

Computer Vision-Based Contactless Estimation of Asphalt Pavement Surface Friction

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ICT Project R27-247

September 2026

ISSN: 0197-9191

ICT Series Report No. 26-019

<https://doi.org/10.36501/0197-9191/26-019>

TECHNICAL REPORT DOCUMENTATION PAGE

1. Report No. FHWA-ICT-26-017	2. Government Accession No. N/A	3. Recipient's Catalog No. N/A	
4. Title and Subtitle Computer Vision-Based Contactless Estimation of Asphalt Pavement Surface Friction		5. Report Date September 2026	
		6. Performing Organization Code N/A	
7. Authors Imad L. Al-Qadi (https://orcid.org/0000-0002-5824-103X), Mani Golparvar-Fard (https://orcid.org/0000-0002-9432-9370), Mohammad Fakhreddine (https://orcid.org/0000-0002-2921-3910), Hong Lang (https://orcid.org/0000-0003-1015-5797), William D. Villamil (https://orcid.org/0009-0003-1839-2807)		8. Performing Organization Report No. ICT-26-019 UILU-2026-2019	
9. Performing Organization Name and Address Illinois Center for Transportation Department of Civil and Environmental Engineering University of Illinois Urbana-Champaign 205 North Mathews Avenue, MC-250 Urbana, IL 61801		10. Work Unit No. N/A	
		11. Contract or Grant No. R27-247	
12. Sponsoring Agency Name and Address Illinois Department of Transportation (SPR) Bureau of Research Materials Testing and Research Center 2420 South Dirksen Parkway Springfield, IL 62764		13. Type of Report and Period Covered Final Report 7/1/22–9/30/26	
		14. Sponsoring Agency Code	
15. Supplementary Notes Conducted in cooperation with the U.S. Department of Transportation, Federal Highway Administration. https://doi.org/10.36501/0197-9191/26-019			
16. Abstract This study developed a contactless and automated technique to estimate hot-mix asphalt pavement surface friction by combining computer vision image-based 3D reconstruction with machine learning. Existing continuous friction estimation equipment, including high-speed laser scanners, are costly to purchase and operate—limiting routine, frequent monitoring. This study addressed this limitation through the development and utilization of cost-effective and scalable equipment. A Structure-from-Motion computer vision framework was developed to reconstruct pavement macrotexture in three dimensions and compute mean profile depth (MPD). Ground-control-based measurements agreed with a reference laser scanner within 15% across all test locations. A high-speed prototype using industrial cameras and a real-time kinematic positioning system was built. It was able to collect data up to 35 mi/hr and perform 3D reconstruction on cloud environments, increasing processing speed. The prototype was validated against a laser scanner at a controlled test track. The results demonstrated that contactless texture measurement and friction prediction are feasible and provide a foundation for more frequent, lower-cost monitoring of pavement surface characteristics, supporting proactive pavement management, safety screening, and more cost-effective maintenance decisions. The developed device measures texture and estimates friction for \$61/mile, about 65% less than the \$140/mile needed to collect both with current methods, and it costs only \$73,500 to buy, compared with about \$1,100,000 for a combined laser scanner and a transverse profiler. In addition, a data-driven model was developed to predict sideways friction measured by a Sideway-force Coefficient Routine Investigation Machine using pavement texture, traffic, roadway geometry, operating speed, and surface temperature. Three datasets collected in Florida and Illinois were used to evaluate the influence of dataset size, available features, and data distribution. Among the tree-based ensemble models evaluated, the Extra Trees model performed best, explaining approximately 85% of the variance, with MPD, traffic, operating speed, and surface temperature identified as the most influential variables. Finally, a finite element framework coupling a 3D tire model, texture-based friction model, and water film was developed to evaluate hydroplaning. The framework demonstrated that coarser macrotextures resulted in relatively better tire-pavement contact at higher speeds because of their improved surface drainage capacity.			
17. Key Words Pavement Friction, Pavement Macrotexture, Photogrammetry, Machine Learning, Hydroplaning, Traffic Safety		18. Distribution Statement No restrictions. This document is available through the National Technical Information Service, Springfield, VA 22161.	
19. Security Classif. (of this report) Unclassified	20. Security Classif. (of this page) Unclassified	21. No. of Pages 81	22. Price N/A

ACKNOWLEDGMENT, DISCLAIMER, MANUFACTURERS' NAMES

This publication is based on the results of **ICT-R27-247: Automated and Contactless Identification of Asphalt Pavement Surface Friction Based on Computer Vision Image-based 3D Reconstruction and Machine Learning Techniques**. ICT-R27-247 was conducted in cooperation with the Illinois Center for Transportation; the Illinois Department of Transportation; and the U.S. Department of Transportation, Federal Highway Administration.

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EXECUTIVE SUMMARY

Pavement friction is a critical surface characteristic that allows drivers to brake, accelerate, and corner safely, and it is closely related to traffic safety, particularly under wet conditions.

Transportation agencies measure friction and the surface texture that controls it to identify locations potentially requiring maintenance. However, continuous friction measurement equipment, including high-speed laser scanners, are expensive to purchase and operate, require significant training, and may be difficult to deploy frequently at the network level. The primary objective of this study was to develop a relatively inexpensive and scalable approach that infers pavement friction from texture reconstructed in three dimensions (3D). This development would enable frequent and broader monitoring of pavement surface characteristics. The result was a contactless and automated technique to identify hot-mix asphalt (HMA) pavement surface friction, using image-based 3D reconstruction and machine learning.

The study was organized into four major components. First, a computer vision algorithm was developed to reconstruct pavement texture in 3D and compute texture metrics. Second, a prototype was designed, built, and validated to collect pavement images from a moving vehicle and process them into texture and friction estimates. Third, a machine learning model was developed to predict continuous sideways friction from pavement texture and other influencing factors. Fourth, a finite element framework was developed to evaluate hydroplaning potential. Together, these components formed a pipeline that moved from raw images to texture estimation, hydroplaning speed calculation, and friction prediction.

To measure texture without contact, a 3D reconstruction framework based on Structure from Motion (SfM) was developed for network-level scalability. The framework produces 3D point clouds from 2D images. The framework was evaluated using a digital single-lens reflex camera with surveyed ground control points, the same camera with positioning data embedded directly in the images, and a pair of action cameras mounted on a moving vehicle. An image acquisition strategy that tilted and shifted the camera between frames was used to prevent reconstruction distortions on the flat pavement surface. Texture was extracted from the resulting point clouds, as explained in the framework, and reported as mean profile depth. The ground-control configuration produced the most accurate reconstructions, and the texture measurements agreed with those reported by an Ames 9400 HD laser texture scanner within 15%. The vehicle-mounted camera setup results confirmed that texture data could be collected on a moving vehicle. However, in-motion captured data require cameras capable of maintaining image sharpness at higher speeds and a georeferencing solution that could match the accuracy of ground control.

A high-speed prototype, on a moving vehicle, was built to collect high-resolution pavement images. The system used industrial cameras with a global shutter, a real-time kinematic positioning system with inertial navigation, a vehicle mounting frame, and custom data collection software. Currently, the system collected data at speeds up to 35 mi/hr. Captured images were processed into 3D point clouds using cloud and cluster computing. This supported parallel processing and increased processing speed. Texture and friction were derived from the reconstructed surfaces.

The system was validated at a controlled research track by comparing its texture measurements with those of an Ames 9400 HD laser scanner. The measurements agreed most closely on the surfaces with shallow texture depth and diverged on deep-texture surfaces.

To predict friction, a data-driven model was developed using friction measured by a sideways-force continuous friction device. Three datasets, two collected by Illinois Department of Transportation and one collected by Florida Department of Transportation, were used to examine the effect of dataset size, available features, and data distribution on prediction accuracy. Several tree-based ensemble models were trained and compared. The Extra Trees model consistently performed best across all datasets. It explained approximately 85% of the statistical variance on the 2025 Illinois dataset and achieved the lowest prediction errors on the larger Florida benchmark dataset. An interpretability analysis demonstrated that mean profile depth, AADT and speed, and surface temperature were the most influential variables, whereas roadway geometry variables such as cross slope, grade, and curve radius had relatively small effects. The relatively larger errors occurred at low operating speeds and at extreme texture levels. In addition, friction was influenced by surface and material characteristics that were not available in the datasets.

Finally, to assess wet-weather safety, a finite element framework was developed to model the interaction between a rolling tire, a water film, and the pavement surface texture. Four pavement surfaces with increasing macrotexture were reconstructed from field measurements in Illinois and incorporated into the model. A finite-element texture-based friction property was assigned to the tire-pavement contact. The simulations demonstrated that water accumulated at the leading edge of the tire footprint and drained through the tire grooves and the surface texture. Coarser surfaces sustained tire-pavement contact to higher speeds because their deeper and more interconnected voids evacuated water more effectively. Pavement macrotexture was an important factor to control hydroplaning.

Overall, the study demonstrated that contactless and automated identification of pavement surface friction is feasible using image-based 3D reconstruction and machine learning. Prediction accuracy is expected to improve as larger and more descriptive datasets become available. Friction surveys cost at least \$125/mile, and texture measurements cost about \$57/mile with transverse profilers and \$50/mile with wide-footprint laser scanners. Collecting both in the same survey could cost \$140/mile, and the equipment costs about \$1,000,000 for a transverse profiler and \$100,000 for a laser scanner. The developed device provides texture measurements and friction estimates for \$61/mile, about 55% less, and costs only \$73,500 to buy. By lowering the cost of collecting and analyzing pavement surface information, the proposed approach supports proactive pavement management, network-level safety screening, and more cost-effective maintenance strategies. Closing this gap aligns with agencies' goals of achieving long-term pavement performance and safety.

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CHAPTER 1: INTRODUCTION

BACKGROUND

Transportation infrastructure is the backbone of economic productivity and societal mobility, making the safety and long-term performance of roadway networks a matter of national importance. However, the functional condition of in-service pavements is challenged continuously by growing traffic demand, environmental loading, and material aging. In 2025, US drivers logged approximately 3.32 trillion vehicle miles across rural and urban roads (FHWA, 2025). This number is primarily for commute/day-to-day transportation, as 97.3% of the American labor force uses transportation methods that require driving on roads (Burrows et al., 2021). Additionally, freight and packages delivered to consumers account for about two-thirds of the US economy. As such, 72% of the nation's goods are transported using roads and highways (ASCE, 2021).

The US road network consists of over 2.9 million miles of paved roads and highways (Bureau of Transportation Statistics, 2021; FHWA, 2021) and serves as the backbone of the US economy. However, the maintenance backlog costs \$435 billion with 43% of the network being in poor or mediocre condition (ASCE, 2021). Around 6 million crashes occur each year, which lead to 2,380,000 injuries and 40,000 fatalities (U.S. Department of Transportation, 2024). The National Highway Traffic Safety Administration estimated that these crashes have an economic impact of \$339.8 billion and a staggering social impact of \$1.37 trillion (Blincoe et al., 2022). Therefore, understanding the root causes of these crashes is critical to improving safety.

Surface frictional properties are among the first functional characteristics to deteriorate as aggregates degrade due to polishing and seasonal environmental cycles, declining toward levels that compromise safe vehicle operation (Plati et al., 2020). Preserving adequate tire-pavement friction is therefore a key objective of pavement management, with direct and quantifiable safety consequences.

A National Highway Traffic Safety Administration investigation (Singh, 2015) identified driver-, vehicle-, and environment-related issues as the main reasons behind crashes. The top reasons related to vehicles and the environment were tire/wheel-related issues (35%) and slick roads (50%), respectively. Driver-related issues were responsible for crashes 94% of the time, but they include errors such as driving too fast for pavement conditions, driving too fast for a curve, and overcompensation in certain situations. Factors related to pavement friction are responsible for 20%–25% of all accidents (Fwa, 2021; Khaleghian et al., 2017).

Pavement friction is the force that deters a tire from sliding on the pavement surface and develops at the interface between the tire and the pavement surface (Noyce et al., 2005). Friction allows a driver to safely control a vehicle by accelerating, braking, and cornering. Because these maneuvers involve the vehicle moving in different directions, longitudinal and transversal friction coefficients are important. The longitudinal friction component represents the availability of the frictional force along the direction in which the vehicle is traveling and has a direct effect on determining a safe braking distance. This component is critical in situations where the driver must slow down unexpectedly and

would require a high longitudinal friction coefficient to minimize the stopping distance (Mayora & Piña, 2009). The transversal coefficient represents the availability of the frictional force along the direction perpendicular to that of the vehicle direction. It relates to the stability and safety of the vehicle when making turns. Pavement friction is expressed in the form of a coefficient and can be calculated as follows in Figure 1:

$$\mu = \frac{F}{F_w}$$

Figure 1. Equation. Friction equation.

where: μ is coefficient of friction; F is tangential friction force between the tire rubber and the pavement surface; and F_w is load acting on the tire and is perpendicular to the plane of contact.

Several theories have been proposed to explain the friction mechanism between the tire and pavement surface (Guo et al., 2021). Total friction force is a result of four components: Van der Waals force between the tire and pavement surfaces, adhesion force between the tire and pavement, hysteresis energy loss in the tire, and plough effect, which is caused by the sliding of the tire against a hard material.

Cohesion and wear losses are also components of friction (Kummer, 1966). However, adhesion and hysteresis are considered the main contributors to friction because the contribution from the other components is relatively insignificant (Hall et al., 2009). Adhesion develops due to the shearing force between the tire and pavement surfaces as they slide against each other. It is mainly affected by aggregate texture properties, which contribute to most of the friction force at low speeds and on a dry and clean surface (Flintsch et al., 2012). Hysteresis occurs due to the deformation of the tire around the aggregates on the pavement surface. This deformation is stored in the tire as potential energy. Because of the viscoelastic nature of the tire rubber, part of this stored energy is lost in the form of heat. The remaining potential energy is recovered as the tire returns to its original shape (Persson, 2001). Hysteresis is influenced by surface macrotexture and contributes to most of the friction force when the vehicle is traveling at high speeds or when the pavement is wet (Heinrich, 1997). Adhesion is greatly reduced on a wet surface, whereas hysteresis is relatively unaffected. Figure 2 illustrates how adhesion and hysteresis act on the tire-pavement contact area.

Several factors influence friction: pavement surface, vehicle operation, tires, and the environment (Table 1). In cases where a vehicle is turning or braking at high speed, a small reduction in friction is enough for a vehicle to lose control and cause an accident. Changes in vehicle speed and trajectory demand high friction forces to maintain contact with the pavement and prevent sliding. The reduction in friction may be due to decreased pavement temperatures, poor quality tires, low inflation pressure, and others. In other cases, vehicles may lose control due to excessive water between the tire and pavement surface, which causes hydrodynamic forces to build up and lift the tire above the pavement surface. This phenomenon is known as hydroplaning, and it can occur even when vehicles are not turning or braking.

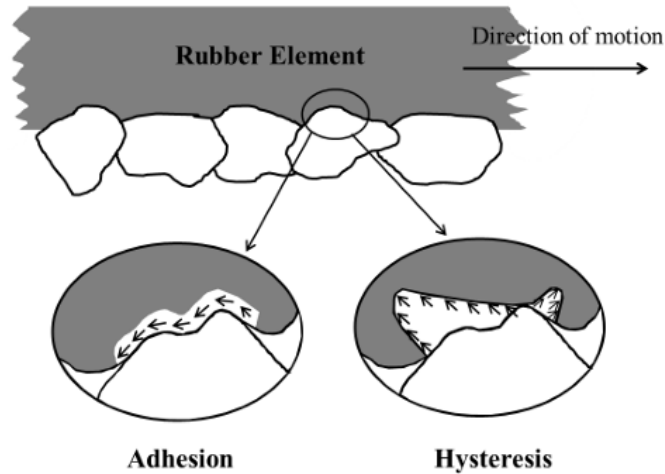


Figure 2. Illustration. Adhesion and hysteresis components of friction.

Source: Hall et al. (2009)

Table 1. Factors Influencing Pavement Friction

Pavement Surface Factors	Vehicle Operational Factors	Tire Factors	Environmental Factors
• Surface texture (micro-texture and macro-texture) • Material properties • Temperature	• Slip speed (vehicle speed and braking action) • Driving maneuvers (turning and overtaking)	• Inflation pressure • Tread design and condition • Load • Rubber composition and hardness	• Temperature • Water (rainfall, condensation) • Snow and ice • Contaminants (Anti-skid material, dirt, mud, debris)

Source: Hall et al. (2009); Wallman & Åström (2001)

A general method to measure friction directly is to drag a rubber element across the pavement surface. The resistance to moving in the specified direction of travel is due to the friction force that develops between the object and the surface. When the direction of travel is straight, this force is oriented longitudinally along the direction of travel. In a similar manner, when the direction of travel changes, an additional transversal friction force that is perpendicular to the direction of travel is formed. Measuring friction varies, depending on which component of the friction force the operator is interested in quantifying and the slip speed at which the friction will be measured. Slip speed represents the relative speed between the vehicle and the tire and is calculated in Figure 3:

$$S = V - V_p$$

Figure 3. Equation. Slip speed.

where: S is slip speed, V is vehicle speed, and V_p is peripheral speed of the tire.

Slip speed can also be represented as a ratio by normalizing it against the speed of the vehicle, and it is calculated as follows in Figure 4:

$$SR = \frac{S}{V}$$

Figure 4. Equation. Slip ratio.

where: S is slip speed, and V is vehicle speed. When the slip ratio is 100%, the tire is locked and being dragged against the pavement surface. While this scenario is not optimal for braking performance and has become unrealistic with the mandate of anti-lock braking systems, the friction force generated is mostly influenced by pavement surface characteristics. This forms the main principle behind the Locked-Wheel Skid Trailer, which operates at 100% slip and is the most common friction test used in the US. Other tests that operate at different slip ratio as well as measurement directions have been developed. Table 2 presents a summary of these methods in addition to their advantages and disadvantages.

Table 2. Summary of Pavement Friction Measurement Methods

Method	Associated Standard	Requirement (Equipment)	Measurement Index	Applications	Pros and Cons
Side-Force	ASTM E670	British Mu-Meter SCRIM	Mu Number Sideways force coefficient	- Field testing - Network-level friction monitoring	Pros: Continuous measurements Cons: Sensitive to road irregularities, Mu-Meter used for US airports only
Fixed-Slip	Various	Roadway and runway FT Airport surface FT Saab FT UK Griptester Finland BV-11 ROAR	Measured resistive drag force and wheel load	- Field testing - Network-level friction monitoring - Project-level friction monitoring	Pros: Continuous and high-resolution friction data Cons: Specified slip speed, large amounts of water, and skillful data reduction
Variable-Slip	ASTM E1859	French IMAG Norwegian Norsemeter RUNAR ROAR/SALTAR	Relationship between slip friction number and slip speed	- Field testing - Network-level friction monitoring - Project-level friction monitoring	Pros: Continuous slip friction, Rado shape factor Cons: Large and complex equip., Large amounts of water

Despite some methods offering major advantages, such as network-level continuous monitoring at highway speeds, there are several challenges: the need to constantly refill water tanks, replace worn out tires, control traffic, and develop adjustment factors to compensate for variables such as speed and temperature. Additionally, conducting network-level routine testing is expensive and may be infeasible for some agencies (Hall et al., 2009; Henry, 2000; Kogbara et al., 2016; Yu et al., 2020).

Texture is the main pavement characteristic that controls pavement friction. As a result, agencies conduct texture measurements as an indirect way to measure friction. Texture comprises four ranges based on wavelength, which are presented in Table 3. Microtexture is formed by irregularities and deviations on the surface of the coarse aggregates. It highly influences adhesion at all vehicle speeds

and on dry and wet pavements (Kogbara et al., 2016). For vehicles traveling at low speeds on dry and smooth pavements, microtexture is of great importance because most of the friction force is generated by adhesion (Hall et al., 2009). Macrotexture, on the other hand, highly influences hysteresis. It is formed by the deviations between the aggregate particles on the pavement surface, which are dependent on factors such as the aggregate size and shape as well as the mix gradation and construction techniques (Noyce et al., 2005).

Macrotexture contributes to most of the friction force when a vehicle is traveling on a wet pavement surface at a high speed because adhesion is diminished due to water presence. Macrotexture also facilitates the drainage of water from the tire-pavement contact area and reestablishes adhesion if the aggregate surface is above the water film level (Kogbara et al., 2016). Although both microtexture and macrotexture are important for friction, field measurement is mostly done for macrotexture as there is no direct way to measure microtexture in the field except for spot testing using a laser texture scanner.

Table 3. Pavement Texture Wavelength Ranges

Texture Classification	Relative Wavelengths
Microtexture	$\lambda < 0.5 \text{ mm}$
Macrotexture	$0.5 \text{ mm} < \lambda < 50 \text{ mm}$
Megatexture	$50 \text{ mm} < \lambda < 500 \text{ mm}$
Roughness/Smoothness	$0.5 \text{ m} < \lambda < 50 \text{ m}$

Source: Flintsch et al. (2003)

Mean profile depth (MPD) is a common way of reporting macrotexture measurements. MPD is calculated as the average of mean segment depths (MSD) over the survey distance (ASTM E1845-15, 2015). The sampling length for MSD is 3.94 in, and the calculation process is illustrated in Figure 5.

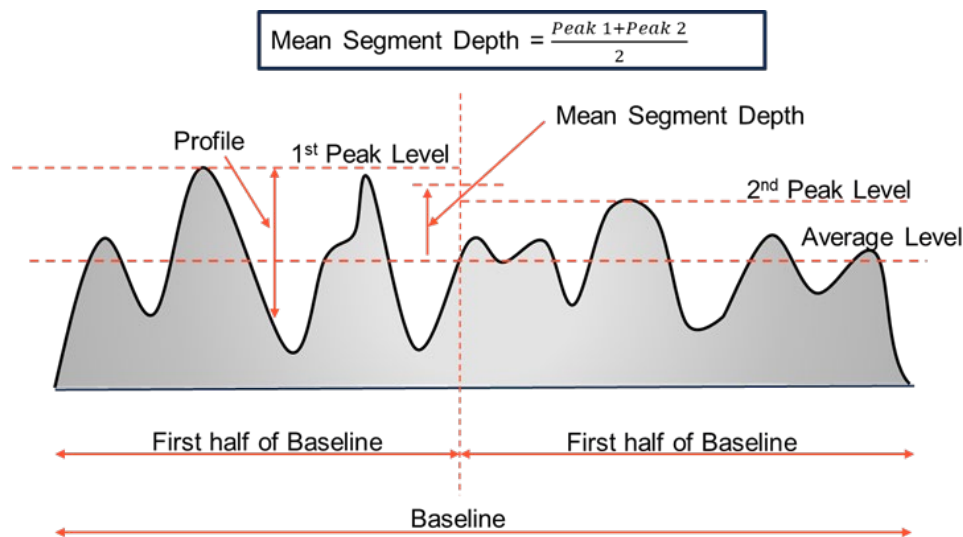


Figure 5. Illustration. Mean segment depth calculation.

Transportation agencies typically use high-speed laser equipment (HSLE), summarized in Table 4, to collect texture data. HSLE are accurate and able to collect data at highway speeds, which makes them suitable for network-level data collection. However, HSLE are expensive to purchase and operate, require skilled labor to collect and analyze data, and may suffer from outliers known as spikes. As a result, only 15 states and Puerto Rico collect network-level macrotexture data (Flintsch et al., 2021). Because of the limited ability to monitor texture evolution across roads and highways, traffic safety may be jeopardized.

OBJECTIVES AND SCOPE

The objective of this project was to develop a contactless and automated 3D scanning and analysis technique to identify pavement surface friction. Because existing continuous friction measurement equipment and high-speed laser scanners have high cost for purchase and operation, this research utilized image-based 3D reconstruction for texture measurement and machine learning methods for surface friction inference. To achieve this objective, the following tasks were accomplished:

1. A computer vision algorithm was developed to accurately reconstruct pavement texture in 3D. The algorithm was developed in a way that allows scalability for network-level data collection and included components for georeferencing, texture extraction, profile filtering, and MPD calculation.
2. A high-speed prototype was built that utilizes advanced imaging with geolocation to collect images on a moving vehicle at speeds up to 35 mi/hr at this point. The images were then processed on cloud servers to create 3D models that were used for texture measurement and friction prediction.
3. A machine learning model was developed to predict pavement surface friction accurately. The model predicted friction measured by SCRIM and incorporated texture measurement obtained using the computer vision algorithm. The model incorporated texture, temperature, AADT, vehicle speed, and road geometry data.
4. A finite-element-based method was utilized to evaluate hydroplaning potential. The method includes tire and pavement surface models and water film between them.

POTENTIAL IMPLEMENTATION

This study presents a novel method to measure pavement surface texture and predict friction using a pipeline of computer vision and machine learning techniques. The accuracy of the prediction model is expected to increase as training data improve in quantity and quality. The data collection system enables inexpensive monitoring of pavement surface characteristics, which enhances proactive pavement management, reduces the risk of deadly vehicle accidents, and contributes to more cost-effective pavement condition assessments and maintenance strategies. In 2024, the Illinois Department of Transportation reported 303,913 crashes, resulting in 1,178 fatalities, 89,023 injuries, and \$8.3 billion in economic damage (Illinois Department of Transportation, 2026). With 19.7% of all accidents occurring on wet roads, accurate measurement of pavement texture and friction could help improve safety, aligning with IDOT's long-term performance and safety goals.

Table 4. Summary of HSLE for Texture Measurement

Commonly Used Single-Point Lasers										
Product Name	Manufacturer	Technology	Laser Wavelength (mm)	Maximum Sampling Rate (kHz)	Standoff (mm)	Measurement Range (MR) (mm)	Vertical Resolution (%MR)	Maximum Vertical Resolution (mm)	Average Laser Spot Size (mm)	Laser Power (mW)
Gocator 13xx	LMI Technologies	Single-Spot Laser	660	32	200-562	200-375	0.00075%-0.001%	0.0015	0.5-1.8	3B (<130)
Optocator 20xx	LMI Technologies	Single-Spot Laser	780	78	180-1200	32-1024	0.0030%	0.00096	0.2	20
RoadRun System	LIMAB	Single-Spot Laser	635-670	62	100-300	200-1000	0.001%-0.005%	0.002	1	20-40
AR 700 Series	Acuity (AMES partner)	Single-Spot Laser	670	100	12.7-1422	3.175-1270	0.01%	0.0002	0.1	1-20
Emerging Technologies										
Product Name	Manufacturer	Technology	Laser Wavelength (mm)	Maximum Sampling Rate (kHz)	Standoff (mm)	Measurement Range (MR) (mm)	Vertical Resolution (%MR)	Maximum Vertical Resolution (mm)	Field of View (mm)	Data Points per Profile
Gocator 2342	LMI Technologies	Line Laser and Sensor	660	5	190	120	0.0079%-0.0190%	0.001659	64-140	1280
Gocator 2375	LMI Technologies	Line Laser and Sensor	808 (near infrared)	5	650	1350	0.0114%-0.0415%	0.1539	3450-1028	1200
LCMS	Pavemetrics	Line Laser with Line Scan Camera	Invisible	11.2	Near Roof	250	0.100%	0.25	2000	2080
LCMS 2	Pavemetrics	Line Laser with Line Scan Camera	Invisible	28	Near Roof	250	0.040%	0.1	2000	2080
AR 500 Series	Acuity	Single-Spot Laser Distance Triangulation	405 (blue)	100	12.7-1422	3.175-1270	0.005%	0.0002	0.1	1-20

Source: Flintsch et al. (2021)

CHAPTER 2: COMPUTER VISION ALGORITHM

INTRODUCTION

With advances in computing hardware, imaging sensors, and software, image-based (computer vision) methods have become widely used in multiple sectors, including autonomous navigation, security and surveillance, and medical imaging. In civil engineering, computer vision has been applied to monitor structures and infrastructure assets by inferring information from 2D images using artificial intelligence (AI) models. Typical tasks include detecting and classifying objects (e.g., traffic signs and construction equipment). The 2D images can also be used to recreate the photographed object in 3D and extract measurements. Table 5 presents examples of computer vision applications in civil engineering.

