmosphere freezes into ice crystals and falls to the ground. Water on the road surface, either due to rain, melting snow, or other sources make wet roadway conditions, which could decrease the road surface skid resistance. Wet surfaces can be slippery, especially if other contaminants are present, such as oil or other oil-like substances on the surface.

Slippery road conditions are influenced by various factors, including temperature, precipitation, weather conditions, oil spills, and worn-out pavement. Snow and ice significantly increase the risk of slipping as shown by previous studies, but most slips occur when the temperature is near zero degrees or slightly beneath it (Marjo, 2022). Any moisture on the road can freeze from ice due to the temperature dropping below the freezing point, making the road extremely slippery. Cold temperatures can cause the road surface to become icy, even if there is no precipitation, posing a significant risk to drivers and pedestrians.

Rainwater can create a thin layer of water on the road that reduces the grip and makes it easier for vehicles to slide. Accumulated snow and sleet forming a layer of ice or slush significantly reduces friction, making driving hazardous. Weather conditions such as rain, snow, sleet, and black ice can make the road surface wet and reduce the friction between the tires and the road. Additionally, strong wind can blow debris into the road, further reducing traction. Understanding these factors in relationship with friction is crucial for drivers and road maintenance authorities to respond appropriately to ensure road safety.

2.3 Assessing Winter Roadway Surface States

Throughout recent years, numerous investigations have been conducted to assess the state of pavements during winter conditions, ranging from indirect estimates based on pavement images and weather forecasts (Pang et al., 2023), to advanced deep learning algorithms and connected vehicle (CV) data for precise prediction of dry, snowy, and icy pavement conditions (Hu et al., 2023).

The Road Weather Management Program (RWMP) of the Federal Highway Administration (FHWA) (2024) collects weather data, performs quality check, and disseminates atmospheric and road weather observations through a map interface. Field observations were collected from the department of Transportation's RWIS fixed and transportable Environmental Sensor Stations (ESSs) and from mobile sources using external road weather sensors. This system encompassed a central processing unit, a communications network, and various ESSs for the gathering of weather data, pavement conditions, etc. The collected data was transmitted to the central system, enabling the generation of timely nowcasts and forecasts crucial for effective road management and maintenance strategies. The RWIS data, once processed, became pivotal for the operation and management of roadways.

Similarly, Linton and Fu (2016) introduced the Road Surface Condition Monitoring System that integrated pavement imagery with meteorological data to facilitate real-time pavement condition monitoring. Three machine learning classifiers - Artificial Neural Network (ANN), Classification and Regression Trees (CART), and Random Forest – were tested for their model efficacy in field applications, with the Random Forest algorithm particularly standing out for its superior classification accuracy. Additional research was conducted to predict road friction levels using vehicle-derived data for slippery road conditions. Panahandeh et al. (2017) illustrated the effectiveness of combining vehicle data with weather reports for road friction prediction using a binary classification approach (slippery vs. non-slippery), and machine learning techniques including support vector machine algorithm (SVM), Artificial Neural Network (ANN), and logistic regression. Their findings underscored the feasibility of their methodology in accurately identifying slippery surfaces. Irschik and Stork (2014) developed a hazard identification system that utilized standard vehicle sensor data to categorize current pavement conditions to enable the provision of timely warnings to motorists (Irschik and Stork, 2014). This system facilitates preventive driver responses to imminent road hazards, thereby enhancing road safety.

Enriquez et al. (2012) introduced a versatile On-Board Diagnostics (OBD) tool capable of not just gathering a wide array of vehicular data but also identifying real-time vehicular slip events. Hou et al. (2017) designed a system that employed smartphones and OBD-II adapters to signal slippery conditions on roads by utilizing the discrepancy between wheel speed and the ground speed (the vehicle's actual running speed) as the primary indicator for potential skidding events and proactive monitoring of such incidents. The detection algorithm for skidding was formulated and tested through field experiments in Buffalo, New York. Field application results demonstrated the algorithm's high precision and minimal false-positive occurrences. Heiman (2016), Shi (2018) and Padarthy Heyns (2019) introduced similar systems for detecting slipperiness and assessing friction.

Recently, the transfer-learning system (Grabowski and Czyżewski, 2020) was developed to monitor road slippery using data collected from CCTV cameras and a convolutional neural network (CNN) architecture. The Densenet201 network could achieve 98.34% accuracy. However, the data was collected in limited lighting conditions and a limited number of weather stations that can detect snow on the road. In addition, different weather stations had different sets of available sensors that limited the development of more accurate slippery surface detection models. Additionally, utilizing wheel slip and wheel acceleration data was proposed by Jang (2021). for the identification of road slipperiness, by employing sensor data derived from a digital tachograph (DTG), a device widely available in commercial vehicles. The approaches detected road slipperiness using support vector machine algorithms and achieved an accuracy of over 98%.

In 2022, Yang et al. (2022) integrated vehicle-infrastructure cooperative systems to detect road- slippery conditions. The system included a trained recognition model, a vehicle-road cooperative network, and a mobile app for visualization. The results demonstrated high real-time performance, low omission rate, and good recognition accuracy. Nonetheless, the study focused only on slippery road condition recognitions and did not address other types of road conditions or hazards. Secondly, the system's performance and accuracy may vary in different real-world scenarios and road conditions that were not specifically tested. Thirdly, the study did not provide information on its feasibility for implementation on a larger scale, and fourthly, it did not discuss any limitation of the vehicle-infrastructure cooperative network. Finally, it missed a comprehensive analysis of the system's performance in terms of false positives or false negatives, which could impact its practicality and reliability (Yang et al., 2022).

The latest research in connected vehicles (CV) has also been used to acquire surface data and then to implement deep learning algorithms to predict pavements' slippery conditions (Hu et al., 2023). The algorithms could predict the accuracy of 100%, 99.06%, and 98.02% for dry pavement, snowy pavement, and icy pavement, respectively. The research relies on simulated CV data in VISSIM for training the deep learning algorithm, which may not capture the complexity and variability of real-world pavement.

2.4 Road Surface Characteristics and Condition Measurement

Recognizing the importance of integrating weather data with adverse road conditions and pavement surface characteristics, countries in winter climates invest significant financial resources into winter road maintenance (WRM) initiatives to enhance mobility and public welfare. In the U.S., state governments collectively spend over $2.3 billion annually on snow and ice control, accounting for approximately 20% of their WRM budget ("FHWA Statistics," 2022). Given these substantial maintenance expenses, transportation agencies have consistently pursued cost-efficient strategies to optimize the return on investment (Arvidsson, 2017). A critical element in developing such strategies is access to detailed information about spatially variable road surface conditions. State highway agencies typically evaluate pavement conditions using four major categories: pavement distress, pavement roughness, deflection, and surface friction.

- Pavement Distress: This assessment identifies visible surface issues such as cracking, potholes, and rutting, which are indicative of structural deterioration or wear. Common methods include visual inspections, manual surveys, and automated data collection using imaging and laser technology.
- Pavement Roughness: Roughness measurements quantify the ride quality and smoothness of the road surface, often expressed as the International Roughness Index (IRI. Testing is performed using inertial profilers or laser-equipped vehicles.
- Deflection: Deflection testing evaluates the structural capacity of the pavement by measuring its response to applied loads. Common techniques include Falling Weight Deflectometer (FWD) tests and Dynaflect systems.
- Surface Friction: Surface friction testing assesses the road's ability to provide adequate tire grip. This is typically measured using equipment such as locked-wheel skid trailers or dynamic friction testers.

These evaluations are conducted under standard testing and weather conditions and are not designed to directly detect slippery road conditions caused by inclement or winter climates, such as ice, snow, or water on the pavement surface. Road friction can be influenced by several factors, including, not restricted to tire and pavement texture, as well as contaminants on the road surface (Novikov et al., 2018). Research also showed that environmental factors significantly impact road friction (Alexandersson et al., 1991; Crevier and Delage, 2001; Hermansson, 2004; Kangas et al., 2015; Li et al., 2022; Nowrin and Kwon, 2022; Tarleton, 2015; Vignisdottir et al., 2019; Walker et al., 2019).

Climatic factors are generally measured or estimated from RWIS (Liu et al., 2021). There are two primary sorts of RWIS, particularly stationary RWIS (sRWIS) and mobile RWIS (mRWIS). The former continuously monitors variable values through ESSs for long-term data measurements. However, these stations do not directly provide road friction measurements and coverage issues due to the considerable spacing between adjacent stations. In recent years, various mRWIS sensors have been deployed by various agencies to assist in winter maintenance decisions. The mobile climate information is frequently employed to supplement the information collected by sRWIS. MARWIS has been adopted and mobilized on driving vehicles by several state agencies to collect various parameters such as road conditions, temperatures, friction, and more in real time. As MARWIS traverses the network, it offers spatially continuous measurements of road friction values and the surrounding weather/environmental conditions. It is acknowledged that data collected by MARWIS would experience lags due to travel time, resulting in temporal gaps between adjacent data points.

In particular, the MARWIS by Lufft is a state-of-the-art solution designed to provide real-time road weather data. Unlike stationary sensors, MARWIS is a mobile device mounted on vehicles, capturing critical road conditions such as surface temperature, dew point, water film height, relative humidity, and friction levels while on the move. This capability makes it effective in assessing road safety under various weather scenarios, including rain, snow, and icy conditions. In addition, MARWIS seamlessly integrates with fleet management and RWIS to deliver data in real time via Bluetooth or cellular networks. The system's ability to measure friction and grip levels helps identify hazardous conditions for winter road maintenance operations and resource allocation optimization.

The Finnish Meteorological Institute alongside the Road Administration introduced a classification system for road friction by establishing friction ranges according to the types of road surface contaminants (such as wet ice, icy conditions, packed snow, rough ice or packed snow, clear and wet, and clear and dry), friction class estimates through a hybrid criterion that considers meteorological factors including air temperature, precipitation, humidity, and wind velocity (Juga et al., 2013).

In the United States, mobile RWIS models are employed by state highway agencies to monitor critical road and weather parameters:

- Road parameters: including road conditions (e.g., dry, moist, wet, icy, snowy, chemically treated wet surfaces), road surface temperature, water film height, ice percentage, and friction levels.
- Weather parameters: such as ambient air temperature, dew point temperature, and relative humidity.

Several organizations and entities actively utilize and evaluate the Lufft MARWIS sensor for its innovative capabilities. These include the state DOTs of Arkansas, Minnesota, Missouri, Indiana, North Dakota, Nevada, Ohio, New York City, and Colorado; the Michelin Tire Company for tire performance testing; and various school districts along the East Coast (El-Rayes and Ignacio, 2022). According to the OTT HydroMet website, the Maryland DOT leveraged MARWIS in 2022 to enhance the efficiency of winter maintenance operations, resulting in improved safety on Maryland roads and optimized operational effectiveness during inclement weather. Additionally, the California DOT retrofitted Caltrans' Road weather stations in 2020 by integrating new stationary RWIS sensors into their existing infrastructure, as a valuable tool for improving roadway safety and facilitating data-driven decision-making under various weather.

By providing real-time data on critical metrics such as surface temperature, ice percentage, and water film height, MARWIS assists DOTs in responding effectively to adverse weather. Furthermore, these advancements enhance the capabilities of Maintenance Decision Support Systems (MDSS. MDSS integrates weather forecasts, road condition data, maintenance practices, and resource allocation models, enabling winter maintenance professionals to devise precise and effective road treatment strategies.

2.5 Summary

Slippery roads can have a significant negative impact on highway safety. Although various works have been conducted for the identification of slippery road conditions, they were generally developed using weather sensors and vehicular data sets. Since state agencies collect PMS data regularly for their highway systems, this significant amount of surface condition data sets could be of great value for the prediction of slippery road surfaces to enhance safety.

Chapter 3. Field Data Collection and Processing

3.1 Pilot Data Collection Sites

This study considered multiple ice and rain events in January and February 2024 to gather field data in Oklahoma. The weather data was collected using MARWIS, while pavement surface characteristics and pavement geometry data were obtained using state-of-the-art laser imaging techniques Pave 3D 8K. Field data were collected from several state highways in Oklahoma, namely SH-177, and SH-33, and one county road connected with SH-33 and SH-51. In total, 51 miles of routes were selected for field data collection, as shown in Figures 1 and 2. The data collection process for ice events, rain events, pavement characteristics, and pavement geometry was conducted multiple times along these same routes at regular driving speeds.

Figure 1 Field Data Collection Routes

Figure 2 Example Field Data Display

3.2 Field Data Collection Instruments

Firstly, weather data was collected utilizing the MARWIS sensor (Figure 3), a mobile road weather information sensor from Lufft. Multiple DOTs have adopted MARWIS technology to support winter maintenance activities. The sensor was mounted on top of the testing vehicle at a specific angle and securely fastened to ensure stability during data collection, while also maintaining power and continuous internet connectivity. The MARWIS sensor emits lights within a 2-inch by 2-inch area to collect data at vehicle speed. The collected data is simultaneously uploaded to the cloud. MARWIS provides data on various parameters, including road surface temperature, dew point temperature, water film height, ice percentage, and estimated road conditions. The data collection frequency is set at 10Hz.

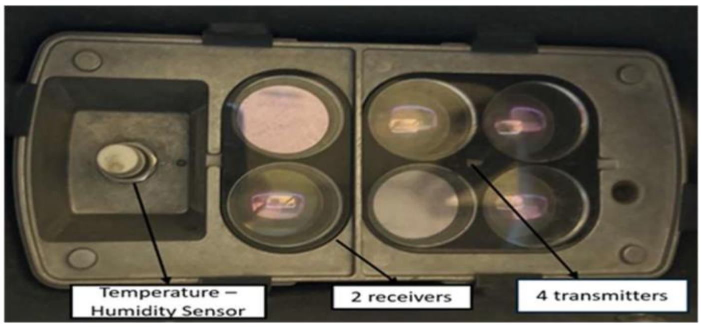


Figure 3 MARWIS-UMB Components

The 3D laser imaging data were collected for pavement surface characteristics and road geometry data at the selected locations shown in Figure 4. This innovative technology utilizes high-precision 3D laser imaging to capture pavement surfaces in both 2D and 3D representations. The Pave 3D 8K system offers a transverse resolution of 0.5 mm and features over 8000 pixels across the lane width, providing detailed and comprehensive data for pavement surface analysis.

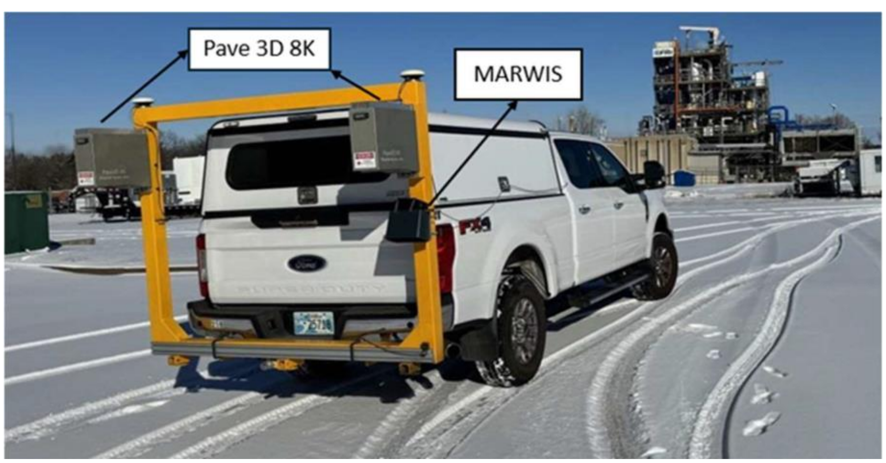


Figure 4 Data Collection on Pave 3D 8K with MARWIS in Ice Events

After the completion of pavement field data collection, the raw data, consisting of high-resolution 2D and 3D images of the pavement surface, was processed using customized software that utilized a deep learning framework to extract key pavement conditions parameters. The parameters of pavement include IRI, rut depth, texture indicators (mean profile depth - MPD, mean texture depth - MTD, Root Mean Square - RMS, skewness, kurtosis), crack density on Wheel Path (WP) and Non-wheel Path (NWP), crack area, cross slope, and grade. Thereafter, ice and rain data, pavement surface characteristics, and geometric data were compiled and aligned to a maximum distance of 0.05 miles which ensured that the weather data and pavement data aligned with the same locations.

