

Article

Prediction of Friction Coefficient Based on 3D Texture Characteristics of Road Surfaces

Matúš Kováč , Matej Brna , Peter Pisca  and Martin Decký

Department of Highway and Environmental Engineering, Faculty of Civil Engineering, University of Žilina, Univerzitná 8215/1, 010 26 Žilina, Slovakia; matus.kovac@uniza.sk (M.K.)

* Correspondence: matej.brna@uniza.sk; Tel.: +421-41-5135942

Abstract: Accurate assessment of road pavement friction is crucial for maintaining road safety. This study explores the prediction of the friction coefficient (μ) using 3D texture parameters of pavement surfaces. Measurements were conducted on 17 different rural road sections using the Traction Watcher One (TWO) for friction coefficients and a newly developed Static Road Scanner (SRS) for surface texture. Multiple linear regression models were created, incorporating texture parameters such as the valley material portion ($S_{mr2,MIC}$), arithmetic mean peak curvature ($S_{pc,MAC}$), and dale void volume ($V_{vv,PS}$). The results demonstrate a strong correlation between texture characteristics and friction, with R^2 values up to 0.80 and an RMSE as low as 0.076, validating the model's accuracy. This approach highlights the potential of using non-contact texture measurements for reliable prediction of friction, offering a significant advancement in pavement management and safety.

Keywords: skid resistance; friction coefficient; 3D texture parameters; pavement texture; predictive modeling



Citation: Kováč, M.; Brna, M.; Pisca, P.; Decký, M. Prediction of Friction Coefficient Based on 3D Texture Characteristics of Road Surfaces. *Appl. Sci.* **2024**, *14*, 7549. <https://doi.org/10.3390/app14177549>

Academic Editor: Luís Picado Santos

Received: 25 July 2024

Revised: 21 August 2024

Accepted: 24 August 2024

Published: 26 August 2024



Copyright: © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

Accurate diagnostics and assessment of road pavement friction are crucial to maintaining road safety throughout the pavement's lifecycle. Road safety is a critical concern, with a significant percentage of accidents potentially linked to insufficient skid resistance on pavements. While not all accidents can be attributed to this factor, the loss of human lives due to road conditions underscores the urgency of addressing this issue. According to [1], improving pavement friction has been shown to significantly reduce wet-pavement crash rates, emphasizing the need for ongoing research in this area. Our study aims to contribute to reducing such risks by enhancing the understanding and prediction of pavement friction through the analysis of 3D texture parameters.

Numerous methods and devices have been developed for skid resistance measurement [2]. Generally, these methods fall into two categories: those measuring the tangential force at the tire–pavement interface, resulting in a dimensionless friction coefficient [3], and those capturing the pavement surface texture. The surface texture of pavements is defined by irregularities with wavelengths shorter than 0.5 m, as noted in [4]. These textures are categorized into microtexture, macrotexture, and megatexture, which influence various tire–road interactions, including tire wear [5], rolling resistance [6,7], tire–road noise [8], and friction. The most significant impacts of these textures, based on their wavelength, are detailed in [4]. It is well-recognized that tire–road friction is mainly governed by micro and macrotextures [9,10].

Many different kinds of devices are actively used for direct friction coefficient measurement, each operating on different principles and under varied test conditions such as speed, slip (variable or fixed), tire type, water film depth, wheel load, and inflation pressure. These varied conditions, along with temperature and limited water availability, complicate the harmonization of skid resistance measurements and reduce practicality.

Considering the aforementioned details and the rapid advancements in surface sensing and data processing technologies, there is a growing focus on predicting skid resistance through non-contact texture measurements. In [11], an analytical model was proposed, demonstrating the importance of hierarchical surface structures in predicting anisotropic friction, adhesion, and wear in rough surface interactions. To predict the friction coefficient, mathematical models simulating a rubber element sliding over a rough surface have been developed [12–14]. The authors of [15] compare the results obtained by the proposed analytical model [14] with numerical results. The article [16] shows how the theory of contact mechanics and rubber friction developed by B.N.J. Persson was further extended. These models, though complex and physically grounded, require input on the rubber's viscoelastic properties, which can vary. Nevertheless, promising results have emerged from combining Persson's model with texture measurements on asphalt samples [17]. However, for texture-based skid resistance prediction, only pavement surface characteristics should be considered, keeping other variables constant for accurate comparisons and degradation model determinations. Researchers often use statistical regression models to predict skid resistance by correlating texture descriptors with measured friction coefficients. Various methodologies exist within this approach. For instance, the pavement texture–friction relationship was analyzed using image analysis techniques in [18]. Another study [19] explored the correlation between texture spectral levels and friction values at different speeds. A multiresolution analysis using three-dimensional (3D) asphalt pavement texture was used for asphalt pavement friction estimation [20]. The studies [21,22] explored pavement surface fractal characteristics regarding the friction coefficient. Additionally, a model for evaluating pavement skid resistance using 3D texture data was developed, yielding satisfactory test results as documented in [23]. The research on the skid resistance performance of asphalt pavement based on 3D texture feature parameters [24,25] introduces 3D texture characteristics to investigate the mechanism of pavement wear in rainy weather and conducts a comparative analysis of aggregate wear. Recent advancements in road surface perception using vision sensors, such as convolutional neural networks for classifying road surface conditions, have demonstrated significant potential in vehicle trajectory planning and driving assistance systems, particularly for autonomous vehicles [26,27].

Despite extensive research and several promising studies, the relationship between texture and friction remains not fully understood. No single texture parameter or evaluation method has yet achieved the high reliability and practical usability required for global acceptance in predicting friction through non-contact measurements.

This study aims to enhance the prediction of tire–road friction through contactless surface measurements. The primary contribution involves using a newly developed device that captures pavement surface details down to the microtexture level on road pavements in situ.

2. Measurement Tools and Experimental Methods

2.1. Traction Watcher One

Skid resistance was determined by measuring the longitudinal coefficient of friction (μ) using the Traction Watcher One (TWO) shown in Figure 1. The TWO is a vehicle-mounted instrument designed to measure fixed-slip friction on roads and runways. It uses a power transmission chain to connect two wheels, creating a precise slip value of 17.8% from the forward reference wheel to the rear measuring wheel. A water pump and control valve supply a water film in front of the measuring wheel. Friction coefficients can be accurately measured at speeds ranging from 10 to 110 km/h. The entire process is managed by the TWO's computer software (version V22.01) which displays real-time data on a monitor and simultaneously saves them to a database. Continuous measurement data can be exported with intervals as small as 0.5 m.

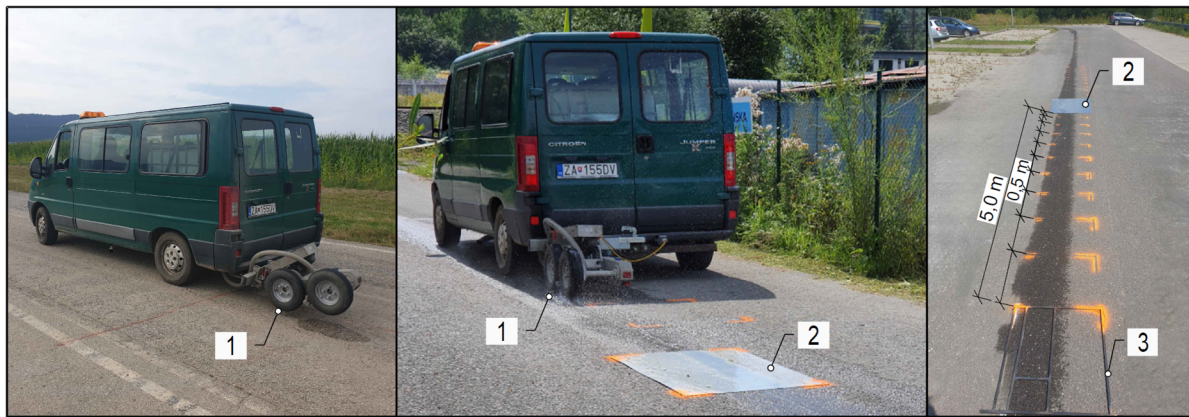


Figure 1. The TWO—Traction Watcher One and the metal sheet for the determination of the point of beginning. (1—Traction Watcher One; 2—Metal sheet; 3—Steel grid).