Table 5. Examples of Computer Vision Applications in Civil Engineering

Application	Reference
Measure surface deformations	Knyaz & Chibunichev (2016)
Classify aggregates by shape	Al-Rousan et al. (2005)
Quantify coarse aggregate angularity	Rao et al. (2002)
Detect pavement potholes	Koch & Brilakis (2011); Dhiman & Klette (2019); Haq et al. (2019)
Detect pavement cracks	Pauly et al. (2017); Zhang et al. (2018)
Monitor construction site progress	Golparvar-Fard et al. (2015)
Inspect railroad tracks	Edwards et al. (2009); Resendiz et al. (2013)
Inspect railway ballast permeability	Huang et al. (2018)

The primary method that enables 3D reconstruction is Structure from Motion (SfM), a photogrammetric method that estimates camera poses and sparse 3D structure from a sequence of overlapping images. Although SfM has been refined and made widely available in recent years, the underlying principles of deriving 3D geometry from image data started in the early 1900s, when aerial photographs were used to derive elevations and produce topographic maps using optical, mechanical, and analytical stereoplotters (Paine & Kiser, 2012). SfM can be viewed as a digital and automated evolution of these earlier workflows.

The first step in SfM is identifying unique features that can be tracked across the images. The scale-invariant feature transform (SIFT) algorithm (Lowe, 1999, 2004) was a major revolution due to its ability to extract features that remain stable under scale, rotation, illumination, and lighting changes. The algorithm consists of a feature detector that identifies stable, repeatable interest points, and a 128-dimensional descriptor that characterizes the local image structure around each feature.

Recently, other features like SURF (Bay et al., 2006), ORB (Rublee et al., 2011), and DSPSIFT (Dong & Soatto, 2015) have been introduced, offering improvements related to computational efficiency and robustness. The detected features then are matched across overlapping images by comparing their 128-dimensional SIFT descriptors using Euclidean distance. The closest descriptor pairs form tentative correspondences, although some may be incorrect.

To remove outliers, a robust estimation of the fundamental matrix is performed using RANSAC (Fischler & Bolles, 1981), which retains only geometrically consistent matches, known as inlier correspondences. Using the inlier correspondences, the SfM pipeline jointly estimates the camera poses (positions and orientations) and the 3D positions of the matched points. These initial estimates are then refined through bundle adjustment, which optimizes all camera parameters and 3D point locations simultaneously. Figure 6 illustrates the process.

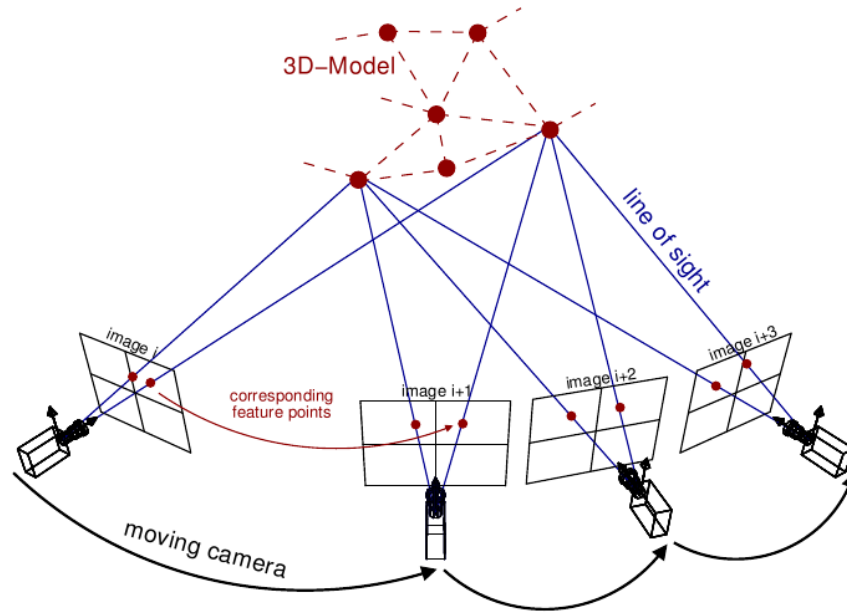


Figure 6. Illustration. Structure-from-Motion method.

Source: theia-sfm.org

SfM produces a sparse point cloud that only includes point correspondences and typically does not have sufficient density for precision applications like surface texture measurements. Therefore, SfM is followed by multi-view stereo (MVS) techniques such as patch-based MVS to create dense point clouds by recovering the depth of pixels that have sufficient surface texture, multi-view visibility, and photometric consistency. More information about MVS can be found in Furukawa and Hernández (2015).

In addition, SfM reconstructions are generated in an arbitrary coordinate system with unknown scale because image measurements are expressed in pixels. To anchor the reconstruction to a global reference system and recover the true scale, location data must be provided in the form of ground control points (GCPs) or geotagged camera centers. In either case, the arbitrary coordinates of the points and camera centers are mapped to the global coordinates by solving a 7-degree-of-freedom similarity transformation which applies scale, rotation, and translation mappings. Figure 7 presents the Helmert transformation:

$$X_T = t + sRX$$

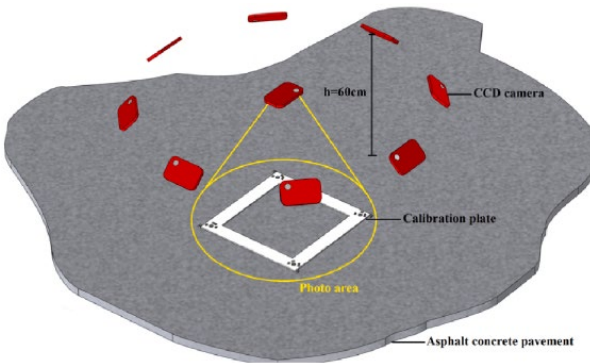
$$\begin{bmatrix} x_T \\ y_T \\ z_T \end{bmatrix} = \begin{bmatrix} t_x \\ t_y \\ t_z \end{bmatrix} + s \cdot \begin{bmatrix} r_{11} & r_{12} & r_{13} \\ r_{21} & r_{22} & r_{23} \\ r_{31} & r_{32} & r_{33} \end{bmatrix} \cdot \begin{bmatrix} x \\ y \\ z \end{bmatrix}$$

Figure 7. Equation. Helmert similarity transformation for georeferencing and scaling.

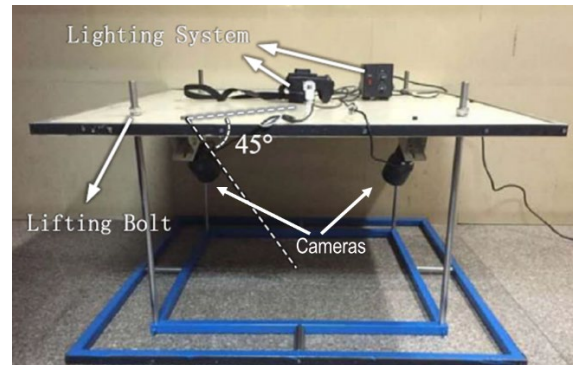
where: X_T is coordinate vector of the transformed points, t is translation vector, s is scale factor, and X is coordinate vector of the points in the arbitrary system. The Helmert transformation applies uniform scaling across the X-, Y-, and Z-axes. It also prevents shear and warping, which distorts geometry and renders the point cloud unsuitable for precise measurements.

Several studies have utilized SfM for texture measurement and reported accuracy comparable to laser-based systems like AMES 9400 LTS and ZGScan (Chen et al., 2019; Tian et al., 2020). However, many proposed workflows are not readily scalable to network-level deployment. Prior efforts often focused on small pavement patches in the field (Dan et al., 2022; Tian et al., 2020) or slabs in a laboratory setting (Chen et al., 2019; Pranjić & Deluka-Tibljajš, 2022) where imaging equipment was fixed to a table and difficult to transport. In other studies, the imaging equipment was placed in a portable enclosure, eliminating environmental variables and allowing easy transport (Mataei et al., 2022). However, data could only be collected statically and covering a small patch. Figure 8 presents examples of these setups. To resolve the scale ambiguity, references like a ruler (Chen et al., 2019), control frame (Dan et al., 2022; Tian et al., 2020), or simple ground markers (Roberts et al., 2021) were used. Though effective, this method is not scalable.

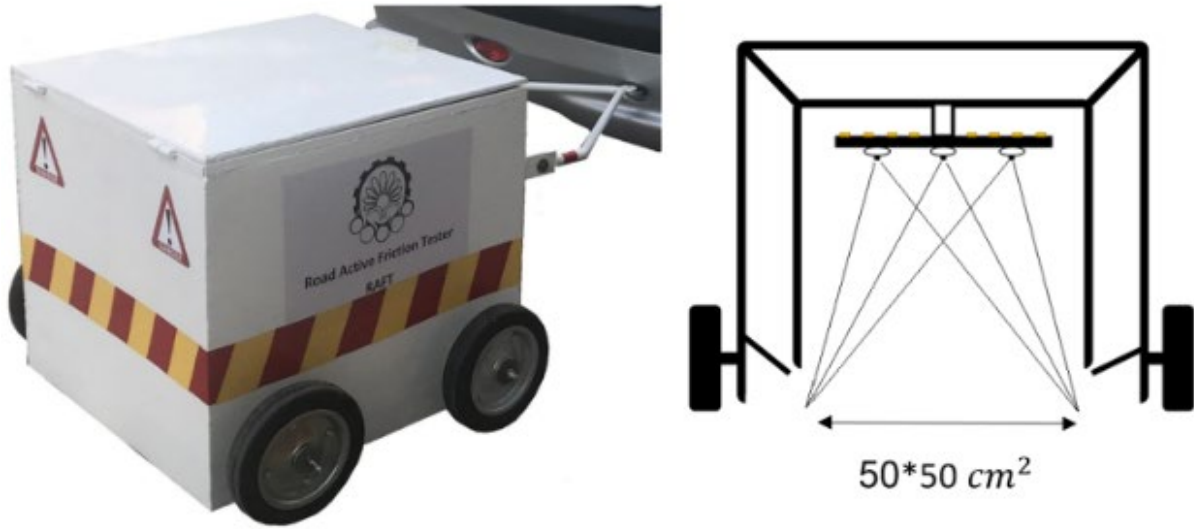
Recently, drones were used as a platform to collect pavement images using onboard or attached cameras, and GCPs were utilized to resolve the scale ambiguity (Inzerillo et al., 2018; Roberts et al., 2020). While the point clouds were accurate, the flight height resulted in resolutions that were inadequate for surface texture measurement. Additionally, drones that have a flight time of 30 to 45 minutes may not be able to fly in dense urban areas, windy conditions, or restricted areas close to airports. As a result, drone use may not be scaled to network-level data collection.



A. Data collection in the field
(Dan et al., 2022)



B. Data collection in the lab
(Chen et al., 2019)



C. Mobile enclosure for pavement texture data collection (Mataei et al., 2022)

Figure 8. Illustrations. Examples of proposed data acquisition setups.

This chapter presents an SfM-based framework for pavement macrotexture measurement designed to support network-level scalability. The framework includes the following items: (i) an image acquisition strategy that mitigates reconstruction distortions on planar surfaces, (ii) georeferencing and scaling using RTK-grade (real-time kinematics) positioning via either GCPs or camera-centered RTK geotagging, and (iii) a point-cloud post-processing pipeline to compute macrotexture metrics and compare against laser-based measurements.

COMPUTER VISION EQUIPMENT

The equipment, presented in Figure 9, included a camera, global navigation satellite system receiver (GNSS), tags for establishing GCPs, computing device to run the photogrammetry-based workflow, and laser-based device for texture measurements comparison. GNSS is a satellite-based service used for navigation. It comprises many satellite constellations, including the United States' global positioning system (GPS). For simplicity, GNSS and GPS will be used interchangeably herein.

Camera—A Canon Rebel T3i was used to collect pavement surface images. It has a resolution of 18 megapixels and an image size of 5184×3456 pixels. The sensor measures 22.3×14.9 mm with a pixel size of $4.3 \mu\text{m}$. The sensors on DSLR cameras are considerably larger than those on mobile phones. This is advantageous because larger sensors produce less noise, which is important for detailed evaluation applications such as pavement texture. The camera was used with an EFS 18-55 mm lens. Additionally, a pair of GoPro Hero 11 Black cameras were used. The camera has a resolution of 27 megapixels, an image size of 5568×4872 pixels, and a sensor size of 6.74×5.05 mm. While the smaller sensor reduces image quality, the GoPro can be easily mounted on a vehicle, controlled remotely, and is equipped with an onboard GPS receiver.

RTK GNSS Receiver—To ensure that recorded location data are accurate, GNSS signals are corrected for errors relating to receiver and satellite clocks, atmospheric disturbances, and signal reflections (multipath). Real-time kinematics (RTK) technology, which reduces errors down to 0.7 mm horizontally and 1.4 mm vertically, is used. RTK achieves this accuracy by measuring the error with respect to the fixed position of a reference station, known as a base station, and transmitting the corrections to the receiver performing the measurements in the field (rover) over internet or radio. The quality of the corrections depends on the rover’s proximity to the base station, quality of the internet or radio connection, and climatic conditions, among other factors. To survey the position of GCPs, the research team used an Emlid RS2+ GPS receiver.

AprilTags—To georeference and scale point clouds using GCPs, the tags placed on the pavement must be identified in any image in which they appear, and their surveyed GPS coordinates must be entered. This process is often done manually and is time-consuming for large datasets. It is also prone to errors, as the user might not select the precise center of the tag. To eliminate this issue, AprilTag was utilized for ground control. It is a visual fiducial system that can automatically be identified in images. AprilTag looks and works like QR codes. When their detection library is used, the pixel location of their center or corners is automatically extracted, which drastically speeds up the process.

RTK Module—Although GCPs with RTK GPS can achieve accurate results, it comes at the disadvantage of having to physically place the tags on the pavement surface and collect their locations. Although this process is not time-consuming, it requires traffic control and limits the scalability of photogrammetry-based macrotexture measurement to network-level application. An alternative to ground control is using the location of the camera center as a reference. This capability is built into almost all mobile phones, tablets, and high-end DSLRs through onboard GPS receivers. Images are geotagged, and the location where they were captured is stored in the image EXIF tag. This location data can be detected by the SfM algorithm and used for georeferencing and scaling. This is not recommended, however, because the devices’ commercial-grade GPS receivers do not have good accuracy. Recently, new RTK GPS modules have been released. The modules can be synchronized with the shutter release of a DSLR and embed the location data into the image EXIF tag as a post-processing step. Details are discussed in the “Methodology” section. An Emlid Reach M2 RTK module was used for this purpose. It is connected to the camera in Figure 9-D.

Computer—A Dell Precision 7920 workstation was used to run the SfM pipeline. It is powered by an Intel Xeon Silver 4210R CPU with a base frequency of 2.4 GHz. The workstation has 32 GB of RAM and an NVIDIA RTX A4000 GPU with 16 GB of VRAM.

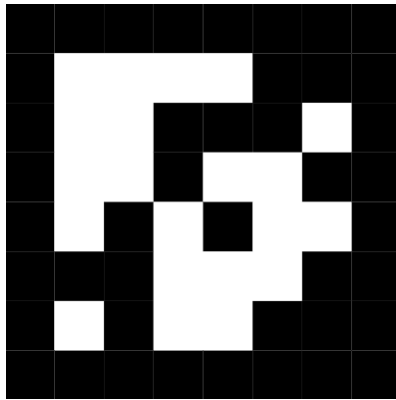
Laser Texture Scanner—Ames 9400HD was used to compare texture measurements from the SfM-based method. The scanner has a vertical resolution of 0.003 mm and a length and width resolution of 0.00635 mm and 0.0247 mm, respectively. The dot size is 25 μm , and scanning is done at an angle of 22 degrees.



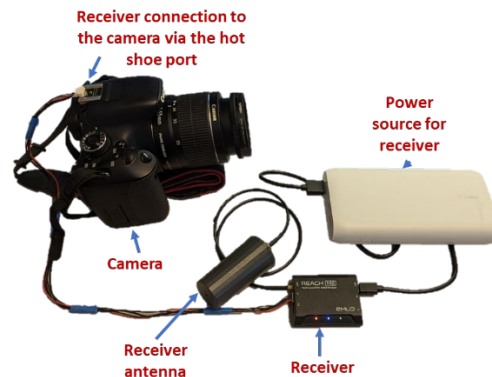
A. Canon Rebel T3i with lens



B. Emlid Reach RS2+



C. AprilTag



D. Camera and RTK Module



E. Ames 9400HD



F. GoPro Hero 11 Black

Figure 9. Illustration. Equipment used.

METHODOLOGY

Image Acquisition

Requirements for input images are high overlap, sharpness, and high resolution. These requirements ensure that features are detected and tracked across consecutive frames, and the resulting point cloud accurately represents the pavement texture. Additionally, the pavement must be photographed from different positions and orientations to get a complete view of the surface and allow for correct calculation of the camera projection matrix. Because road lanes are planar surfaces

and have a relatively narrow width (3.65 m), the first approach was to capture images from the center of the lane with the camera at the same height and orientation. As presented in Figure 10, this resulted in incorrect curvature, known as “bowling” (Lukas Zmejevskis, 2022) or the “banana effect” (Wondolowski et al., 2024). Bowling is mostly unique to planar surfaces like roads, walls, and low-relief terrain. It may occur because images were captured from the same height, using the same orientation and from a nadir perspective, or do not have GPS data or GCPs. Another reason could be using an incorrect camera model in the SfM algorithm.

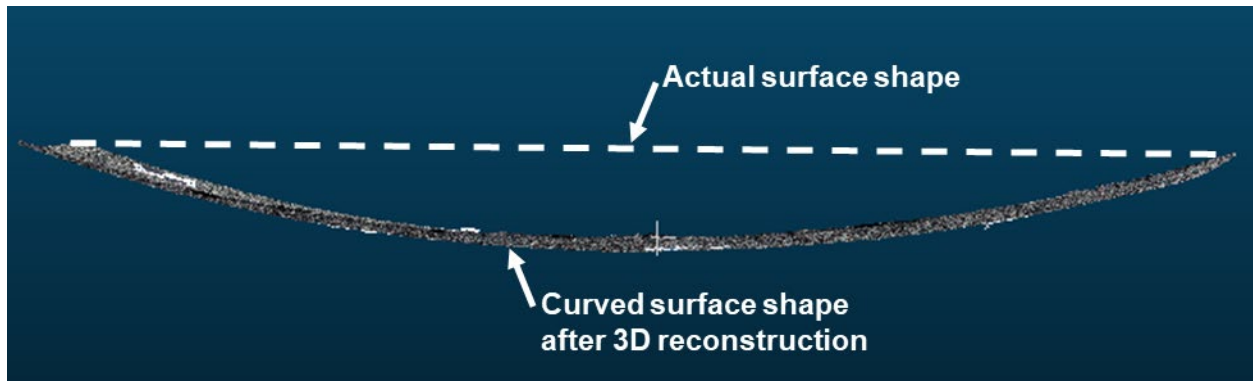
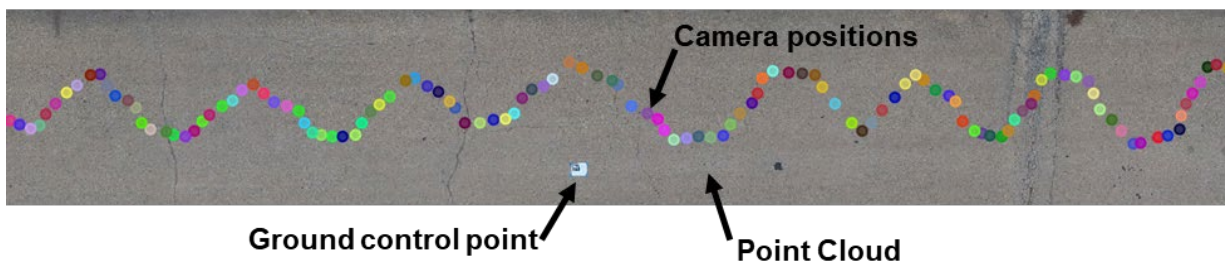


Figure 10. Illustration. Side view of pavement point cloud with bowling effect.

Bowling was greatly reduced by capturing images with a 30-to-45-degree forward tilt while slightly changing the height at which they were captured between successive frames. Additionally, images were captured with 85% front and side overlap using the Canon camera from different lateral positions within the lane. Figure 11-A presents this step, where the colored dots are the camera positions, and Figure 11-B displays the change in camera orientation between different images.



A. Camera positions within the lane



B. Camera orientations

Figure 11. Illustration. Image acquisition method.

Capturing images statically ensures optimal image quality and sharpness and, thus, serves as a reference case but does not scale to network-level data collection. To acquire data on a moving vehicle, the GoPro cameras were fixed to the front of a golfcart and oriented toward the pavement with at least 80% side overlap, as presented in Figure 12. The cameras were programmed to synchronously capture images at their maximum rate of 2 frames/sec (each). Additionally, the vehicle moved at a speed of 2 mph to ensure sufficient front overlap.



Figure 12. Photo. GoPro cameras attached to a golfcart.

Georeferencing and Scaling

Georeferencing and scaling was done using RTK-capable GPS devices with AprilTags for ground control or by directly embedding the GPS information into the EXIF tags of the captured images. This section explains the procedure for both methods.

Ground Control Using AprilTags

This operation generally involves four steps:

1. Place the GCPs on the pavement and survey their location. For consistency, the GPS device was always placed at the center of the tag. A minimum of three GCPs are required to calculate the Helmert similarity transformation, but 5–10 GCPs should be placed to understand the goodness of fit by calculating the root mean square error (RMSE). This metric indicates the error between the known coordinates from the GPS device and the projected coordinates based on the SfM algorithm. RMSE is calculated using the equation in Figure 13, where n is total number of GCPs. The GCPs must not be collinear, so the transformation represents the entire area accurately.

$$\sqrt{\frac{\sum_{k=1}^n (x_{projk} - x_{realk})^2}{n}}$$

Figure 13. Equation. RMSE calculation for ground control point accuracy.

2. Capture the images and ensure the GCPs clearly appear in them.
3. Import images and GCPs data. The GCPs data are organized in a text file that includes the tag ID and its corresponding 3D world coordinate.
4. Identify the GCPs in the images. This is the most time-consuming part of the process because the user must examine all images and find the pixel location of the center of the tags for each image in which they appear. It is also prone to pixel-level errors due to inaccurate selection of the center of the tags. These challenges are eliminated by using AprilTags. A Python code was written to access the file in which the images and GCPs data are located, loop through all images, and match the detected AprilTags with their 3D world coordinate. This information was organized in a text file (Table 6) and is used automatically by the SfM algorithm.

Table 6. Ground Control Point File

Easting	Northing	Altitude	Pixel X	Pixel Y	Image Name
404226.34	4460082.5	222.368	2859.0	1733.0	IMG_8980.JPG
404221.75	4460081.0	223.367	2308.0	148.0	IMG_8987.JPG
404206.16	4460083.0	223.030	3228.0	356.0	IMG_9045.JPG
404196.94	4460081.5	222.387	2320.0	64.0	IMG_9084.JPG
404157.62	4460083.0	222.353	2607.0	114.0	IMG_9304.JPG

GPS Information in EXIF

GPS information was embedded into the image EXIF tag using an Emlid Reach M2 RTK module which was synchronized with the camera shutter by connecting it to the hot shoe port (Figure 9-D). To ensure that location was recorded with centimeter accuracy, images were collected after the module reached a “FIX” solution (Figure 14). The image locations and the corrections received from the base station were stored in separate logs and exported from the module. After collecting all images, both logs were used in a framework called “Post-processed kinematics” (PPK) to apply the corrections collected from the base station to the image location log. The corrected locations were then added to the EXIF tags of the images. All steps were done using the Emlid Studio desktop application.

To check if GPS data were added, the details tab of the image properties can be examined. The data appear under “GPS” (Figure 15). The location is stored as latitude, longitude, and altitude in EXIF but is projected to UTM zone 16N. Projected coordinate systems are used in engineering applications because they provide consistent units of measurement on a gridded 2D surface, unlike geographical coordinate systems (latitude and longitude).

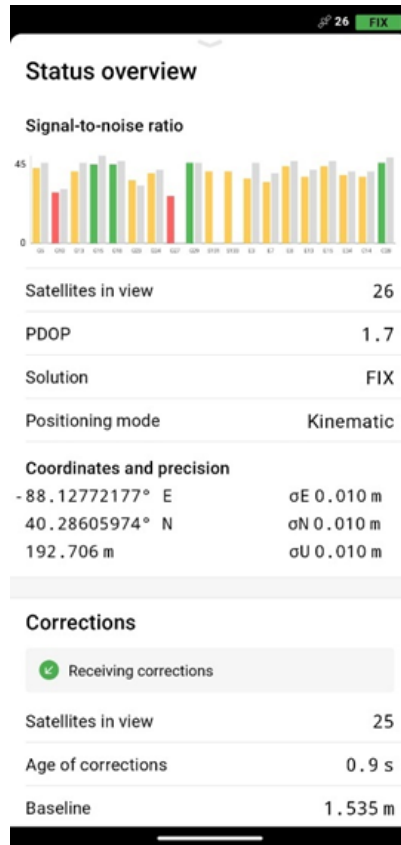


Figure 14. Photo. Mobile app to monitor module status.

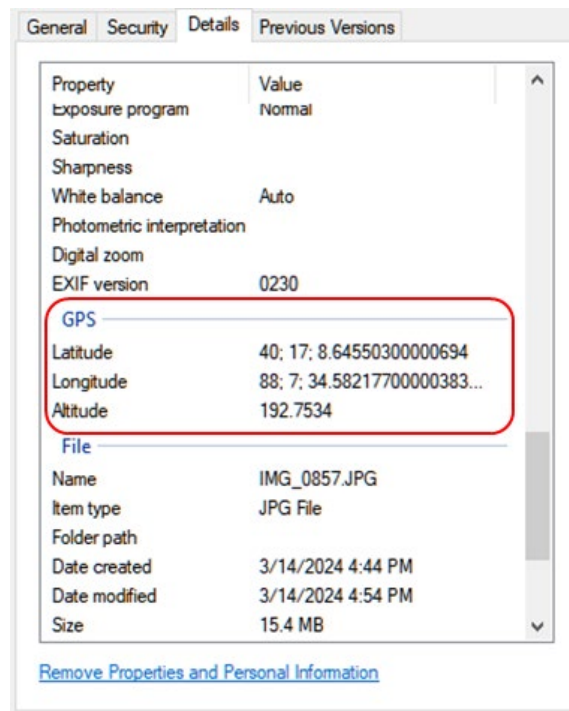


Figure 15. Photo. GPS data in image EXIF.