Finally, the research team concentrated on measuring pavement friction data along the specified data collection routes utilizing Grip Tester, a continuous friction measuring device. The Grip Tester calculates pavement friction by measuring the longitudinal friction coefficient between the road surface and the testing tire with a braked wheel at a constant slip rate of about 15%, close to the optimum level of the anti-blocking system. The slip rate generates the adhesive force, which is derived from the mechanical force between the two carrier wheels and the measuring wheel. The friction data collection is illustrated in Figure 5, in conjunction with the Pave 3D 8K vehicle.

Figure 5 Pavement Friction Data Collection using Grip Tester

3.3 Field Data Processing

The three datasets collected using MARWIS, Pave 3D 8K, and grip tester were synchronized based on the nearest GPS coordinates. Rigorous and detailed coding in Python was performed to match the dataset. The data accumulation process determined that Grip Tester data served as the basis for the model, with data collected every 3 feet along the driving direction. To simplify the data-matching process, the research team defined sections measuring 0.05 miles (264 feet) in length. The Grip Tester data, processed as the final friction data (GN number), were recorded in a spreadsheet along with corresponding GPS coordinates. If multiple GN values were present in the dataset, the GN numbers were averaged.

The GN number data was matched with the weather data, specifically considering water film height. The MARWIS data, uploaded in real-time in Lufft's cloud ViewMondo, was retrieved from the cloud database and matched with the GN number. The Pave 3D 8K data was processed using ADA 3D software, to extract pavement surface condition parameters. The GN number and water film height were matched with the comprehensive pavement surface conditions and geometric data, including IRI, rut depth, cracking, texture indicators, grade, and cross slope.

In summary, Table 1 presents the list of pavement surface characteristic variables, derived and processed from collected field data. These variables will be utilized in Chapter 4 for model development.

Table 1 List of pavement surface characteristic variables

Variable	Description
IRI	IRI, measurement of pavement smoothness. The lower the IRI value, the smoother the road surface
Rut depth	Permanent longitudinal surface depression in WP for flexible pavement due to traffic passage
Crack Density WP	In-WP, longitudinal cracks outside and within 2ft of the pavement edge, referred to as fatigue cracking
Crack Density NWP	In the NWP , longitudinal cracking is not located in the defined wheel at each severity level.
MPD)	MPD average height of roughness of the surface, impact on permeability, and skid resistance
RMS)	RMS deviation of surface texture properties, may impact on interaction between tires and pave surface
Texture Skewness	Asymmetrical measures of surface texture may affect drainage, tire-pavement interaction, and ride quality.
Texture Kurtosis	Distribution of texture heights and impact on surface characteristics; high kurtosis enhances friction.
Cross slope (crsSlope)	The cross slope may lead to multiple safety issues, including hydroplaning, loss of control, and run-off-road crashes (Alzraiee et al. 2024)

3.3.1 Descriptive Statistics

Descriptive statistics presents measures of central tendency (i.e., mean and median) and dispersion (i.e., range, standard deviation, minimum, and maximum) for ice percentage, water film height, and nine explanatory variables, as shown in Table 2. The variability in road surface conditions, water film height, and ice percentage could have a significant impact on road safety and maintenance priorities.

Table 2 Descriptive Statistics of Variables

Variable	Mean	Median	Range	SD	Min	Max
Ice Percentage (%)	42.29	0	100	47.31	0	100
Water Film Height (μm)	55.20	16.83	381.60	74.66	0	381.64
IRI (in/mi)	109.07	91.75	1186.65	97.56	34.25	1220.93
Rut Depth (mm)	1.920	1.26	15.65	2.35	0.46	16.04
Crack Density WP (%)	0.99	0.48	5.50	1.20	0	5.50
Crack Density NWP (%)	1.51	0.82	10.45	1.82	0	10.45
crsSlope (%)	1.24	1.52	13.87	1.86	-6.45	6.97
MPD (mm)	1.33	1.31	5.28	0.45	0.71	5.99
RMS (mm)	2.81	2.40	14.98	1.64	0.92	15.89
Skewness	-0.31	-0.25	2.88	0.32	-2.43	0.45
Kurtosis	2.51	2.28	8.98	0.83	1.73	10.72

Table 2 provides insights into the variability and patterns across ice percentage and water film height. Ice percentage had a mean of 42.29%, indicating moderate ice coverage on average. Its skewed distribution, combined with a high standard deviation (47.31) and a wide range, indicated the sporadic occurrences of ice coverage. Similarly, Water Film Height displayed a mean of 55.20 μm and a median of 16.83 μm, indicating predominantly low values with occasional high readings.

The IRI demonstrated significant variation in road conditions, with a mean of 109.07 in/mi and a median of 91.75 in/mi. However, the wide range and high variance underscore diverse road roughness levels ranging from smooth to highly rough road conditions. The low mean and median of rut depth reflected shallow ruts, though the maximum rutting was 16.04 mm. Greater variability of crack density within NWP, as evidenced by its range of 10.45mm and standard deviation of 1.82, indicated that cracks were more prominent outside the WP. The MPD values were relatively consistent, with a narrow range and low standard deviation, while RMS showed a wider range. The slightly negative skewness suggested generally smooth road conditions with occasional deviations, while high kurtosis in some areas identified some critical locations.

Besides the overall descriptive statistics of the surface characteristics, a glimpse of the collected data for each indicator is represented in the following figures for the four roadway segments. The road-specific examples were shown as follows:

- For SH-177: Figure 6 describes ice percentage, Figure 7 shows water film height, Figure 8 illustrates pavement friction, and Figure 9 represents IRI. Pavement cracking and rutting are displayed in Figures 10 and 11, texture data is presented in Figure 12, and pavement geometry is illustrated in Figure 13.
- For SH-33: Figures 14 to 21 follow the same flow.
- For SH-51: Figures 22 to 29 depict the collected data.
- For the county road: Figures 30 to 37 provide an overview of data collection following the same structure.

