Development of Pavement Performance Prediction Models Using Regression Methods

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Abstract - This research focuses on developing pavement performance prediction models using regression methods, examining two distinct climate zones, Dry-Non-Freeze and Wet-Freeze, and utilizing data from the Long-Term Pavement Performance (LTPP) program. This research aims to identify and analyze factors affecting pavement performance. The study investigates three main types of pavement distress: roughness (International Roughness Index), rutting, and alligator cracking, which significantly influence the overall pavement condition. The research assesses the impact of several variables obtained from the Literature Review on pavement performance, which are expected to affect pavement performance by applying multiple linear and logistic regression models. Multiple linear regression models were used for predicting pavement roughness and rutting, while logistic regression was used to predict the occurrence of alligator cracking. Findings from this comprehensive analysis are expected to provide actionable insights that can optimize pavement design, construction, and maintenance practices, ultimately enhancing road safety and extending pavement life across different environmental conditions.

Key Words: International Roughness Index (IRI), Rutting, Alligator Cracking, Pavement Performance Modelling, Multiple Linear Regression, Logistic Regression

1. INTRODUCTION

Pavement damage is a critical issue rapidly increasing due to various factors. The deterioration of pavements over time is a complex process influenced by multiple variables, including vehicle loads, structural capacity, materials, construction quality, and environmental conditions. Among these factors, heavy vehicle loads, and insufficient structural capacity of pavements have been identified as significant contributors to poor road conditions. To address this issue, researchers have been focusing on understanding the effects of these factors on pavement performance, with the goal of developing effective strategies for pavement preservation and life extension (Bhandari, Luo & Wang 2023).

This study focuses on three primary types of distress used as performance measures of road conditions: alligator cracking, rutting, and roughness. Alligator cracking is fatigue cracking that appears as interconnected cracks resembling an alligator's skin pattern. Rutting is a longitudinal depression along the wheel paths caused by the accumulation of permanent deformation in the pavement layers. Roughness, on the other hand, refers to the irregularities in the pavement surface that affect ride quality and safety. Pavement Roughness is known as the International Roughness Index (IRI). Understanding the development and extent of these distresses is crucial for effective pavement management and maintenance decision-making (Bhandari, Luo & Wang 2023).

The main objective of this study is to develop multiple linear regression and logistic regression models to predict the pavement performance and understand the variables that affect pavement performance in two different climate zones (i.e., Dry-Non-Freeze and Wet-Freeze climate zones) of USA. This research utilizes pavement performance data from the Long-Term Pavement Performance (LTPP) Program, with a primary focus on Specific Pavement Studies (SPS-1). The LTPP data is publicly accessible and can be downloaded from the LTPP InfoPave website. The SPS-1 experiment is designed to investigate the effects of various structural factors on the performance of flexible pavements, including the base type, hot mix asphalt concrete (HMAC) layer thickness, base layer thickness, traffic loading, age, and environmental conditions such as precipitation and temperature.

In summary, this comprehensive study investigates the factors affecting pavement roughness, rutting, and alligator cracking by utilizing multiple linear regression and logistic regression models and the extensive LTPP SPS-1 dataset; the researchers aim to provide actionable insights that can help optimize pavement design, construction, and maintenance practices, ultimately leading to improved road conditions and extended pavement life. The findings of this study are expected to contribute to understanding the factors that affect pavement performance in two different climate zones of the USA.

2. BACKGROUND

Pavement condition data is essential for evaluating the structural health and serviceability of road pavements. Accurate data collection requires assessing both the pavement surface and structural condition, as pavement structural condition cannot be predicted based on the pavement surface condition (Ahmed et al., 2022). To make informed pavement maintenance decisions, it is crucial to gather data on both functional and structural conditions (Huynh et al., 2021). Pavement data is categorized into various metrics such as Ride Quality, Distresses, and Structural Integrity, which comprehensively assess pavement condition. Specifically, Ride Quality refers to the smoothness of the pavement surface as experienced by road users. Rutting and Cracking, significant indicators of pavement distress, quantify the extent of deformation along wheel paths and the occurrence of cracks in the pavement surface, respectively. These indicators are critical for maintaining road safety and optimizing maintenance interventions. Pavement quality indicator metrics used by this research (Hafez, 2019) are mentioned below:

2.1 Ride Quality

The Pavement Roughness Index measures ride quality, reflecting distortions along the road surface in the direction of travel. As such, higher levels of pavement roughness result in reduced ride quality. The International Roughness Index (IRI), established by Sayers et al. in 1986, is the most used metric for assessing this roughness. It calculates roughness by dividing the total suspension travel of a vehicle by the distance covered, with results expressed in meters per kilometer/inches per mile. Consequently, greater IRI values indicate increased road roughness.