Texture Measurement from Point Clouds

The point clouds produced by the SfM pipeline are not organized in a grid system, which means they do not have constant spacing along the x- and y-axes. This makes it difficult to apply a bandpass filter to remove wavelengths that do not correspond to macrotexture because this requires uniform sampling.

To overcome this issue, the point clouds were rasterized in a grid, and the cell size for the raster was chosen based on the ground sampling distance (GSD) of the camera. GSD is a measure of the distance between 2 pixels on the ground. It is a function of the camera focal length (mm), sensor width (mm), image width (pixels), and height above the surface (mm). GSD was calculated as presented in Figure 16, and the cell size was chosen to be slightly above the GSD to minimize interpolation in empty cells. For example, a point cloud with a GSD of 0.7 mm can be rasterized to 1 mm cells.

$$\text{GSD (mm/pixel)} = \frac{\text{height (mm)} * \text{sensor width (mm)}}{\text{focal length (mm)} * \text{image width (pixels)}}$$

Figure 16. Equation. Ground sampling distance calculation.

After the point cloud is rasterized, the area of interest is highlighted and extracted as a text file. This file is loaded into Python, where the points are separated into profiles along the direction of travel. The Butterworth bandpass filter is applied in accordance with ASTM E1845 (2015) at 2,000 Hz for the lowpass and 20 Hz for the highpass. These thresholds retain wavelengths within 0.5 mm and 50 mm, which is the macrotexture range. The mean profile depth (MPD) for each profile is calculated, and the average is reported. Figure 17 presents a section of the point cloud where the area for texture measurement is highlighted. The blue tape marks the location where the laser scanner was placed so that the same area can be measured with a laser scanner and the SfM-based approach.

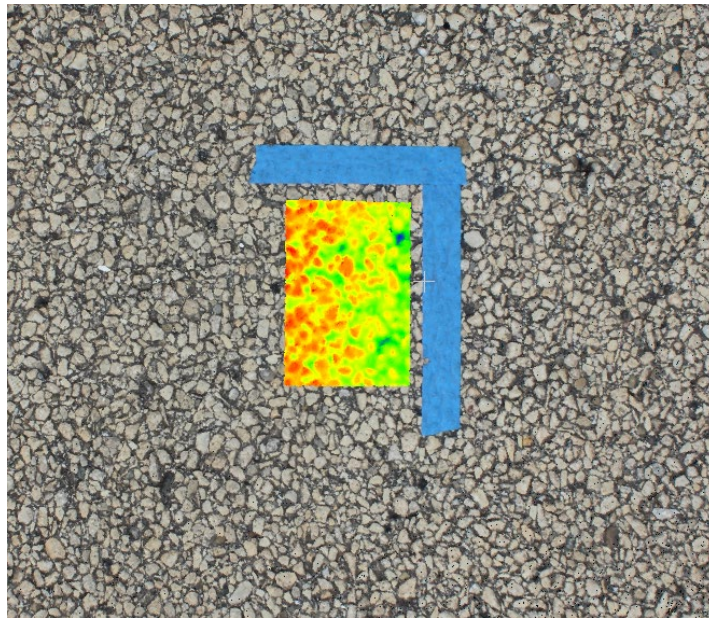


Figure 17. Illustration. Point cloud displaying area of texture measurement.

RESULTS AND DISCUSSION

This section discusses the 3D reconstruction results of the SfM-based method with the proposed image acquisition and georeferencing techniques. The results of MPD comparison between the SfM-based method and AMES 9400HD are also presented.

Canon Camera with AprilTag GCPs

Using the proposed image acquisition technique, 369 images of a pavement surface were captured. The images covered around 76 m, and they were taken from a height of 1.6 to 1.8 m above ground level while maintaining 85% front and side overlap. The images were captured statically, and the focus was readjusted prior to capturing an image to ensure sharpness. Eight GCPs were placed on the surface while ensuring they are not collinear, and they were surveyed with the Emlid Reach RS2+ in RTK mode after the solution status became “FIX.” All 369 images were used successfully in the reconstruction (Figure 18). The point cloud was examined visually to check for any shape distortions, bowling effect, and discontinuities, but there were none. The accuracy of the georeferencing and scaling was assessed by examining the RMSE of the GCPs. The total RMSE for all GCPs was reported as 0.000 m along the X-, Y-, and Z-axes. This value reflects rounding within the software output, as the GCPs were used as control points during bundle adjustment and the solution was tightly constrained to them. This indicates a sub-millimeter fit but does not represent independent validation accuracy. The 3D RMSE, which is an indication of the spatial accuracy of the reconstruction, was reported as 9 mm. Furthermore, the average reprojection error was reported as 0.87 pixels. These metrics indicate that the reconstruction geometry is consistent, as evident by the lack of visible distortions in the point cloud.

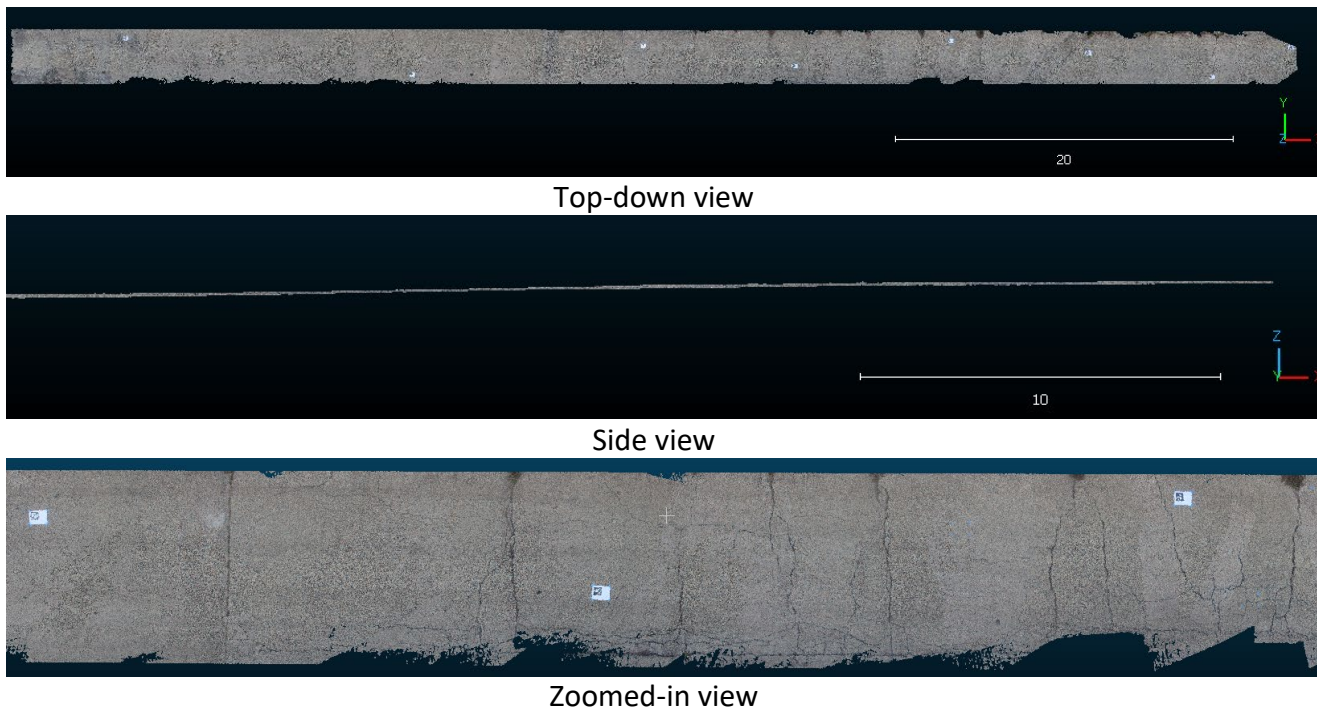


Figure 18. Illustration. Point cloud generated with Canon camera and GCPs.

Canon Camera with RTK Module

Although ground control with AprilTags produced excellent results, this process does not extend to network-level inspection because it is not feasible to place and survey so many GCPs. Instead, the location of the camera center can act as a reference for georeferencing and scaling if it can be recorded with the same level of accuracy as GCPs. An Emlid Reach M2 was used for this purpose. A new dataset was captured using the proposed image acquisition method, and all images had GPS information added to their EXIF tags after post-processing the logs from the M2 and the base station. Figure 19 presents the results of the reconstruction. From the top-down view, the point cloud does not appear to have any distortions or discontinuities. When examining from the side view, the point cloud should appear as a thin line that is perpendicular to the global Z-axis. However, it appeared as a tilted, thick strip, indicating the point cloud was not correctly oriented along the global coordinate system.

The RMSE based on the image GPS coordinates was 0.181, 0.084, and 0.582 m along the X-, Y-, and Z-axes, respectively. This indicates a significant error between the recorded and projected positions of the images. Furthermore, the high error along the Z-axis may explain why the point cloud was tilted. On the other hand, the 3D and reprojection errors were reported as 4 mm and 0.67 pixels, respectively, indicating that the model geometry was captured accurately, despite the high georeferencing errors.

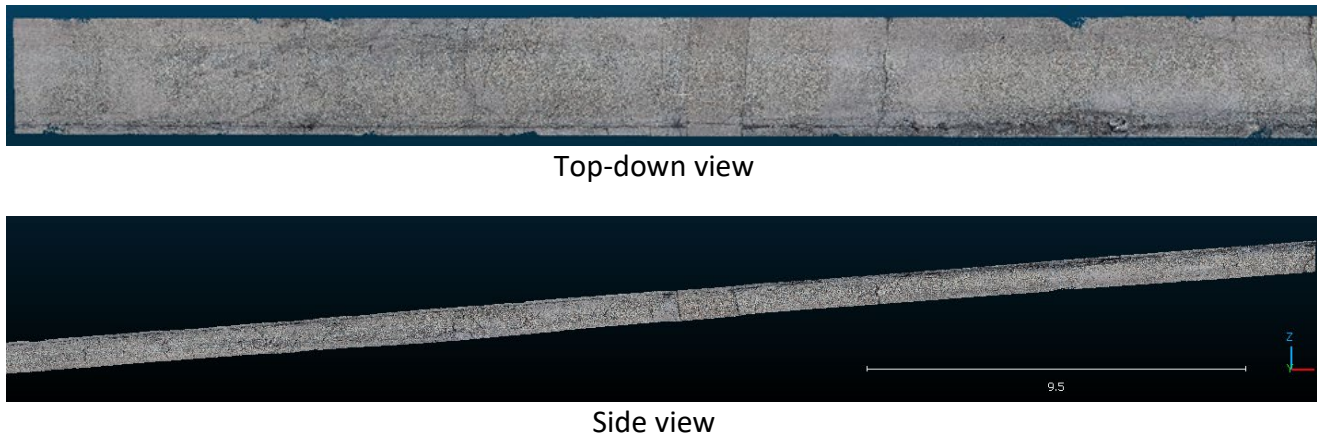
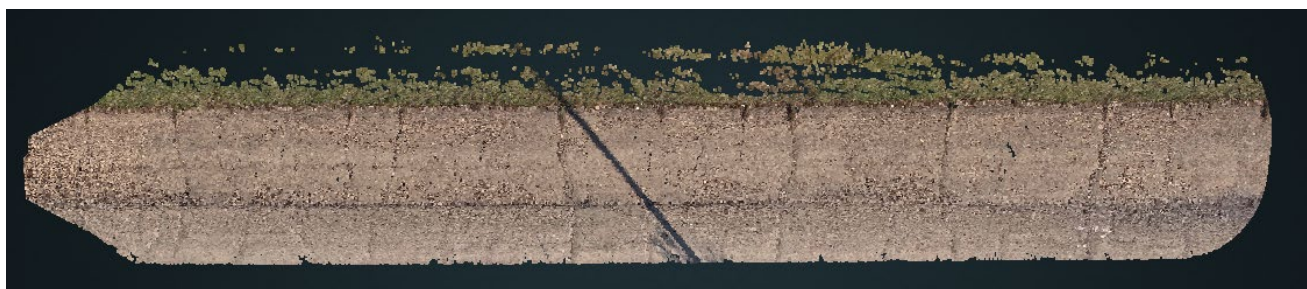


Figure 19. Illustration. Point cloud generated with Canon camera and RTK module.

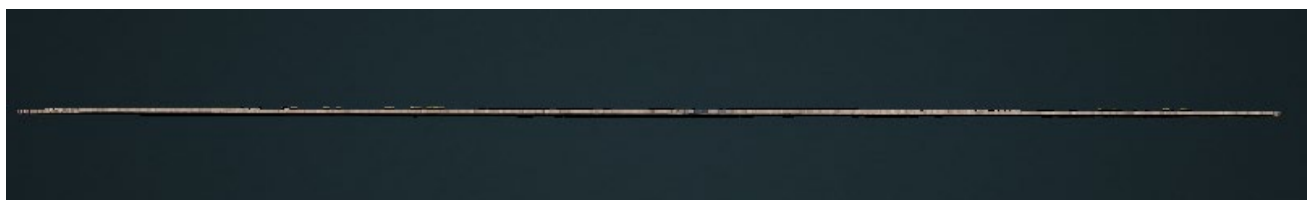
GoPro Cameras Mounted on Vehicle

To capture images more efficiently, two GoPro cameras were attached to a golfcart and synchronized to capture images at 2 frames/sec, each. The golfcart was moving at 2 mph, and the images were captured with 80% side overlap and 85% front overlap. Figure 20 presents the reconstruction results from two datasets. The point clouds did not exhibit any distortions, and shadows from objects like light poles and trees did not affect the reconstruction. On the other hand, there was inconsistent point density, which could only be seen when zooming into the point clouds. For all datasets presented in Figure 21, the vehicle was moving from left to right and discontinuities started appearing when images were collected in motion. This finding indicates that the image quality degraded as the vehicle started to move, which is related to the camera's rolling shutter and

exposure time. This issue causes images to become blurry, which in turn prevents pixels from being projected into the point cloud and renders the point cloud inadequate for texture measurement. To ensure sharp images while in motion, industrial-grade cameras with global shutter and the ability to tightly control exposure time and maintain shooting speed are required. Nonetheless, the image acquisition method proved that dual cameras mounted on a vehicle can be scaled for high-speed data collection, if the appropriate cameras are used.



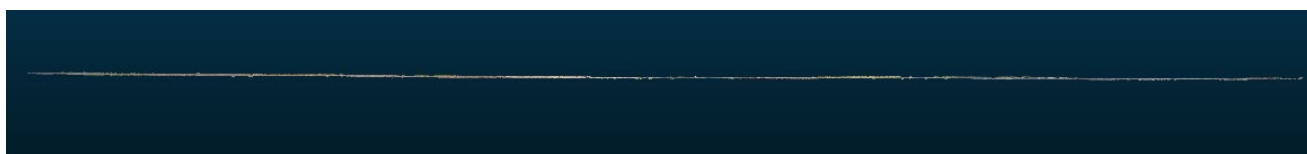
Top View (dataset 1)



Side View (dataset 1)

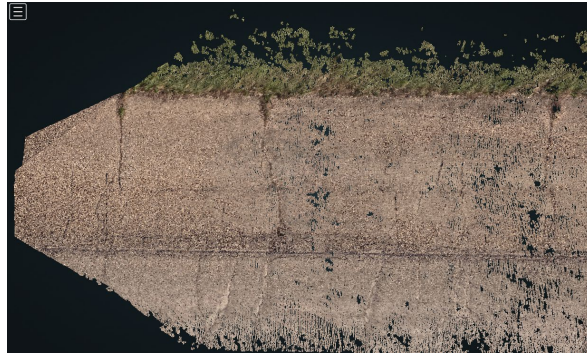


Top View (dataset 2)

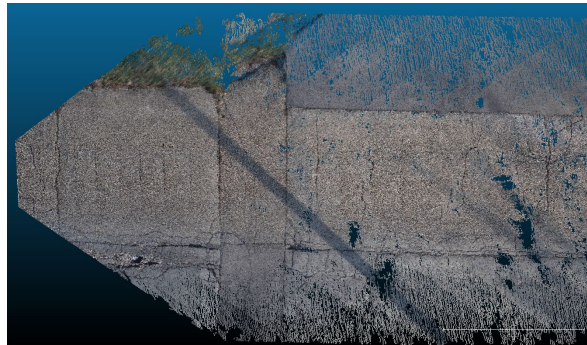


Side View (dataset 2)

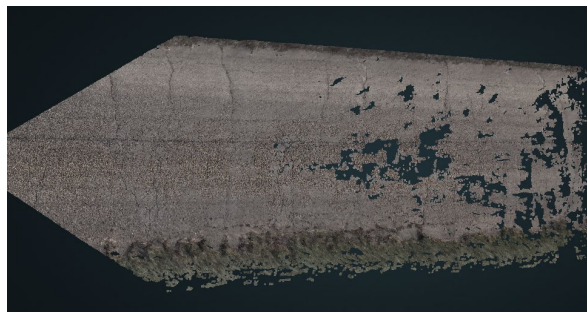
Figure 20. Illustration. Point clouds generated with GoPro cameras on vehicle.



Dataset 1



Dataset 2



Dataset 3

Figure 21. Illustration. Point cloud discontinuities.

Comparison between Proposed Methodology and Ames 9400HD

Preliminary testing evaluated the accuracy of the proposed methodology for texture measurement. Three spots on a dense-graded hot-mix asphalt surface and three spots on a stone-mastic asphalt surface were chosen in the field. The MPD was measured with the SfM-based approach using the proposed methodology and by AMES 9400HD. At first glance, the results (Figure 22) indicate that measurements using the SfM-based method are less than those by AMES 9400HD. There are many factors to consider while interpreting these results:

- The approach yielded reasonable results. MPD has a large degree of variability even among other well-established laser scanners (Bongioanni et al., 2019; Flintsch et al., 2005). Therefore, a degree of variability should be expected from different technology. More testing spots are needed to determine the degree of error and fine-tune the approach.

- Tracking the exact same profiles using the laser scanner and the SfM-based approach was almost impossible. Small deviations would lead to different measurements due to the unique configuration of aggregates along the profiles.
- Puzzo et al. (2017) reported that MPD measurements using SfM were less than those measured using a CT Meter. This was also reported by Gendy and Shalaby (2007) who compared the MPD values from a photometric stereo system to those from a laser profilometer. Furthermore, Tian et al. (2020) reported errors up to 17% when comparing MPD from AMES 9400 to SfM using a smartphone camera and control frame.
- The rasterization process may have a smoothing effect, which may lead to lower MPD values. Different cell sizes and point cloud resolutions must be tested to determine if rasterization impacts MPD.

In general, preliminary measurements were within 15% for all six spots and within 4% for two of them.

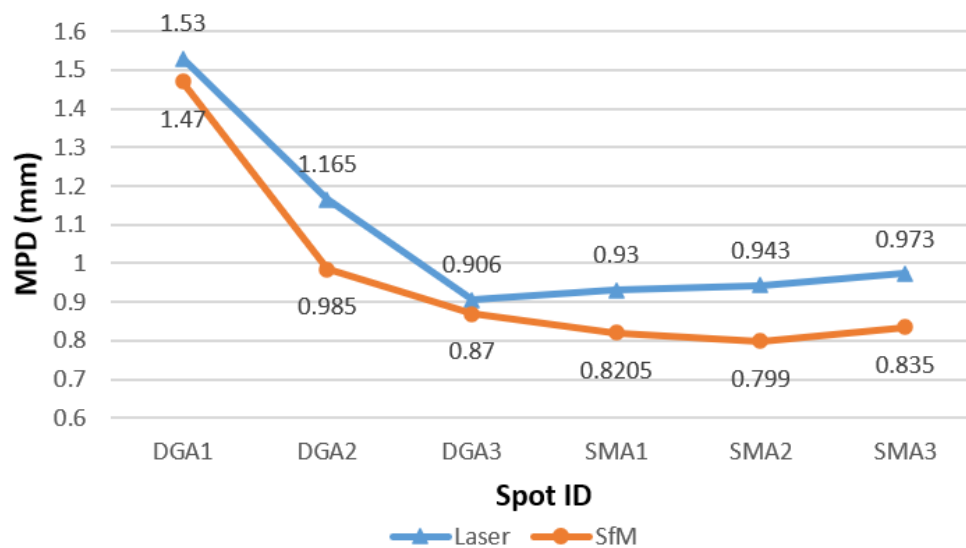


Figure 22. Graph. MPD values based on SfM and laser equipment.

SUMMARY

An SfM-based computer vision framework was developed for pavement macrotexture measurement to support network-level scalability. The framework was evaluated using three data acquisition configurations: a Canon Rebel T3i camera with AprilTag GCPs, a Canon camera with RTK GPS-embedded EXIF tags, and GoPro cameras mounted on a moving vehicle. Georeferencing and scaling were achieved using either RTK-surveyed GCPs combined with AprilTags or by embedding GPS coordinates directly into image EXIF metadata via an RTK module. Texture was extracted from the resulting point clouds by rasterizing the data to a uniform grid, applying a Butterworth bandpass filter consistent with ASTM standards, and computing the MPD.

The Canon camera with AprilTag GCPs produced high-quality point cloud reconstructions over a 76 m stretch of pavement, with accurate georeferencing and surface detail suitable for texture measurement. By contrast, the RTK module approach yielded significant positioning errors, particularly along the Z-axis (RMSE = 0.582 m), which degraded the quality of the resulting reconstruction. The GoPro camera configuration captured the surface on a moving vehicle but produced discontinuities in the point clouds due to synchronization and speed constraints. MPD values from the SfM-based method compared to measurements from the AMES 9400HD laser scanner were within 15% for all six test spots and within 4% for two of them. The observed underestimation of MPD was consistent with findings in the literature and may be partly attributed to a smoothing effect introduced during the rasterization process. Results demonstrate that SfM-based photogrammetry is a viable and scalable approach for pavement macrotexture measurement, with the GCP-based configuration providing the highest reconstruction accuracy.

CHAPTER 3: HIGH-SPEED SYSTEM DEVELOPMENT

INTRODUCTION

The developed imaging technique and computer vision algorithm demonstrated that contactless acquisition of accurate pavement texture data could be done. However, scaling this process to the network level requires a hardware system capable of collecting high-quality data at traffic speed. This chapter presents the development of a high-speed device. The device can collect high-resolution images of pavement surfaces on a moving vehicle, process data into 3D point clouds, and calculate texture. The device consists of two industrial cameras, an RTK GNSS (real-time kinematics global navigation satellite system receiver) system, a vehicle mounting system, and data collection software. A validation study was conducted at the Illinois Certification and Research Track (ICART).

SYSTEM ARCHITECTURE

Cameras

Most commercial-grade cameras use rolling shutters, which expose the sensor line by line from top to bottom, producing distorted images when capturing at low height and high speed. This occurs because pixels in the scene move quickly relative to the sensor, which results in stretching and compression distortions. Images can also be blurry due to high exposure time, the time in which the camera sensor is exposed to light. To ensure high-quality images and accurate 3D reconstruction, cameras must be placed close to the pavement surface and have sufficient resolution to accurately capture pavement surface texture, which can be evaluated using ground sampling distance (GSD). Modern cameras in smartphones and DSLR/mirrorless devices are equipped with sensors that can achieve sub-millimeter GSD and capture sharp images at low exposure times. However, the sensors cannot maintain image quality on a vehicle moving at high speed because of their rolling shutter, exposure time, and frame rate. In addition, Smartphones use small sensors that require long exposure times, producing blurry images of fast-moving objects.

To address the limitations of consumer-grade imaging equipment, a pair of Basler boA5328-100cc industrial cameras were utilized. The cameras are equipped with a global shutter and can capture 24 megapixel images at up to 100 frames/second (fps) with exposures as short as 1 microsecond. Global shutter cameras greatly reduce blurriness in images of fast-moving objects by exposing all pixels on the sensor simultaneously. Figure 23 demonstrates this effect, where the blades of a spinning fan are captured with significantly less distortion using a global shutter camera. The Basler camera sensor is of 1.2" (19.3 mm diagonal) format, which balances pixel density and acquisition speed while also allowing more light per pixel compared to smaller format sensors.

Because the cameras were mounted at a low height above the pavement surface, an 8 mm focal length variant of the lens was chosen. The short focal length provides a wider field of view than lenses with longer focal lengths, so images captured from both cameras covered approximately 3 m in lane width. A Fujinon CF-ZA-1S lens was used with the camera. Figure 24 presents the camera body and lens.

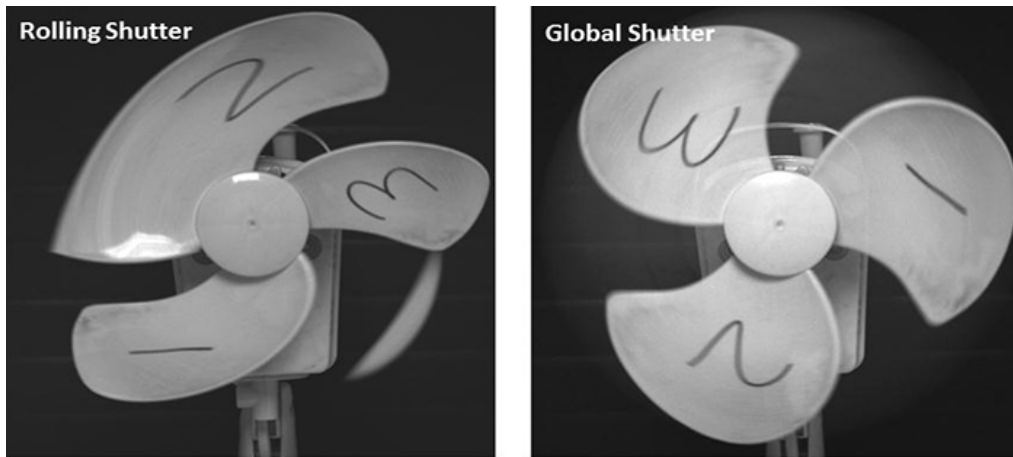


Figure 23. Photo. Comparison of rolling and global shutter camera images.

Source: Oxford Instruments/Andor



Figure 24. Photo. Camera body and lens.

Source: Basler AG

RTK GNSS

Precise positioning data are another critical requirement for accurate 3D reconstruction. The real-world 3D position of each image is utilized by the computer vision pipeline for georeferencing the point cloud and recovering its true scale. According to the results presented in Chapter 2, utilizing ground control points (GCPs) surveyed with an RTK GNSS receiver yielded accurate results but was not practical for network-scale data collection. Georeferencing images using an RTK module was more scalable but suffered from errors. To address the limitations of GCPs and consumer-grade modules, an RTK system composed of a base station, caster, and receiver was utilized.

A Trimble BX992 receiver was configured as a base station, and its antenna was fixed on the roof of a building (Figure 25), ensuring it was clear of any obstructions that might interfere with satellite

signals. The receiver averaged its position over a period of at least 48 hours to obtain its fixed position, which enabled it to calculate corrections for future observations. The corrections were streamed over an internet connection using an Emlid caster. For the rover, a Trimble BX992-INS receiver was used. The receiver uses an inertial navigation system (INS), which enables it to maintain centimeter-level accuracy even if satellite connection is lost. The INS also allows the receiver to output data at 100 Hz, which matches the maximum capture rate of the cameras. Corrections were streamed from the base to the rover using the Emlid caster service over the internet.