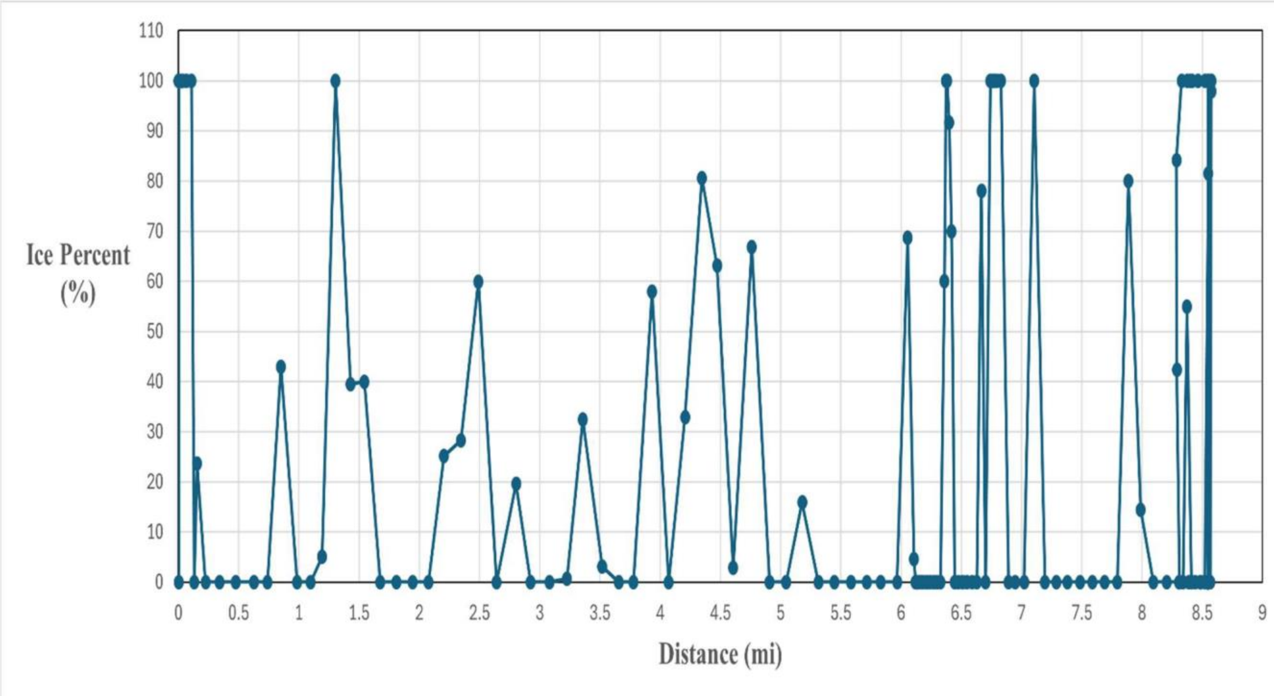


Figure 6 Ice Percent - MARWIS on SH-177 in Ice Events

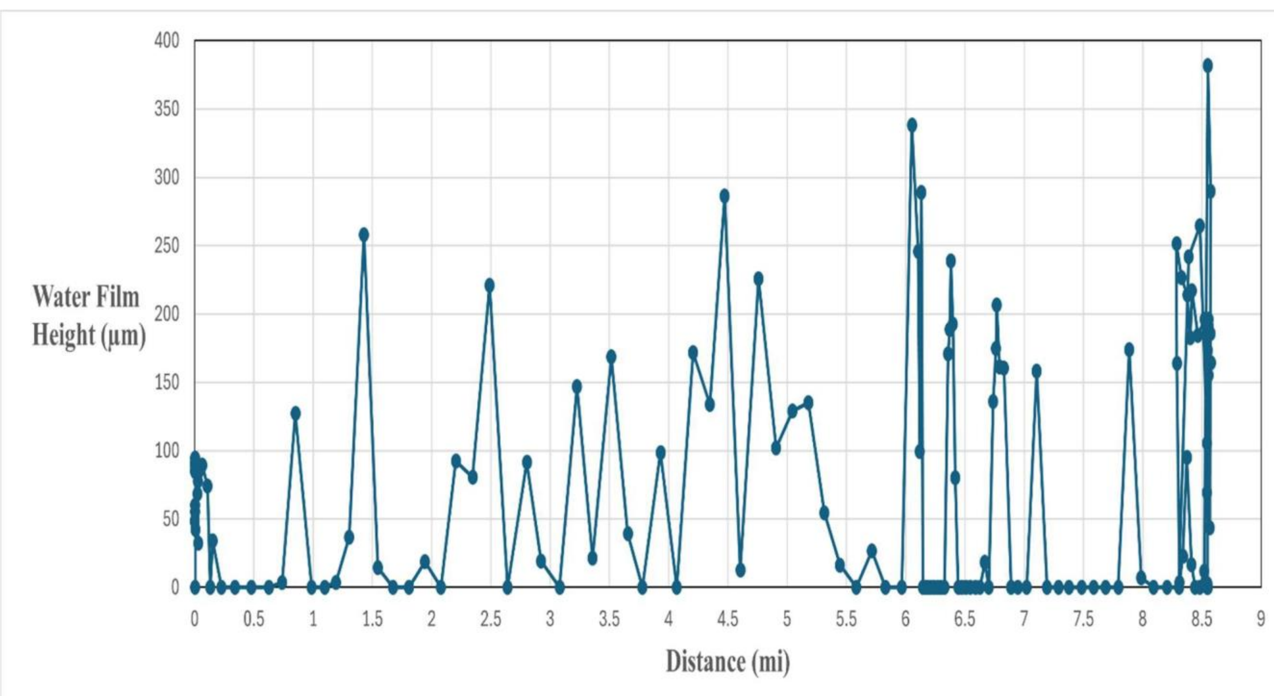


Figure 7 Water Film Height - MARWIS on SH-177 in Rain Events

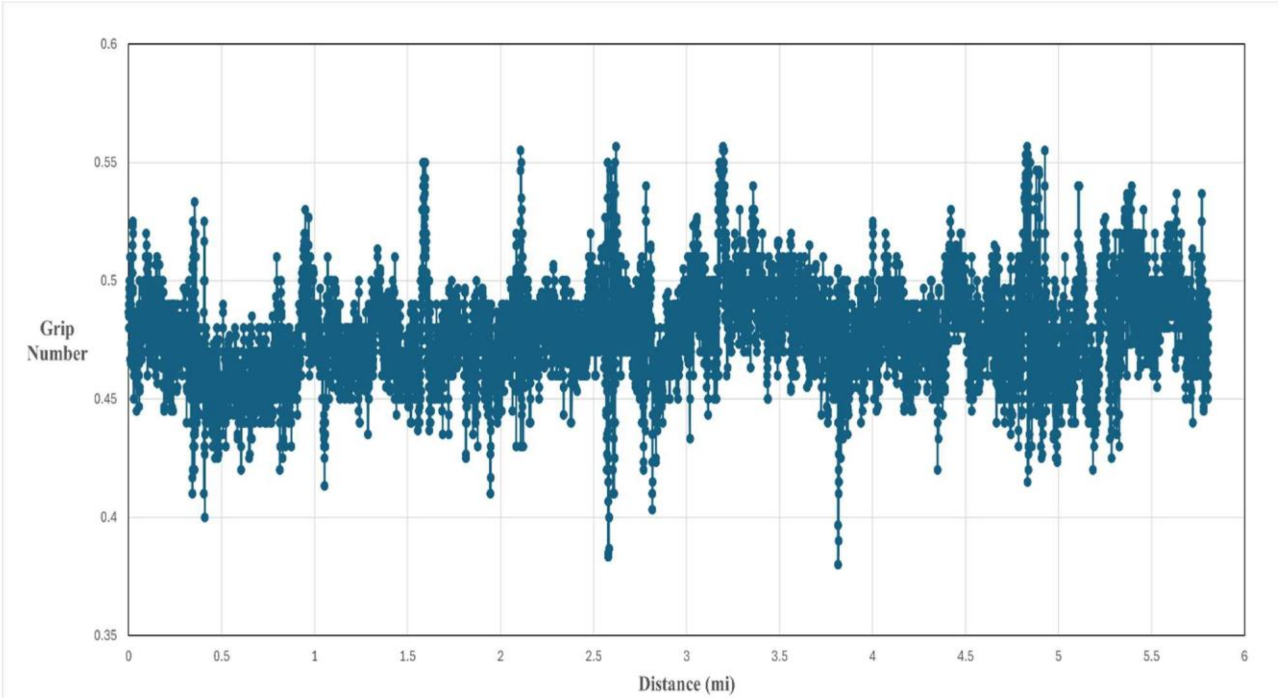


Figure 8 Pavement Friction – Grip Tester on SH-177

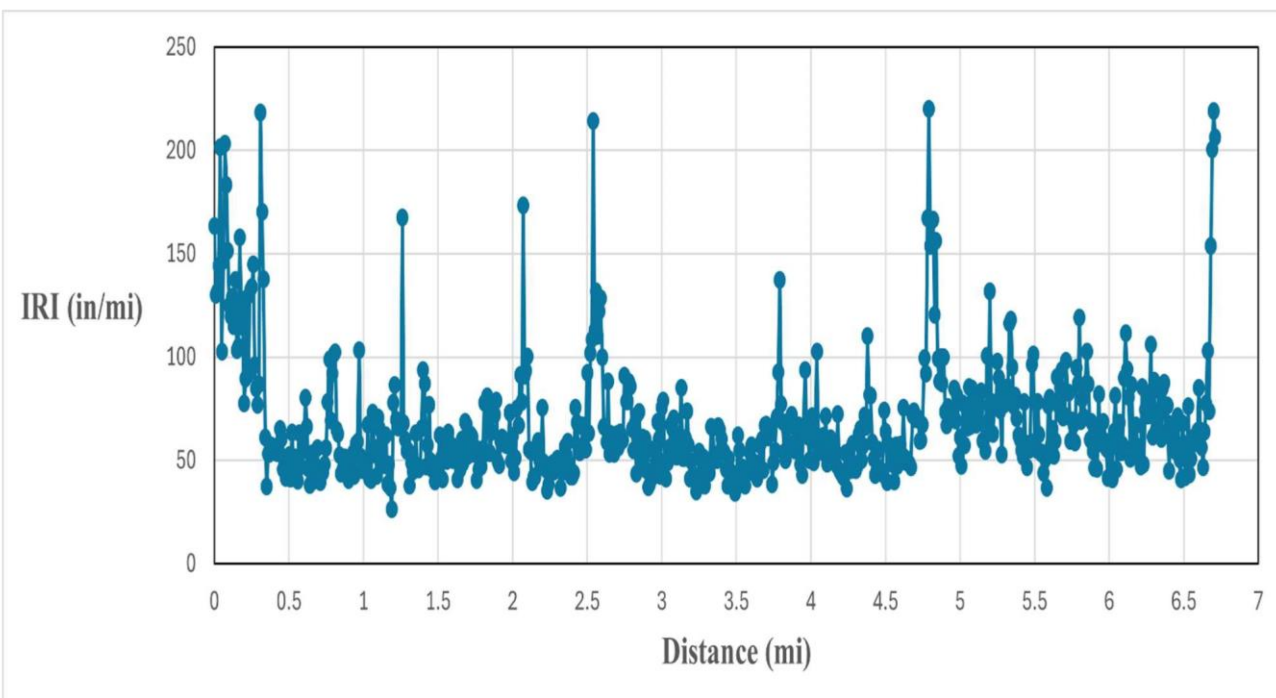


Figure 9 IRI – OSU Pave 3D 8K on SH-177

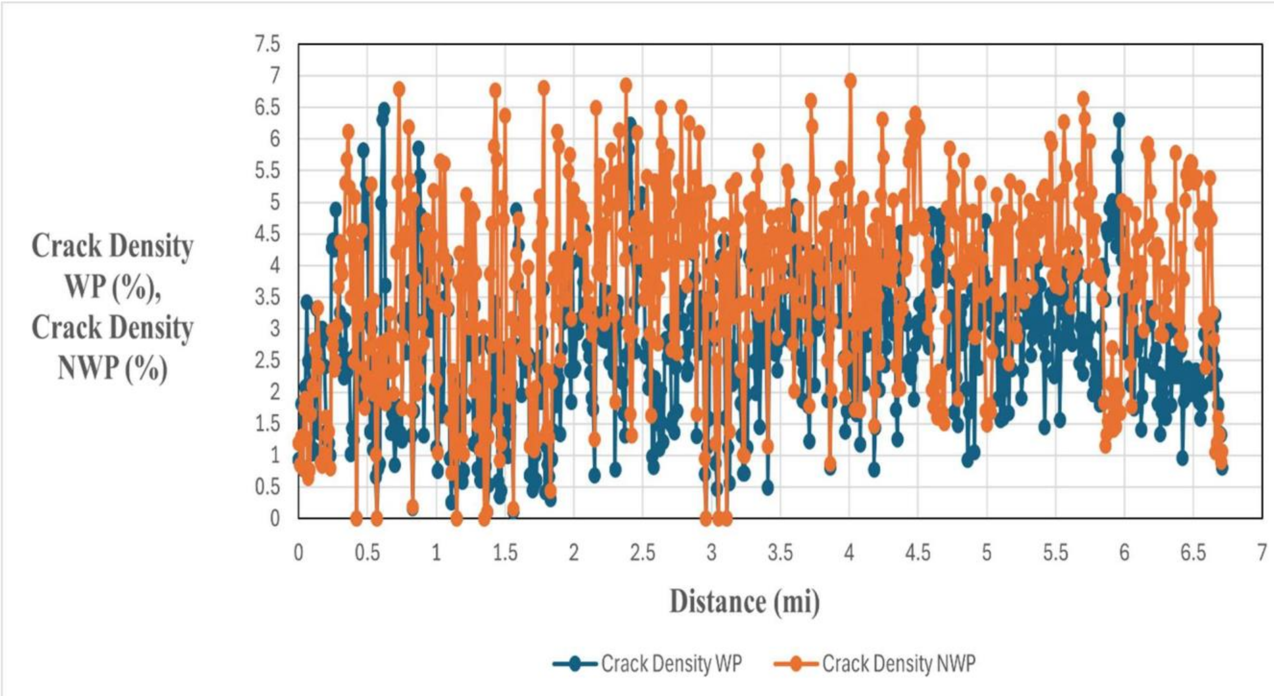


Figure 10 Crack Density – OSU Pave 3D 8K on SH-177

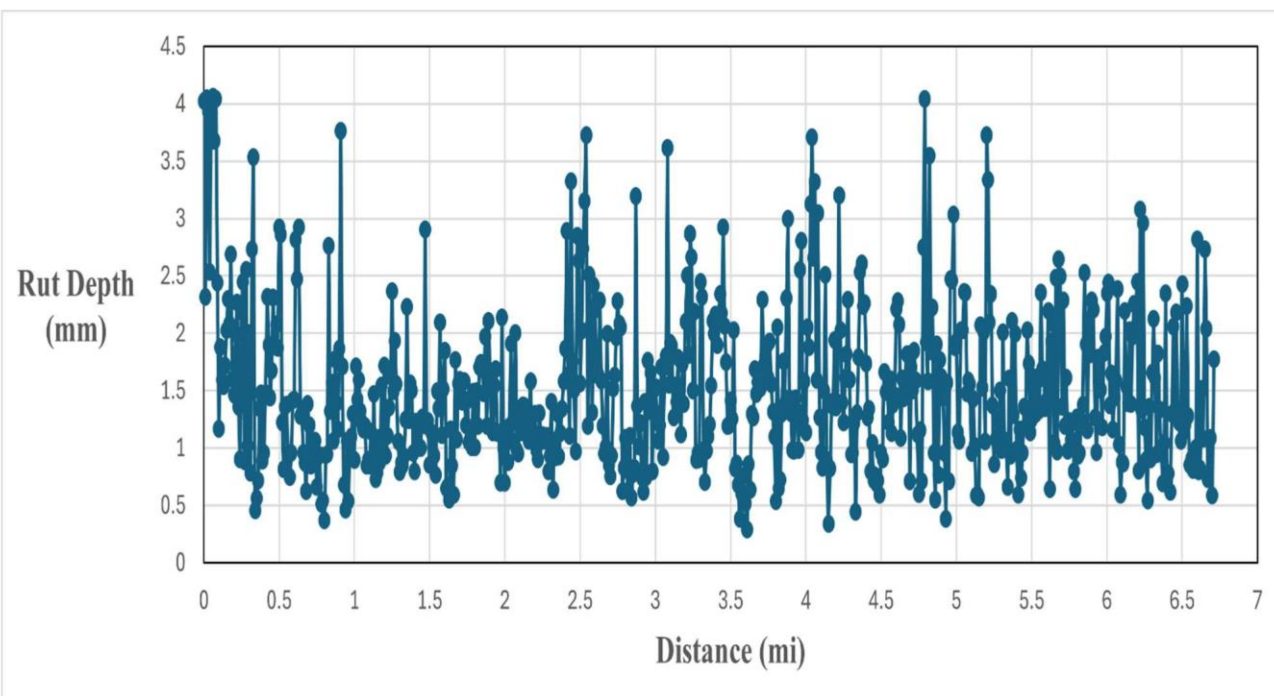


Figure 11 Rut Depth – OSU Pave 3D 8K on SH-177

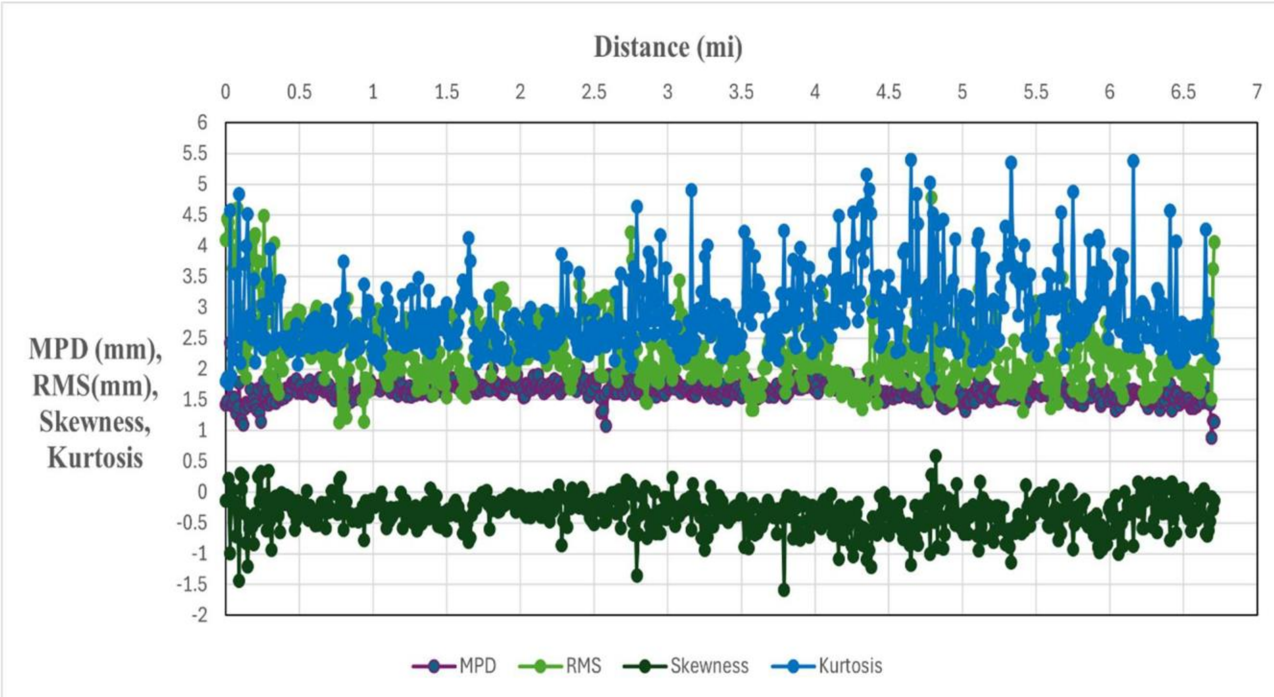


Figure 12 Pavement Texture – OSU Pave 3D 8K on SH-177

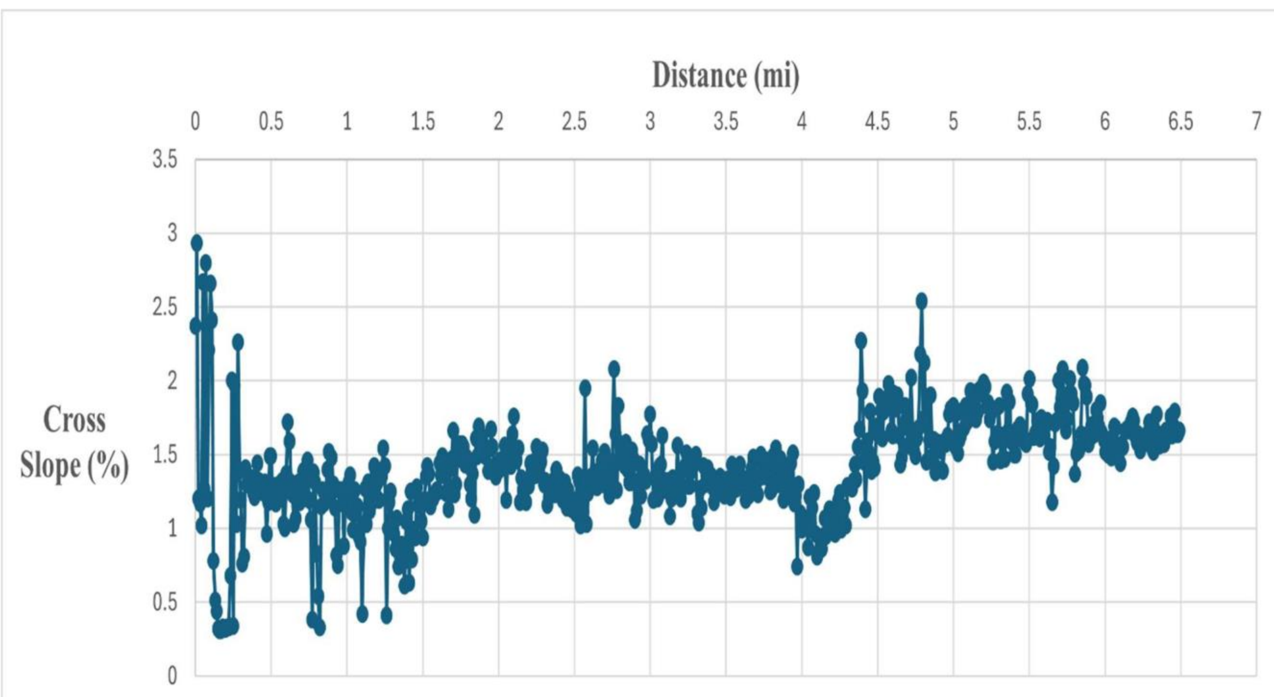


Figure 13 Pavement Geometry – OSU Pave 3D 8K on SH-177

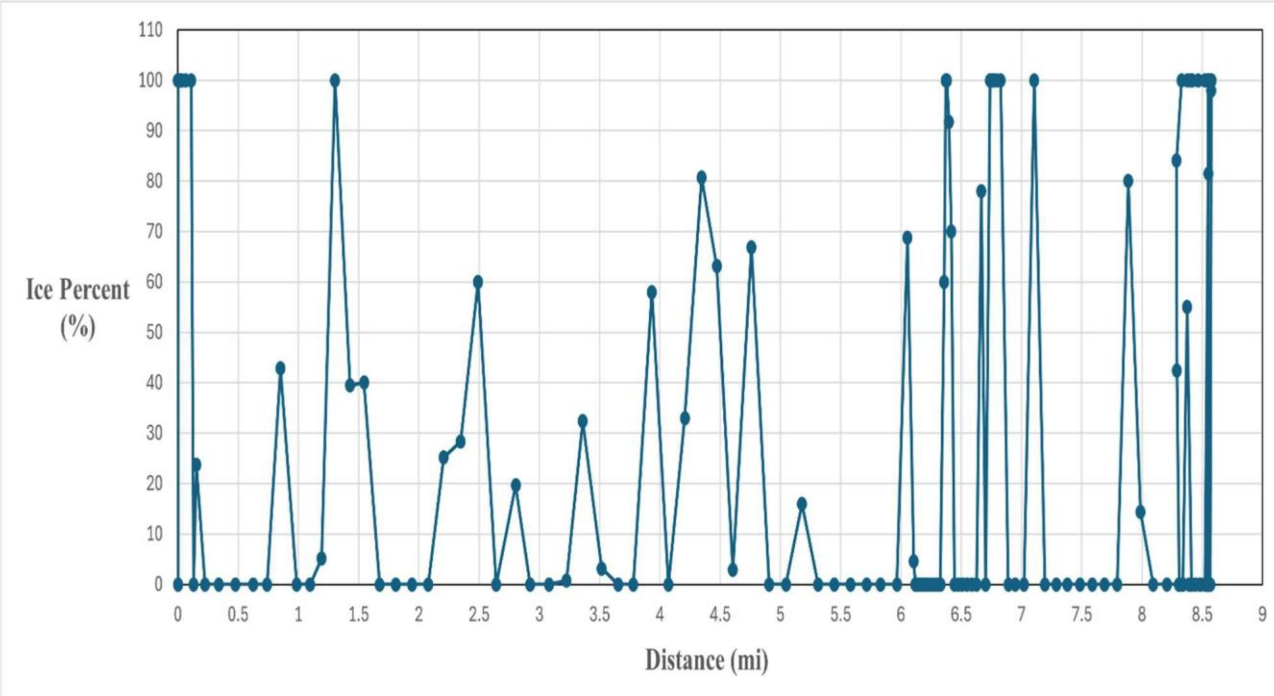


Figure 14 MARWIS on SH-51 in Ice Events

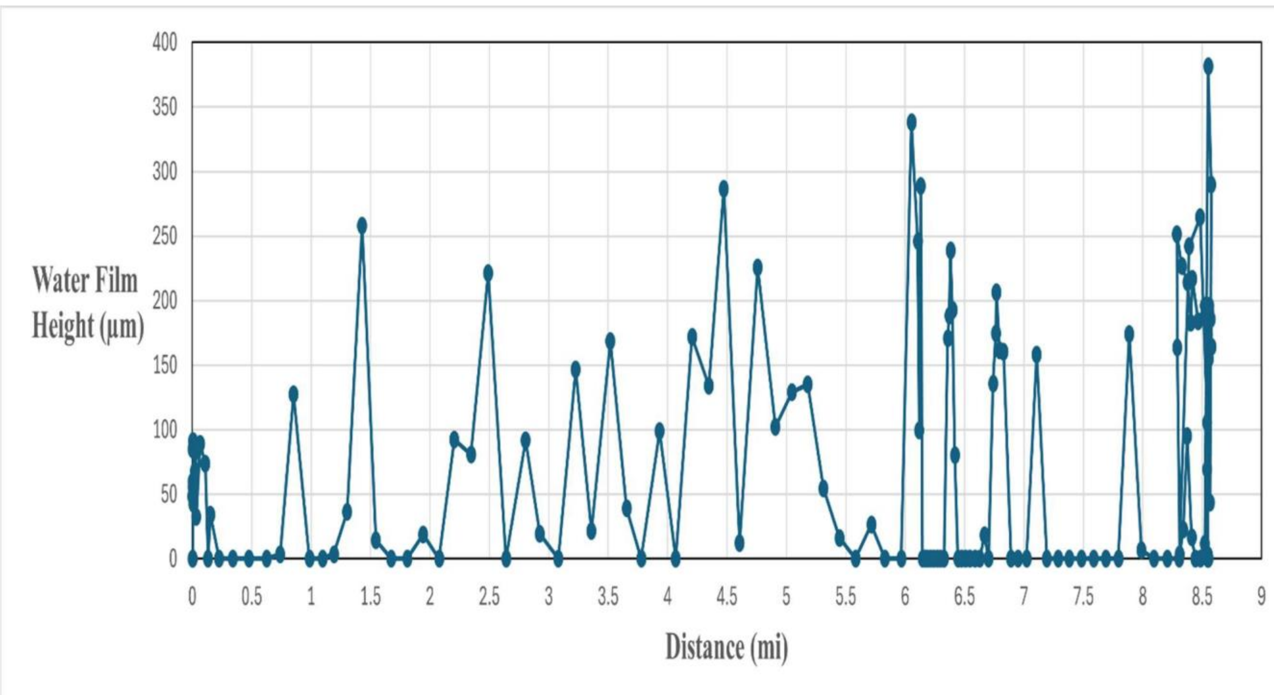