A smooth test tire and a water film with a thickness of 1.0 mm were used for the experiment. The water film was applied during the experiments to simulate real-world conditions wherein road surfaces are often wet, especially under adverse weather conditions. Measuring friction under wet conditions provides a more comprehensive understanding of how surface textures affect skid resistance, which is critical for safety assessments. The measuring speed for all sections was set to 40 km/h for safety reasons. Ensuring precise localization of measuring spots was crucial for accurate correlations between single-point texture measurements and continuous skid resistance measurements. Therefore, the results' interval was minimized to 0.5 m, and the exact point of the beginning of the measurement section (POB of MS) was marked using a metal sheet attached to the road (Figure 1, middle and right). Figure 2 illustrates how the metal sheet influences friction coefficient values and determines measuring point locations.

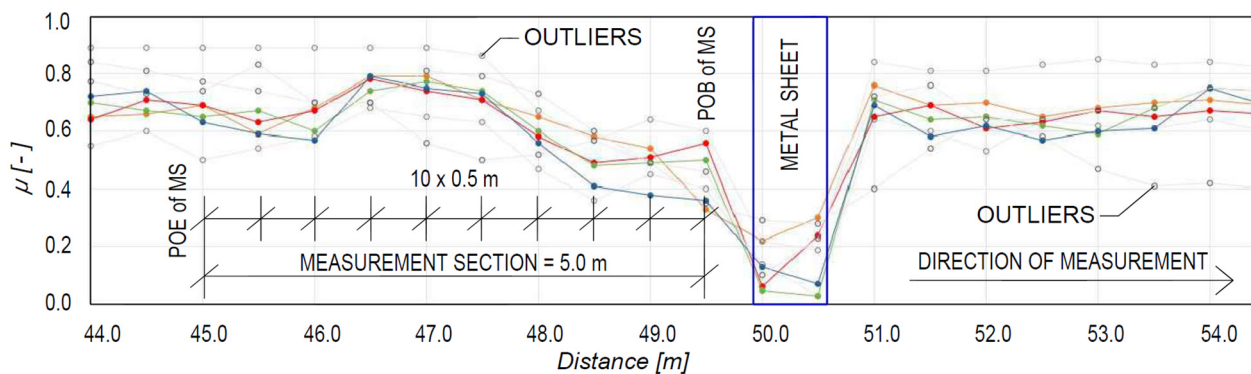


Figure 2. An example of results measured by TWO (friction coefficient μ) with the influence of metal sheet on obtained values. (Different line colors represent individual passes of the TWO device).

2.2. Static Road Scanner

Several studies have demonstrated that 3D texture analysis yields more accurate results than 2D profiles. Evaluating 2D texture parameters from profiles often falls short in describing particle shape and distribution, which are also crucial for determining tire–road interactions. One challenge in establishing a reliable relationship between texture parameters and coefficient of friction is the resolution limitations of 3D surface analyzers. Low-resolution scanners fail to capture essential microtexture surface properties crucial for determining friction levels. To address these issues and gather information on road surface texture, a newly developed device, the Static Road Scanner (SRS), was utilized in this study.

The SRS was developed at the University of Zilina and is shown in Figure 3. To enhance data accuracy and minimize blind spots, the SRS uses dual red lasers with 15 μm resolution,

scanning in opposite directions. The device can measure an area of 120×100 mm per scan. The system is generator-powered and computer-operated, enabling immediate computation of texture parameters post-scan. For subsequent processing and analysis, surface coordinates in the format X, Y, Z were utilized.

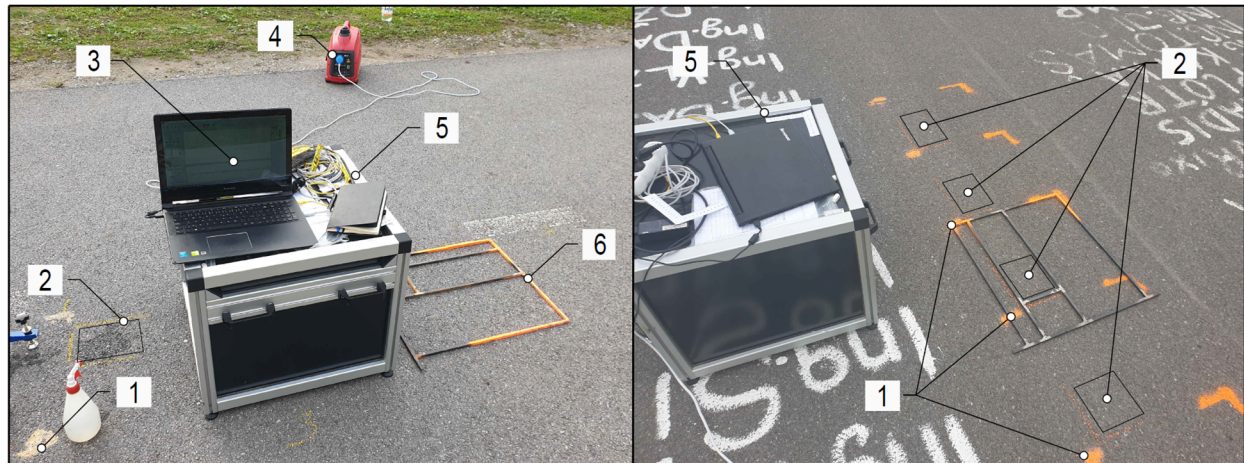


Figure 3. The Static Road Scanner and the measurement points marked on the road surface. (1—Marked corners; 2—Measurement points; 3—Computer; 4—Generator; 5—Static Road Scanner; 6—Steel grid).

Ensuring precise localization of all measurements was crucial to investigate the relationship between friction coefficients and texture parameters. A steel grid was created to achieve this with its corners marked on the pavement. The SRS device was positioned over this grid to determine the scanning locations. Each scan's position was then marked on the pavement. Figure 3 illustrates these marked locations on the pavement of the measurement section. This meticulous process was essential for maintaining accuracy and consistency in the measurements, creating reliable data for the study.

2.3. Methodology

To explore the potential of predicting the friction coefficient using texture parameters, measurements were carried out on 17 different rural road pavements. The key criterion for site selection was maximizing the diversity of friction coefficients, representing a range of pavement surfaces with varying levels of microtexture and macrotexture. The profiles for key texture parameters were acquired on dry surfaces, as this is standard practice for capturing surface morphology accurately. The friction measurements, however, were conducted with a water film to simulate wet conditions. Friction coefficient (μ) measurements were performed 6 to 9 times, depending on value variability, with outliers omitted. For further evaluation, average values for each interval were considered over a 5 m section, totaling 170 points across all sections, with measurements at 0.5 m intervals.

Measurements were conducted under similar weather conditions within a short time-frame to minimize climatic influences. This study did not consider pavement material, type, degradation, wearing course composition, or traffic load.

Adhering to previous experimental recommendations, special care was taken to ensure precise localization of measurements. Prior experiments showed that 2D texture parameters inadequately described friction levels, prompting the evaluation of surface morphology using 3D texture parameters.

Following the use of the SRS, raw data were processed and analyzed. Using X, Y, Z coordinates, surfaces for each measuring spot were created and aligned horizontally. An example of a measured and leveled surface with a selected profile is shown in Figure 4.

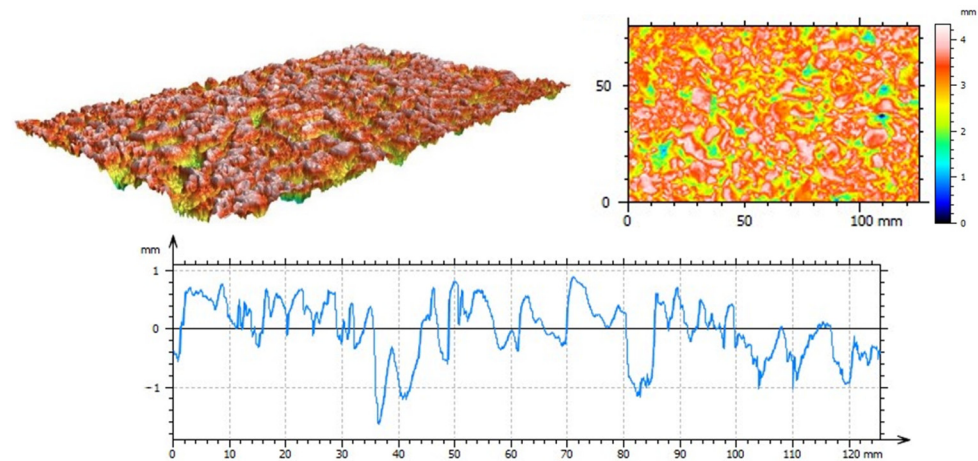


Figure 4. 3D Surface model (Top Left), height map (Top Right), and surface profile (Bottom).