2.2 Rutting

Rutting, characterized by permanent deformations along the wheel paths of pavement, is primarily influenced by high temperatures and the properties of the asphalt binder. Typically, rutting occurs during warmer seasons when the asphalt binder becomes softer, allowing the pavement to deform under the pressure of the vehicular load. The Superpave Performance Grading (PG) System evaluates asphalt binders based on their ability to resist rutting and withstand low-temperature cracking (NCHRP, 2011). Various methodologies are employed to measure rut depth, with the 3-sensor and 5-sensor rut bars being the most prevalent. These devices are mounted on the front bumper of a van, enabling the collection of rut measurements at highway speeds. Rut depth can then be determined using edge or string-line methods (Chen and Li, 2008).

2.3 Alligator Cracking

Alligator or fatigue cracking appears as interconnected cracks resulting from fatigue failure of the asphalt concrete (AC) surface. This type of failure typically arises due to repeated traffic loads. The cracking begins at the base of the AC surface or stabilized base, where tensile stress and strain are maximized under the load of a wheel. Initially, the cracks appear as parallel lines, but with continuous traffic loading, these lines intersect, creating many-sided, sharp-angled fragments that resemble an alligator's skin. Alligator cracking initially occurs in areas exposed to repeated traffic, such as within wheel paths, and is a significant indicator of structural distress. The extent of alligator cracking is quantified by measuring the affected area in square feet or square meters. Table 1 shows different Cracking types and the units for Asphalt Concrete Pavement.

Table -1: Different Crack Types and Units

Crack Types	Unit of Measurement
Alligator Cracking	Square Meters
Block Cracking	Square Meters
Edge Cracking	Meters
Longitudinal Cracking	Meters
Transverse Cracking	Meters

Several studies have developed pavement performance models using the multiple linear regression model. For instance, Rahman et al. (2017) developed multiple linear regression models to predict the four different pavement performance indicators: Pavement Quality Index (PQI), Pavement Service Index (PSI), Pavement Distress Index (PDI), and International Roughness Index (IRI). The independent variables were the Average Annual Daily Traffic (AADT), Free Flow Speed (FFS), precipitation, temperature, and soil type. Abdelaziz et al. (2018) proposed a multiple linear regression model to predict the IRI using pavement age, initial IRI, transverse cracks, alligator cracks, and standard deviation of rut depth. This research listed some other studies that used various input variables to predict the IRI, such as age, initial IRI, distress, climate (Precipitation, Freezing – Precipitation, and Precipitation-Temperature), soil parameters, traffic (ESAL), and structural parameters (Structural Number, Asphalt Thickness, Structural Number – Deflection, Structural Number – Percent Asphalt Concrete, and Structural Number – Construction Number). Similarly, Elhadidy et al. (2018) predicted IRI using various pavement distresses (i.e., Fatigue Cracking, Edge Cracking, Block Cracking, Longitudinal Cracking, Transverse Cracking, Patching, Potholes, Shoving, Bleeding, Polished Aggregate, Rutting, and Raveling) as the input variables.

3. OBJECTIVES

This research aims to enhance our understanding of pavement performance across two different climatic conditions, contributing to more effective pavement management and maintenance strategies in two different climate zones. The objectives of this research are outlined as follows:

- **Development of Pavement Roughness Prediction Models**: This study aims to develop accurate pavement roughness (International Roughness Index) prediction models for two distinct climate zones: Dry-Non-Freeze and Wet-Freeze. The models will be constructed using multiple linear regression techniques, enabling us to understand the factors affecting pavement roughness in two different climate zones.

- **Development of Pavement Rutting Prediction Models**: This research seeks to create reliable models for predicting pavement rutting within the same two climate zones. Utilizing multiple linear regression, this objective focuses on understanding the factors affecting pavement rutting in two different climate zones.
- **Development of Alligator Crack Prediction Models**: The third objective of this research is to develop prediction models for alligator cracking. For this purpose, logistic regression will be developed to predict the occurrence and extent of alligator cracking in both the Dry-Non-Freeze and Wet-Freeze Zone. This approach will help identify the probability of such cracks occurring in two different climate zones.

4. RESEARCH HYPOTHESIS

The hypotheses of this research are clearly and comprehensively outlined below. Each hypothesis is defined to explore specific aspects of the research question, providing a structured framework for investigation.

4.1 Pavement Roughness Prediction Hypothesis:

- **Hypothesis 1**: The factors affecting pavement roughness differ significantly between Dry-Non-Freeze and Wet-Freeze climate zones.
- **Hypothesis 2**: Multiple linear regression models can accurately predict pavement roughness in Dry-Non-Freeze and Wet-Freeze climate zones using relevant variables expected to affect the pavement performance.

4.2 Pavement Rutting Prediction Hypothesis:

- **Hypothesis 1**: There are distinct predictors of pavement rutting that vary between Dry-Non-Freeze and Wet-Freeze climate zones.
- **Hypothesis 2**: Multiple linear regression models can effectively predict the extent of pavement rutting in two different climate zones using relevant pavement historical information and traffic load factors.