Figure 15 Water Film Height - MARWIS on SH-51 in Rain Events

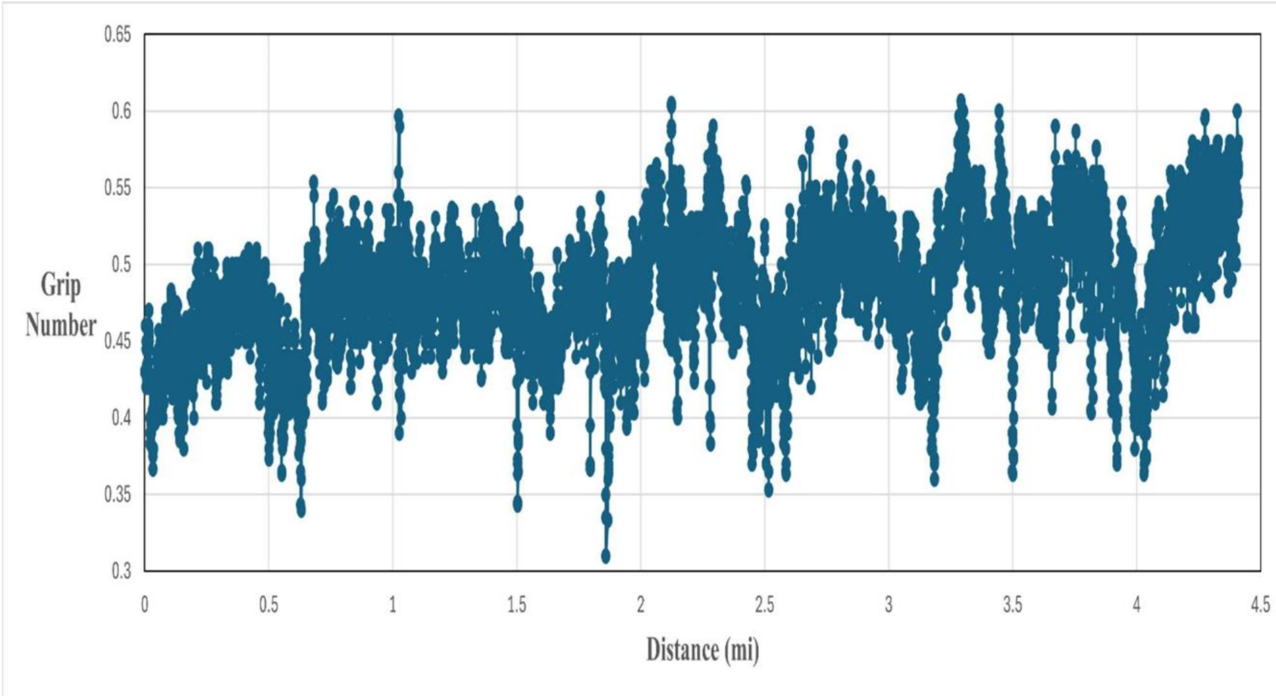


Figure 16 Pavement Friction – Grip Tester on SH-51

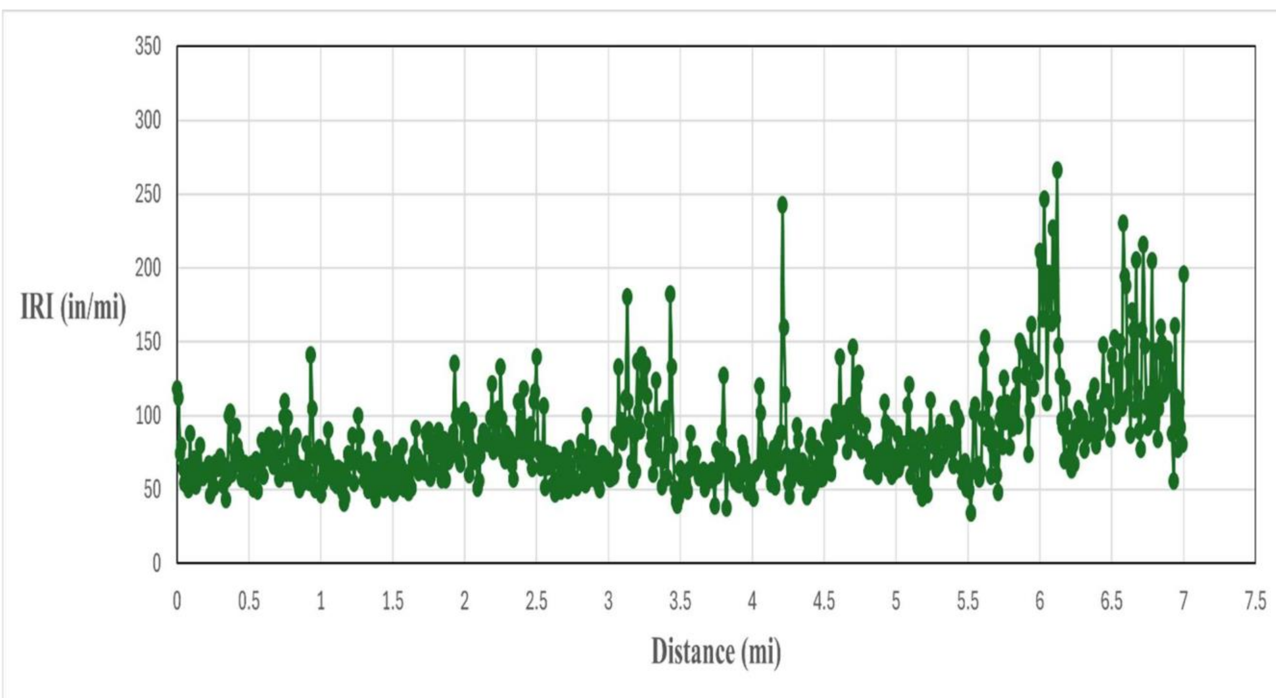


Figure 17 IRI – OSU Pave 3D 8K on SH-51

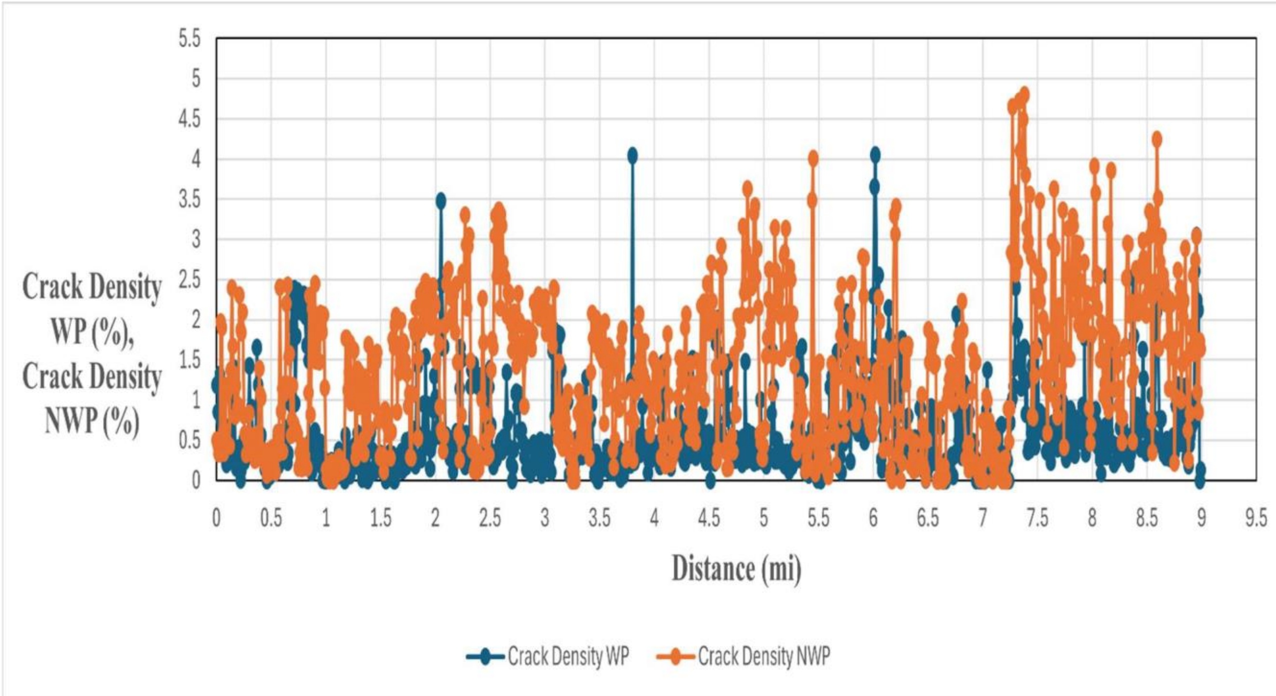


Figure 18 Crack Density – OSU Pave 3D 8K on SH-51

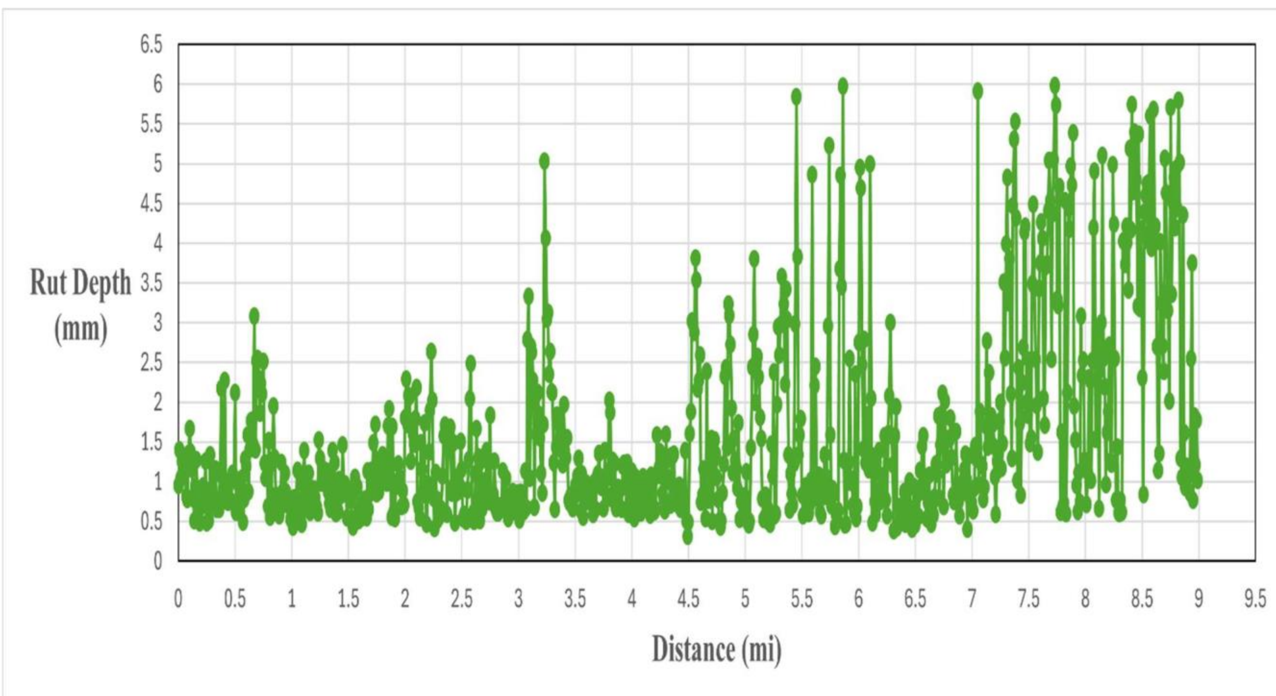


Figure 19 Rut Depth – OSU Pave 3D 8K on SH-51

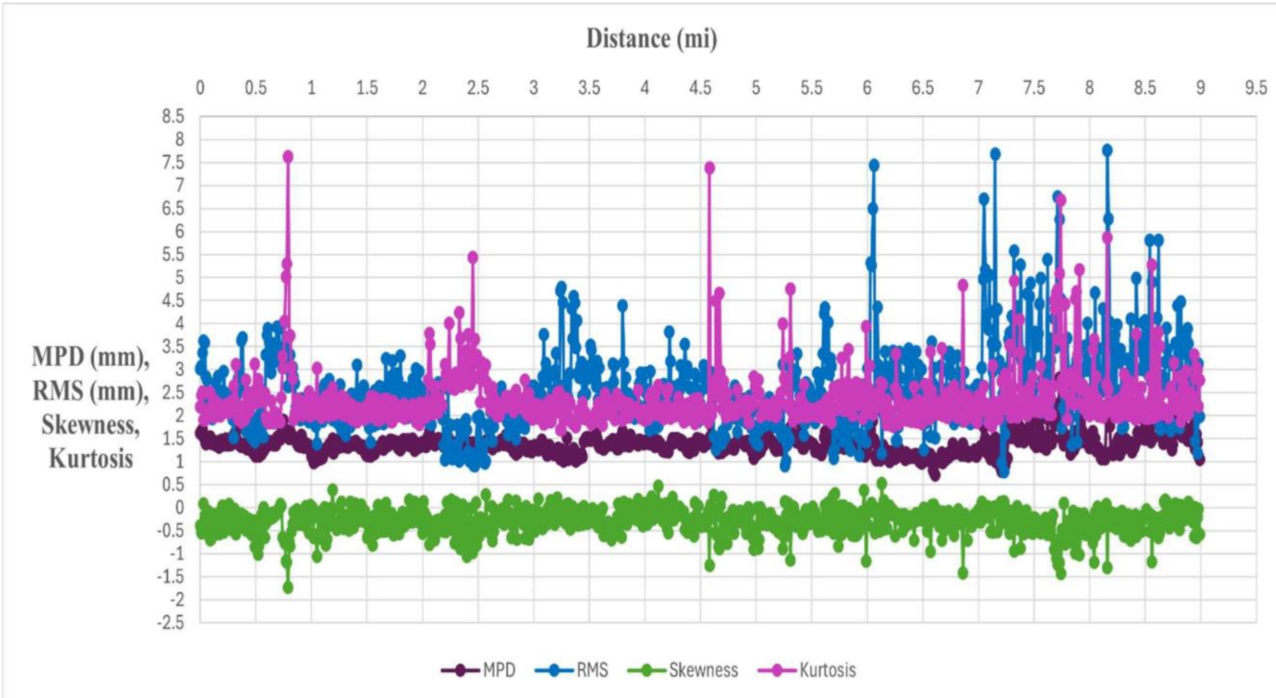


Figure 20 Pavement Texture – OSU Pave 3D 8K on SH-51

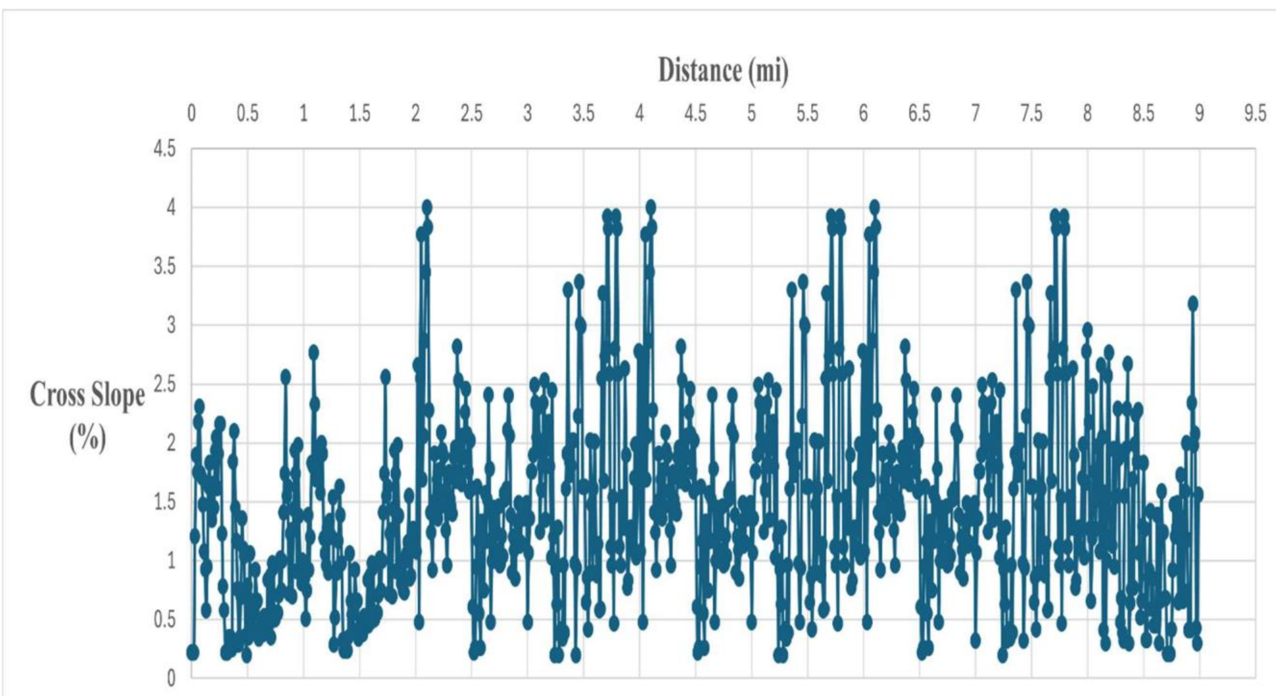


Figure 21 Pavement Geometry – OSU Pave 3D 8K on SH-51

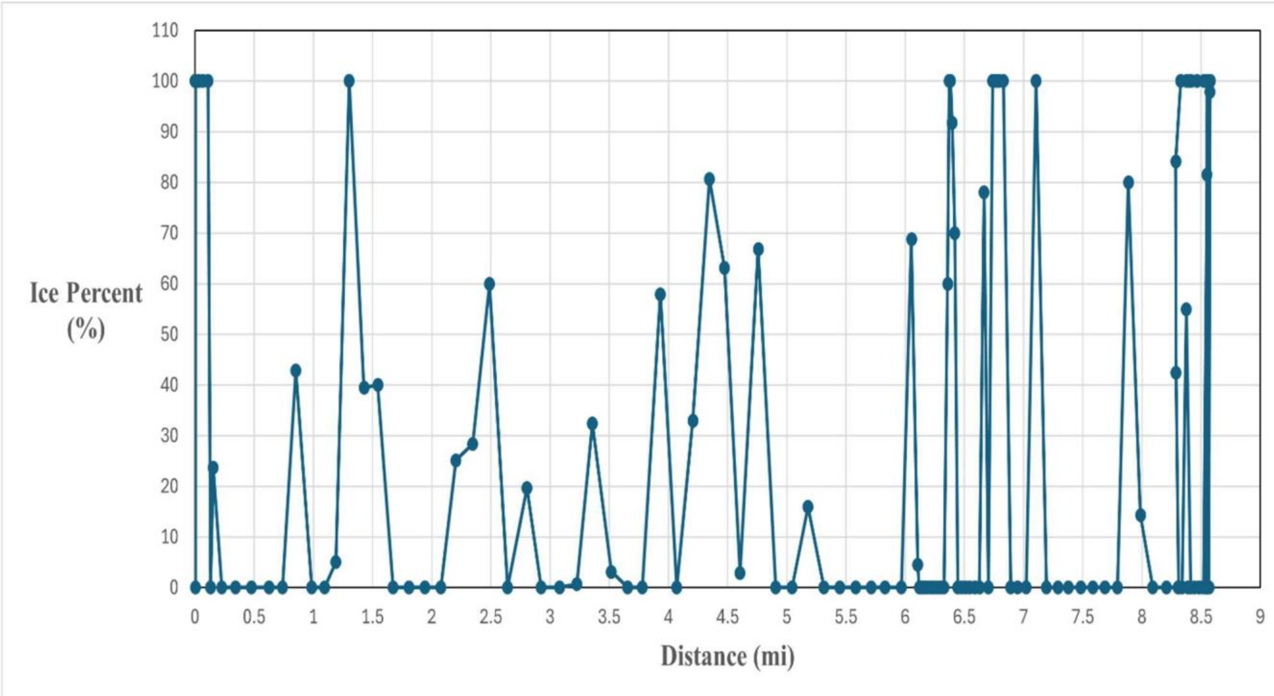


Figure 22 Ice Percent - MARWIS on SH-33 in Ice Events

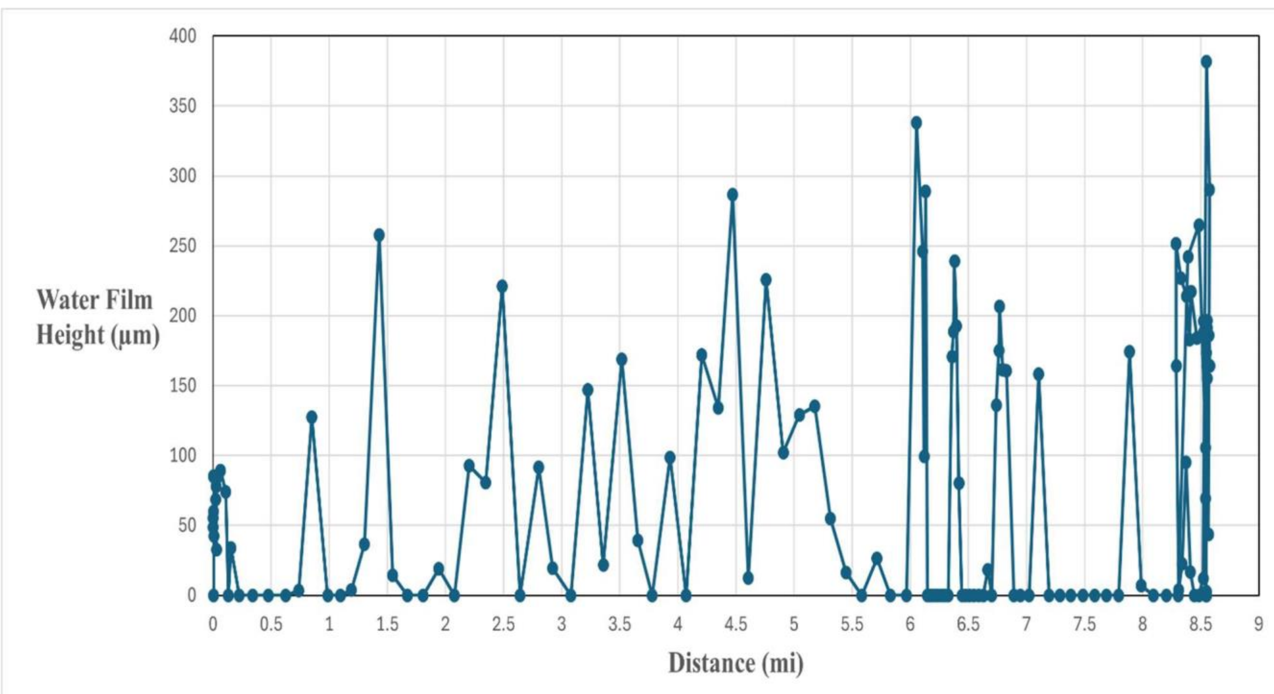


Figure 23 Water Film Height - MARWIS on SH-33 in Rain Events

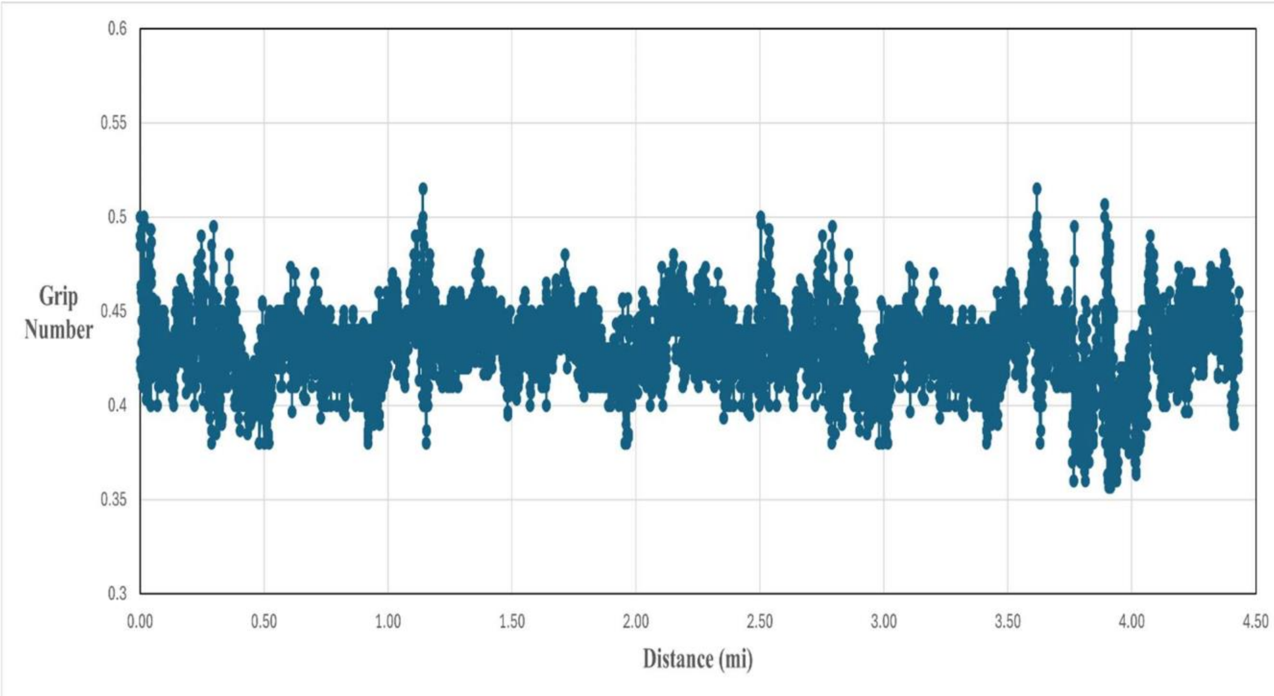