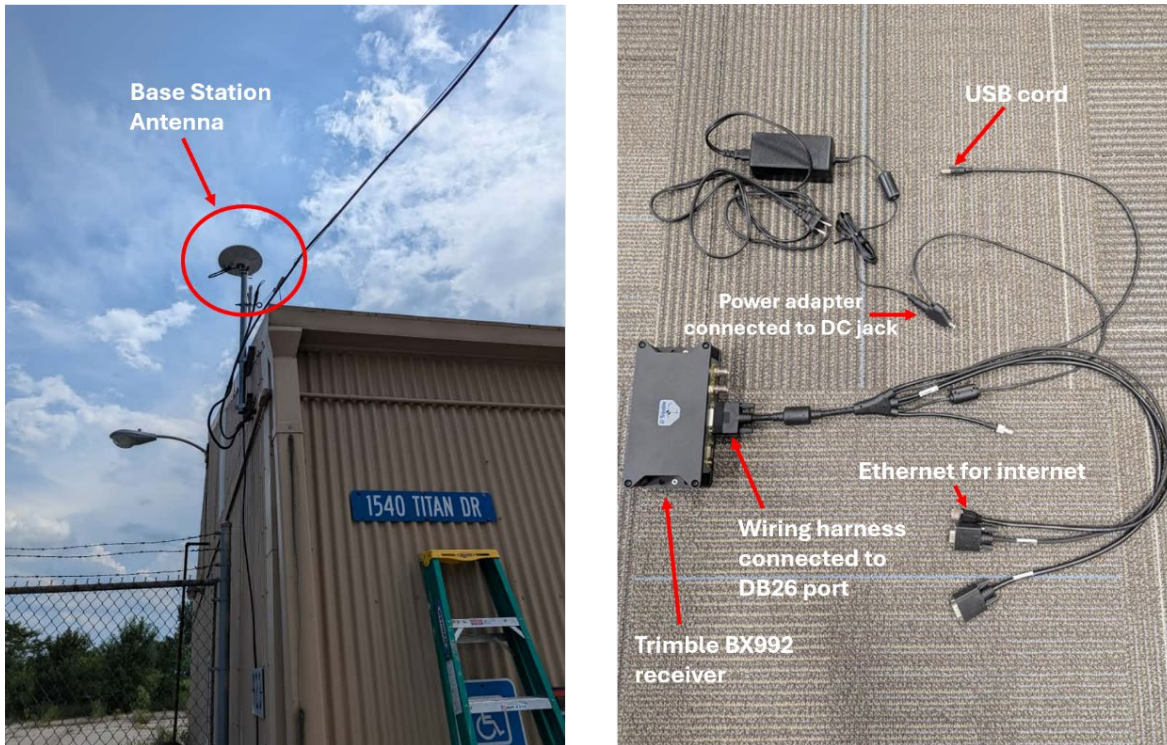


Figure 25. Illustration. Base station antenna and receiver.

Mounting

To securely mount the GNSS and imaging equipment to the data collection vehicle, T-slot rails were used to create a mounting system. Horizontal rails were attached to the roof rack of the van using U-bolts, and vertical rails were attached to the extended bumper using L-shaped brackets (Figure 26). For increased lateral stiffness, X-bracing was added to the horizontal roof rails. To support the cameras, two cantilever rails with adjustable height were added to the vertical rails extending from the bumper, and they were connected using a horizontal rail to minimize camera vibration. The cantilevers also served to provide enough clearance to exclude the end of the vehicle from the captured image. The cameras were attached to the horizontal rail between the cantilevers using an L-bracket and a Swivellink, which includes two ball joints for easy adjustment of camera tilt in any direction. The camera baseline was set at 0.8 m, and the cameras were mounted 1 m above ground level. The cameras were also tilted to ensure approximately 80% horizontal overlap between images.



Figure 26. Photo. Camera mounting setup on a vehicle.

The rover antennas were mounted on the roof of the vehicle using a crossbar (Figure 27). To ensure that the receiver outputs a heading that aligns with the direction of travel, the main and vector antennas were mounted with a lateral offset. The receiver was securely mounted inside the vehicle in an orientation that matches the coordinate system of the vehicle (Figure 28).



Figure 27. Illustration. Rover antenna mounting on vehicle.

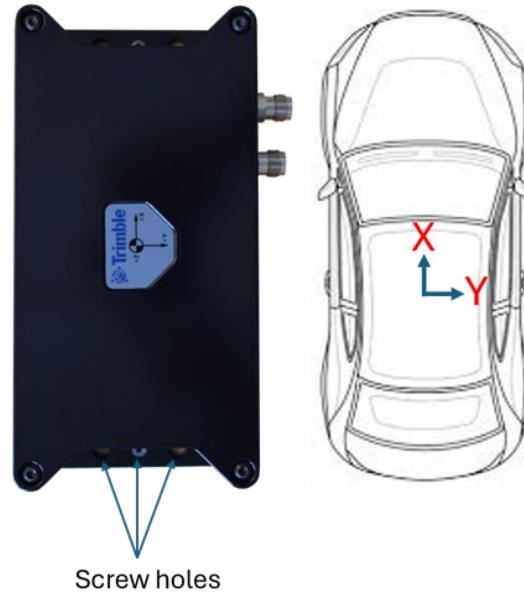


Figure 28. Illustration. IMU and vehicle coordinate system alignment.

Data Collection Computer and Software

A Premio 6000 Series industrial computer was fixed inside the vehicle to receive the images and GNSS information. The rover was configured to output all INS data, which include longitude, latitude, altitude, heading, and many other fields. The data were delivered to the computer at 100 Hz using the USB cord on the wiring harness, displayed in Figure 25.

To transfer data from the Basler cameras to the computer, a Basler CXP-12 Interface Card 4C was utilized. The card was connected to the computer via an expansion PCIe 3.0 x8 slot, and each camera was connected to the card using two data cables. This setup, presented in Figure 29, ensured maximum camera bandwidth. The cameras were powered using one data cable (dashed line in Figure 29) after connecting a 6-pin power cable from the computer's power supply unit to the plug found on the card.



Figure 29. Illustration. Camera and interface card connections.

To capture images, Basler's Pylon software development kit (SDK) was utilized. A data acquisition tool was developed in C++ to synchronously collect a GNSS observation and a pair of images from both cameras. The tool allows the user to set the acquisition rate (fps), the exposure time (microseconds), and the port number on which the GNSS data are being streamed. A series of tests at different speeds and in different light conditions determined that an exposure time between 100 and 250 microseconds is optimal for capturing high-quality images at speeds up to 35 mi/hr (56 km/hr), but sufficient light is required to generate a bright image.

Figure 30 presents two images captured at the same exposure time at 5:00 p.m. (left) and 5:02 p.m. (right). The image on the left was captured with direct sunlight on the pavement, and the image on the right was captured as a cloud obstructed sunlight. The difference in brightness demonstrates the importance of having sufficient illumination, which directly affects the 3D reconstruction results. For robust image capture under changing illumination conditions, a dedicated illumination system that can synchronize with each camera will be needed. The research team tested a machine vision lighting system to evaluate its effect, but its mismatch with the camera electronics caused delays, while not improving image brightness. A high-wattage system and dedicated circuit to synchronize all equipment are needed. Acquisition rate was set to directly match the speed at which the vehicle was moving, in mi/hr. This translated to one image per camera approximately every 0.4 m, which is equivalent to approximately 80% longitudinal overlap.



Figure 30. Photo. Effect of light intensity on image brightness.

Image data for each camera were saved in binary format, and GNSS data were saved to a JSON file. Saving images in binary format minimized CPU overhead, ensuring the data acquisition software would not be slowed down by converting images to a common format such as PNG or JPG. Instead, the conversion was performed after the data had been collected. Figure 31 presents the output of a data collection session. The camera_x_raw_index JSON files track frame numbers, timestamps, and other image metadata, whereas the GNSS_camera_x JSON files contain important session statistics like total frames captured, total GNSS observations captured, as-measured FPS, duration, and more. In addition, the INS data (Figure 32) were saved per frame in the GNSS JSON files. The location data

were added to the respective image's EXIF tag after the images were processed from binary to JPG. Because the GNSS receiver tracked only one camera, the location of the other camera was calculated by applying a 3D transformation that considers the relative position of the second camera in the vehicle's coordinate system. This process avoided the need for another receiver to track the position of the second camera.

Name	Date modified	Type	Size
 camera_0_raw.bin	3/30/2026 5:28 PM	BIN File	10,119,375 ...
 camera_0_raw_index.json	3/30/2026 5:28 PM	JSON Source File	120 KB
 camera_1_raw.bin	3/30/2026 5:28 PM	BIN File	10,158,750 ...
 camera_1_raw_index.json	3/30/2026 5:28 PM	JSON Source File	121 KB
 GNSS_camera_0.json	3/30/2026 5:28 PM	JSON Source File	735 KB
 GNSS_camera_1.json	3/30/2026 5:28 PM	JSON Source File	737 KB

Figure 31. Illustration. Data collection software output.

```

"camera_id": 0,
"frame_number": 0,
"filename": "camera_0_frame_000000.jpg",
"full_path": "D:/baslerimages\\20260330_170742\\camera_0_frame_000000.jpg",
"timestamp_ns": 1774908463280336900,
"timestamp_readable": "2026-03-30 17:07:43.280337",
"gsf_data": {
  "gps_week": 2412,
  "gps_time_ms": 166081340,
  "imu_status": 3,
  "quality": 4,
  "latitude": 40.28746445993214,
  "longitude": -88.13138525742139,
  "altitude": 190.25319453403438,
  "velocity_north": -0.6824531555175781,
  "velocity_east": -0.00022860821627546102,
  "velocity_down": 0.03815353289246559,
  "speed": 0.6824531555175781,
  "roll": 4.47627375897197,
  "pitch": 0.35343999697727774,
  "heading": 179.5248955333719,
  "track_angle": 180.01919294427017,
  "angular_rate_x": 0.5588268637657166,
  "angular_rate_y": 0.4282876253128052,
  "angular_rate_z": 0.21030691266059875,
  "acceleration_x": 1.1255958080291748,
  "acceleration_y": 0.04407372325658798,
  "acceleration_z": 0.09043621271848679,
  "decode_timestamp_ns": 1774908463280336900,
  "decode_timestamp_readable": "2026-03-30 17:07:43.280336"
}

```

Figure 32. Illustration. INS JSON file contents.

Data Processing

After the raw images were processed to JPG and the location data were added to the EXIF tag, they were processed using the computer vision pipeline discussed in Chapter 2. To speed up processing,

GPU-accelerated nodes on the Illinois Campus Cluster were utilized. The computer vision algorithm also supports horizontal scaling, which allows clusters of images to be processed in parallel. Due to restrictions on the number of nodes that can be requested as well as the duration, this capability is better suited to non-academic compute clusters like Amazon Web Services, Google Cloud Platform, Microsoft Azure, and others. Besides GPU acceleration, processing was sped up by optimizing the number of images that must be matched with neighboring images. This step was done by only matching each image with the nearest five images based on its position. Because the images were captured sequentially per camera, a real-world match can only be found within a small radius around each image. Therefore, exhaustively searching for matches across the entire dataset would waste time and resources. Additionally, the number of features to be extracted per image was set to 5,000, which reduced unnecessary feature extraction with no effect on reconstruction accuracy.

After the point cloud was obtained, longitudinal profiles were extracted in the vehicle's direction of travel. When the vehicle was traveling in a straight path, this step was done by rotating the point cloud so that the direction of travel was parallel to the x-axis and then sampling points along fixed y-coordinates to obtain individual profiles. When the vehicle was turning, this approach failed because the direction of travel no longer aligned with any axis. To overcome this issue, the geolocation of the captured images was used to trace the path of the vehicle. Rather than using the recorded image position, which may contain errors in the event of GNSS signal degradation, the camera position was utilized, which was calculated and optimized in the SfM bundle-adjustment stage. Figure 33-A demonstrates this effect, where the SfM algorithm correctly calculated the true positions of the camera despite high GNSS errors when the images were captured. Figure 33-B demonstrates that the calculated positions correctly traced the circular path of the vehicle for each of the two cameras. After that, MPD was calculated for each profile, which is one of the main inputs for the friction prediction model.

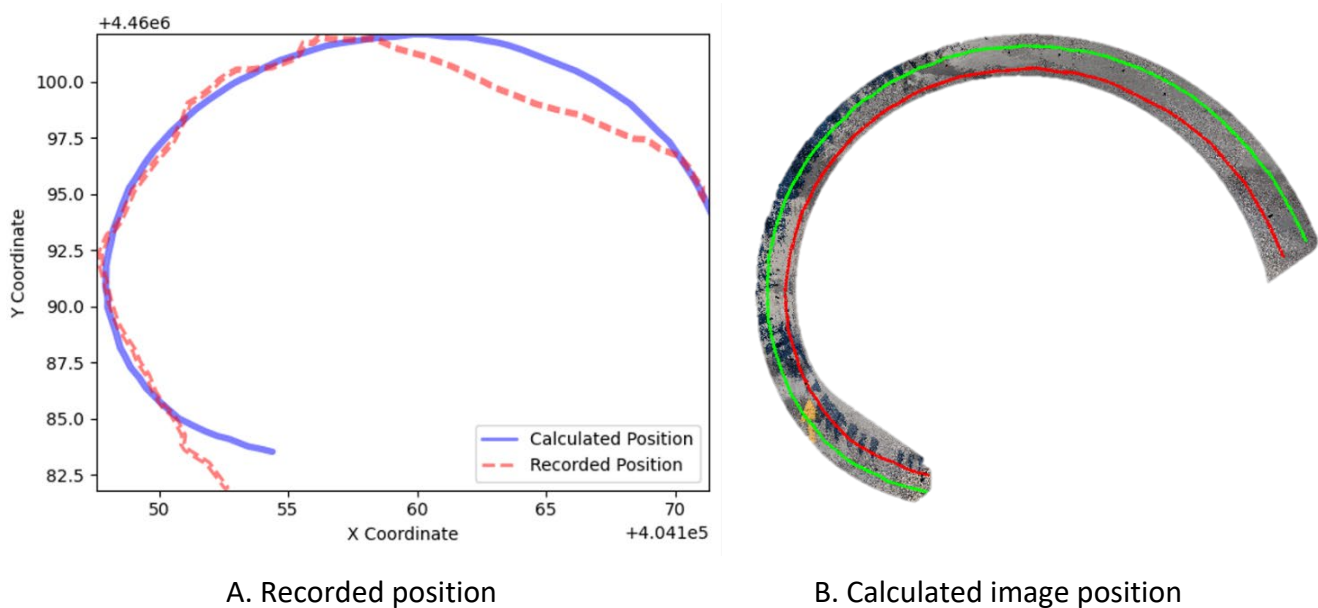


Figure 33. Illustration. Accuracy of recorded and calculated image position.

ICART VALIDATION STUDY

To validate the accuracy of the developed system, a study was conducted at ICART in Trenton, Illinois. The track consisted of two Portland cement concrete (PCC) lanes and one hot-mix asphalt (HMA) lane. Each lane had multiple surface types, presented in Figure 34. The system was tested on the HMA lane, which consisted of dense-graded HMA (DGHMA), microsurfacing (MS), stone-matrix asphalt (SMA), and chip seal (CS) surfaces, listed by increasing mean profile depth (MPD) order.

	Accel/Decel Zone				Accel/Decel Zone	
Lane 1	CRCP - Turf Drag	CRCP - Smooth Finish with Diamond Grooving	CRCP - Turf Drag with Diamond Grooving	CRCP - Smooth Finish with Diamond Grinding	CRCP - Smooth Finish (Float Only)	CRCP - Turf Drag
Lane 2	Stone Matrix Asphalt	Stone Matrix Asphalt with Artificial Rutting	Stone Matrix Asphalt	9.5 MM NMAS Dense Graded HMA	Micro surfacing - High Friction (30% Calcine Bauxite + 70% ACBF Slag)	Chip Seal with Fog Seal 9.5 MM NMAS Dense Graded HMA
Lane 3	JPCP - Turf Drag	JPCP - Artificial Faulting	JPCP - Longitudinal Tining	JPCP - Random Transverse Tining	JPCP - Turf Drag	
	244 m	122 m	238 m	238 m	122 m	122 m 122 m

Figure 34. Illustration. ICART track layout.

An Ames 9400HD laser texture scanner was used to validate the accuracy of the developed system. The location, where the Ames scanner performed a measurement, was marked on the ground using chalk, and a measurement was performed at the same location using the system. Figure 35 illustrates this process. To obtain GNSS corrections, the Missouri Department of Transportation's base station was used. Because Trenton was not within the optimal coverage area of the network, there were instances of minor signal disruption that affected 4 of the 18 measurements performed. The affected measurements were removed from the data analysis to eliminate bias. Additionally, data were collected in the westbound direction to avoid capturing shadows in the images, which reduced reconstruction accuracy. Although the system can predict friction from the measured texture, the surfaces at ICART are not subjected to local traffic and are not well-represented in the dataset that was used to train the machine learning friction model, which would result in incorrect predictions. Therefore, the validation study was limited to texture.

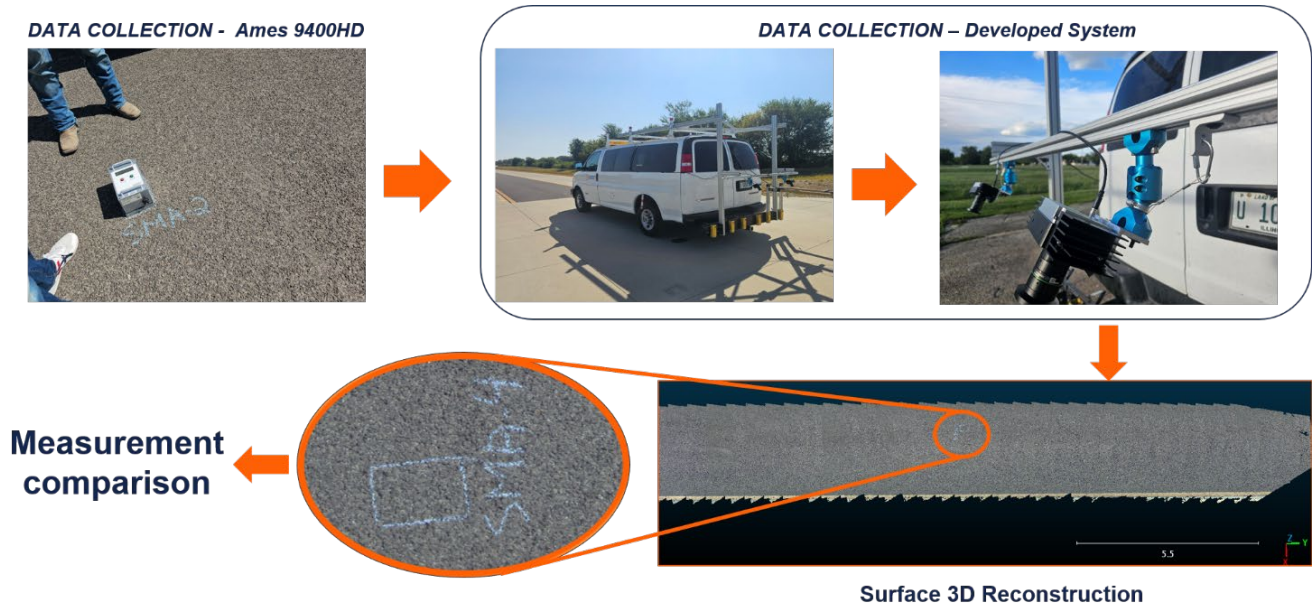
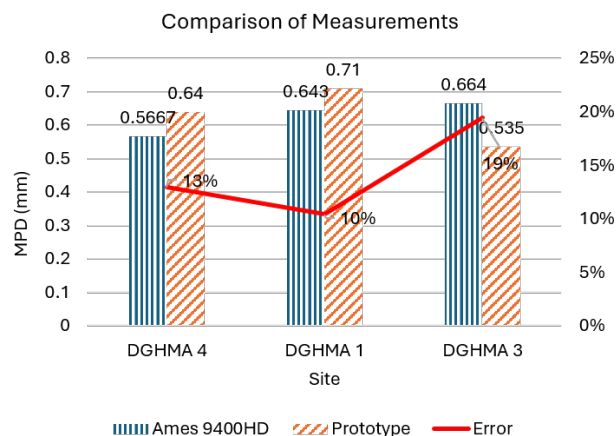


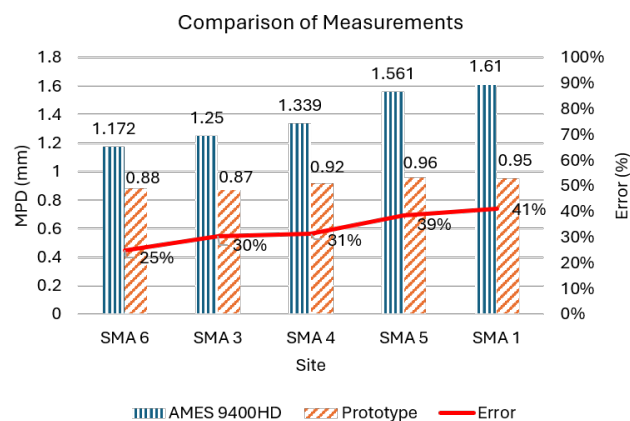
Figure 35. Illustration. Data collection and comparison at ICART.

The collected data were analyzed using the methodology discussed in Chapter 2. The results, summarized in Figure 36, demonstrate that the developed system produced measurements that correlated well with those from the Ames scanner. On the DGA surface, the measurements were closest between the two devices. The laser scanner produced higher measurements than the camera-based system for two of the three spots, and the average absolute error for all three spots was 14%. For the remaining surfaces, all measurements from the laser scanner were higher than those from the camera-based system, which was also observed in Chapter 2's results and in other research efforts (Gendy & Shalaby, 2007; Puzzo et al., 2017; Tian et al., 2020). As MPD increased, the error between the two devices increased, reaching a consistent value of approximately 37% for the CS surface. On the other hand, the correlation (R^2) between both devices also increased as MPD increased.

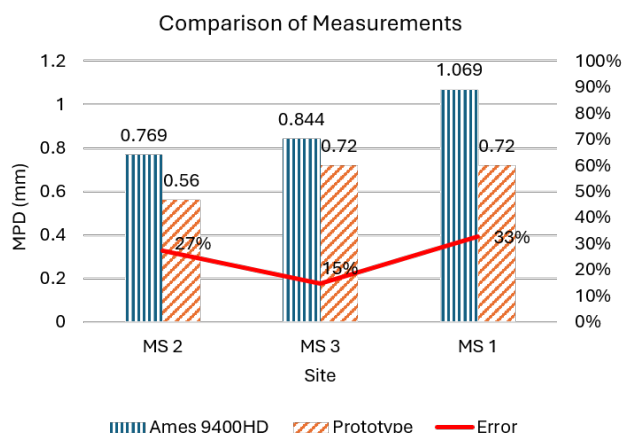
The lower MPD measured by the camera-based system may have been due to the Fujinon lens, which may be better suited for assembly line inspection systems rather than pavement inspection in uncontrolled light conditions. Additionally, validating the developed system against a single laser device may not comprehensively assess its capabilities because of the relatively large variability of MPD measurement by laser equipment.



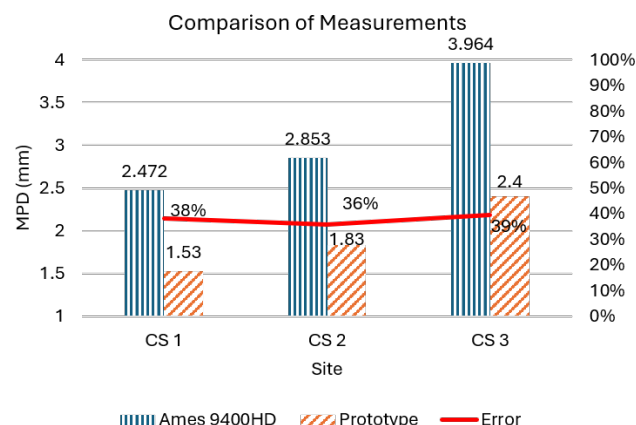
A. On DGHMA section



B. On SMA section



C. On MS section



D. On CS section

Figure 36. Bar Plot. Measurement comparison summary.

SUMMARY

A high-speed system was developed to collect images and GNSS data on a network scale. The system consisted of dual high-resolution industrial cameras, an RTK base-station and rover setup, a vehicle mounting system, an industrial computer, and data collection software system. The developed system was able to collect data up to 35 mi/hr in binary format, which was post-processed to high-resolution, georeferenced JPG imagery after the capture session. The images were then processed by the 3D reconstruction algorithm to produce sub-millimeter resolution 3D point clouds of pavement surfaces.

The accuracy of the developed system was validated by comparing its measurements to those by an Ames 9400HD laser texture scanner at ICART. Measurements were taken on dense-graded hot-mix asphalt, stone-matrix asphalt, microsurfacing, and chip-seal surfaces. The developed system exhibited

excellent correlation with the laser-based scanner, and the error between both pieces of equipment increased proportionally with surface texture depth. The variation in MPD measurements could be due to optical challenges in representing deep textures. Nonetheless, the developed system demonstrated that a photogrammetry-based approach is viable and scalable for network-level evaluation of pavement texture.

CHAPTER 4: MACHINE LEARNING MODEL DEVELOPMENT FOR ROAD SURFACE FRICTION PREDICTION

INTRODUCTION

Highway agencies routinely conduct friction testing to identify pavement sections that require maintenance (Izeppi et al., 2017). Equipment such as the British Pendulum Tester (BPT) and Dynamic Friction Tester (DFT) are used for spot checks; however, testing is time-consuming, labor-intensive, and exhibit large variability in measurements. The Locked-Wheel Skid Trailer (LWST) has been commonly used since the 1960s (Henry, 2000), but it has several drawbacks. Constant stops are required to refill the water tank and replace the tire, and measurements are sporadic and can only be taken on straight sections of roadway (Kogbara et al., 2016; Yu et al., 2020).

For continuous measurement, the Sideway-force Coefficient Routine Investigation Machine (SCRIM) has been assessed recently by transportation agencies in the United States (de León Izeppi et al., 2019; Flintsch et al., 2023). It has a larger water tank, which allows for relatively longer distances before the need to refill. Because the tire is free-rolling and mounted with a constant 20° slip angle, it can continuously measure friction on all highway geometries, not just straight sections (Flintsch et al., 2012). However, SCRIM is relatively expensive to own and operate, which may hinder its adoption as part of routine testing and as a pavement management system (Zou et al., 2022).

To improve traffic safety by reducing the cost and complexity of network-wide friction testing, research efforts were launched to develop contactless techniques for friction measurement. Several studies have tried to predict friction by developing correlations with texture because pavement surface texture is known to be a significant factor in friction. Kane et al. (2015) characterized texture measurements obtained from a Circular Texture Meter (CTM) using parameters such as density and sharpness and correlated them to friction measurements from a DFT. The results demonstrated good correlation between friction and (density $\times$ sharpness) with a correlation coefficient of 85%. Hu et al. (2016) used a 3D scanner to capture surface texture data and compute multiple parameters that were correlated to friction values from a DFT. Testing speed had a major influence on friction, and multiple texture parameters were required to obtain relatively more accurate prediction models.

Underwood et al. (2022) studied the evolution of friction and texture after hot-mix asphalt (HMA) overlays using a BV-11 skid trailer, Ames 8300 Inertial Profiler, and field core samples. Their analysis included several texture parameters as well as HMA volumetric parameters such as percent binder, voids filled with asphalt binder, and passing #200 sieve (P_b , VFA, and P_{200} , respectively). Results demonstrated that single texture parameters, such as mean profile depth (MPD), may not accurately predict friction. In addition, seasonal climate effects and mixture properties were reported as important factors.