During road surface scanning, outliers can occur due to dust particles or measurement errors from reflections, resulting in inaccurate surface images. That is why the raw dataset was filtered and outliers were removed. Various methods exist for removing outliers, each targeting specific inaccuracies. In this study, outliers were removed according to the maximum slope of surface irregularities, set to 60° based on the SRS device specifications.

The processed result was the primary surface (PS), which includes irregularities spanning microtexture and macrotexture levels. As well as for primary surface, all texture parameters were also analyzed for filtered surfaces representing macrotexture and microtexture. The microtexture surface (MIC) was derived from the primary surface by applying a high-pass L-filter to suppress macrotexture wavelengths, while the macrotexture surface (MAC) was created using a low-pass S-filter to suppress microtexture wavelengths. The filtration process utilized Gaussian filters, as specified in [28].

After the primary processing of pavement surface data, more than 80 texture parameters were evaluated to establish the connection between texture and road friction. These parameters included standard height measures, as well as spatial, hybrid, functional, functional volume, and feature characteristics.

2.4. Key Texture Parameters for Friction Coefficient Prediction

After processing the correlations between the friction coefficient and all evaluated texture parameters, key parameters were selected. These key parameters underwent cross-validation to determine the optimal combination of texture parameters for predicting the friction coefficient. Analysis revealed that these key texture parameters were valley material portion (functional), dale void volume (functional volume), and arithmetic mean peak curvature (feature).

Functional texture parameters are measures that describe the performance-related aspects of a surface's texture, focusing on how the texture affects fluid retention, wear resistance, and other properties that influence the interaction between the road surface and tires. Road surface functional characteristics can be calculated from the peak and valley regions using the Abbott–Firestone curve, which represents the cumulative distribution of surface heights (Figure 5).

Valley material portion S_{mr2} [%] quantifies the percentage of the measured area comprising deeper valley structures, which correlate with the reduced valley depth (S_{vk}). S_{mr2} represents the areal material ratio distinguishing the reduced valleys from the core surface. S_{vk} denotes the arithmetical mean depth of these reduced valleys, derived from the areal material ratio curve.

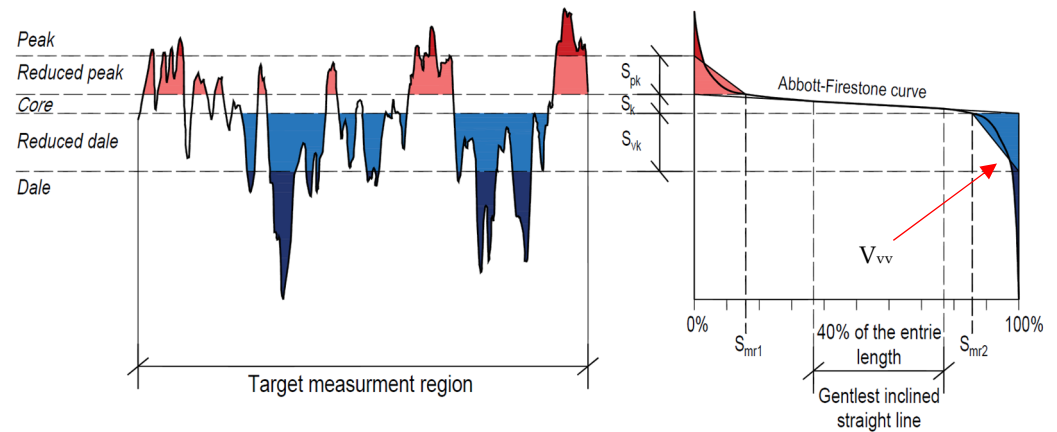


Figure 5. The Abbott–Firestone curve, the profile, and the functional parameters.

Dale void volume (V_{vv}) is a functional volume surface texture parameter that quantifies the volume of the valleys or voids within a surface texture profile. This parameter is significant for understanding the surface's capacity to retain fluids, such as water, which is critical for applications involving friction and wear. This parameter is also derived from the Abbott–Firestone curve, which represents the bearing area curve of the surface.

Arithmetic mean peak curvature S_{pc} [1/mm] is a feature parameter that quantifies the average curvature of the peaks within a given surface area. This metric is crucial for understanding the sharpness and distribution of surface asperities, which directly affect the interaction between road surface and tire. Higher S_{pc} values indicate sharper peaks, which can lead to increased friction. S_{pc} is determined according to the following formula:

$$S_{pc} = -\frac{1}{2} \frac{1}{n} \sum_{k=1}^n \left(\frac{\partial_z^2(x, y)}{\partial_x^2} + \frac{\partial_z^2(x, y)}{\partial_y^2} \right) \quad (1)$$

where n is the number of peaks, $z(x, y)$ is ordinate values, and (x, y) is used to identify the position of the calculation point.

3. Results and Discussion

3.1. Assessment of Friction Metrics

The device used for the skid resistance determination was the TWO, used for continuous measuring of friction coefficient μ . The results obtained on 17 measurement sections (170 measuring intervals, 0.5 m long) are shown in Table 1 and Figure 6.

Table 1. Results obtained by TWO on 17 measurement sections.

μ	Measurement Section																
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
MIN	0.44	0.38	0.35	0.60	0.47	0.50	0.52	0.28	0.21	0.20	0.17	0.07	0.12	0.44	0.62	0.38	0.35
MAX	0.49	0.50	0.61	0.67	0.56	0.68	0.76	0.55	0.29	0.27	0.23	0.13	0.23	0.78	0.72	0.64	0.66
AVERAGE	0.46	0.46	0.48	0.64	0.52	0.62	0.67	0.45	0.23	0.23	0.20	0.10	0.16	0.62	0.67	0.54	0.48

As shown in Figure 6, there is a wide range of friction coefficient μ values on different surfaces and at different points within some single-measurement sections. Measured μ values range from approximately 0.1 to 0.8, indicating significant variability both between different road sections and within individual sections with varying pavement surfaces.

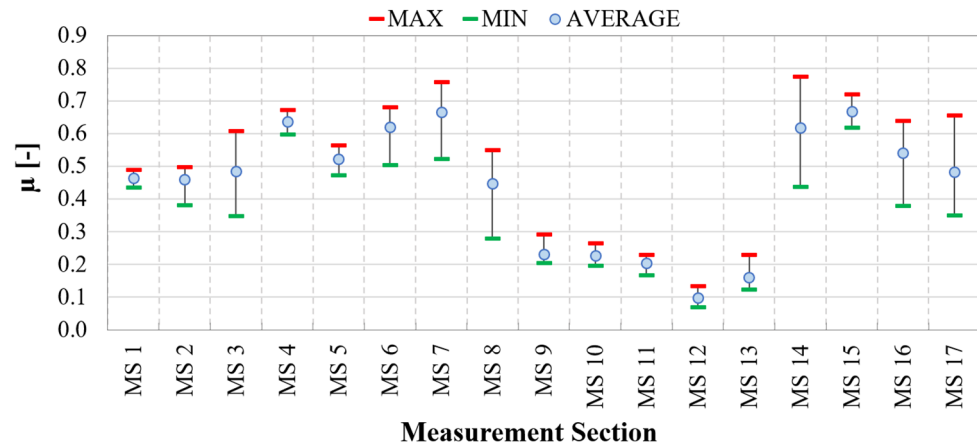


Figure 6. TWO results on 17 measurement sections.

3.2. Assessment of Surface Texture Metrics

For each surface, more than eighty different parameters were calculated. Table 2 provides examples of the calculated parameters, selected based on their statistical significance in the later-created prediction model. For clarity, the table presents data rounded to one, or two decimal places, though all decimal places were used in the analysis.

Table 2. Results of selected texture parameters on 17 measurement sections.