Figure 24 Pavement Friction – Grip Tester on SH-33

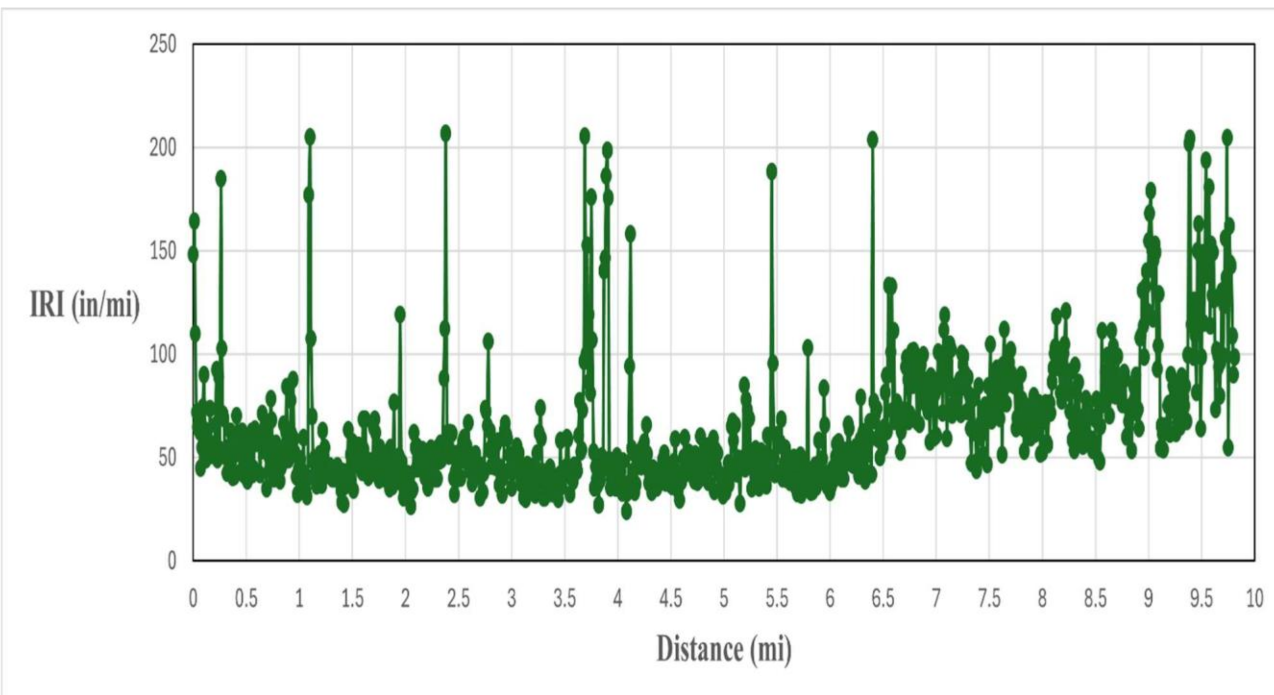


Figure 25 IRI – OSU Pave 3D 8K on SH-33

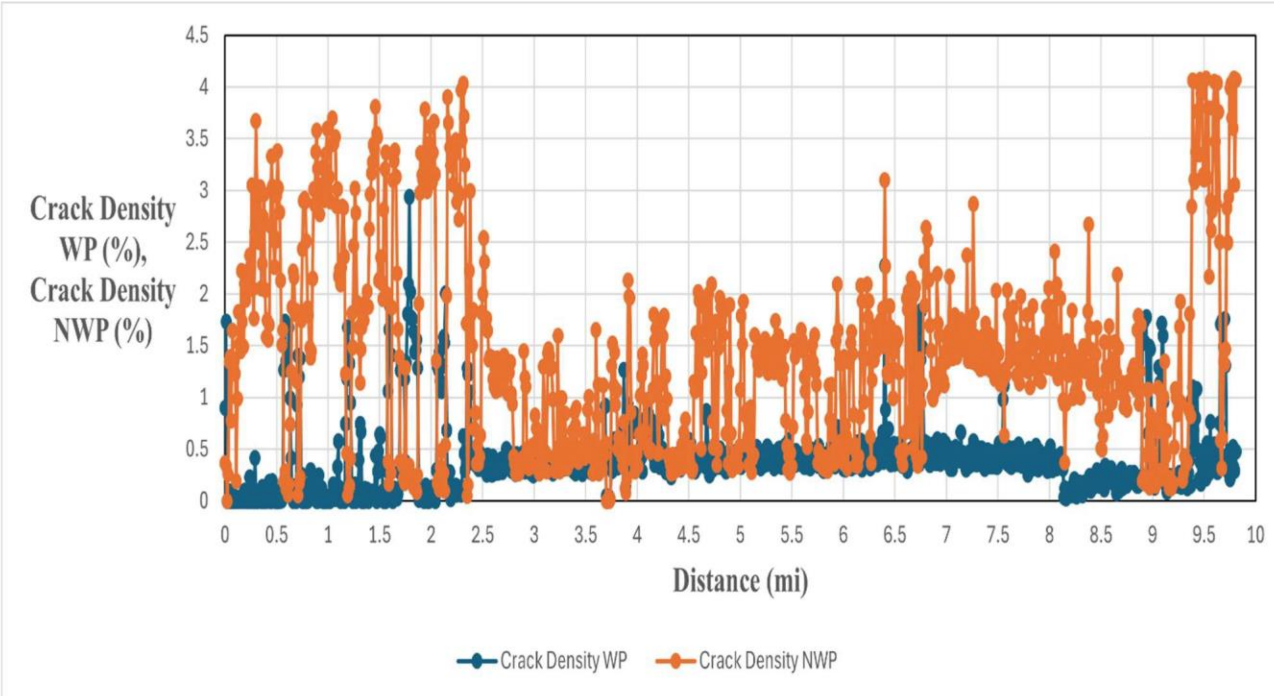


Figure 26 Crack Density – OSU Pave 3D 8K on SH-33

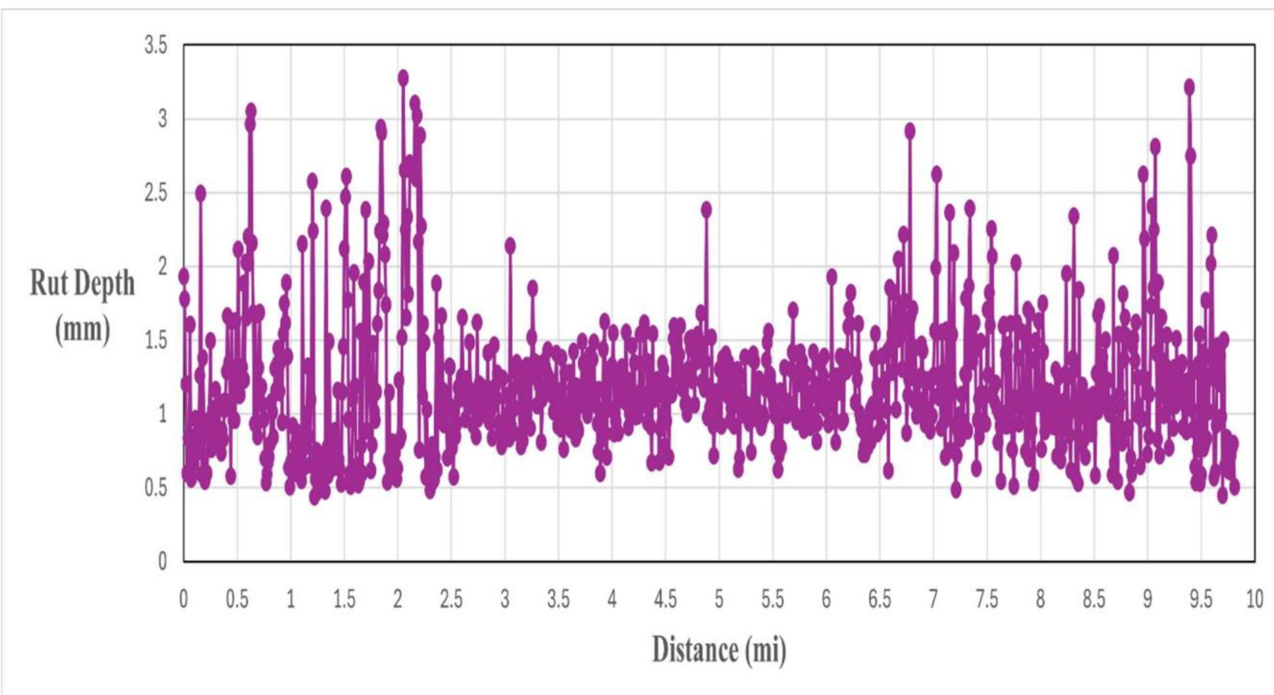


Figure 27 Rut Depth – OSU Pave 3D 8K on SH-33

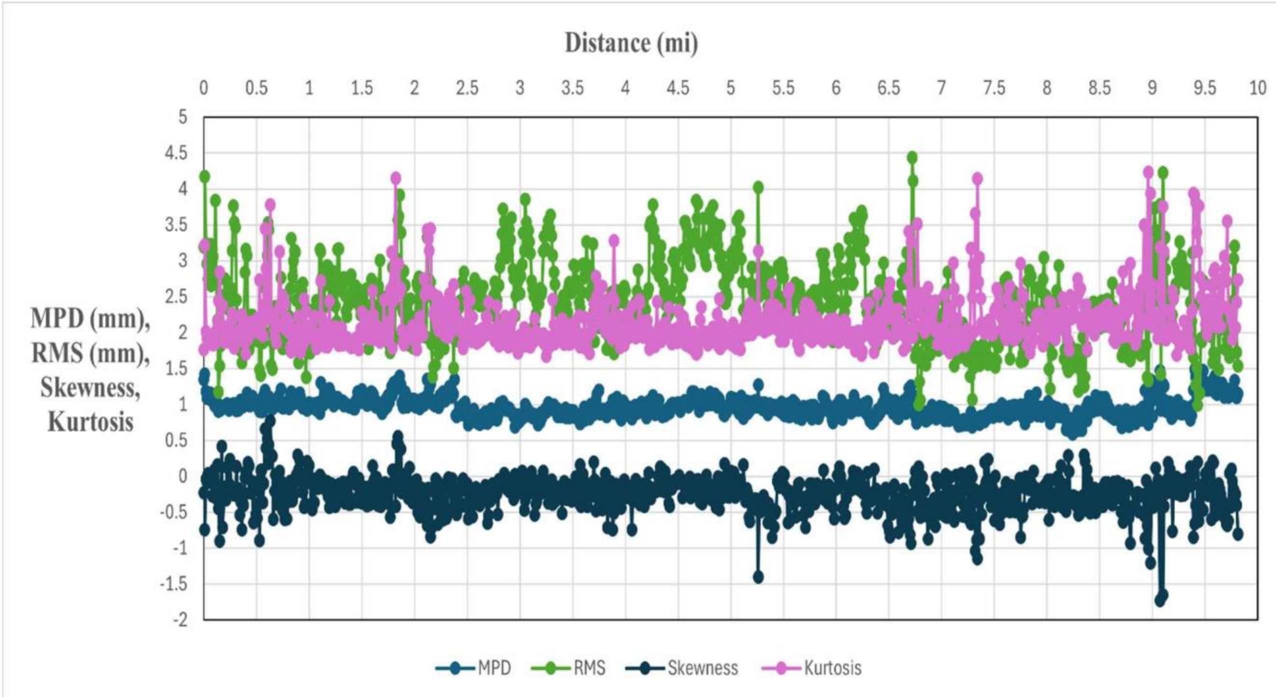


Figure 28 Pavement Texture – OSU Pave 3D 8K on SH-33

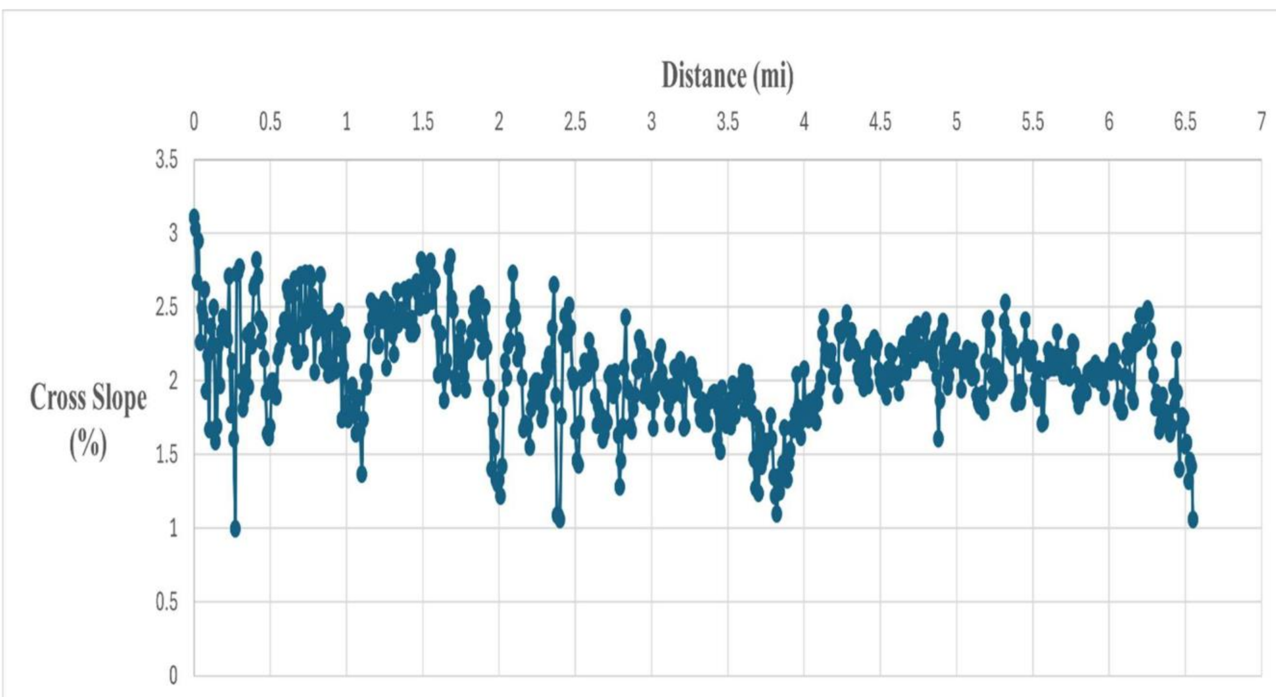


Figure 29 Pavement Geometry – OSU Pave 3D 8K on SH-33

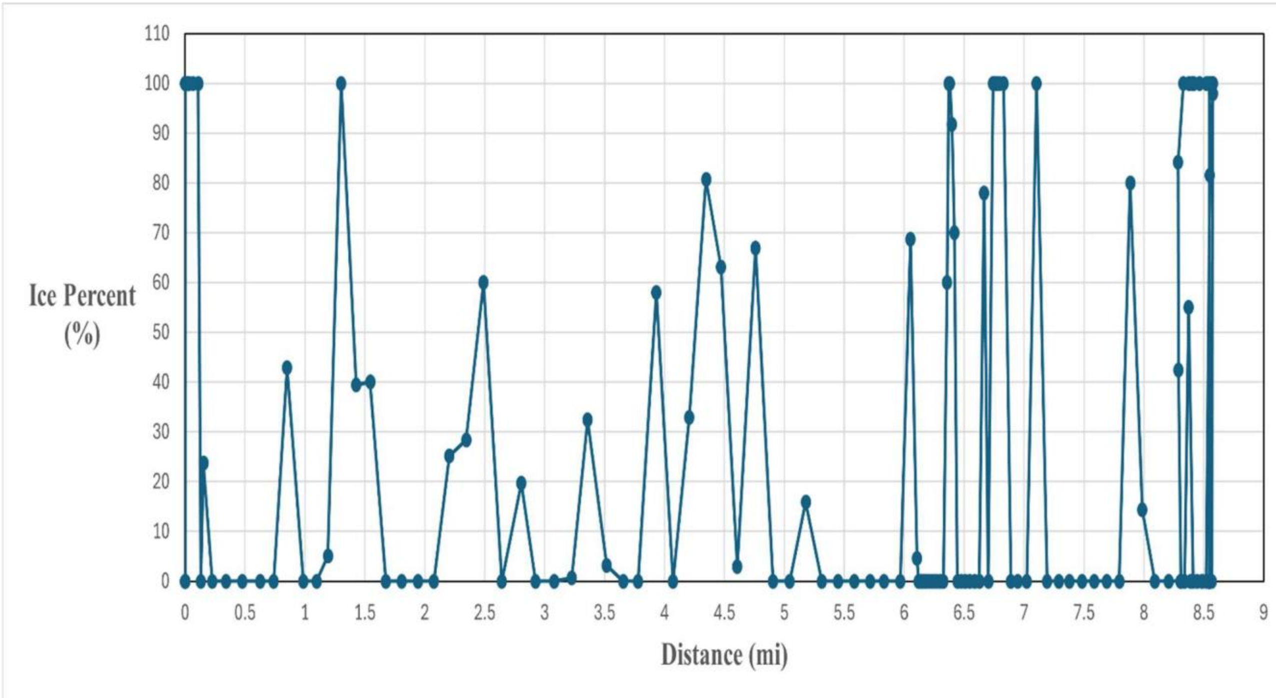


Figure 30 Ice Percent - MARWIS on County Road in Ice Events

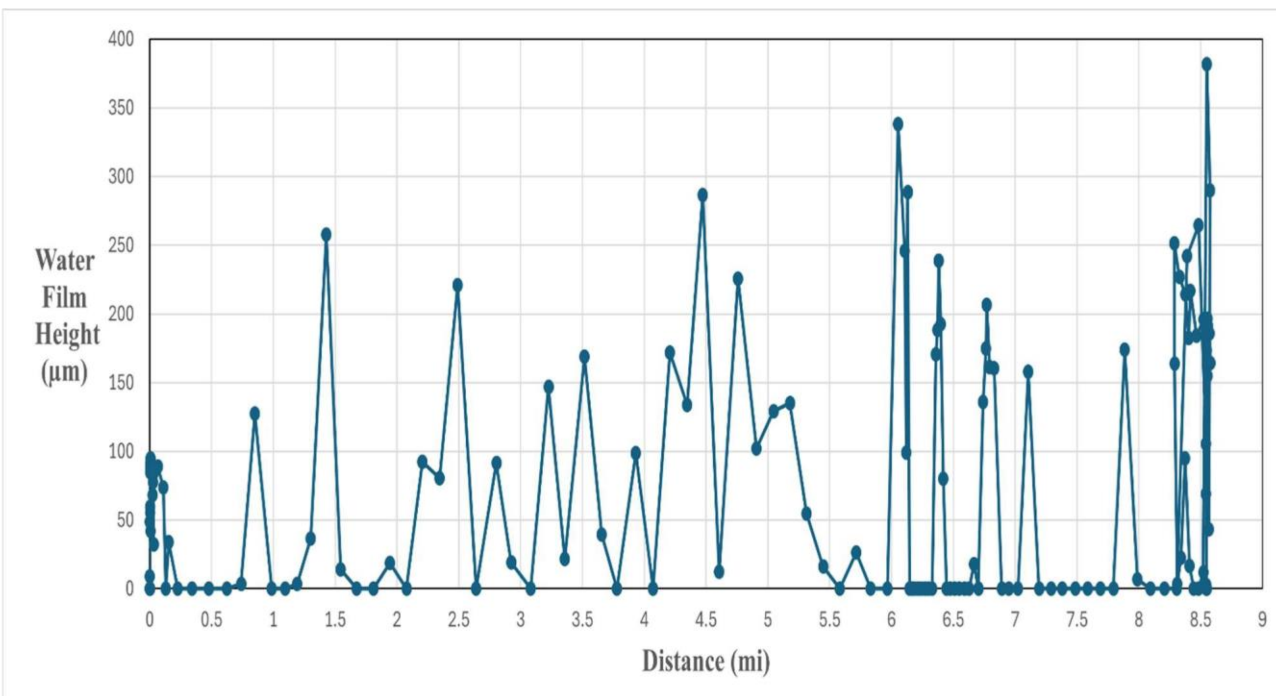


Figure 31 Water Film Height - MARWIS on County Road in Rain Events

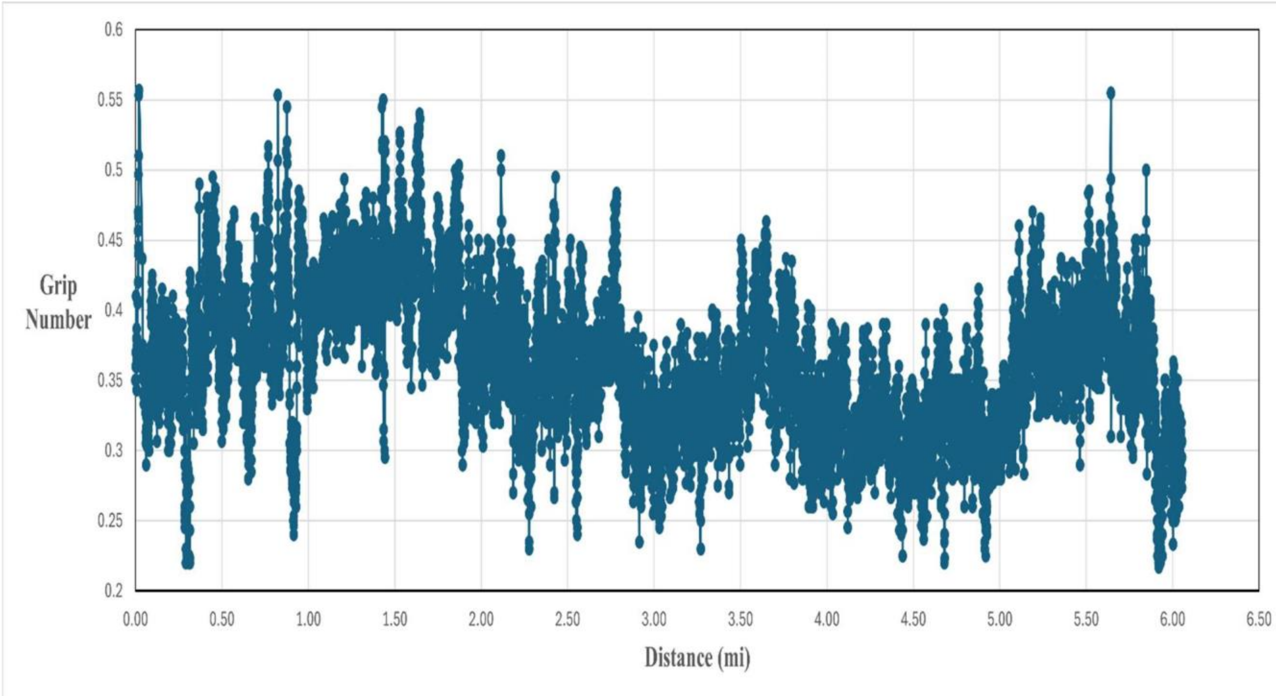


Figure 32 Pavement Friction – Grip Tester on County Road

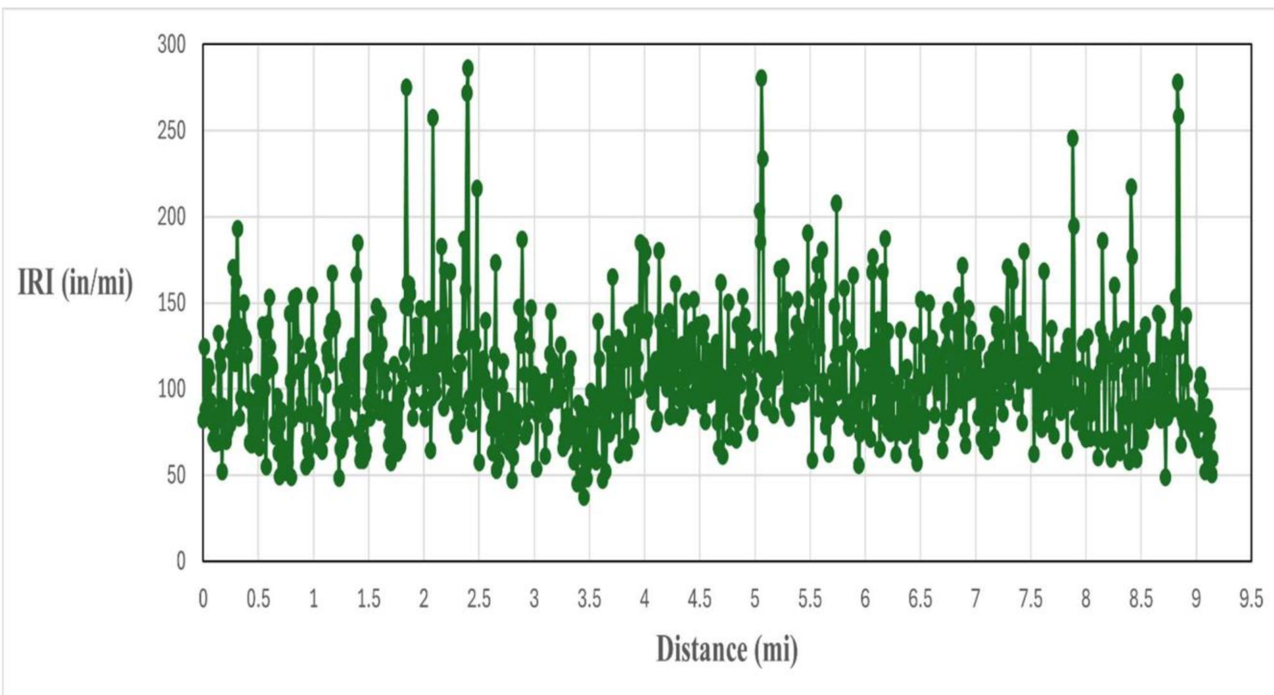