Zuniga-Garcia and Prozzi (2019) investigated the effect of different texture components on friction using a texture laser scanner and friction measurement by a BPT, DFT, and Micro-GripTester. They concluded there was no unique relationship between texture and friction, but that it depended on the surface type. They reported that MPD was the most descriptive predictor of friction.

The studies generally emphasized that factors other than texture ought to be considered. Additional data under various conditions are also needed to capture the complex relationship between friction and its influencing parameters. Hence, current correlation analyses are inadequate. To overcome this limitation, researchers have recently leveraged data-driven methods to predict pavement friction. Artificial intelligence techniques may better capture the relationship between a set of features and the target variable. Additionally, data-driven methods may benefit from expansive datasets to possibly improve model accuracy and generalizability.

Several studies have utilized the convolutional neural network (CNN). Its ability to extract unique and representative features makes it a desirable approach for predicting pavement friction. To create the feature vector, researchers have used images from front-facing vehicle cameras (Du et al., 2019), texture wavelet decomposition (Liu et al., 2023), and 3D texture images (Weng et al., 2025). While these approaches result in a rich feature set, the number of samples that were used for training the models was extremely limited, resulting in models that may be overfitted or may not generalize well. Additionally, the friction data used for training were collected using devices like BPT, DFT, and T2GO, which are not used for network-scale evaluation.

Other studies utilized tree-based machine learning models like the Light Gradient Boosting Machine (Hu et al., 2022), XGBoost (Peng et al., 2025; Zhong et al., 2025), and Random Forest (Yang et al., 2021; Zhan et al., 2021) and used features such as vehicle AADT, aggregate properties, texture parameters, and pavement temperature to predict friction. Although these studies incorporated features that are known to influence friction, devices used in those studies measured spot friction. For network, Zou et al. (2022) acquired friction measurements from SCRIM and developed a neural network to predict the friction coefficient using 3D texture parameters. Texture data were obtained from a handheld 3D laser scanner. While the friction values were measured with a widely used network-level device, only 60 samples were available for that study, limiting generalizability and reliability.

Yang et al. (2018) obtained texture profile data using a high-speed laser and collected the corresponding friction data using a GripTester on another vehicle. A total of 63,000 samples from sites with different surface properties in 12 states were collected with both vehicles at the same time and later paired using their GPS coordinates. The authors used the frequency information in the texture profile as the main input to a CNN by converting the profile data into spectrograms. The resulting model achieved an accuracy of 88.37%. However, the predictions were reported in 0.1 unit bins rather than as continuous friction values, which may reduce the model's accuracy because there is a 0.1 unit band of uncertainty. Additionally, the data were collected using separate vehicles, which the authors acknowledged as a possible source of errors.

In a later study, Yang et al. (2023a) used a 3D image with 1 mm resolution from a high-speed laser system (Wang et al., 2015) as the input to a CNN. A total of 28,000 samples from 28 sites across 10 states were available for model development. The resulting model had an explanation of results of 81.07% and underperformed on pavement sections having friction numbers of 0.4 and 0.5, which represent most HMA surfaces. The authors used the average friction number for sections that have the same surface, which eliminates the local variability and may result in missed slippery spots.

In the latest study, Wang et al. (2025) used 0.1 mm 3D images that were upsampled from a lower resolution using a Generative Adversarial Network (GAN) as an input for a two-step deep learning approach (Wang et al., 2023). The two-step approach comprised a CNN and three attention modules to increase accuracy, and friction was collected using a GripTester. A total of 4,344 samples representing 10 types of pavement surfaces in Oklahoma were available for model development. The model achieved 99.17% prediction accuracy. However, a significant amount of filtering and interpolation of friction and texture data were done, and input was limited to texture. Despite the model's complexity, the friction number was still classified into bins rather than predicting the actual value. The approach is computationally intensive as well, limiting the number of input images and results in long training and fine-tuning times. Furthermore, the GripTester may not measure lateral friction, which is crucial for safety on curves, ramps, and intersections. Its relatively small size also makes the measurements vulnerable to noise and abnormal data and may not be suitable for network-level surveys (Yang et al., 2023b).

The current state of knowledge, summarized in Table 7, indicates that although advanced techniques have been used, the following limitations still exist: (i) large datasets collected with the same vehicle across a road network, (ii) friction measurements that include a lateral component, and (iii) using independent variables other than texture. Addressing these limitations is essential for developing reliable and interpretable prediction models that can support safety-oriented decision-making and improve understanding of the underlying factors.

Table 7. Summary of Using Data-driven Methods to Predict Pavement Friction

Reference	Friction Data Source	Predictors	Learning Model	Number of Samples
Du et al. (2019)	BPT	Custom texture indicators	CNN	100
Yang et al. (2018)	GripTester	Texture profile spectrogram	CNN	63,000
Liu et al. (2023)	Finite Element Simulation	Texture wavelet decomposition	CNN	880
Hu et al. (2022)	BPT	3D texture indicators	LightGBM	200
Yang et al. (2021)	DFT	3D texture indicators	Random Forest	108
Zhan et al. (2021)	GripTester	AADT, temperature, aggregate properties, IRI, rutting, pavement age, texture indicators	Random Forest	179
Zou et al. (2022)	SCRIM	3D texture indicators	Feedforward neural network, linear regression	60
Peng et al. (2025)	DFT	Multi-view fractals	XGBoost	221
Weng et al. (2025)	T2GO	3D texture	CNN with spatial attention mechanism	500
Yang et al. (2023a)	GripTester	3D texture image	CNN	28,000
G. Wang et al. (2025)	GripTester	3D texture image	GAN to increase texture resolution, CNN with triple attention mechanism	4,344
Zhong et al. (2025)	DFT	3D texture indicators (from profiles) and 3D feature maps (from CNN)	XGBoost	700

A robust data-driven model, which could predict sideways friction measured by SCRIM, was developed. To ensure accuracy, a dataset collected in Florida with 380,980 samples, including features such as road geometry, test speed, AADT, texture, and temperature, was used for model development. A dataset collected in Illinois with 288,564 samples, and different data distributions from that of Florida, was used as well. To evaluate the influence of dataset size and additional predictors on model performance, a third dataset, collected in Illinois, with 18,086 samples and additional features such as surface type and age was utilized.

DATA COLLECTION AND CHARACTERISTICS

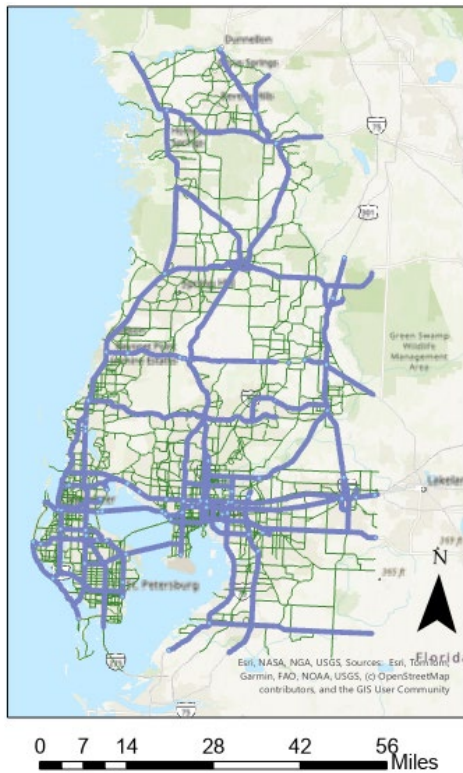
Data were acquired from the Florida Department of Transportation (FDOT) and Illinois Department of Transportation (IDOT). All datasets were collected using SCRIM (Figure 37). The FDOT dataset was collected in District 7 around Tampa, whereas the IDOT datasets were collected across the entire state in 2023 and central-eastern part in 2025 (Figure 38). The FDOT data covered 1,905 miles and were reported at 26.4 ft intervals, resulting in 380,980 samples. The 2023 IDOT data covered 1,808 miles and were reported at 528 ft intervals, which resulted in 18,086 samples, whereas the 2025 data covered 1,792 miles and were reported at 32.8 ft intervals, resulting in 288,564 samples. A major advantage of SCRIM is that it collects information that impacts friction demand such as vehicle speed, curve radius, grade, and cross-slope. It also collects pavement MPD using a 64 kHz spot laser scanner mounted behind the tire that measures friction, eliminating errors that may result from measuring texture using a different vehicle (de León Izeppi et al., 2019). Other data that may be useful for analyzing friction values, such as average annual daily traffic (AADT), road type, surface type, and surface age, can be included in the dataset if the corresponding shapefiles are available.

Table 8 summarizes both datasets, including source, survey distance, reporting interval, number of samples, and features. MPD, AADT, grade, cross-slope, and curve radius were common features of the data. The FDOT and 2025 IDOT data included vehicle speed and surface temperature, whereas the 2023 IDOT data included site type, pavement type, and pavement age. It was not possible to include the same features in all datasets due to the specificity of requested data for each survey.

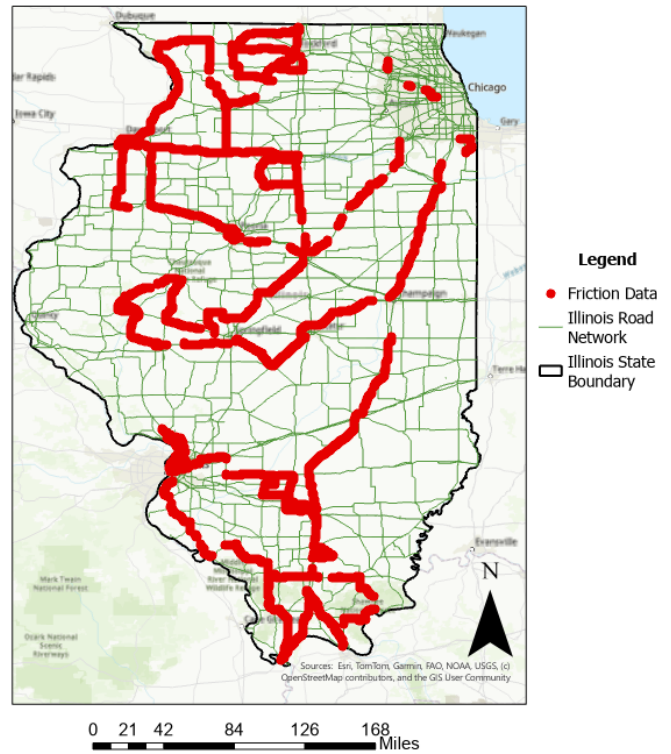


Figure 37. Photo. SCRIM.

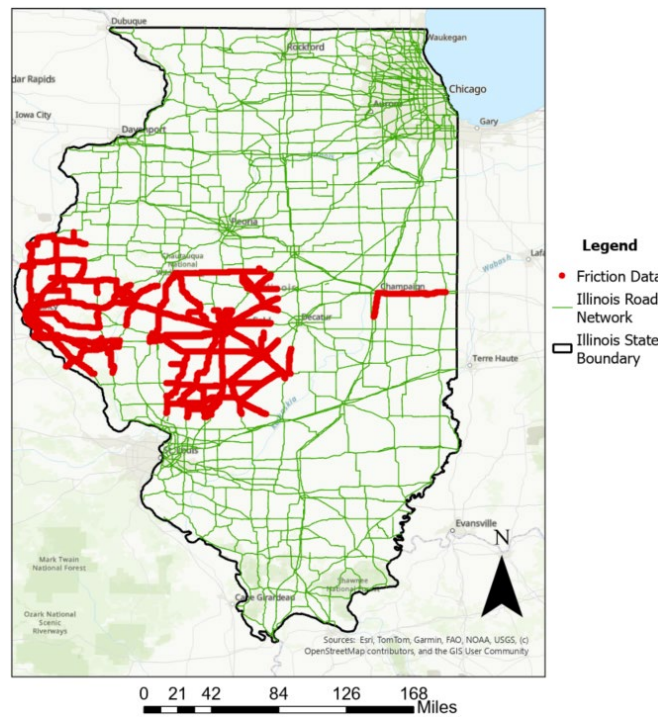
Source: Virginia Tech Transportation Institute



A. FDOT



B. 2023 IDOT



C. 2025 IDOT

Figure 38. Illustrations. Location of collected data in Florida and Illinois: (a) FDOT, (b) 2023 IDOT, and (c) 2025 IDOT data.

Table 8. Summary of FDOT and IDOT Datasets

Source	Survey Distance (mi)	Reporting Interval (ft)	Number of Samples	Features
FDOT	1,905	26.4	380,980	MPD (mm), speed (mph), cross-slope (%), curve radius (ft), grade (%), AADT, surface temperature (°F)
IDOT (2023)	1,808	528	18,086	MPD (mm), cross-slope (%), curve radius (ft), grade (%), AADT, surface age (years), site type (Categorical: tangent, intersection, ramp, etc.)
IDOT (2025)	1,792	32.8	288,564	MPD (mm), speed (mph), cross-slope (%), curve radius (ft), grade (%), AADT, surface temperature (°F)

METHODOLOGY

Exploratory Data Analysis

The data were initially examined by computing the Pearson correlation coefficient (r) to understand the linear relationship between the features. It was calculated in accordance with the equation in Figure 39, where x_i and y_i are individual sample points and $\bar{x}$ and $\bar{y}$ are means of corresponding variables.

$$r = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \cdot \sum (y_i - \bar{y})^2}}$$

Figure 39. Equation. Pearson correlation coefficient calculation.

Figure 40 summarizes the pairwise relationship among the FDOT data features and demonstrates that there is no significant correlation between them, particularly between SCRIM coefficient and the other variables. This observation was common among all datasets and aligns with the conclusions from other studies, suggesting that friction is complex and its relationship with texture is nonlinear (Hu et al., 2016; Underwood et al., 2022; Zuniga-Garcia & Prozzi, 2019).

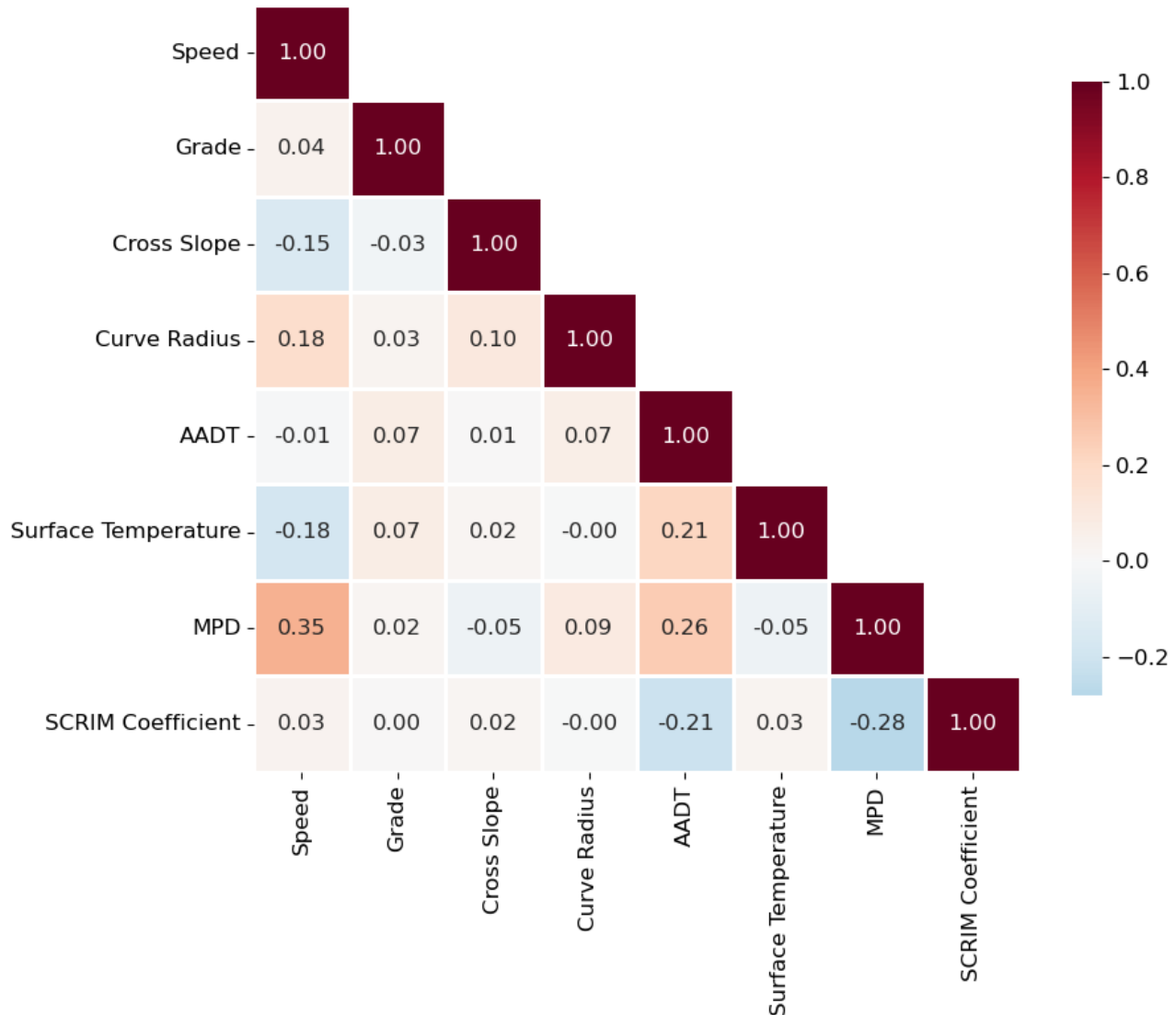


Figure 40. Graph. Heatmap of Pearson correlation coefficient for FDOT data.

Data Preprocessing

To filter the data for erroneous values, the distribution for each feature was plotted. Ranges for each feature that were not well-represented and would thus result in high errors during model inference were excluded (Figure 41). For the FDOT data, this resulted in the removal of 33,457 samples. Additionally, 3,323 samples had missing data in one or more features, and they were also removed. As a result, a total of 344,200 samples, which accounted for 90.35% of the original FDOT dataset, were available for model development. The curve radius values were adjusted by considering all curves that have a radius above 2,000 ft as straight sections (Flintsch et al., 2023). The radius for these sections was set to 2,000 ft, whereas all other values were not adjusted. This was done to define a clear distinction between friction demand on straight and curved roads. A similar approach was adopted for the 2023 and 2025 IDOT datasets, which resulted in 14,988 and 246,439 samples for model development, respectively.

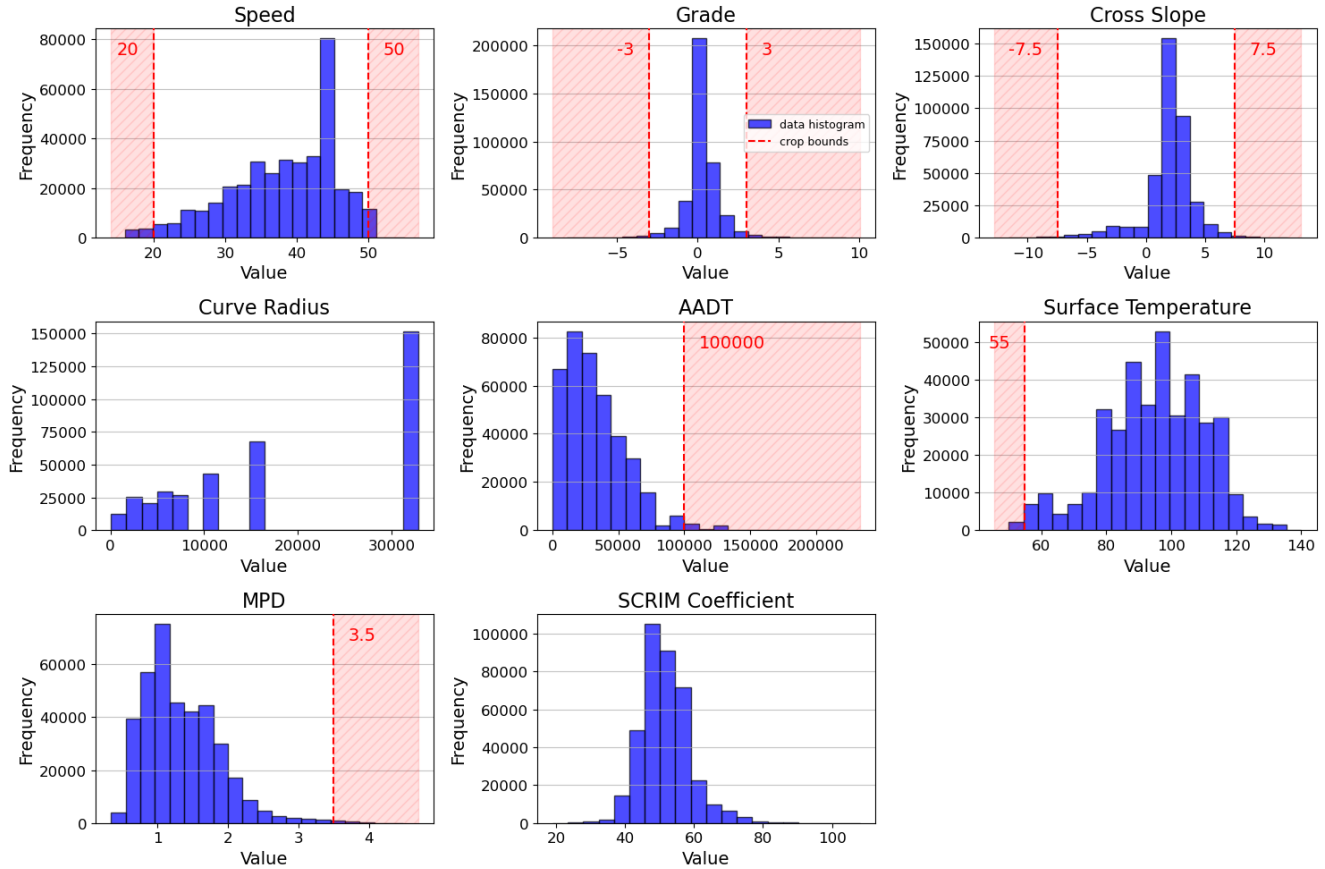


Figure 41. Graph. Data distribution for FDOT dataset.

Machine Learning Techniques

Ensemble learning is a machine learning technique whereby two or more models are combined to produce predictions that are more accurate than a single model. The Decision Tree (DT) is typically used as the base learner, and training is done either in parallel (bootstrap aggregating) or sequentially (boosting). Bootstrap aggregating, also known as bagging, aims to reduce variance and overfitting by training several DTs in parallel on a randomly sampled subset of the available data. The final prediction is an average of the results by every individual tree. The most well-known implementation of bagging is the Random Forest (RF) algorithm, but other implementations like Extremely Randomized Trees, or Extra Trees (ET), have been used.

ET differs from RF in its sampling and node split criteria. Unlike RF, ET is trained on the full dataset and randomly chooses the cut point to split nodes, which reduces bias, variance, and training time. On the other hand, boosting aims to reduce bias by sequentially training a group of models such that a new model is trained to correct the mistakes of the previous model, which increases accuracy. There are several implementations of boosting which differ by regularization, training speed, handling of categorical features, and other factors. In this study, the boosting models used were Gradient Boosting Decision Tree (GB) and XGBoost, whereas the bagging models used were Random Forest and Extra Trees.

Model Development

The tree-based models were implemented in Python using packages such as scikit-learn and XGBoost. Eighty percent of the dataset was reserved for training, and the remaining 20% was split between validation and testing. Techniques such as cross-validation and randomized grid search were used to fine-tune the model hyperparameters. Because tree-based models do not rely on distance calculations and do not assume a particular distribution for the features, the features were not standardized. Table 9 presents the final hyperparameters that were chosen for the tree-based model. Most influential hyperparameters for RF, ET, and GB were max_depth and n_estimators, which control the depth and number of trees for each model, respectively. Other hyperparameters, such as min_samples_split and min_samples_leaf, which respectively control the minimum number of samples to split an internal node and be at a leaf node, did not significantly influence model performance.

Table 9. Final Hyperparameters Used with Tree-based Models

Model	Hyperparameter	Value
RF, ET	max_depth	30
	n_estimators	100
	Criterion	squared error
	Min_samples_split	2
	Min_samples_leaf	1
GB	max_depth	32
	n_estimators	100
	criterion	absolute error
	Min_samples_split	2
	Min_samples_leaf	1
XGBoost	Max_depth	20
	n_estimators	500
	Early_stopping_rounds	50
	Learning_rate	0.05
	Subsample	0.8
	Colsample_bytree	0.8
	Gamma	0.2
	Reg_lambda	2
	Reg_alpha	1

Performance Evaluation

Model performance was assessed using mean absolute error (MAE), root mean square error (RMSE), and coefficient of determination (R^2). MAE demonstrates how close the predictions are to the measured values and can easily be interpreted because it preserves the unit of the original measurement. RMSE provides similar insights but is more sensitive to outliers and can therefore differentiate models that make large errors. R^2 measures the percentage of variance of the target variable that can be explained by the model. The three metrics are defined as follows in Figure 42, Figure 43, and Figure 44:

$$MAE = \frac{1}{n} \sum_{j=1}^n |y_j - \hat{y}_i|$$

Figure 42. Equation. Mean absolute error.

$$RMSE = \sqrt{\frac{1}{n} \sum_{j=1}^n (y_j - \hat{y}_i)^2}$$

Figure 43. Equation. Root mean square error.

$$R^2 = 1 - \frac{\sum_{j=1}^n (y_j - \hat{y}_i)^2}{\sum_{j=1}^n (y_j - \bar{y})^2}$$

Figure 44. Equation. Coefficient of determination.

where $Y = \{y_0, y_1, \dots, y_n\}$ denotes a set of all ground truth SCRIM friction coefficient values in a case, $\hat{Y} = \{\hat{y}_0, \hat{y}_1, \dots, \hat{y}_n\}$ denotes a set of all predicted friction coefficient values in the test set, and $\bar{y}$ represents mean of the ground truth values. For each model, a checkpoint with lowest validation loss was selected for final testing.

Model Interpretation

Shapely Additive Explanation (SHAP) (Lundberg & Lee, 2017) was used to understand the contribution of the available features to the final prediction. SHAP is model-agnostic and can be applied to any machine learning model. It operates by computing SHAP values for each data point to uncover how each feature influenced the prediction. At a higher level, this reveals the importance of the feature relative to other features in the dataset, and whether a change in the feature value increases or decreases the prediction. This makes SHAP a powerful tool that is widely used to interpret machine learning models and verify the logic behind predictions.

RESULTS AND DISCUSSION

Comparison of Prediction Performance for All Models and Datasets

Table 10 presents the performance of the tree-based models on the test data from FDOT and IDOT. The performance of tree-based models was generally similar for RF, GB, and XGBoost. The ET model outperformed the other models across all datasets. For the Florida data, the correlation coefficient for ET was 83.16%, which is around 1.2% higher than the next best model. Additionally, the MAE and RMSE were 1.89 and 2.85, indicating the ET model prediction error is low and reasonable compared to the prediction errors by the other tree-based models. For the 2023 IDOT data, the ET model demonstrated an even greater advantage across all metrics.