Characteristics		Road Section																
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
$S_{mr1,MIC}$	MIN	13.0	12.8	13.1	14.1	11.4	11.0	11.1	11.8	11.3	11.6	13.6	12.2	13.3	11.6	11.6	11.5	11.6
	MAX	14.0	13.4	14.3	14.5	12.3	11.9	11.9	13.4	12.5	13.2	14.6	13.1	14.3	12.4	12.1	12.0	11.9
	AVER.	13.2	13.1	13.7	14.2	11.9	11.5	11.5	12.5	11.9	12.3	13.9	12.8	13.8	11.9	11.8	11.6	11.7
	SD	0.29	0.19	0.41	0.13	0.30	0.30	0.28	0.51	0.37	0.47	0.30	0.29	0.31	0.23	0.15	0.15	0.13
$S_{mr2,MIC}$	MIN	84.6	84.5	85.1	84.8	85.8	86.3	86.5	84.7	83.9	83.9	83.1	83.4	83.4	85.7	86.4	85.8	85.7
	MAX	85.2	85.0	86.2	85.6	86.6	87.3	87.1	85.8	85.7	85.0	84.7	84.2	84.3	86.1	86.6	86.4	86.3
	AVER.	84.9	84.8	85.6	85.2	86.2	86.8	86.8	85.3	84.6	84.4	83.8	83.7	83.9	85.9	86.5	86.1	86.0
	SD	0.20	0.19	0.32	0.29	0.25	0.39	0.26	0.38	0.68	0.34	0.47	0.25	0.32	0.18	0.09	0.15	0.21
$S_{pc,MAC}$	MIN	1.45	1.40	1.38	1.50	1.46	1.16	1.14	1.31	0.56	0.49	1.34	1.18	1.22	1.44	1.58	1.38	1.52
	MAX	1.62	1.57	1.70	1.72	2.04	1.80	1.52	1.99	0.83	0.81	1.75	1.46	1.39	1.76	2.20	1.63	1.70
	AVER.	1.52	1.48	1.53	1.60	1.70	1.43	1.31	1.62	0.70	0.67	1.53	1.32	1.31	1.59	1.83	1.50	1.62
	SD	0.07	0.05	0.09	0.08	0.18	0.19	0.11	0.26	0.08	0.10	0.15	0.09	0.07	0.10	0.18	0.09	0.07
$S_{mc,PS}$	MIN	0.62	0.48	0.54	0.50	0.81	0.90	0.70	1.12	0.37	0.35	1.28	0.79	0.93	0.87	0.85	0.74	0.72
	MAX	0.70	0.60	0.63	0.66	1.22	1.39	1.18	1.79	0.58	0.59	1.93	0.93	1.29	1.16	1.02	1.03	1.17
	AVER.	0.65	0.53	0.58	0.58	1.03	1.19	0.85	1.42	0.44	0.46	1.59	0.86	1.06	0.98	0.93	0.84	0.88
	SD	0.03	0.03	0.03	0.05	0.15	0.15	0.15	0.21	0.07	0.08	0.17	0.05	0.12	0.08	0.06	0.10	0.15
$V_{vv,PS}$	MIN	0.09	0.07	0.09	0.09	0.15	0.07	0.06	0.08	0.03	0.04	0.11	0.06	0.09	0.09	0.09	0.09	0.10
	MAX	0.12	0.09	0.12	0.12	0.32	0.14	0.09	0.16	0.09	0.11	0.19	0.11	0.15	0.12	0.12	0.12	0.12
	AVER.	0.11	0.08	0.10	0.11	0.23	0.10	0.08	0.12	0.06	0.07	0.15	0.08	0.12	0.11	0.10	0.10	0.11
	SD	0.01	0.01	0.01	0.01	0.06	0.02	0.01	0.02	0.02	0.02	0.02	0.01	0.02	0.01	0.01	0.01	0.01

Figure 7 illustrates examples of the scans and surfaces on selected measurement sections.

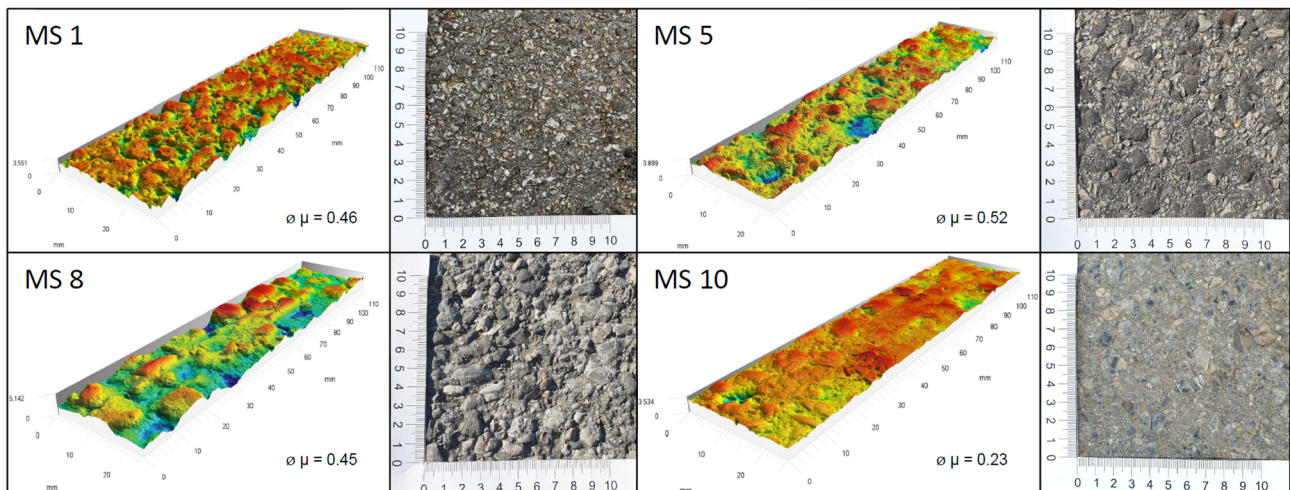


Figure 7. Three-dimensional models of scanned pavement surfaces.

3.3. Texture–Friction Relationship Analysis

Following the evaluation of texture and friction, their relationships were investigated. The correlations were assessed for the primary surface and micro- and macrotexure surfaces. Although more than 80 parameters were calculated, this section highlights only the parameters with the highest impact on the friction prediction model, as determined by the multinomial regression analysis presented below.

- **Microtexture:**

As an example, the valley material portion ($S_{mr2,MIC}$) parameter was selected. Initially, it was hypothesized that parameters like peak density (S_{pd}) representing the number of peaks per unit area, or kurtosis (R_{ku}) describing the sharpness of the surface profile peaks and valleys, would have the most significant influence on the friction coefficient. Nevertheless, the analysis demonstrated that the strongest relationship was achieved with $S_{mr2,MIC}$, which represents the areal material ratio separating the reduced valleys from the core surface. Figure 8 illustrates the obtained values, along with a comparison to the friction coefficient (μ).

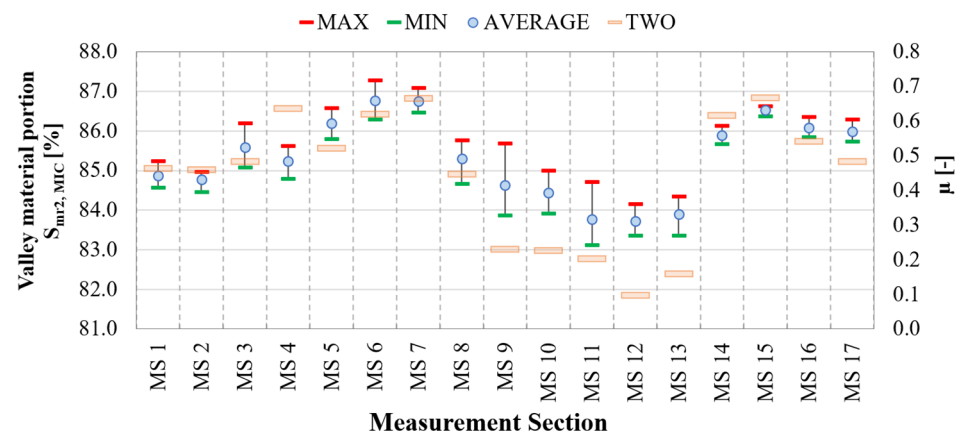


Figure 8. Valley material portion $S_{mr2,MIC}$ and friction coefficient μ (orange lines).