Figure 33 IRI – OSU Pave 3D 8K on County Road

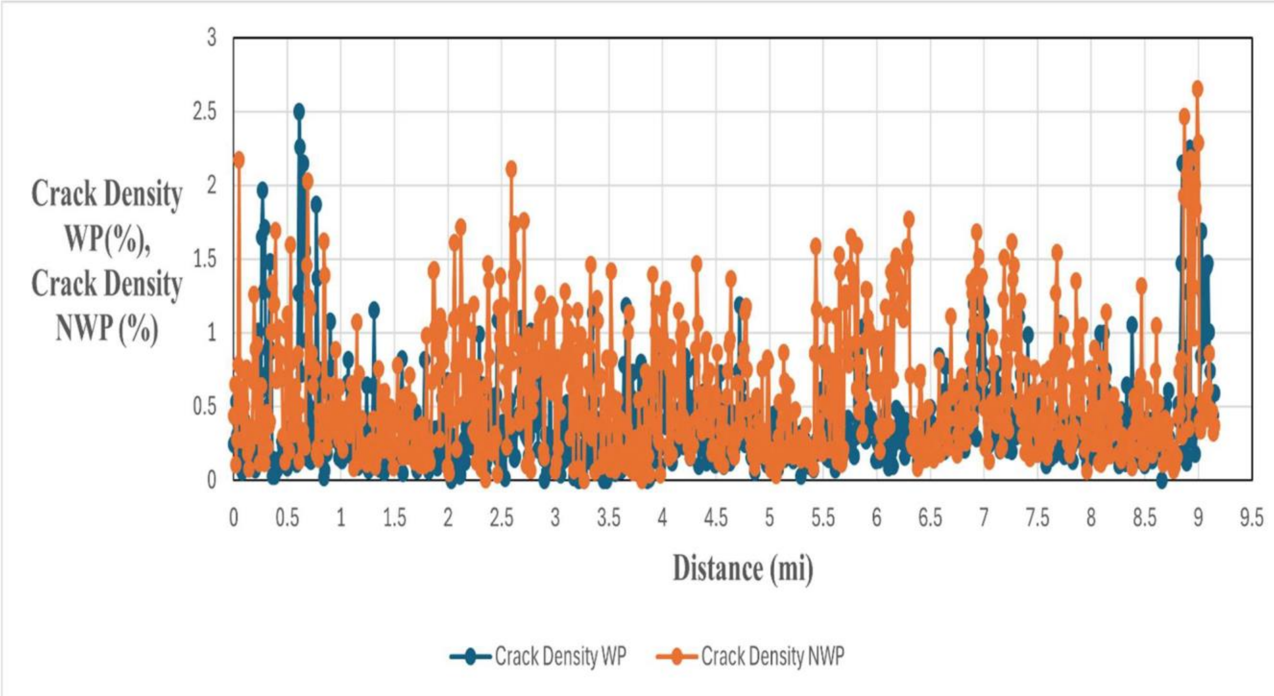


Figure 34 Crack Density – OSU Pave 3D 8K on County Road

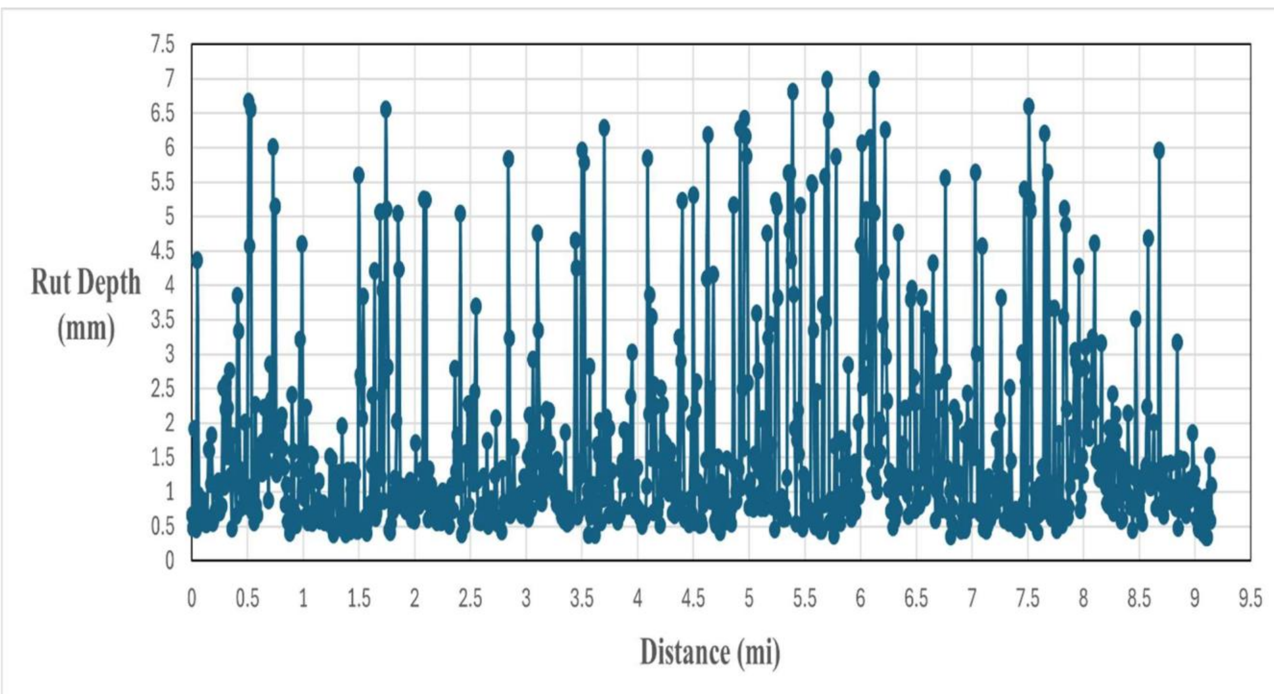


Figure 35 Rut Depth – OSU Pave 3D 8K on County Road

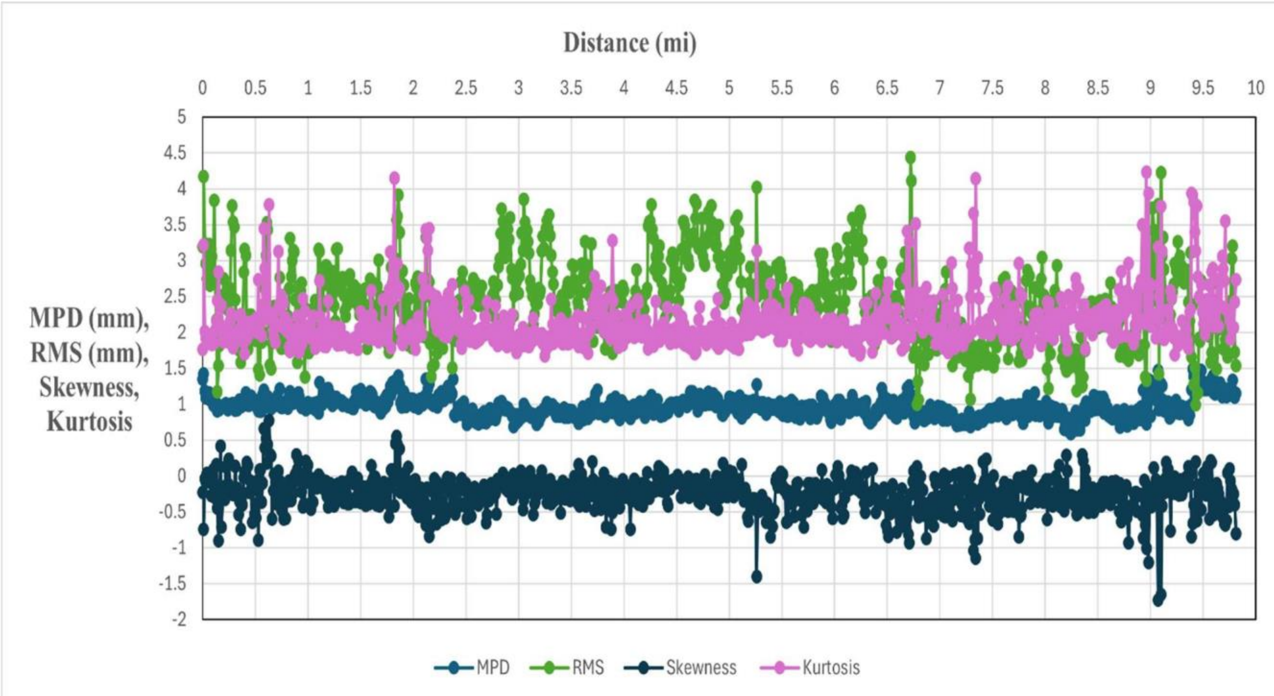


Figure 36 Pavement Texture – OSU Pave 3D 8K on County Road

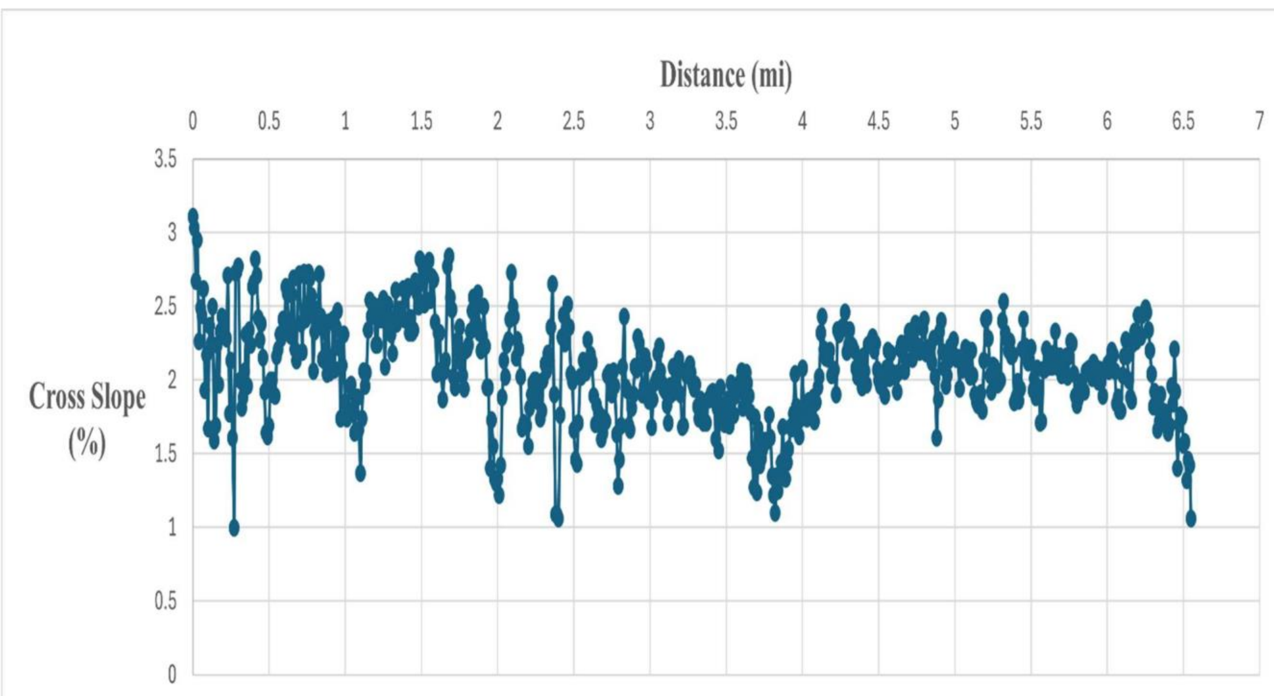


Figure 37 Pavement Geometry – OSU Pave 3D 8K on County Road

Chapter 4. Slippery Conditions Prediction Models

4.1 Response and Independent Variables

Three response variables that relate to the roadway surface slippery conditions were chosen for modeling: ice percentage, water film height (expressed in micrometers, um), and pavement friction. All the variables were categorized into low and high levels based on the percentiles of the data sets collected. Nine variables, as discussed in Chapter 3 associated with weather conditions, roadway geometry, and pavement surface conditions, were included in the model development as independent variables.

4.2 Machine Learning Model Development

Using Python, two tree-based machine learning algorithms—random forest and gradient boosting—were applied due to their ability to interpret feature importance, manage non-linear relationships, and resist overfitting, thus offering reliable insights into the factors affecting selected pavement measures. These algorithms were selected because of their capacity for producing interpretable results to determine feature importance and handle non-linear relationships. Also, these models provide robust techniques for assessing the significance of various features and are less likely to overfit the data, thereby producing more reliable outcomes.