The performance improvement in R^2 , MAE, and RMSE were 4.48%, 7.72%, and 6.0%, respectively, compared to the average performance of RF, GB, and XGBoost (Table 10). The ET model also displayed the best performance on the 2025 IDOT data, but the increase in training data relative to the 2023 IDOT dataset did not translate into higher prediction accuracy. MAE and RMSE values were very close, and R^2 was around 10 points higher for the 2025 data due to the higher variance of friction values. The ET model was expected to have similar performance on the 2025 IDOT data as it did on the FDOT data, but this was not the case. The 2025 IDOT data distribution (Figure 45) demonstrates that the target variable has high variance and the features have lower variance when compared to the FDOT data, which may suggest that other factors may be needed to explain the large variability in the recorded friction values.

Table 10. Model Performance on Test Dataset

	FDOT			IDOT 2023			IDOT 2025		
MODEL	R^2	MAE	RMSE	R^2	MAE	RMSE	R^2	MAE	RMSE
RF	82%	1.96	2.96	72.98%	3.19	4.74	84.4%	3.06	4.59
ET	83.16%	1.89	2.85	75.19%	2.99	4.54	85%	2.98	4.48
GB	81.66%	1.99	2.99	71.07%	3.31	4.91	83.7%	3.14	4.69
XGBOOST	82%	2.02	2.95	71.84%	3.22	4.84	82%	3.45	4.92

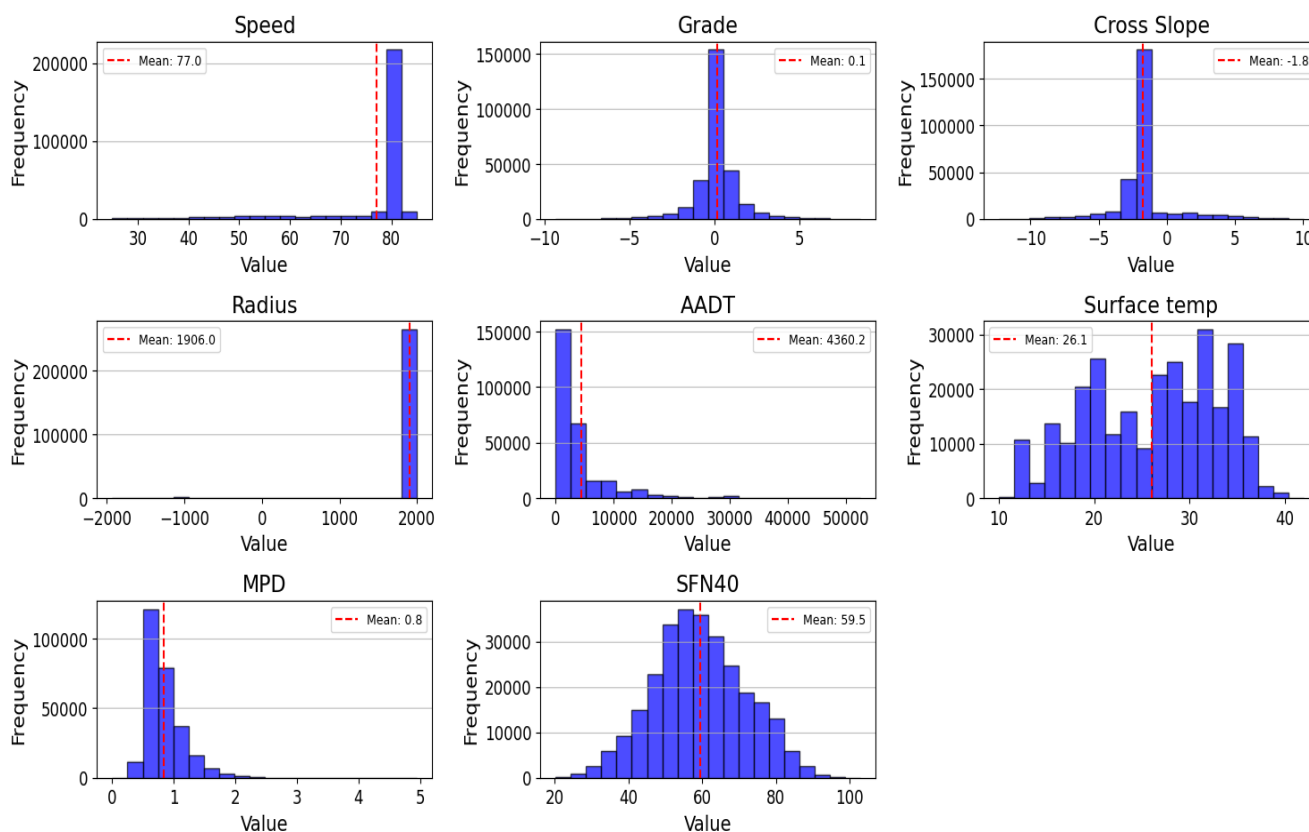


Figure 45. Graph. Data distribution for 2025 IDOT dataset.

For further model analysis, the distribution of normalized prediction errors for the ET model in all datasets was plotted. As presented in Figure 46, all distributions approximate normal distribution, but both IDOT datasets exhibit positive skewness, which indicates that the model tends to overpredict friction for certain cases. This finding was confirmed by the positive mean and near-zero median of the distribution, which is presented along with other statistics in Table 11. Seventy-five percent of the prediction errors for the 2023 dataset were between -7.50% and 10.66% , which may be acceptable given the relatively limited size of the training data. For the 2025 dataset, 75% of prediction errors were between -6.08% and 7.6% , demonstrating that the increase in the number of training samples resulted in improved performance despite both models having similar MAE and RMSE values.

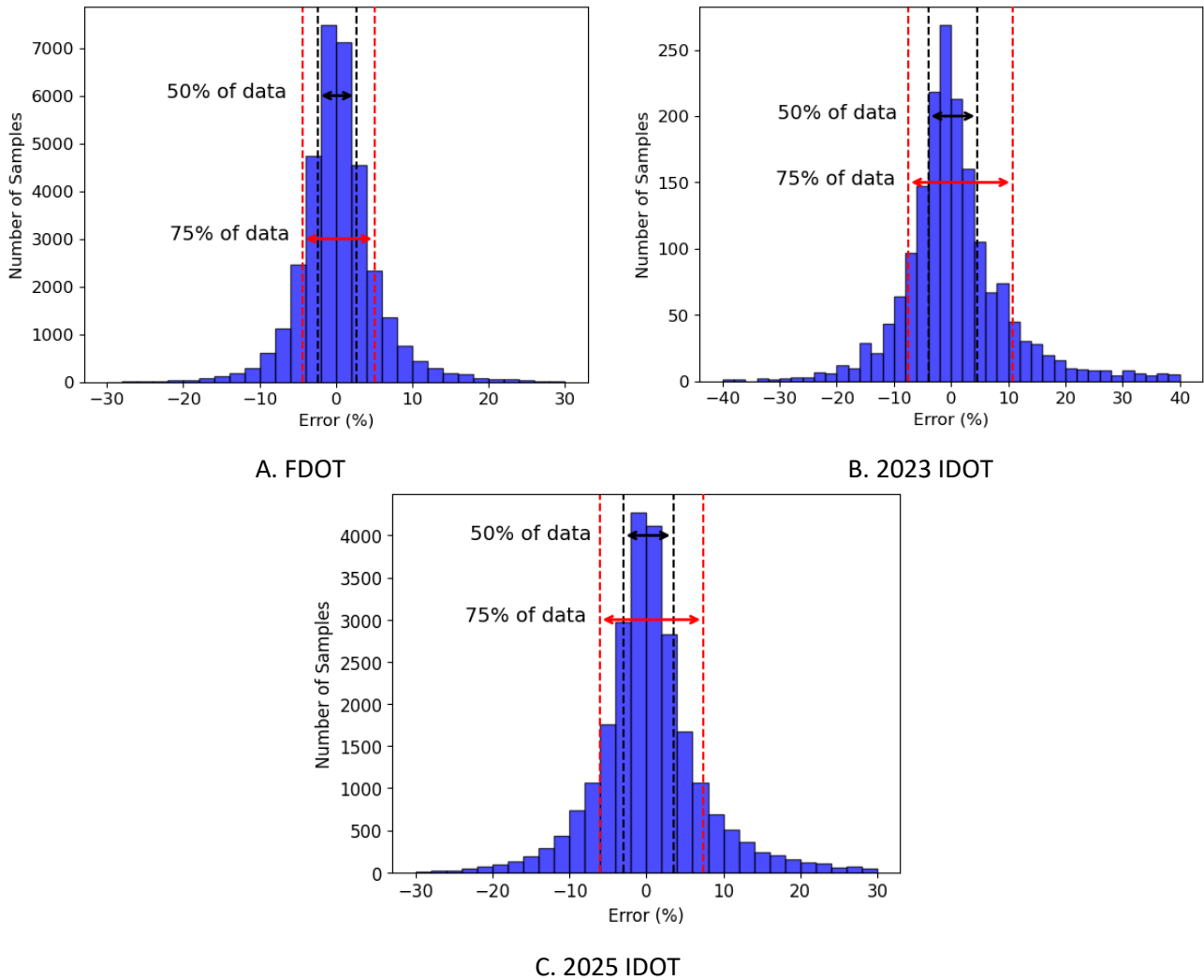


Figure 46. Prediction error distribution for ET model on test data for (a) FDOT, (b) 2023 IDOT, and (c) 2025 IDOT data.

Table 11. Summary Statistics of Prediction Errors for ET Model on All Datasets

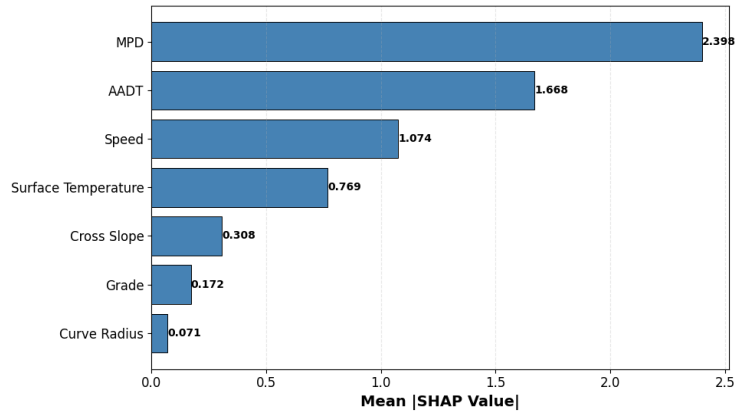
Statistic	FDOT	IDOT 2023	IDOT 2025
Mean	0.34%	1.87%	0.87%
Median	0.03%	-0.28%	0.14%
Standard deviation	5.38%	13.51%	8.65%
12.5th percentile	-4.39%	-7.5%	-6.08%
25th percentile	-2.34%	-3.99%	-2.97%
75th percentile	2.63%	4.65%	3.59%
87.5th percentile	5.11%	10.66%	7.60%

On the other hand, the FDOT error distribution closely approximates a normal distribution and exhibits no bias or skewness, as evident by the zero mean and zero median. The standard deviation was significantly lower than that for the IDOT data, demonstrating the model can make significantly more accurate predictions. Furthermore, 75% of the predictions were within -4.39% and 5.11% of the measured friction value, which indicates that the model can make accurate predictions under most conditions.

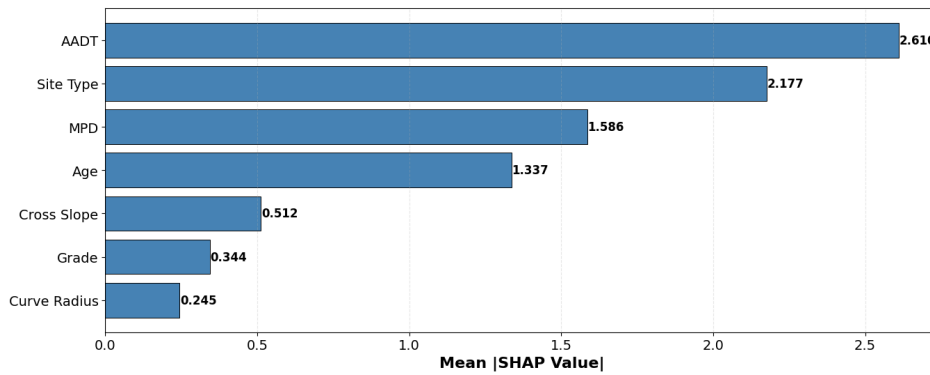
The superiority of the ET model can be attributed to its sampling method, which uses the full training dataset for each learner. While it increases bias, it allows the model to better understand the complex relationship between friction and the other features and generalize better. Furthermore, the increased randomness in node splitting gave ET a computational advantage, requiring only 56 seconds for training on the FDOT dataset.

Model Interpretation

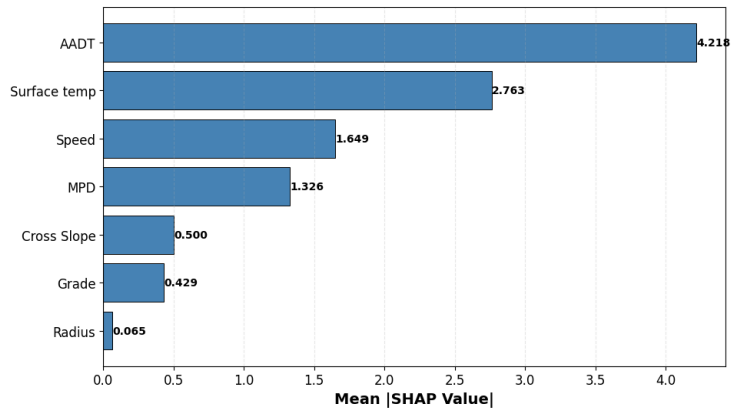
The ET model demonstrated superior performance, so it was selected for further interpretation using SHAP analysis. Figure 47 presents the ranking of the features in terms of their impact on the final prediction. Figure 48 highlights how individual data points within each feature influence the prediction. For the FDOT data, MPD ranked as the highest contributing feature, which intuitively aligns with engineering knowledge and previous studies. On the other hand, a negative correlation was observed between MPD and the predicted friction values, which is unintuitive because pavement surfaces with deeper textures usually have good drainage, which improves wet weather friction. The negative correlation indicates that other surface-related information that is not captured by MPD is contributing to the prediction.



A. FDOT

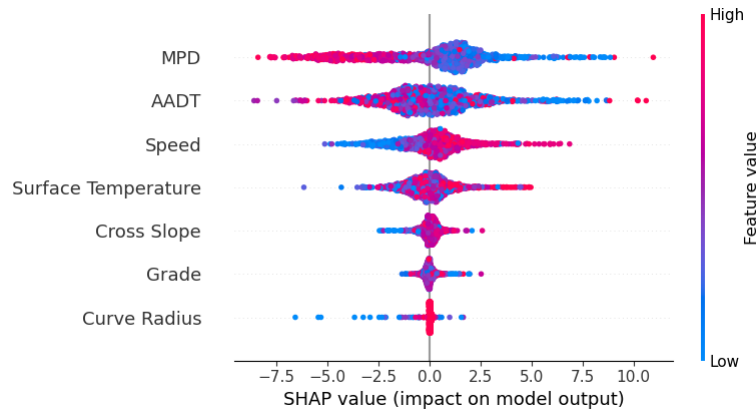


B. 2023 IDOT

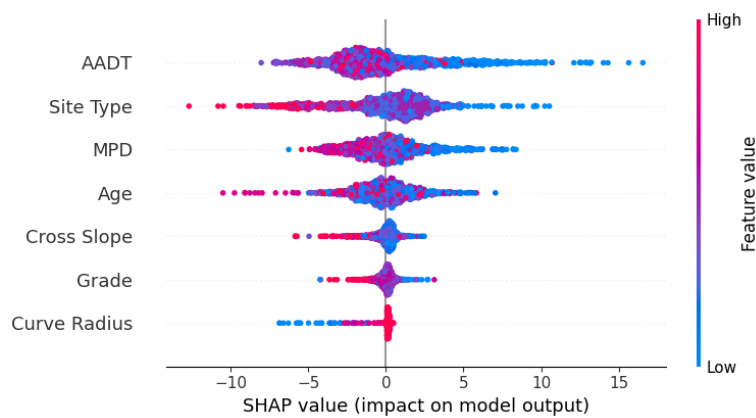


C. 2025 IDOT

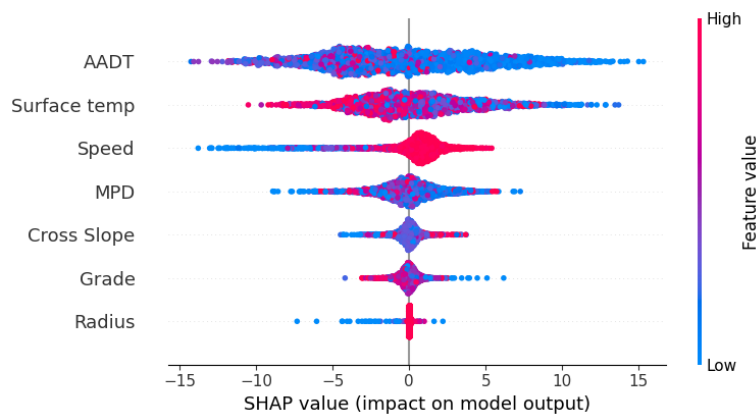
Figure 47. Graph. ET feature importance for (a) FDOT, (b) 2023 IDOT, and (c) 2025 IDOT data.



A. FDOT



B. 2023 IDOT



C. 2025 IDOT

Figure 48. Graph. ET model interpretation for (a) FDOT, (b) 2023 IDOT, and (c) 2025 IDOT data.

AADT ranked as the second most influential feature and had a negative correlation with the final prediction. Higher AADT may decrease friction due to accelerated wear and polishing of aggregates. Additionally, AADT was likely used by the model as a proxy for pavement information like mix design, binder characteristics, and surface age, all of which are important for friction and may be related to construction and maintenance criteria that are connected to traffic levels.

Speed of test vehicle and surface temperature were the third and fourth most impactful features, respectively. They exhibited a positive correlation with the final prediction. As expected, increasing vehicle speed, while maintaining slip angle, would generate less resistive force. Similarly, increasing temperature would decrease tire-pavement friction due to the viscoelastic nature of tire rubber and HMA surface. Road geometry data such as cross slope, grade, and curvature were the least influential features. This finding was expected because of the limited data on curved roads. Most of the data were collected on highways, where roads are relatively straight, and the land around Tampa and Saint Petersburg is mainly flat.

For the 2023 IDOT data, MPD ranked as the third most influential feature, whereas AADT and site type ranked as the first and second, respectively. This finding is likely because the data were collected across the entire state of Illinois, where there are multiple temperature zones with different binder grades and aggregate sources. These changes in materials and design affect friction but do not have a feature to identify them. It is likely that AADT was interpreted as a proxy for these changes. Similarly, site types such as ramp, tangent, and intersection were likely used as a proxy for driving behavior as vehicle speed data were not available in this dataset. Similar to the FDOT data, road geometry information ranked as the least influential.

Despite having the same features and a comparable number of samples as the FDOT dataset, the influence of the features on the final prediction was different. AADT ranked as the most influential feature, whereas surface temperature, speed, and MPD ranked as the second, third, and fourth, respectively. Cross slope, grade, and curve radius ranked as the least influential features, which was observed for all datasets. While it is possible to predict friction using features like MPD, surface temperature, and vehicle speed, the relationship is not consistent and varies based on other factors that are not available. Such factors may include more detailed texture characterization, aggregate type, or binder characteristics, some of which may be encoded in AADT.

Discussion of High-Error Predictions

The FDOT model demonstrated superior performance, and the SHAP analysis showed reasonable logic behind the final friction prediction. While these results inspire confidence to deploy this model for real-world inference, further scrutiny may reveal biases that would lead to ill-informed decisions. To examine the model for such biases, points from the test set with an absolute error above 10% were isolated, and their distribution was compared against the distribution of the full test set (Figure 49). Ideally, the test set and the high-error subsample would have the same distribution, as that would indicate no biases for high-error predictions, but that was not the case.

The cross-hatched areas are where both distributions are identical, whereas the areas with right hatches are where there is a greater density of high-error points. The data indicate that high errors occur when speed is less than 35 mph, AADT is between 18,000 and 42,000, and MPD is less than 1 mm and greater than 2.5 mm. Part of the uncertainty stems from the lack of surface-related information beyond texture. This may explain the high errors related to MPD and AADT. On the other hand, high errors related to surface temperature and speed may indicate a complex relationship between friction and these features that require further data.

Corrections were applied to the reported friction value, as noted from the original data that include “SCRIM reading” and “SCRIM coefficient.” Although the applied corrections are unknown, other reports indicate that friction values were corrected for speed, temperature, and seasonal effects (de León Izeppi et al., 2019; de León Izeppi et al., 2019; Hacker et al., n.d.). Furthermore, other sources of error may be due to the limited number of data points and high friction values (Figure 41). In addition, other contributors may include noise from the machine and unpredictable factors like surface contaminants. Overprediction (percentage error greater than 10%) was noted when actual SCRIM is low (30–40); 14.3% of the test sample has this error, and they are mostly for MPD < 1.5 and speed less than 35 mph.

To reduce the high-error biases related to speed and temperature and improve the overall robustness of the model, the model was retrained using SCRIM readings instead of the SCRIM coefficient, while retaining only friction values between 35 and 75. This resulted in reducing MAE and RMSE from 1.89 and 2.85 to 1.74 and 2.57, respectively. However, the high-error trend remained identical, which suggests that more features are needed to explain these complex interactions.

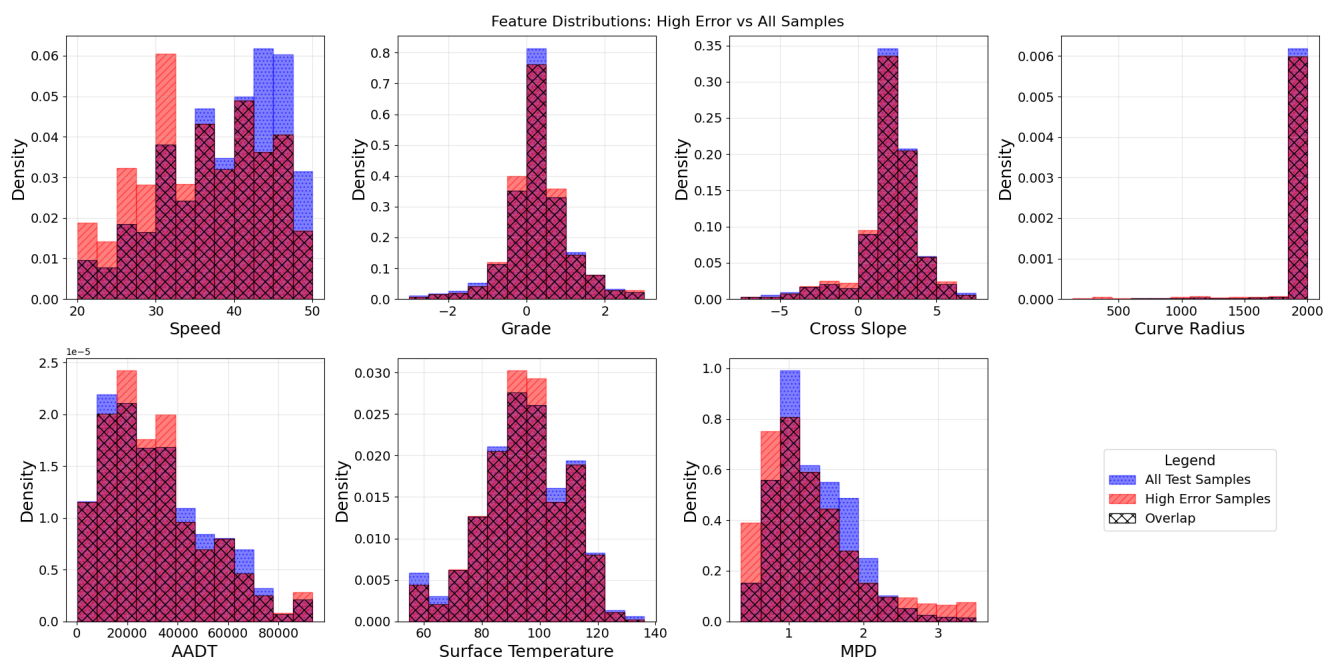


Figure 49. Graph. Data distribution for test set and high error subsample.

SUMMARY

A data-driven framework for predicting pavement SCRIM sideways friction was developed for the network level. Three datasets collected by FDOT and IDOT were used to evaluate the effects of dataset size, reporting interval, feature availability, and data distribution on model performance. The input variables included pavement texture, AADT, road geometry, test vehicle speed, and surface temperature. After data preprocessing and filtering, several tree-based ensemble learning models, including Random Forest, Gradient Boosting, Extreme Gradient Boosting, and Extra Trees, were developed and compared using MAE, RMSE, and R^2 . Among the evaluated models, the Extra Trees

model consistently demonstrated the best overall performance across all datasets. The IDOT results demonstrated that the proposed model remained effective under different data collection conditions, sample sizes, and feature sets. The remaining prediction errors suggest that pavement friction is influenced by additional surface and material characteristics that were not available in the current datasets. Error distribution analysis demonstrated that the model predictions were generally stable, although larger errors were more likely for low-speed conditions and at extreme friction, below 1 mm and above 2.5 mm texture. SHAP-based model interpretation further demonstrated that MPD, AADT, operating speed, and surface temperature were the most influential variables in friction prediction, while roadway geometry variables such as cross slope, grade, and curve radius had relatively smaller effects. Results demonstrate that tree-based machine learning models can provide an effective and scalable approach for network-level pavement friction prediction. However, relatively large and optimized-interval SCRIM-related datasets shall be available.

CHAPTER 5: HYDROPLANING

INTRODUCTION

The influence of pavement friction on crash occurrence is well established. The Federal Highway Administration and the National Transportation Safety Board estimate that up to 70% of wet-pavement crashes could be prevented or mitigated by increasing pavement friction (Merritt et al., 2015). While the impact is greater on crashes in wet weather conditions, increasing friction also decreases crash risk under dry conditions (McCarthy et al., 2021). Recent safety performance analyses quantified that a 10-unit increase in skid number is associated with a 14%–21% reduction in wet-weather crash frequency on highways, with the strongest effects observed on interstate facilities and curved alignments where friction demand is highest (Subedi et al., 2025). Wet-weather friction is particularly critical because the presence of water at the tire-pavement interface suppresses both the adhesion and hysteresis components of rubber friction. In-depth crash investigations, using the German In-Depth Accident Study database, confirmed that full hydroplaning, although a rare event that produces total loss of longitudinal and lateral grip, is an identifiable contributor to road crashes (Spitzhüttl et al., 2020).

The mechanism connecting surface water to friction loss is the progressive flooding of the tire contact patch. On a wet surface, the available friction depends on the drainage capacity of the tire tread and the pavement surface texture capacity to evacuate (Ong & Fwa, 2007; Yu et al., 2020). When the rate of water encountered by the rolling tire exceeds this drainage capacity due to high speed, relatively thick water film, or insufficient texture, hydrodynamic pressure develops in the water wedge at the leading edge of the contact patch. This pressure progressively lifts portions of the tire from the surface, reducing the contact area and, therefore, the friction. Full hydroplaning occurs when such hydrodynamic lift equals the wheel load, and the vehicle becomes unresponsive to driver inputs (Fwa & Ong, 2008; Ong & Fwa, 2007). This transition is gradual rather than discrete because friction decays continuously with increasing speed well before full hydroplaning manifests.