The correlation between valley material portion $S_{mr2,MIC}$ and friction coefficient μ is shown in Figure 9.

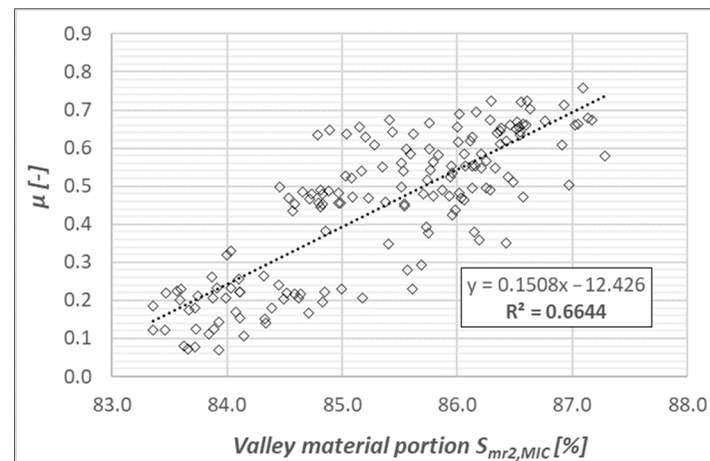


Figure 9. Correlation between valley material portion $S_{mr2,MIC}$ and friction coefficient μ .

As illustrated in Figure 9, there is a notable trend indicating a considerable correlation between the valley material portion ($S_{mr2,MIC}$) and the friction coefficient (μ). The results suggest that the combination of surface peaks and the core roughness significantly influences the friction. Nevertheless, this relationship alone is insufficient to predict tire–road friction accurately. For this reason, it is necessary to combine this parameter with other relevant texture characteristics derived from primary or macrotexture surfaces, such as mean peak curvature (S_{pc}) or dale void volume (V_{vv}), to improve prediction accuracy.

- **Macrotexture:**

When considering the role of macrotexture in the interaction between the wheel and the road, it was hypothesized that the shape of surface irregularities would play a key role due to the interaction between rubber and surface grains. To investigate this, the arithmetic mean peak curvature ($S_{pc,MAC}$) calculated from waviness surfaces was analyzed. Figure 10 illustrates the obtained values, along with a comparison to the friction coefficient (μ).

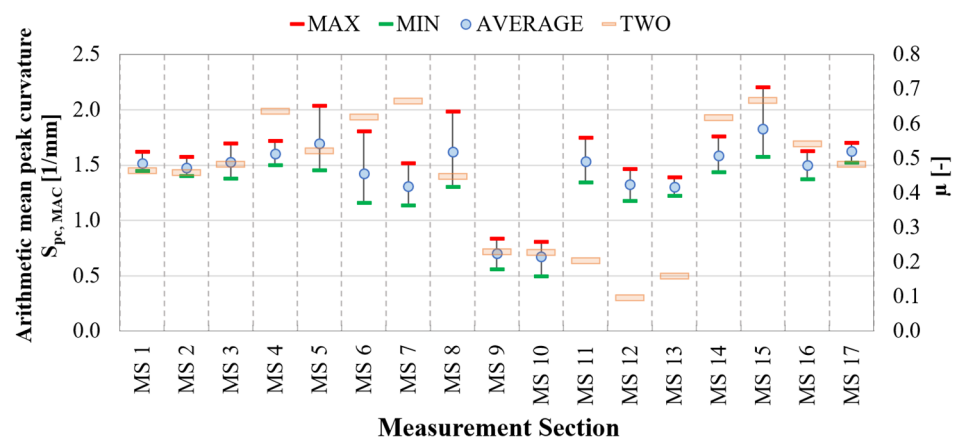


Figure 10. Arithmetic mean peak curvature $S_{pc,MAC}$ and friction coefficient μ (orange lines).

There is a clear disparity between the $S_{pc,MAC}$ and friction values across different measurement sections, as seen in Figure 10. For MS 6 and MS 7, with relatively large and rounded surface features, $S_{pc,MAC}$ values are low, yet the friction coefficients are high, indicating good microtexture. In contrast, MS 11 to MS 13 exhibit significant irregularities with large and sharp grains. Here, although $S_{pc,MAC}$ values are high, the friction coefficients are low due to the smoother surface of these grains. Overall, MS 6, MS 7, MS 12, and MS 13 show similar grain shapes, with the primary difference being in microtexture and its impact on friction.

The correlation between the arithmetic mean peak curvature $S_{pc,MAC}$ and friction coefficient μ is shown in Figure 11.

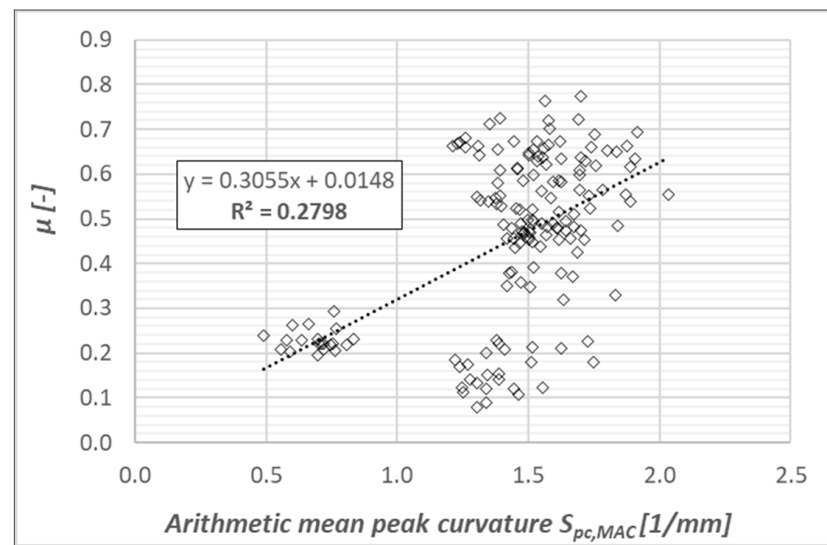


Figure 11. Correlation between the arithmetic mean peak curvature $S_{pc,MAC}$ and friction coefficient μ .

As illustrated in Figure 11, a visible trend demonstrates a moderate association between the arithmetic mean peak curvature and friction coefficient μ . This indicates that the hypothesis regarding the impact of aggregate particle shape on friction is valid.

The graph shows a cluster of points on the left that appear to deviate from the main trend, seemingly acting as outliers. These measurements were recorded on measurement sections MS 9 and MS 10, where the surface layers have low levels of both microtexture and macrotexture, resulting in low friction values. Therefore, these measurements are considered accurate, not as outliers. In contrast, sections MS 6, MS 7, MS 12, and MS 13 exhibit similar grain shapes with consistent $S_{pc,MAC}$ values but different friction coefficients due to varying microtexture levels, impacting the overall correlation strength. Despite this, $S_{pc,MAC}$ was included in the friction prediction model, as grain shape undoubtedly affects the wheel–road interaction in terms of friction.

Comparative analysis of values obtained from texture and friction measurements led to the following preliminary conclusions:

- The relationship between $S_{mr2,MIC}$ and μ confirmed the undeniable impact of surface microtexture on skid resistance;
- The influence of macrotexture on the friction was best demonstrated using the parameter arithmetic mean peak curvature ($S_{pc,MAC}$), as evidenced by a moderate–strong relationship with friction coefficient μ . A more pronounced effect of this parameter was observed when combined with the microtexture parameter $S_{mr2,MIC}$ in further analysis;
- Under the given test conditions, characteristics related to the surface features' density, as well as some volume characteristics, did not exhibit as strong correlations as anticipated;
- It was confirmed that high values of individual texture characteristics, both on primary and micro and macrotexture surfaces, do not necessarily represent high friction coefficient values;
- It has been demonstrated that predicting the friction coefficient based solely on individual texture parameters from non-contact measurements is insufficient.

Building upon these preliminary conclusions, the subsequent phase of the research examined the impact of combining surface texture parameters.