The Random Forest model, introduced by Breiman (2001), executes as an ensemble machine learning algorithm for classification and regression tasks. It operates by adding decisions from different decision trees to derive outcomes. Constructing multiple decision trees across different data sets enables the model to generate results for each tree, which are then combined through a voting mechanism to determine the optimal outcomes. In both categorical and continuous data, this algorithm can effectively address overfitting issues for enhanced precision. In this study, the research team applied 500 decision trees.

Secondly, the gradient boosting model, proposed by Friedman (2001) is another ensemble of machine learning algorithms widely utilized for classification and regression tasks. It employs a sequence of decision trees to predict results iteratively. The fundamental principle of gradient boosting is to progressively strengthen a weak learner to a strong one by technically resampling and creating models that minimize differentiable loss functions, such as cross-entropy or the sum of squared error. The key advantages of this model include reducing both bias and variance, however, overfitting remains a potential drawback. In this study, the gradient boosting model consists of 500 decision trees with a 0.1 learning rate.

To construct classification models, it was necessary to transform continuous pavement condition data into categorical data. Traditionally, the process follows an established rating system from existing literature. The collected ice percentage data were mostly within two ranges, one being 0 to 10 percent, which was classified as lower than 50 percentiles, and another one being close to 100% which was referred to as greater than 50 percentiles. Similarly, the collected water film height data were divided into two parts, one being 0 to 30μm which was referred to as lower than 50 percentiles, and the other water film height greater than 50μm to more than 200μm, noted as greater than 50 percentiles. Chatterjee et al., (2024) employed similar data binning techniques for enhancing pavement performance modeling. The models were constructed using a 10-fold cross- validation method, and the variable importance was evaluated by averaging the importance scores across the cross-validation iterations.

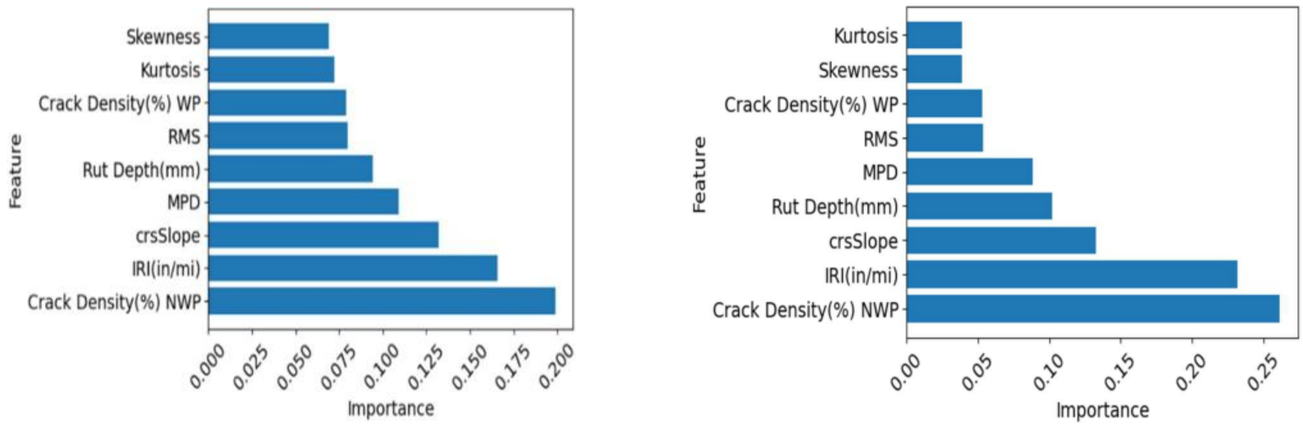
4.3 Ice Percentage Model and Results

For ice percentage, the random forest multi-class classification model, employing a 0.1-mile data sampling interval, achieved an accuracy of 75.79%. Figure 38 and Table 3 display the significant parameters influencing ice percentage, including crack density in the NWP (0.19), IRI (0.16), crsSlope (0.13), MPD (0.10), Rut Depth (0.09), RMS (0.07), crack density in the WP (0.07), kurtosis (0.07), and skewness (0.06).

Similarly, the gradient-boosting multi-class classification model, using a 0.05 mile as a sampling interval, exhibited an accuracy of 71.76%. Figure 38 identifies the important features, including crack density on the NWP, IRI, crsSlope, Rut Depth, MPD, RMS, crack density in the WP, skewness, and kurtosis, with their respective importance value.

The feature importance values shown in Figure 38 were measured based on the mean decrease in impurity, which is also known as Gini importance. The metric calculates each feature's contribution to reducing variance across all decision trees in the ensembles. Those features contribute to larger reductions in prediction error, attain higher importance scores. The feature scores describe the importance of these parameters. The importance scores are normalized and sum to 1 across all features.

A comparison of the two models revealed that skewness was the least important parameter in the Random Forest model, while kurtosis was the least important in the GB model. Also, several changes were observed in importance value; for example, MPD in the Random Forest model had an importance value of 0.11, as compared to 0.08 in the GB model.



Random Forest Model Gradient Boosting Model

Figure 38 Feature Importance for Ice Percentage Model

Table 3 Feature Importance Number for Ice Percentage ML Models (Random Forest)

Random Forest (Average Cross-Validation Score: 75.79)	
Variable	**Feature Importance**
Crack Density NWP	0.1991
IRI	0.1656
crsSlope	0.1320
MPD	0.1091
Rut Depth	0.0942
RMS	0.0798
Crack Density WP	0.0791
Kurtosis	0.0720
Skewness	0.0692

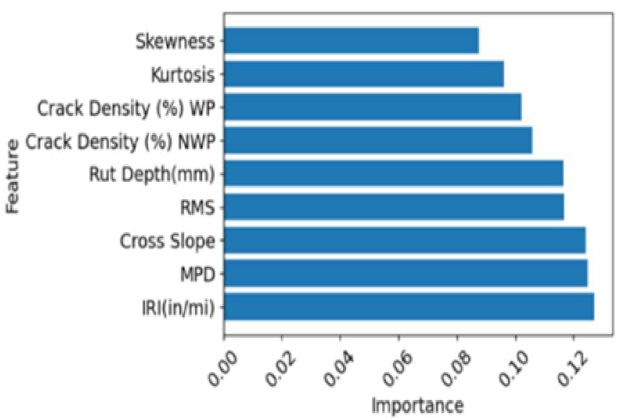
Table 4 Feature Importance Number for Ice Percentage ML Models (Gradient Boosting)

Gradient Boosting (Average Cross-Validation Score: 71.76)	
Variable	**Feature Importance**
Crack Density NWP	0.2614
IRI	0.2317
crsSlope	0.1328
Rut Depth	0.1020
MPD	0.0881
RMS	0.0537
Crack Density WP	0.0532
Skewness	0.0385
Kurtosis	0.0385

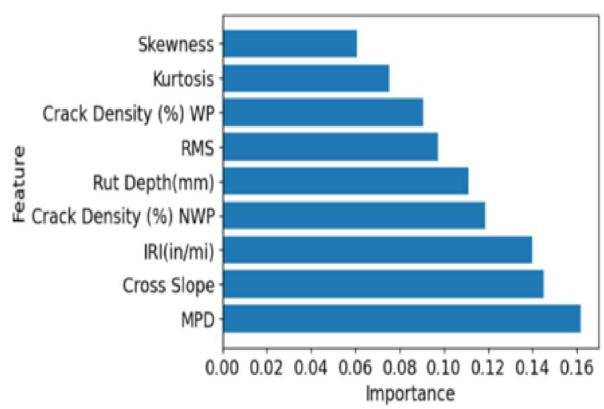
4.4 Water Film Height Model and Results

The water film height model is illustrated in Figure 7 for both the Random Forest and gradient- boosting models, developed using a 0.05-mile sampling interval. The gradient-boosting model achieved higher accuracy at 65.19% compared to the random forest model, which displayed an accuracy of 63.27%. On average, the cross-validation accuracy for random forests was 71.682%, while gradient boosting achieved 68.145%.

For the random forest model, Figure 39 and Table 4 highlight the importance of variables, including IRI (0.13), MPD (0.13), crsSlope (0.13), RMS (0.12), rut depth (0.12), crack density in the NWP (0.11), crack density in the WP (0.10), kurtosis (0.09), and skewness (0.08). Similarly, the gradient-boosting model identified MPD, crsSlope, IRI, crack density in NWP, rut depth, RMS, crack density in WP, kurtosis, and skewness as key variables, with their respective importance values. A comparison of the two models indicates that IRI was the top parameter in the Random Forest model, while MPD ranked highest in the GB model.



Random Forest Model



Gradient Boosting Model

Figure 39 Feature Importance for Water Film Height Model

Table 5 Feature Importance Number for Water Film Height Models (Random Forest)

Random Forest (Average Cross-Validation Score: 63.26)	
Variable	**Feature Importance**
IRI	0.1269
MPD	0.1248
crsSlope	0.1241
RMS	0.1168
Rut Depth	0.1164
Crack Density NWP	0.1057
Crack Density WP	0.1020
Kurtosis	0.0960
Skewness	0.0874

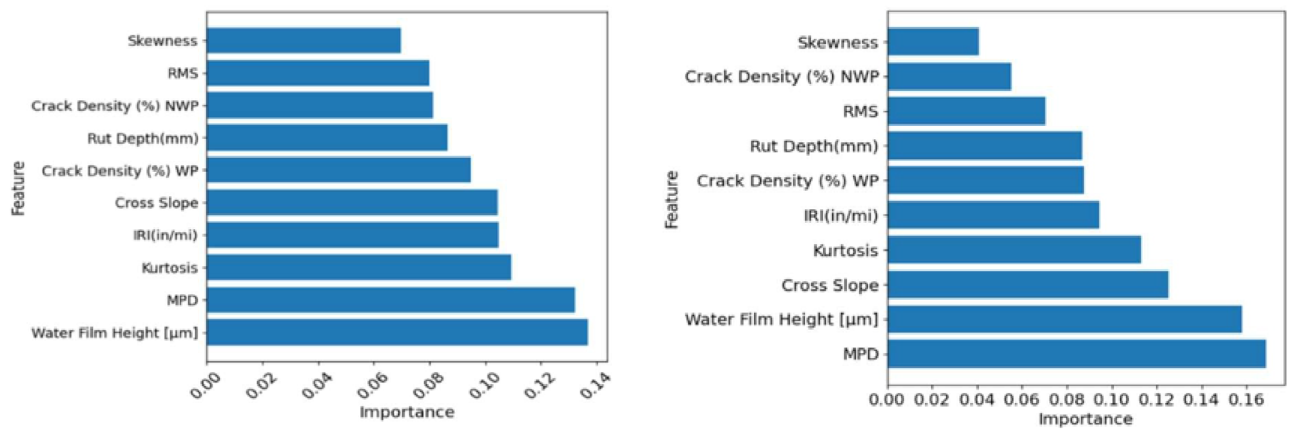
Table 6 Feature Importance Number for Water Film Height Models (Gradient Boosting)

Gradient Boosting (Average Cross-Validation Score: 65.19)	
Variable	**Feature Importance**
MPD	0.1616
crsSlope	0.1450
IRI	0.1399
Crack Density NWP	0.1187
Rut Depth	0.1109
RMS	0.0971
Crack Density WP	0.0908
Kurtosis	0.0753
Skewness	0.0608

4.5 Pavement Friction Model and Results

The pavement friction model, illustrated in Figure 40 and Table 5, was developed using both the random forest and gradient-boosting models with a 0.05-mile sampling interval. The gradient- boosting model achieved a lower accuracy of 68.14% compared to the random forest model, which demonstrated an accuracy of 71.68%.

In Figure 18, the random forest model identified significant variables, including water film height (0.13), MPD (0.13), kurtosis (0.10), IRI (0.10), crsSlope (0.09), crack density in the WP (0.08), crack density in the NWP (0.08), rut depth (0.08), and RMS (0.08). Similarly, the gradient-boosting model highlighted significant variables, including MPD (0.16), water film height (0.15), crsSlope (0.12), kurtosis (0.11), IRI (0.09), crack density in the WP (0.08), rut depth (0.08), RMS (0.07), and crack density in the NWP (0.05). When combining the results of both models, MPD and water film height emerged as the most important variables, while other variables were similar in significance but varied in their rankings and importance values.



Random Forest Model

Gradient Boosting Model

Figure 40 Feature Importance for Pavement Friction Model

Table 7 Feature Importance Number for Pavement Friction Model (Random Forest)

Random Forest (Average Cross-Validation Score: 71.68)	
Variable	**Feature Importance**
Water Film Height	0.1370
MPD	0.1322
Kurtosis	0.1095
IRI	0.1048
crsSlope	0.1044
Crack Density WP	0.0947
Rut Depth	0.0864
Crack Density NWP	0.0812
RMS	0.0800
Skewness	0.0698

Table 8 Feature Importance Number for Pavement Friction Model (Gradient Boosting)

Gradient Boosting (Average Cross-Validation Score: 68.15)	
Variable	**Feature Importance**
MPD	0.1684
Water Film Height	0.1580
crsSlope	0.1253
Kurtosis	0.1132
IRI	0.0943
Crack Density WP	0.0875
Rut Depth	0.0869
RMS	0.0705
Crack Density NWP	0.0552
Skewness	0.0407

4.6 Potential Implementation of Research Findings

ODOT collects annual pavement condition data, which is aggregated into a Pavement Quality Index (PQI). The PQI evaluates overall pavement surface conditions on a scale of 0 to 100, with 100 representing the best condition. For each pavement type, several summary condition indices are calculated based on aggregated subsection pavement distress data. These indices are weighted and combined to derive the overall PQI.

This data is stored in ODOT's PMS database, a comprehensive repository supporting planning, maintenance, and decision-making. The PMS database includes critical information such as route numbers, lane details, surface and pavement types, and various surface condition parameters. Cracking is classified into categories such as transverse, longitudinal, alligator, patching, and raveling. Pavement texture, primarily represented by macrotexture in terms of MPD, is also recorded, along with road geometry data, including grade and curve radius. Additionally, measurements for IRI, rutting, and faulting are collected.

Table 6 summarizes the most significant variables and their feature importance values. Among the ten identified variables, six are included in ODOT's PMS database. For the three Random Forest models—ice percentage, water film height, and pavement friction—the combined feature importance values of these six significant variables are 0.7791, 0.6999, and 0.6037, respectively. In a Random Forest model, the feature importance values for all features in the model sum up to 1.0. Feature importance in Random Forest measures the relative contribution of each feature in reducing the model's overall error, such as Gini impurity (for classification) or mean squared error (for regression). These high feature importance values indicate that ODOT's PMS data can be confidently used to estimate ice percentage, water film height, and surface friction when focusing on the most critical features. In other words, the existing ODOT PMS data allows for reasonably accurate estimation of variables closely associated with pavement slipperiness. Notably, aside from the six variables collected by ODOT, RMS is a key variable for the water film height model. For the pavement friction model, kurtosis and water film height are the most significant variables; however, these are not currently reported in ODOT's PMS database.

Table 9 Feature Importance of Significant Variables in the Random Forest Models

Variable	Ice Percent	Water Film Height	Paveme nt Friction	Included in the ODOT PMS Database
IRI	0.1656	0.1269	0.1048	Yes
Rut Depth	0.0942	0.1164	0.0864	Yes
crsSlope	0.1320	0.1241	0.1044	Yes
Crack Density WP	0.0791	0.1020	0.0947	Yes
Crack Density NWP	0.1991	0.1057	0.0812	Yes
MPD	0.1091	0.1248	0.1322	Yes
RMS	0.0798	0.1168	0.0800	No
Skewness	0.0692	0.0847	0.0698	No
Kurtosis	0.0720	0.0960	0.1095	No
Water Film Height	NA	NA	0.1370	No
Sum of Feature Importance: ODOT PMS Indicators	0.7791	0.6999	0.6037	

4.7 Summary

This analysis provides valuable insights into identifying the key parameters that influence pavement safety during winter and adverse weather conditions. It also demonstrates the potential for supporting an MDSS. However, it is important to note that the models developed in this study were based on limited data collected from a small roadway network. It is expected that more extensive datasets will become available for future network-wide surveys.

Additionally, incorporating a broader range of weather parameters, such as surface temperature and dew point temperature, is recommended to better understand their effects on pavement safety under adverse weather conditions. It is worth mentioning that during the one-year study period, only one extreme weather event involving snow and one involving ice were observed. As a result, many weather-related parameters were not included in the analysis.

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