Hydroplaning is governed by interacting vehicle, tire, fluid, and pavement variables. Vehicle speed is the dominant parameter, because hydrodynamic lift grows approximately with the square of velocity (Hermange et al., 2022). Tire inflation pressure is also correlated with hydroplaning speed, a relationship formalized in the classical National Aeronautics and Space Administration empirical equation (Horne & Dreher, 1963; Horne & Joyner, 1965) and consistently reproduced in subsequent experimental and numerical studies (Cerezo et al., 2010). Tire tread geometry controls the volumetric flow that can be evacuated through the grooves. Therefore, worn or smooth tires hydroplane at substantially lower speeds than fully treaded tires.

Full-scale experimental testing confirmed water depth, vehicle speed, tread depth, and tire load as the leading parameters controlling the loss of contact area (Hermange et al., 2022). On the pavement side, water film thickness, drainage path length, cross slope, surface texture, and texture depth determine the hydroplaning threshold (Cerezo et al., 2010). Because of this multifactor dependence, agencies have implemented hydroplaning prediction tools that combine water film thickness models with hydroplaning speed models to screen roadway geometric designs (Lee et al., 2021).

Among the pavement-related factors, macrotexture provides the drainage channels through which water escapes the contact interface. Hence, it directly reduces both the equilibrium water film thickness during rainfall and the hydrodynamic pressure beneath the tire (Yu et al., 2020). Laboratory testing results suggested that a 77% increase in MTD produces a 9% increase in hydroplaning threshold speed (Dehnad & Khodaii, 2019). Numerical simulations have also corroborated this trend. While microtexture governs friction at low to moderate speed, where direct rubber-aggregate contact is largely maintained, macrotexture controls the decay of friction with increasing speed and the occurrence of hydroplaning by governing water drainage from the contact patch (Ong & Fwa, 2007). These findings support the integration of friction and hydroplaning requirements as explicit criteria in HMA design, rather than relying on friction properties to emerge as a byproduct of material selection (Chu & Fwa, 2016).

Because of the complexity and cost of full-scale experiments, numerical modeling has become the principal tool for quantifying tire-water-pavement interaction. Early mechanistic work by Ong and Fwa (2007) established 3D finite element (FE) models coupling solid mechanics and fluid dynamics to predict hydroplaning speed and the speed-dependent decay of wet friction. More recently, the coupled Eulerian-Lagrangian (CEL) formulation has emerged as the dominant framework for hydroplaning simulation. It avoids severe mesh distortion that a purely Lagrangian description of the water film would incur. Ding and Wang (2018) developed a 3D grooved tire-water-pavement CEL model to predict hydroplaning speed as a function of pavement surface, rainfall intensity, number of traffic lanes, and rutting depth. Zhu et al. (2022) extended the CEL approach to incorporate measured 3D textures of SMA, open-graded friction course, and dense HMA surfaces, capturing the influence of pavement morphology, slip ratio, and water film thickness on the simulated skid number. At the network scale, these interaction models have been combined with spatial-temporal water film prediction to estimate lane-by-lane hydroplaning probability during rainfall events and to derive variable speed limits as a mitigation strategy (Chen & Wang, 2023).

Building on the FE and CEL approaches, hydroplaning to quantify wet-weather tire-pavement interaction is modeled. A developed framework, which integrates measured pavement surface textures into the tire-water-pavement interaction problem, provided a mechanistic basis for evaluating the influence of macrotexture on hydroplaning critical speed and, by extension, on driving safety.

MODEL DEVELOPMENT

Pavement Texture

The pavement surface texture workflow adopted in this study consisted of three main stages: (i) data acquisition and 3D reconstruction, (ii) point cloud preprocessing, and (iii) FE model generation, as summarized in Figure 50. The surface macrotexture of each pavement was captured by close-range photogrammetry and reconstructed into a high-resolution 3D point cloud using the Structure-from-Motion (SfM) pipeline described in Chapter 2.

The reconstructed point clouds were then processed through a standardized pipeline that ensured geometric consistency and prepared the data for numerical implementation. The processed surfaces

were incorporated into the FE framework to represent realistic pavement textures in the tire-water-pavement interaction simulations. The same preprocessed surfaces also provided the height fields used for the power spectral density and friction characterization described in the “Tire-Pavement Friction Model” section.

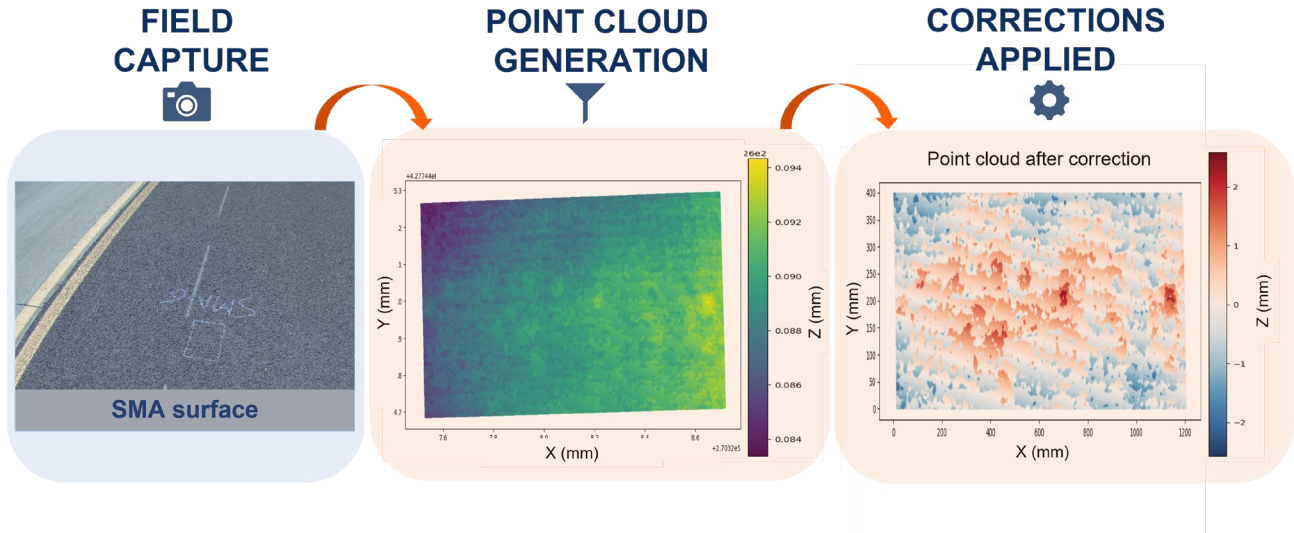


Figure 50. Schematic. Pavement surface texture processing workflow.

The pavement surface data corresponded to four surface macrotextures—SMA, chip seal (CS), dense-graded HMA (DGHMA), and microsurfacing (MS)—each acquired as a 3D point cloud stored in a space-delimited text file, in which every point was defined by its spatial coordinates (X, Y, Z) in meters. Prior to FE model generation, all datasets were processed through a standardized preprocessing pipeline implemented in Python. The pipeline consisted of four sequential steps: (i) removal of invalid points, (ii) coordinate conversion, (iii) spatial cropping, and (iv) slope removal. The DGHMA surface is used throughout this section as a representative example to illustrate each step. This procedure was identical for the remaining three surfaces.

In the first step, points with a Z-coordinate equal to zero were identified as invalid returns and removed, as they did not represent valid surface elevations. The remaining coordinates were then converted from meters to millimeters for consistency with the unit system adopted in the tire-water-pavement interaction model. A local coordinate system was established by translating each axis so that its minimum value coincided with the origin. Figure 51-A presents a top-down view of the DGHMA surface after this step.

The point clouds were subsequently cropped in both the transverse (Y) and longitudinal (X) directions. A fixed-width window centered at the midpoint of the Y-range was applied in the transverse direction, and a window of the target length centered at the midpoint of the X-range was applied in the longitudinal direction. These operations matched the geometric requirements of the tire-water-pavement interaction model and ensured that the retained data formed a rectangular domain suitable for subsequent matrix-based processing. Each cropped axis was re-referenced to zero. Figure 51-B presents the cropped DGHMA surface colored by elevation.

Finally, the global surface slope was removed by fitting a plane of the form $Z = aX + bY + c$ to the elevation data by ordinary least-squares regression and subtracting it from the measured surface. This detrending step isolated the surface texture by eliminating the systematic longitudinal and transverse gradients present in the raw measurements. Figure 51-C presents the resulting height (Z) distribution of the detrended DGHMA surface, while Figure 51-D presents a top-down view of the final preprocessed surface.

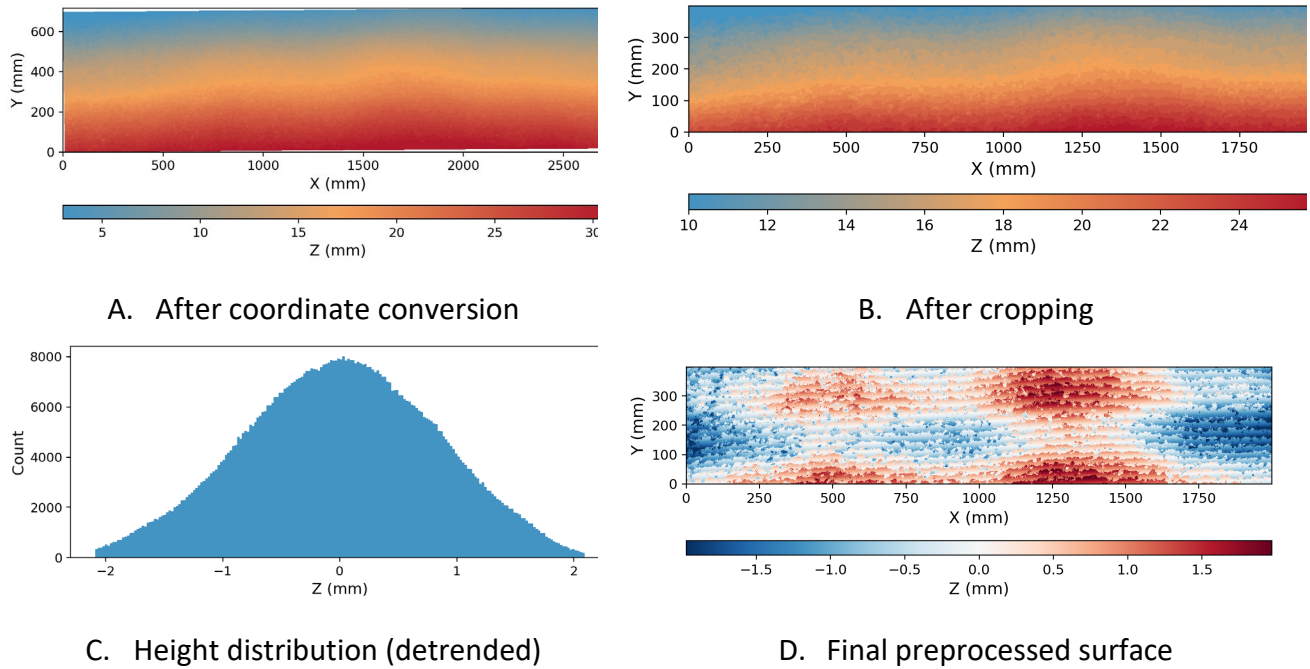


Figure 51. Graph. Dense-graded hot-mix asphalt point cloud at successive preprocessing stages: (a) after coordinate conversion, (b) after cropping, (c) height distribution after detrending, and (d) top-down view of the final preprocessed surface.

After preprocessing, each surface was converted into a numerical surface model and imported into Abaqus, a commercial FE software, using the Rough Surface Generator plug-in (Lim & Ha, 2023). The reconstructed pavement surfaces were modeled as rigid 3D shell surfaces discretized with 1 mm rigid quadrilateral elements (R3D4 in Abaqus nomenclature). It provided sufficient geometric resolution to capture the wavelength range associated with pavement macrotexture while maintaining numerical stability in the fluid-solid interaction analysis. Figure 52 presents the four FE-modeled pavement macrotextures, and Table 12 summarizes their main characteristics. The four surfaces spanned a wide range of macrotexture, with mean profile depths (MPDs) increasing from 0.535 mm for the DGHMA to 2.4 mm for the CS.

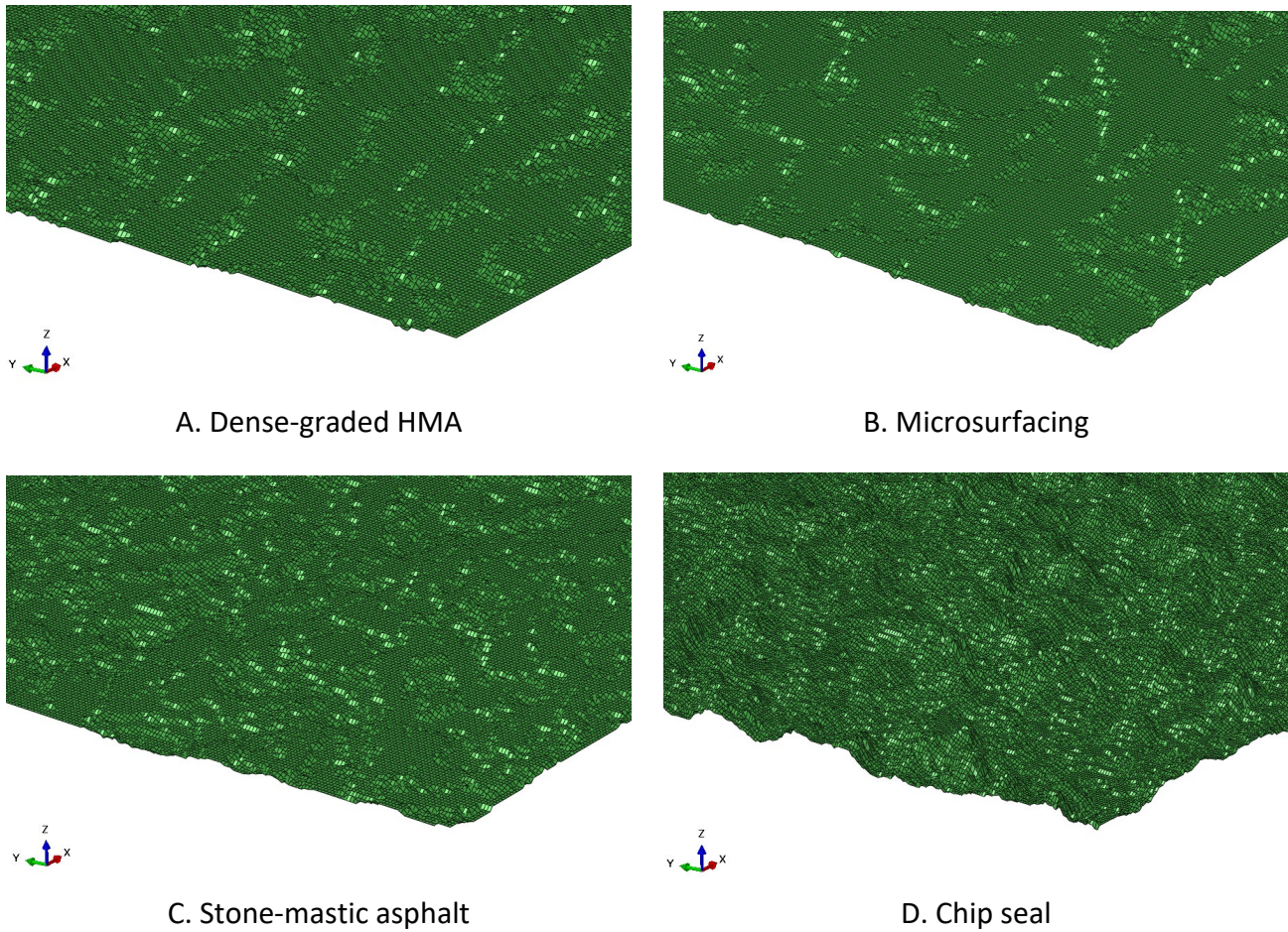


Figure 52. Schematic. FE-modeled pavement macrotextures: (a) dense-graded hot-mix asphalt, (b) microsurfacing, (c) stone-mastic asphalt, and (d) chip seal.

Table 12. Summary of the Modeled Pavement Surface Textures

Surface type	Abbreviation	Nominal size, L × W (mm)	MPD (mm)
Dense-graded HMA	DGHMA	2000 × 400	0.535
Microsurfacing	MS	1150 × 400	0.720
Stone-mastic asphalt	SMA	2000 × 400	0.920
Chip seal	CS	1900 × 400	2.4

Tire-Pavement Friction Model

A physics-based friction model was implemented to link measured pavement texture and tire rubber viscoelasticity to the tire-pavement friction coefficient. The model followed Persson’s multiscale rubber friction framework, in which friction was generated primarily by hysteretic losses within the rubber as pavement asperities repeatedly deformed it across many length scales (Liu et al., 2019; Persson, 2001).

Pavement surface texture was characterized using high-resolution 3D measurements. The measured height field was converted into an isotropic (radially averaged) power spectral density (PSD), denoted $C(q)$. In this notation, q is wavevector magnitude (spatial frequency) associated with texture wavelength $\lambda = \frac{2\pi}{q}$. The PSD provided a compact statistical description of roughness distribution across wavelengths and served as the primary texture input to friction calculation.

As the tire moved relative to the surface at speed V , each texture wavelength excited the rubber at an effective angular frequency $\omega = qV$. As the tire rubber is viscoelastic, part of the deformation energy was dissipated rather than stored. The rubber response was represented using a Prony series relaxation function in Abaqus and transformed to the frequency domain to obtain the complex modulus $E^*(\omega) = E'(\omega) + iE''(\omega)$. The storage modulus $E'(\omega)$ governs the recoverable elastic response, whereas the loss modulus $E''(\omega)$ quantifies the deformation energy dissipated per cycle and, therefore, controlling the contribution strength of each wavelength to hysteretic friction.

Real contact did not extend across the entire nominal footprint at all texture scales. At coarse scales (longer wavelengths), the rubber conformed to the surface, and contact approached the nominal area. At finer scales (shorter wavelengths), the local pressure was generally insufficient to press the rubber into the smallest valleys, and the effective contact fraction decreased. This scale-dependent effect was represented by the contact function $P(q)$, defined as the fraction of the nominal contact area that remained in contact when roughness components up to wavevector q were resolved. In the friction integral, $P(q)$ acted as a weighting factor that reduced the contribution from short-wavelength texture that did not fully participate in contact. The friction coefficient was expressed as follows in Figure 53:

$$\mu = \frac{1}{2(1 - \nu^2)\sigma_o} \int_{q_o}^{q_1} q^3 * C(q)P(q)E''(qV) dq$$

Figure 53. Equation. Persson friction calculation.

where σ_o is mean contact pressure over the nominal contact area, ν is Poisson ratio of rubber, and V is relative speed at interface. The integral is evaluated over the wavevector range represented by the measured texture and the selected spatial resolution, from the lowest resolved wavevector q_o to the highest q_1 . The factor q^3 represents the geometric excitation strength of each texture scale, $E''(qV)$ introduces speed and temperature dependence through the rubber viscoelasticity, and $P(q)$ reduces the contribution from wavelengths for which contact was incomplete. Speed is considered through $\omega = qV$ of the loss modulus.

The inputs required for the Persson-based hysteresis calculation were the following: (i) measured PSD $C(q)$ from the provided texture; (ii) rubber loss modulus $E''(\omega)$ obtained from viscoelastic characterization; (iii) mean contact pressure σ_o ; and (iv) scale-dependent contact function $P(q)$. Once these inputs were established, the μ was calculated over the operating speed range and used as the baseline in the 3D FE tire model. The rubber loss modulus was taken from literature studies owing to

the unavailability of the measured data (Lorenz et al., 2015). Figure 54 presents the final obtained hysteresis friction curve for all surface textures.

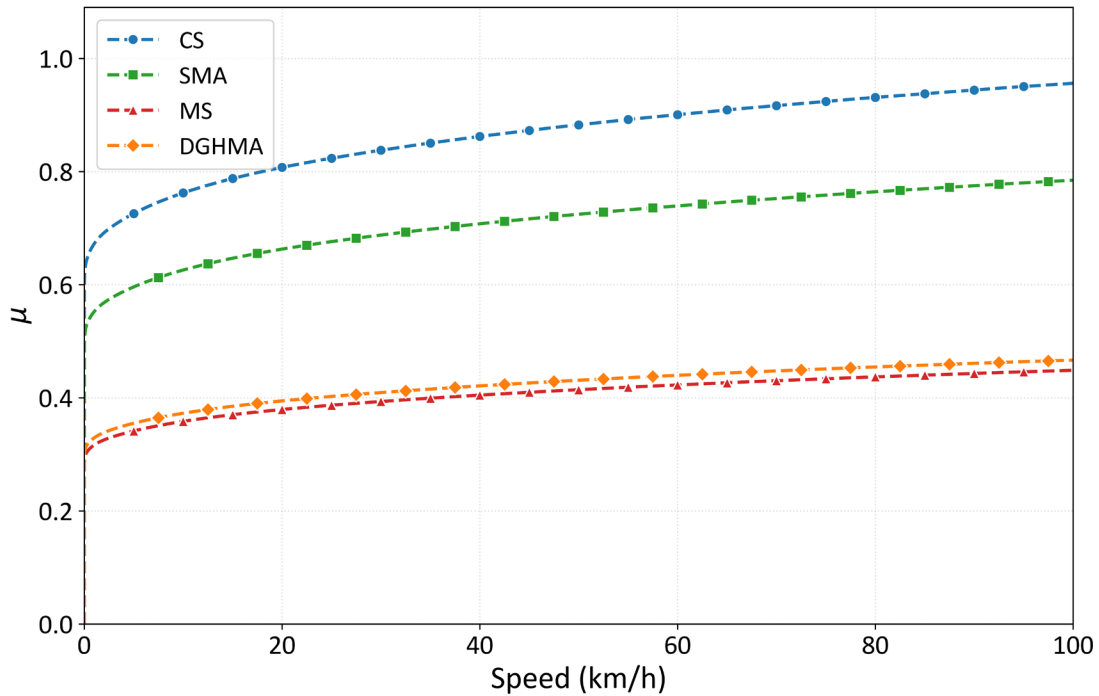


Figure 54. Graph. Friction versus speed curve.

This approach offers several practical advantages over an empirical velocity-dependent friction model. It directly links friction to measurable pavement texture, enabling the effects of mixture type, macrotexture level, and texture evolution to be evaluated without recalibrating the friction model. It also introduces speed- and temperature-dependent behavior through the viscoelastic modulus. The model captures the macrotexture-driven hysteresis component of friction, which is most relevant at moderate to high speeds, particularly on wet surfaces and in hydroplaning-related safety assessments.

Tire Model Generation

The FE model of a passenger car tire was generated in Abaqus through a sequence of four simulation stages, each building upon the previous one through the restart capability. This staged approach was adopted to incrementally construct the 3D tire assembly and to establish the steady-state free-rolling condition that served as the starting point for the hydroplaning analysis. Figure 55 illustrates the tire model at the successive construction stages.

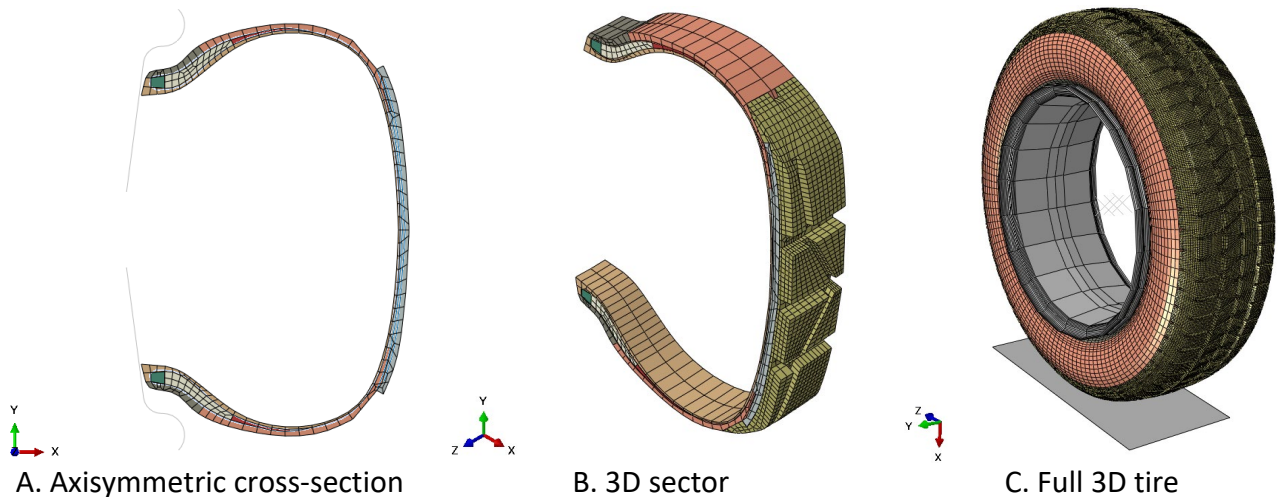


Figure 55. Schematic. Stages of the passenger-car tire FE model generation: (a) axisymmetric cross-section, (b) 3D sector, and (c) full 3D tire.

In the first stage, an axisymmetric representation of the tire cross-section was constructed (Figure 55-A). The tire carcass was discretized using generalized axisymmetric elements with twist (CGAX4R and CGAX3), while the reinforcement plies and steel belts were modeled as surface elements with embedded rebar layers (SFMGAX1). The left and right rim flanges were defined as analytical rigid surfaces controlled by reference nodes. The rubber components were described using Neo-Hookean hyperelastic constitutive models. The belt and ply cords were described with Marlow hyperelastic formulations calibrated from uniaxial test data. A linear elastic characterization was assigned to the steel bead. A static mounting step established the reference configuration under the prescribed boundary conditions.

In the second stage, a 3D sector model was generated from the axisymmetric cross-section by revolving the mesh 5.806° about the tire axis using the symmetric model generation capability (Figure 55-B). A 3D tread pattern was incorporated and tied to the carcass outer surface through a surface-to-surface tie constraint. Cyclic symmetry was imposed on the sector faces through multi-point constraint equations. The rim flanges were positioned at their nominal axial locations, and a uniform inflation pressure was applied to the inner surface of the tire.

In the third stage, the sector was developed into a complete 360° tire by a periodic symmetric model generation over 62 circumferential segments (Figure 55-C). A new analytical rigid rim, defined as a surface of revolution, replaced the original planar rim definitions of the axisymmetric model, and an analytical rigid road surface was introduced as the support against which the tire was loaded. A sequence of static steps then transferred the rim contact, reapplied the inflation pressure, raised the rim-tire friction coefficient to unity, displaced the rim toward the road, and applied the prescribed vertical load to the rim reference node.

In the fourth stage, a steady-state transport analysis established the free-rolling condition. The tire angular velocity was prescribed as a transport velocity corresponding to the target rolling speed, and the friction coefficient computed with the model described in the “Tire-Pavement Friction Model”

section was assigned to the road-tire contact. The resulting deformed, pre-stressed, free-rolling tire provided the initial state for the hydroplaning analysis presented in the “Tire-Water-Pavement Interaction” section.