3.4. Development of a Friction Prediction Model Using Texture Parameters

In creating the mathematical model for predicting the friction coefficient μ , it was assumed that, under constant boundary conditions for measurements on different types of road surfaces, is the arrangement of surface irregularities what influences the friction between the tire and the road most. The shape and distribution of these irregularities, or surface texture, were characterized in the previous section using 3D parameters calculated from the primary, micro, and macrotexture surfaces. A linear regression model, represented by Equation (2), was chosen to determine the prediction formula for the friction coefficient using a combination of various texture characteristics:

$$\mu_{predicted} = a + b \cdot TP_1 + c \cdot TP_2 + \dots + m \cdot TP_m \quad (2)$$

where $\mu_{predicted}$ is the predicted value of friction coefficient, $TP_1, TP_2 \dots TP_m$ are texture parameters, $a, b, c, \dots m$ are parameters of the regression model, and m represents the number of parameters included in the model. The multiple linear regression analysis was conducted using MATLAB software (version R2023a), specifically utilizing the Regression Learner application. This software allowed us to efficiently model the relationships between the texture parameters and the friction coefficient, and to perform cross-validation for evaluating the robustness and accuracy of the models.

The model included texture characteristics representing microtexture and macrotexture surfaces, as well. The selection of individual texture characteristics was based on theoretical knowledge of their potential impact on the friction coefficient as well as the results obtained from comparing individual texture parameters with the friction coefficient. Ultimately, the selection and combination of texture parameters were validated through statistical significance tests of individual parameters and the overall regression models.

Cross-validation was employed to identify the combination of texture characteristics that best represent the measured friction coefficient values and to determine the model's accuracy. To optimize the number of texture parameters used in the model, $R^2_{adjusted}$ values were calculated in addition to basic statistical indicators (R^2 and p -value). The inclusion of texture parameters in the regression model was guided by the adjusted R^2 metric. Parameters were incorporated if both R^2 and $R^2_{adjusted}$ values increased with their addition. If $R^2_{adjusted}$ started to decline despite rising R^2 values, the inclusion process was stopped. Each independent variable's statistical significance was checked using the p -value, with those exceeding 0.001 being excluded. The overall model significance was then validated by comparing the calculated F -value to the critical value, ensuring it surpassed the threshold for statistical validity.

Given that the valley material portion $S_{mr2,MIC}$ showed the strongest correlation with the friction coefficient, this parameter was used as the foundation of the prediction model. Additional texture parameters were progressively tested and evaluated to determine their suitability for inclusion in the model.

The formula for predicting friction coefficient μ measured by TWO was, after many combinations of different texture parameters, compiled using the valley material portion $S_{mr2,MIC}$ representing the surface microtexture, and the arithmetic mean peak curvature $S_{pc,MAC}$ representing the surface macrotexture. Using multiple linear regression analysis, the following formula for the $\mu_{predicted}$ calculation was obtained:

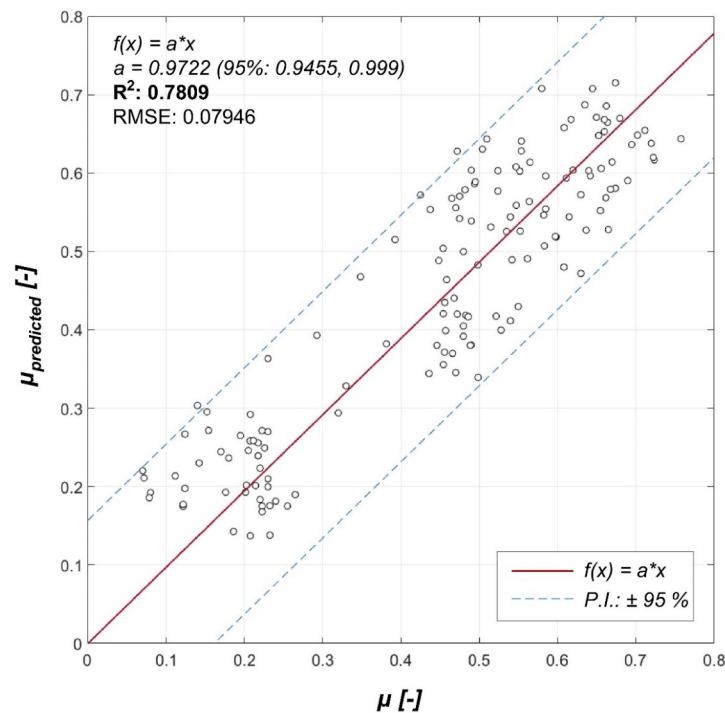
$$\mu_{predicted} = -11.526 + 0.138 \cdot S_{mr2,MIC} + 0.153 \cdot S_{pc,MAC} \quad (3)$$

The outcome of the regression model, along with the comparison between the measured and predicted friction coefficient (μ) values, is depicted in Figure 12.

Table 3 illustrates the outcomes of the statistical evaluation of the prediction model's accuracy and significance.

Table 3. Model statistical significance and regression coefficients for texture parameters $S_{mr2,MIC}$, $S_{pc,MAC}$.

	Coefficients		Standard Error	p-Value	r	R^2	$R^2_{adjusted}$	F-Value	Ftab
Intercept	a_0	−11.526	0.557	3.94×10^{-45}	0.8837	0.7809	0.814	321.740	3.058
$S_{mr2,MIC}$	a_1	0.138	0.007	2.50×10^{-45}					
$S_{pc,MAC}$	a_2	0.153	0.021	1.86×10^{-11}					

**Figure 12.** Correlation of measured and predicted friction coefficients μ vs. $\mu_{predicted}$.

The statistical significance and credibility of the regression model are evident from Figure 12 and Table 3. An R^2 value of 0.7809 suggests a strong correlation between the predicted and measured values, while a low RMSE of 0.07946 indicates high accuracy in the model's predictions. The slope close to 1 (0.9722) with a narrow confidence interval further supports the model's reliability. While the overall trend is strong, there is some scatter around the regression line. This indicates variability in the prediction accuracy, with some predicted values deviating from the measured values. There appear to be a few outliers that do not fit the general trend. These points can impact the overall model accuracy and may need further investigation to understand their cause.

The daled void volume of the primary surface ($V_{vv,PS}$) was another texture parameter included in the prediction model. The hypothesis was that the accuracy and credibility of the regression model could be enhanced by including this parameter, which describes the effect of the drainage properties of the road surface. The equation determined using multiple linear regression analysis for calculating the friction coefficient $\mu_{predicted}$, by combining the texture parameters $V_{vv,PS}$ and $S_{mr2,MIC}$, $S_{pc,MAC}$, is shown below:

$$\mu_{predicted} = -11.362 - 0.568 \cdot V_{vv,PS} + 0.136 \cdot S_{mr2,MIC} + 0.192 \cdot S_{pc,MAC} \quad (4)$$

The outcome of the refined regression model, along with the comparison between the measured and predicted friction coefficient (μ) values, is depicted in Figure 13.

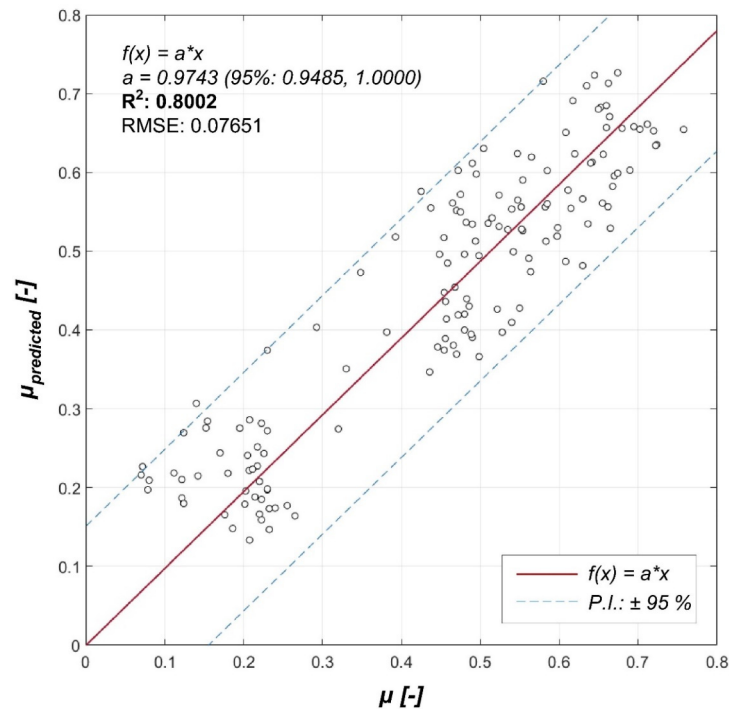


Figure 13. Correlation of measured and predicted friction coefficients μ vs. $\mu_{predicted}$.

Figure 13 and Table 4 demonstrate the effectiveness and statistical significance of the regression model for predicting the friction coefficient (μ). The inclusion of the daled void volume ($V_{vv,PS}$) improved the model's accuracy, evidenced by an increase in the coefficient of determination ($R^2 = 0.8002$) and a decrease in the RMSE (0.07651) in comparison with the model without this parameter. Despite the improvement, there is still some variability and a few outliers which suggest that the model could be further refined.

Table 4. Model statistical significance and regression coefficients for texture parameters $S_{mr2,MIC}$, $S_{pc,MAC}$, $V_{vv,PS}$.

Coefficients			Standard Error	p-Value	r	R^2	$R^2_{adjusted}$	F-Value	Ftab
Intercept	a_0	−11.362	0.540	8.44×10^{-46}	0.8945	0.8002	0.826	234.100	2.667
$V_{vv,PS}$	a_1	−0.568	0.167	8.41×10^{-4}					
$S_{mr2,MIC}$	a_2	0.136	0.006	4.69×10^{-46}					
$S_{pc,MAC}$	a_3	0.192	0.023	9.07×10^{-14}					

The R^2 value of 0.8002 and the $R^2_{adjusted}$ value of 0.826 indicate the model's strong explanatory power. Despite the higher p -value for $V_{vv,PS}$, which suggests lower statistical significance compared to $S_{mr2,MIC}$ and $S_{pc,MAC}$, the overall model remains robust and credible. The F -value of 234.1 far exceeds the critical value of 2.667, confirming the model's statistical significance. There is a well-founded assumption that the significance of $V_{vv,PS}$ may increase at higher speeds, enhancing the model's predictive capability.

In comparison with [29], which explores the correlation between morphology parameters and skid resistance on asphalt pavements, our research advances this field by incorporating a more diverse set of 3D texture parameters for predicting friction coefficients on rural road surfaces. While both studies emphasize the importance of texture in determining skid resistance, our approach uniquely integrates microtexture and macrotexture measurements, resulting in a more comprehensive prediction model with higher accuracy, as indicated by our R^2 values. The study in [29] found that increased texture depth and fractal dimension significantly improve skid resistance, with notable contributions from

macrotexture. Similarly, our study investigates skid resistance using 3D texture parameters across different road sections. The key difference lies in our prediction model, which integrates multiple texture parameters, including the valley material portion ($S_{mr2,MIC}$), arithmetic mean peak curvature ($S_{pc,MAC}$), and void volume ($V_{vv,PS}$), for a more accurate prediction of friction. This contrast highlights our study's novelty in combining these parameters within a regression model to enhance prediction accuracy.

The study in [30] evaluates the correlation between the Pendulum test value (PTV) and mean texture depth (MTD) using the Sand Patch Test for porous asphalt pavements, highlighting the challenges in achieving a strong correlation between these parameters. Our research advances this discussion by employing a more sophisticated approach using 3D texture parameters to predict friction coefficients across various road surfaces. Unlike the stationary Pendulum test, our study utilized a continuously operating device, the Traction Watcher One (TWO), providing a more dynamic and comprehensive assessment of friction over extended road sections. While the study in [30] focuses on porous asphalt and its initial performance, our work integrates a broader set of texture parameters, offering a comprehensive prediction model applicable to different road surface types. The inclusion of both microtexture and macrotexture parameters in our regression model provides a more detailed understanding of the surface interactions, ultimately leading to more accurate and reliable friction predictions.

The study in [31] focuses on the impact of macrotexture on the skid resistance of asphalt pavements, using a handy laser scanner and a dynamic friction tester. It identifies peak density and arithmetic mean peak curvature as significant factors influencing the friction coefficient, though these effects are speed-dependent. In contrast, our study not only examines macrotexture but also integrates microtexture parameters using a more comprehensive set of 3D texture data. We employed a continuously operating device, the Traction Watcher One (TWO), for dynamic friction measurements across different road surfaces, offering a broader analysis of friction coefficients. While both studies emphasize the importance of texture, our research provides a more holistic approach by considering a wider range of texture parameters and their combined effect on friction, regardless of speed.

The study in [23] presents a model for evaluating pavement skid resistance using 3D texture data, established through a multiple quadratic multinomial regression model. This approach emphasizes the importance of both macrotexture and microtexture in influencing different components of friction. Similar to our research, this study integrates 3D texture indicators but focuses on harmonizing different skid resistance detection methods through the IFI concept. In contrast, our study uses a more direct measurement of friction across various road sections and incorporates a broader range of texture parameters, providing a comprehensive analysis of real-world conditions. Our model's practical application is further enhanced by its ability to predict friction coefficients with high accuracy, considering both microtexture and macrotexture influences.

While the derived regression model offers a robust framework for predicting road friction based on texture parameters, its application in real-world scenarios may face challenges in terms of accuracy and adaptability across diverse conditions. To enhance the model's robustness, future research could explore the integration of convolutional neural networks (CNNs) and machine learning techniques, which have shown promise in related fields for processing complex, high-dimensional data. Incorporating such approaches could improve the model's ability to generalize across varying pavement types and environmental conditions, ultimately leading to more reliable predictions.

4. Conclusions

This study investigated the prediction of road friction coefficients using 3D texture parameters of pavement surfaces. Measurements were conducted on 17 different rural road sections using the Traction Watcher One (TWO) device for friction coefficients and a newly developed Static Road Scanner (SRS) for capturing surface texture. After evaluating the

correlations between individual texture parameters and the friction coefficient (μ), multiple linear regression models were developed, incorporating and combining texture parameters.

This study confirmed that both microtexture and macrotexture parameters are essential for accurate predictions, highlighting the importance of considering different texture scales. Analysis revealed that the strongest relationship between friction coefficient and individual texture parameters was achieved with the valley material portion $S_{mr2,MIC}$, representing the surface microtexture. The mean curvature of the protrusions $S_{pc,MAC}$ was identified as the most significant parameter describing macrotexture. The optimal combination of texture parameters for predicting the friction coefficient μ was $S_{mr2,MIC}$, $S_{pc,MAC}$ and $V_{vv,PS}$, achieving a coefficient of determination (R^2) of 0.8002 between measured and predicted μ values. Using only $S_{mr2,MIC}$ and $S_{pc,MAC}$ resulted in a slightly lower R^2 of 0.7809. However, at higher slip speeds, the significance of $V_{vv,PS}$ is likely to increase due to its role in surface-drainage properties.

Despite the strong overall performance, some variability and outliers were observed in the data. Future research should aim to understand and mitigate these discrepancies, possibly by incorporating more robust data-filtering techniques or exploring additional texture parameters that could account for these variations. Furthermore, integrating other advanced statistical methods or machine learning algorithms could potentially improve the prediction accuracy and robustness of the models developed.

The results underscore the feasibility and accuracy of using non-contact texture measurements for reliable skid resistance prediction, which can significantly enhance pavement management and road safety. This approach offers a non-invasive method to monitor and predict road conditions, potentially reducing the need for more frequent physical inspections.

Future work should focus on additional experiments to further enhance model precision and applicability. Specifically, including a wider range of friction coefficients (μ) from 0.25 to 0.45, which were less represented in the current measurements, and conducting supplemental measurements on surfaces with μ values higher than 0.75, would provide a more comprehensive dataset. Additionally, exploring the influence of higher-speed conditions would help to refine the model and its predictions.

In conclusion, this study contributes valuable insights into the relationship between pavement texture and friction, paving the way for improved road safety measures and more effective pavement management strategies.

Author Contributions: Conceptualization, M.K.; Data curation, M.B. and P.P.; Formal analysis, M.D.; Funding acquisition, M.K. and M.D.; Investigation, M.K. and M.B.; Methodology, M.K.; Resources, M.K.; Software, M.B. and P.P.; Supervision, M.D.; Validation, M.K. and P.P.; Visualization, M.B.; Writing—original draft, M.B.; Writing—review and editing, M.K. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by VEGA grant number 1/0337/22. The APC was funded by VEGA 1/0337/22.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The datasets presented in this article are not readily available because the data are part of an ongoing study.