Tire-Water-Pavement Interaction

Tire-water-pavement interaction was modeled to quantify how a water film reduces the tire-pavement solid contact and, consequently, the available friction. During hydroplaning, undrained water accumulates in front of and beneath the tire and generates hydrodynamic pressure that partially or fully separates the tire from the pavement. This uplift reduces the normal contact force and significantly degrades braking and steering capacity. Laboratory and numerical studies have identified the principal factors that control hydroplaning as (i) water-film thickness, (ii) vehicle speed, (iii) tire inflation pressure and wheel load, (iv) tread and groove design, and (v) pavement texture and drainage capacity (Chen & Wang, 2023; Tang et al., 2019; Zhu et al., 2017). Thicker water films increase the hydrodynamic lift and lower the critical hydroplaning speed, whereas higher inflation pressure raises the mean contact pressure and the hydrodynamic threshold (Maleska et al., 2021; Zhu et al., 2017). Pavement texture and connected void pathways are particularly influential at higher speeds. They provide drainage channels that relieve the water pressure within the tire footprint. Open-graded friction courses and grooved surfaces have frequently been reported to reduce hydroplaning risk by improving water evacuation (Dehnad & Yazdi, 2024; Fwa et al., 2009).

A coupled Eulerian–Lagrangian (CEL) approach in Abaqus/Explicit was used to represent the fluid-structure interaction. The tire was modeled with a Lagrangian mesh, which captured the rubber deformation and the evolving contact tractions, while the water and the surrounding air were carried on a fixed Eulerian mesh. This separation accommodated the large tire deformation and the interfacial contact without the severe mesh distortion that would arise if the fluid were modeled on a purely Lagrangian mesh. The water free surface was tracked through an Eulerian volume fraction field, a volume-of-fluid formulation that represented wave formation, splashing, and local drainage through the grooves and macrotexture channels (Ding & Wang, 2020). Figure 56 illustrates the coupled tire-water-pavement interaction model used in the analysis.

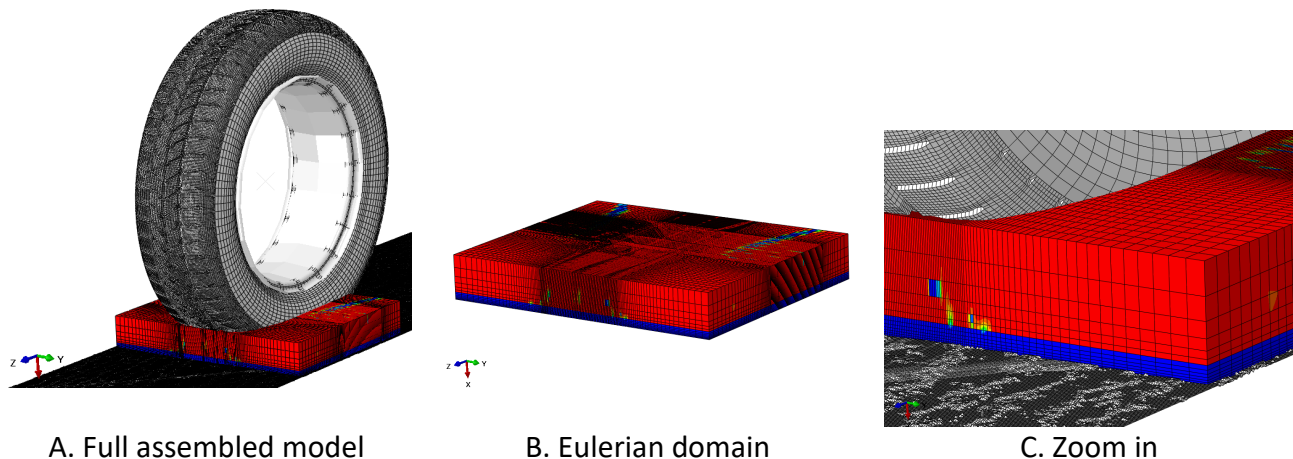


Figure 56. Schematic. Coupled Eulerian–Lagrangian tire-water-pavement interaction model: (a) full assembled model, (b) Eulerian domain, and (c) tire-water-pavement interaction zoom in.

Within the Eulerian domain (Figure 56-B), water flow is governed by the conservation of mass and momentum. The continuity equation is written as follows in Figure 57:

$$\frac{d\rho}{dt} + \nabla \cdot (\rho u) = 0$$

Figure 57. Equation. Continuity equation.

which, under the commonly adopted incompressible assumption (constant ρ), reduces to $\nabla \cdot u = 0$. The momentum equation is expressed as follows in Figure 58:

$$\rho \left(\frac{du}{dt} + u \cdot \nabla u \right) = -\nabla p + \eta \nabla^2 u + \rho g$$

Figure 58. Equation. Momentum equation.

where u is fluid velocity, p is pressure, η is dynamic viscosity, and g is gravitational acceleration. The boundary and initial conditions determine whether the analysis represents thin-film wet friction or approaches full hydroplaning. In the considered model, a prescribed initial water-film thickness was assigned on the pavement surface, and inlet and outlet boundaries allowed water to enter and leave the Eulerian domain as the tire rolled through the wetted region.

The hydroplaning analysis was carried out as an explicit dynamic step that imported the deformed, pre-stressed, free-rolling tire from the steady-state rolling stage. The Eulerian domain was initially filled with water, modeled by a linear U_s – U_p equation of state (bulk sound speed 1,500 m/s, density 1,000 kg/m³) with a Newtonian viscous deviatoric response. The textured rigid pavement surface introduced earlier replaced the analytical road used during tire generation (Figure 56-A). The tire was free to spin about its axis and to translate vertically, the wheel load was maintained as a concentrated force on the rim reference node, and the inflation pressure was held constant. The pavement translated beneath the tire at the prescribed rolling speed, while an inlet boundary supplied water at the same speed to sustain the film. General contact resolved the interaction among the Lagrangian tire, the Eulerian water, and the pavement (Figure 56-C), with the road-tire friction defined as in the steady-state rolling stage.

NUMERICAL MATRIX OF SIMULATED TIRE ROLLING CONDITIONS

A simulation matrix was developed to evaluate the hydroplaning potential of the passenger-car tire across the four pavement macrottextures. Table 13 summarizes the parameter combinations considered in the numerical study. The vertical wheel load and the inflation pressure were held constant at 3.92 kN and 0.24 MPa, respectively, representing standard half-axle loading for a passenger vehicle. A water-film thickness of 10 mm was maintained in all simulations to represent a critical ponding condition.

Table 13. Simulation Matrix of Tire Rolling Conditions for the Hydroplaning Analysis

Parameter	Value or Range	Role
Vertical wheel load	3.92 kN	Constant
Inflation pressure	0.24 MPa	Constant
Water-film thickness (above road plane)	10 mm	Constant
Pavement macrotexture	DGHMA, MS, SMA, CS	Varied (four surfaces)
Rolling speed	65–115 km/h, or until hydroplaning	Varied
Tire-pavement friction coefficient	Per texture and rolling speed	Derived

The four pavement macrotextures—DGHMA, MS, SMA, and CS—were modeled to capture the influence of surface texture on the tire-water-pavement interaction and the resulting hydroplaning speed. For each surface, the tire-pavement friction coefficient obtained from the Persson-based hysteresis model presented in the “Tire–Pavement Friction Model” section was assigned to the road-tire contact, yielding one coefficient per texture and rolling speed. The rolling speed was then increased from 65 to 115 km/h, or until hydroplaning occurred. The lowest speed at which hydroplaning developed defined the hydroplaning speed for that surface and served as the primary metric for comparing the four macrotextures.

RESULTS AND DISCUSSION

The hydroplaning response of the tire on each of the four pavement textures was evaluated from the coupled Eulerian-Lagrangian analyses. Three complementary aspects of the response were examined: water flow and drainage through the tread-groove system, the progressive loss of tire-pavement contact force as the water film developed, and the resulting hydroplaning speed of each surface. The hydroplaning speed was taken as the speed at which the hydrodynamic lift approached the applied wheel load and the remaining tire-pavement solid contact dropped to zero. Pavement macrotexture influenced all three aspects, principally through its control of the water-pressure buildup and drainage within the contact patch.

Water Flow Within Tire Groove System

The water flow through the tread-groove system was visualized using the Eulerian volume fraction field, which represents the distribution of water and air within the contact region. Across the four surfaces, the water accumulated as a wedge-shaped bow wave at the leading edge of the footprint, was channeled into the longitudinal grooves as the tire advanced, and was discharged toward the lateral groove exits and the trailing edge. The pavement macrotexture provided additional drainage paths beneath the tread, allowing part of the water to escape through the interconnected surface voids rather than remaining trapped under the tread ribs. Figure 59 presents the computed volume fraction field for the four macrotextures at a representative rolling condition. Regions fully occupied by water are displayed in blue and void (air-filled) regions in red.

The surfaces are presented in order of increasing macrotexture: DGHMA (Figure 59-A), MS (Figure 59-B), SMA (Figure 59-C), and CS (Figure 59-D). On the finer-textured DGHMA and MS, a larger fraction of the water remained beneath the tread ribs. The wetted region extended further across the leading

portion of the footprint. On the coarser SMA and CS surfaces, the deeper and more interconnected surface voids offered additional drainage near the rib edges. The water escaped the footprint more readily, and the wetted region was more confined.

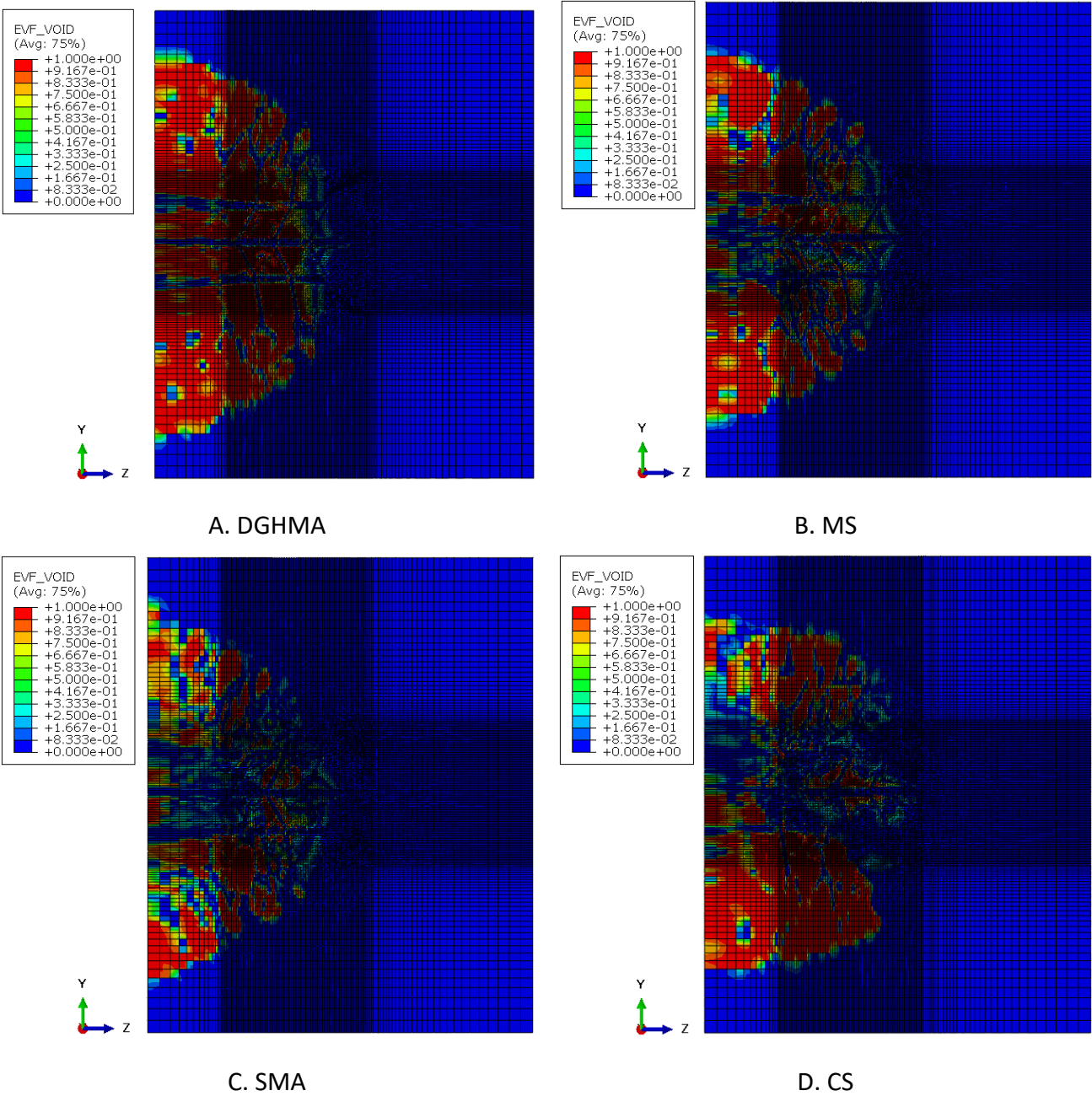


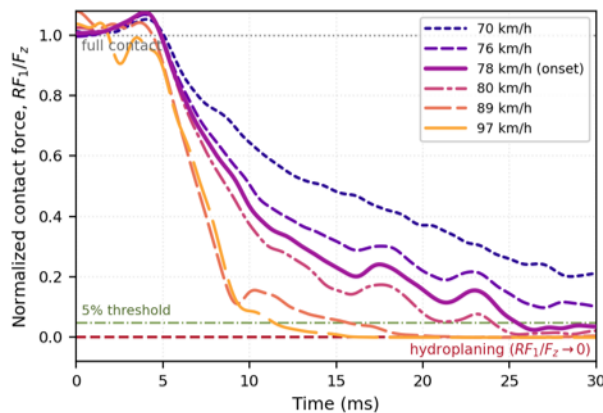
Figure 59. Graph. Water volume fraction field in the tire-pavement contact region for the four pavement macrotextures: (a) DGHMA, (b) MS, (c) SMA, and (d) CS.

Contact Force Drop

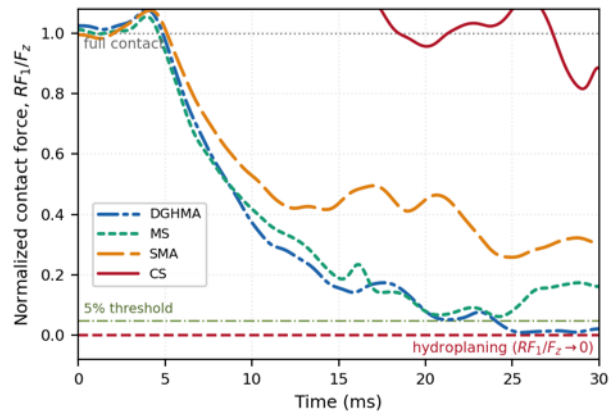
The loss of tire-pavement contact as the water film developed was quantified from the vertical reaction force transmitted through solid contact at the road reference node, normalized by the applied wheel load (RF_1/F_z). A normalized value of one corresponds to full solid contact, whereas a value of zero corresponds to complete hydroplaning, in which the hydrodynamic lift carries the entire wheel load. Figure 60 presents this normalized contact force as a function of time for two complementary cases: (a) a single surface at several rolling speeds and (b) the four macrotextures at a common rolling speed. In both panels the contact force was evaluated in the steady-state window ($t \geq 18$ ms), after the initial drainage transient had decayed.

Figure 60-A presents the response of the DGHMA surface as the rolling speed was increased from 65 to 115 km/h. At the lower speeds, the normalized contact force decreased during the initial interaction with the water film but stabilized at a positive steady-state value, indicating that solid contact was maintained. As the speed increased, the steady-state contact force decreased progressively until, at 78 km/h, it reached zero and the tire fully hydroplaned. Following the criterion adopted in this study, the hydroplaning speed was identified as the lowest rolling speed for which the steady-state contact force fell below 5% of the wheel load—that is, the effective loss of solid tire-pavement contact.

Figure 60-B compares the four macrotextures at a common rolling speed of 80 km/h. At that speed, the DGHMA reached zero contact and therefore hydroplaned, whereas the MS, SMA, and CS surfaces retained a positive contact force and did not. The surfaces that maintained contact were those with the greater macrotexture and drainage capacity, reported in Table 12, indicating that pavement macrotexture raises the speed at which hydroplaning occurs. The resulting per-surface hydroplaning speeds are summarized in the following subsection.



A. DGHMA—speed sweep



B. Texture comparison at 80 km/h

Figure 60. Graph. Normalized tire-pavement contact force (RF_1/F_z) during water-film interaction: (a) DGHMA at several rolling speeds; and (b) the four macrotextures at 80 km/h.

Hydroplaning Speed

Figure 61 summarizes the hydroplaning speed of each pavement surface. The values obtained were 78 km/h for DGHMA, 89 km/h for MS, and 97 km/h for SMA. CS retained solid contact at every rolling speed tested (up to 89 km/h) and did not hydroplane within the speed range examined; its hydroplaning speed therefore exceeds 89 km/h and could not yet be determined.

The hydroplaning speed increased with pavement macrotexture, per the MPD reported in Table 12. The finer-textured DGHMA and MS surfaces hydroplaned at the lowest speeds, whereas the coarser SMA and CS maintained solid contact to higher speeds. Deeper and more interconnected surface voids evacuated water, increased drainage capacity from the contact patch more effectively, and delayed the development of hydrodynamic lift. This behavior reflects the greater drainage capacity of the coarser surfaces.

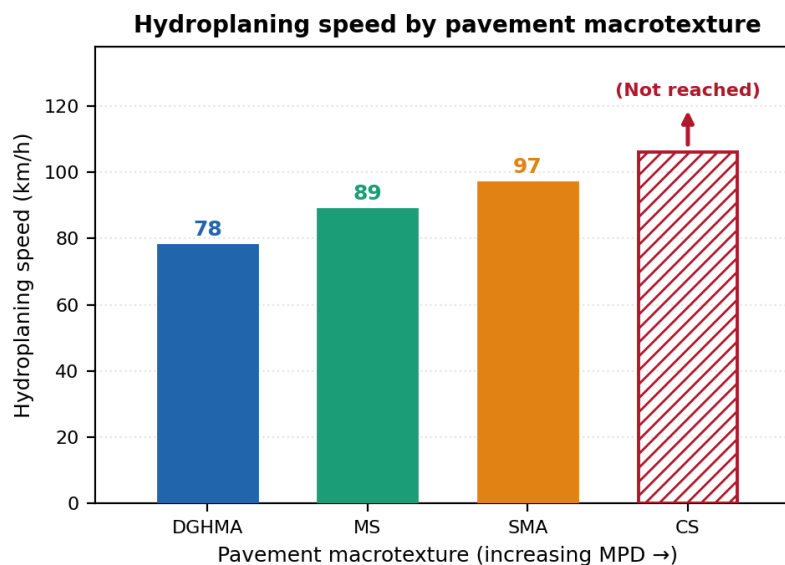


Figure 61. Bar plot. Hydroplaning speed of the four pavement surface macrotextures.

SUMMARY

This chapter presented a FE model simulating hydroplaning performance of a passenger-car tire on textured pavement surfaces. Four pavement macrotextures—DGHMA, MS, SMA, and CS—were reconstructed from field measurements and represented as rigid textured surfaces. A 3D tire model was generated through a staged Abaqus workflow and brought to a steady-state free-rolling condition, and a texture-specific tire-pavement friction coefficient was assigned from a Persson-based hysteresis friction model. The tire-water-pavement interaction was then represented using a coupled Eulerian-Lagrangian formulation, in which the deformable tire rolled through a Eulerian water film over the textured pavement. The analyses were organized into a simulation matrix at a fixed wheel load (3.92 kN), inflation pressure (0.24 MPa), and water-film thickness (10 mm), with the rolling speed swept from 65 to 115 km/h for each of the four surfaces.

Water flow, loss of tire-pavement contact, and resulting hydroplaning speed were examined for each surface. Volume-fraction fields demonstrated that water accumulated at the leading edge of the contact patch. It was evacuated through tread grooves and pavement macrotexture. Coarser surfaces provided additional drainage pathways. As the rolling speed increased, the solid contact force decreased toward zero, and the hydroplaning speed was identified as the speed at which solid tire-pavement contact was lost. The hydroplaning speeds ranged from 78 to 97 km/h and increased with pavement macrotexture. Results indicate that pavement macrotexture, through its control of water drainage within contact patch, is a primary factor governing the hydroplaning resistance of a surface.

CHAPTER 6: SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS

SUMMARY

Loss of pavement surface friction is a key determinant to traffic safety. Agencies rely on continuous friction measurement equipment, including high-speed laser scanners, that are expensive to acquire and operate, require extensive training, and are difficult to deploy at the network level. Consequently, many roadway segments are surveyed infrequently and opportunities to identify and treat low-friction locations are missed. A contactless and automated technique was developed to identify HMA pavement surface friction using inexpensive and scalable equipment, combining computer vision image-based 3D reconstruction of pavement texture with machine learning models that infer friction. An integrated approach was followed that encompassed computer vision algorithm development, design, construction, and validation of a high-speed data collection prototype, friction predictive model development, and hydroplaning modeling.

A computer vision framework based on Structure from Motion was developed to reconstruct pavement macrotexture in three dimensions and compute mean profile depth (MPD) in a manner that could be scaled to network-level data collection. The framework included an image acquisition strategy that mitigated reconstruction distortions on planar pavement surfaces, georeferencing and scaling using real-time kinematic (RTK) positioning through either surveyed ground control points or position data embedded in the images, and a point-cloud processing pipeline that rasterized the surface, applied a bandpass filter consistent with the applicable standard, and computed MPD. The framework was evaluated using a digital single-lens reflex camera with ground control points, the same camera with RTK position data embedded in the images, and a pair of action cameras mounted on a moving vehicle. The resulting texture measurements were compared against a reference laser scanner.

A prototype was designed, built, and validated at 35 mph to demonstrate that the framework could be ultimately deployed at traffic speed. The system integrated two industrial cameras with a global shutter, an RTK positioning system with inertial navigation, a vehicle mounting structure, and custom data acquisition software that synchronized image capture with positioning. Captured images were converted, georeferenced, and processed into 3D point clouds using cluster computing, from which longitudinal profiles, texture, and friction were derived. The system was validated at the Illinois Certification and Research Track in Trenton, Illinois, by comparing its texture measurements with those of a laser texture scanner on four asphalt surfaces of increasing macrotexture.

A data-driven model was developed to predict sideways friction measured by a Sideway-force Coefficient Routine Investigation Machine (SCRIM). The model used pavement texture, expressed as MPD, together with AADT, roadway geometry, vehicle operating speed, and surface temperature. Three datasets collected by the Florida and Illinois Departments of Transportation were used to evaluate the effects of dataset size, feature availability, and data distribution. After preprocessing and filtering, several tree-based ensemble models, including Random Forest, Gradient Boosting, Extreme

Gradient Boosting, and Extra Trees, were trained, tuned, and compared using standard error and goodness-of-fit metrics. The Extra Trees model was selected for interpretation, and the contribution of each feature to the prediction was examined to verify that the model logic was consistent with engineering knowledge.

Finally, a finite element framework was developed to evaluate hydroplaning by modeling the interaction among a rolling tire, a water film, and the pavement surface. Four pavement surfaces spanning a wide range of macrotexture (dense-graded HMA, microsurfacing, SMA, and chip seal) were reconstructed from field measurements and represented as textured rigid surfaces. A 3D passenger-car tire model was generated and brought to a steady-state free-rolling condition, and a texture-specific friction coefficient derived from a multiscale rubber-hysteresis friction model was assigned to the tire-pavement contact. The tire-water-pavement interaction was represented using a coupled approach that tracked the water film as the tire rolled over each surface at a fixed wheel load, inflation pressure, and water-film thickness, with the rolling speed increased until the tire lost contact with the pavement.

CONCLUSIONS

A technique was developed to predict HMA pavement surface friction contactlessly and automatically. Image-based 3D reconstruction of pavement texture was combined with machine learning to provide a practical foundation for lower-cost, high-frequency monitoring. The following are additional conclusions of this study:

- Structure-from-Motion photogrammetry is a viable and scalable alternative to laser scanning for measuring pavement macrotexture. Capturing tilted, height-varied images eliminated the reconstruction distortion that occurs on flat pavement surfaces, and accurate positioning, through surveyed ground control points or real-time kinematic data, was the primary requirement for reliable reconstruction.
 - The ground-control configuration produced the most accurate reconstructions. In preliminary testing, its MPD measurements agreed with a reference laser scanner within 15% at various test locations. The method tended to underestimate MPD relative to the laser scanner, which is consistent with previous studies. This is due in part to the introduction of a smoothing effect during rasterization.
 - A vehicle-mounted prototype using industrial cameras and precise positioning collected the data required for contactless texture evaluation at speeds up to 35 mi/hr, and processing the images in cloud and cluster computing environments increased processing speed and supports scaling. Texture measurements were consistent with laser-based equipment and difference increased with mixture aggregate size.
- A finite element framework was developed that provides a mechanistic basis for relating pavement macrotexture to wet-weather safety. Simulation results demonstrated that coarser surfaces maintained tire-pavement contact at higher speeds, indicating that macrotexture is an important factor in hydroplaning resistance.

- Tree-based ensemble models predicted continuous sideways friction effectively, and the Extra Trees model performed best across all datasets. The approach can be generalized across agencies, as it remained effective under different data collection conditions, sample sizes, and feature sets.
 - The Extra Trees model explained about 85% of the variance on the 2025 Illinois dataset and produced the lowest prediction errors on the larger Florida benchmark dataset, while requiring only a short training time.
 - Mean profile depth, AADT, vehicle operating speed, and surface temperature were the most influential predictors, whereas roadway geometry variables such as cross slope, grade, and curve radius had relatively small effects. Prediction accuracy is expected to improve as larger datasets with additional information related to pavement surface properties become available.
- Friction surveys cost at least \$125/mile, and texture measurements cost about \$57/mile with transverse profilers and \$50/mile with wide-footprint laser scanners. Collecting both in the same survey could cost \$140/mile, and the equipment costs about \$1,000,000 for a transverse profiler and \$100,000 for a laser scanner. The developed device provides texture measurements and friction estimates for \$61/mile, about 55% less, and costs only \$73,500 to buy. By substantially lowering the cost of collecting pavement surface information, the approach can support more frequent and broader monitoring of pavement friction and texture, enabling proactive and safety-oriented pavement management consistent with IDOT's long-term performance and safety goals.

RECOMMENDATIONS

- Most SCRIM friction data were collected on relatively straight sections. To improve friction prediction accuracy, additional SCRIM data should be collected for conditions that were under-represented in the current datasets, particularly low testing speeds, low and high surface texture levels, curved alignments, and a wide range of surface types.
- Residual errors indicated that friction is governed by surface and material characteristics that may not be captured by MPD only. Including raw elevation data (point cloud) and additional texture descriptors (e.g., surface type, aggregate type, binder characteristics, and surface age) would enhance the prediction model.
- A dedicated lighting system with sufficient wattage and the ability to synchronize with the camera shutter is needed to support expanded data collection under varying ambient light conditions and shadow directions.
- Although no delays were encountered during data collection, it is recommended to use a distance measuring instrument, such as a wheel-mounted encoder, to trigger both cameras and the GNSS receiver. In addition, all equipment should be connected to a specialized reliable and robust synchronization circuit.

- The developed system should be configured to process data on an enterprise cloud computing service (e.g., Amazon Web Services and Microsoft Azure), where different types of compute resources can be tested to achieve the lowest cost per mile. In addition, a cost analysis should be conducted to compare the capital and operational cost of the developed system and the current state-of-the-art equipment.

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