Acknowledgments: The paper is a result of the research supported by the research project VEGA 1/0337/22 “Analysis of the influence of road surface texture on skid resistance, driving safety and the potential of particulate matter resuspension”.

Conflicts of Interest: The authors declare no conflict of interest.

References

- Pardillo Mayora, J.M.; Jurado Piña, R. An Assessment of the Skid Resistance Effect on Traffic Safety under Wet-Pavement Conditions. *Accid. Anal. Prev.* **2009**, *41*, 881–886. [\[CrossRef\]](#) [\[PubMed\]](#)
- Kogbara, R.B.; Masad, E.A.; Kassem, E.; Scarpas, A.; Anupam, K. A State-of-the-Art Review of Parameters Influencing Measurement and Modeling of Skid Resistance of Asphalt Pavements. *Constr. Build. Mater.* **2016**, *114*, 602–617. [\[CrossRef\]](#)
- Hall, J.W.; Smith, K.L.; Titus-Glover, L.; Wambold, J.C.; Yager, T.J.; Rado, Z. *Guide for Pavement Friction*; Transportation Research Board: Washington, DC, USA, 2009; ISBN 978-0-309-42974-0.
- ISO 13473-2:2002; Characterization of Pavement Texture by Use of Surface Profiles—Part 2: Terminology and Basic Requirements Related to Pavement Texture Profile Analysis. ISO: Geneva, Switzerland, 2002.
- De Martino, M.; Costa, A.L.A.; Timpone, F.; Sakhnevych, A. A Tire/Road Interaction Tool for the Evaluation of Tire Wear for Commercial Vehicles. In *Advances in Service and Industrial Robotics: Results of RAAD*; Springer: Cham, Switzerland, 2020; pp. 283–293.
- Boere, S.; Arteaga, I.L.; Kuijpers, A.; Nijmeijer, H. Tyre/Road Interaction Model for the Prediction of Road Texture Influence on Rolling Resistance. *Int. J. Veh. Des.* **2014**, *65*, 202. [\[CrossRef\]](#)
- Kane, M.; Riahi, E.; Do, M.-T. Tire/Road Rolling Resistance Modeling: Discussing the Surface Macrotecture Effect. *Coatings* **2021**, *11*, 538. [\[CrossRef\]](#)
- Li, T. Influencing Parameters on Tire–Pavement Interaction Noise: Review, Experiments, and Design Considerations. *Designs* **2018**, *2*, 38. [\[CrossRef\]](#)
- Wesołowski, M.; Blacha, K. Evaluation of Airfield Pavement Micro and Macrotecture in the Light of Skid Resistance (Friction Coefficient) Measurements. *MATEC Web Conf.* **2019**, *262*, 05017. [\[CrossRef\]](#)
- Gierasimiuk, P.; Wasilewska, M.; Gardziejczyk, W. A Comparative Study on Skid Resistance of Concrete Pavements Differing in Texturing Technique. *Materials* **2021**, *14*, 178. [\[CrossRef\]](#)
- Berardo, A.; Pugno, N.M. A Model for Hierarchical Anisotropic Friction, Adhesion and Wear. *Tribol. Int.* **2020**, *152*, 106549. [\[CrossRef\]](#)
- Heinrich, G.; Klüppel, M. Rubber Friction, Tread Deformation and Tire Traction. *Wear* **2008**, *265*, 1052–1060. [\[CrossRef\]](#)
- Singh, D.; Patel, H.; Habal, A.; Das, A.K.; Kapgate, B.P.; Rajkumar, K. Evolution of Coefficient of Friction between Tire and Pavement under Wet Conditions Using Surface Free Energy Technique. *Constr. Build. Mater.* **2019**, *204*, 105–112. [\[CrossRef\]](#)
- Persson, B.N.J. Theory of Rubber Friction and Contact Mechanics. *J. Chem. Phys.* **2001**, *115*, 3840–3861. [\[CrossRef\]](#)
- Persson, B.N.J.; Bucher, F.; Chiaia, B. Elastic Contact between Randomly Rough Surfaces: Comparison of Theory with Numerical Results. *Phys. Rev. B* **2002**, *65*, 184106. [\[CrossRef\]](#)
- Carbone, G.; Lorenz, B.; Persson, B.N.J.; Wohlers, A. Contact Mechanics and Rubber Friction for Randomly Rough Surfaces with Anisotropic Statistical Properties. *Eur. Phys. J. E* **2009**, *29*, 275–284. [\[CrossRef\]](#)
- Ueckermann, A.; Wang, D.; Oeser, M.; Steinauer, B. Calculation of Skid Resistance from Texture Measurements. *J. Traffic Transp. Eng. (Engl. Ed.)* **2015**, *2*, 3–16. [\[CrossRef\]](#)
- Pranjić, I.; Deluka-Tibljša, A. Pavement Texture–Friction Relationship Establishment via Image Analysis Methods. *Materials* **2022**, *15*, 846. [\[CrossRef\]](#) [\[PubMed\]](#)
- Yan, Y.; Ran, M.; Sandberg, U.; Zhou, X.; Xiao, S. Spectral Techniques Applied to Evaluate Pavement Friction and Surface Texture. *Coatings* **2020**, *10*, 424. [\[CrossRef\]](#)
- Yang, G.; Wang, K.C.P.; Li, J.Q. Multiresolution Analysis of Three-Dimensional (3D) Surface Texture for Asphalt Pavement Friction Estimation. *Int. J. Pavement Eng.* **2021**, *22*, 1882–1891. [\[CrossRef\]](#)
- Vallejo, L.E. Fractal Assessment of the Surface Texture of Pavements. *Int. J. Pavement Eng.* **2001**, *2*, 149–156. [\[CrossRef\]](#)
- Panagouli, O.K.; Kokkalis, A.G. Skid Resistance and Fractal Structure of Pavement Surface. *Chaos Solitons Fractals* **1998**, *9*, 493–505. [\[CrossRef\]](#)
- Wang, Y.; Lai, X.; Zhou, F.; Xue, J. Evaluation of Pavement Skid Resistance Using Surface Three-Dimensional Texture Data. *Coatings* **2020**, *10*, 162. [\[CrossRef\]](#)
- Yan, C.; Zhang, Z.; Zhang, Y. Research on Skid Resistance Performance Assessment and Rehabilitation Decision-Making Technology of Asphalt Pavement. *E3S Web Conf.* **2024**, *490*, 03017. [\[CrossRef\]](#)
- Simone, A.; Lantieri, C.; Vignali, V.; Bitelli, G. 3D Laser Scanner Technique for In Situ Analysis of Road Pavement Surface Texture. In Proceedings of the 7th International Conference on Maintenance and Rehabilitation of Pavements and Technological Control, Auckland, New Zealand, 28–30 August 2012.
- Zhao, T.; He, J.; Lv, J.; Min, D.; Wei, Y. A Comprehensive Implementation of Road Surface Classification for Vehicle Driving Assistance: Dataset, Models, and Deployment. *IEEE Trans. Intell. Transp. Syst.* **2023**, *24*, 8361–8370. [\[CrossRef\]](#)
- Zhao, T.; Guo, P.; Wei, Y. Road Friction Estimation Based on Vision for Safe Autonomous Driving. *Mech. Syst. Signal Process.* **2024**, *208*, 111019. [\[CrossRef\]](#)
- ISO 16610-61:2015; Geometrical Product Specification (GPS)—Filtration—Part 61: Linear Areal Filters—Gaussian Filters. ISO: Geneva, Switzerland, 2015.
- Song, W. Correlation between Morphology Parameters and Skid Resistance of Asphalt Pavement. *Transp. Saf. Environ.* **2022**, *4*, tdac002. [\[CrossRef\]](#)

30. Afonso, M.L.; Dinis-Almeida, M.; Fael, C.S. Characterization of the Skid Resistance and Mean Texture Depth in a Permeable Asphalt Pavement. *IOP Conf. Ser. Mater. Sci. Eng.* **2019**, *471*, 022029. [[CrossRef](#)]
31. Hu, L.; Yun, D.; Liu, Z.; Du, S.; Zhang, Z.; Bao, Y. Effect of Three-Dimensional Macrotecture Characteristics on Dynamic Frictional Coefficient of Asphalt Pavement Surface. *Constr. Build. Mater.* **2016**, *126*, 720–729. [[CrossRef](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.