4.3 Pavement Alligator Crack Prediction Hypothesis:

- **Hypothesis 1**: The probability and extent of alligator cracking are influenced by specific factors and differences observable among the variables in the Dry-Non-Freeze and Wet-Freeze zones.
- **Hypothesis 2**: Logistic regression models can reliably predict the occurrence of alligator cracking, providing a probabilistic assessment of pavement deterioration in varying climate conditions.

5. DATA DESCRIPTIONS

This research utilized data from the Long-Term Pavement Performance (LTPP) program to predict the International Roughness Index (IRI), rutting, and alligator cracking in asphalt concrete pavements. The LTPP is managed by the Federal Highway Administration (FHWA) and was established under the Strategic Highway Research Program. The LTPP database serves as a pivotal reference in pavement research due to its extensive and comprehensive data collection. However, one notable challenge with the LTPP data is the presence of a significant number of missing values for certain variables, which could impact the robustness of predictive analyses. Despite this issue, the LTPP database remains a valuable long-term resource for employing advanced analytics in pavement management, providing critical insights that aid in the enhancement of pavement durability and performance. Table 2 describes the description of the several Data Items of the LTPP data (Damirchilo et al. 2021).

Table – 2: LTPP Data Description Table (Bhandari, Luo & Wang 2023)

Data Item	LTPP table	Table Description
LTPP – Section Inventory	EXPERIMENT_SECTION	Identifies test sections and pavement study programs
Maintenance Information	CONSTRUCTION_EVENTS_EXP	Maintenance and rehabilitation details including dates and types of work performed
Average Annual Daily Truck Traffic	TRF_TREND	Records AADTT for vehicle classifications ranging from 4 to 13
Annual Estimated Single Axle Load	TRF_TREND	Estimates annual ESAL (Equivalent Single Axle Load) for vehicle classes 4 through 13
Longitudinal Profile (IRI)	MON_HSS_PROFILE_SECTION	Contains values for the roughness index
Transverse Profile (Rutting)	MON_T_PROF_INDEX	Contains values for pavement rutting
Manual Distress	MON_DIS_AC_REV	Documents survey dates and measures areas of alligator cracking across various severity levels.
Layer Thickness	TST_L05B	Detailing pavement layer types, thicknesses
Precipitation	MERRA_TEMP_YEAR	Records annual precipitation data at the MERRA-2 cell centroid.
Temperature	MERRA_TEMP_YEAR	Measures yearly air temperature 2 meters above the MERRA-2 cell elevation

6. DATA ANALYSIS

Table 3 details the units of measurement for variables used in the explanatory data analysis and model development. This table categorizes each variable and its corresponding unit, providing a clear quantification framework for analytical purposes. The selection of variables is primarily informed by literature reviews, focusing on those significantly influencing pavement performance. Here, some variables are discussed in more detail:

- **Initial IRI:** This is the roughness value recorded at the onset of data collection for each pavement segment. Previous research has highlighted the importance of using the Initial IRI for developing IRI prediction models.
- **Time since initial measurement:** This variable measures the duration between the initial assessment or recording of a pavement's condition and a subsequent evaluation.
- **Pavement Age:** Determined by subtracting the year of last pavement rehabilitation/maintenance from the year of data collection, this variable reflects the time elapsed since the last significant pavement intervention.
- **Layer Thickness (Surface and Base):** These variables indicate the thickness of the pavement's surface and base layers, which are critical for assessing the structural integrity and durability of the pavement.
- **AADTT (Annual Average Daily Truck Traffic):** This measure indicates the daily average number of trucks that travel over a particular section of pavement, reflecting the intensity of heavy vehicle traffic.
- **ESAL (Equivalent Single Axle Load):** This variable quantifies the wear and tear caused on the pavement by traffic, calibrated to the damage typically caused by a single axle load.

Table - 3: Units of the variables

Variables	Unit
IRI	m/km
Intitial IRI	m/km
Rutting	mm
Alligator Cracking	Square Meters
Time Since Initial Measurement	Years
Pavement Age	Years
Surface Layer Thickness	inch
Base Layer Thickness	inch
AADTT (Annual Average Daily Truck Traffic)	Units of trucks per day
ESAL (Equivalent Single Axle Load)	18,000 lb (80 kN) equivalent single axle load (ESAL)

Figures 1 to 5 present a series of visualization plots demonstrating how pavement deteriorates over time and with age. Figures 1 through 3 specifically illustrate that the International Roughness Index (IRI) tends to increase as time progresses, across two distinct climate zones, indicating a correlation between time and increased pavement roughness. Figures 4 and 5, on the other hand, focus on the increasing pattern of rutting, showing that as pavement ages, rutting depths also tend to increase. These visualizations utilize boxplots to effectively showcase variations and trends at different time points and ages, providing a clear statistical summary of IRI and Rutting in two different climate zones. This method of data presentation captures the variability within each dataset, making it easier to observe the impacts of time and environmental factors on pavement conditions.

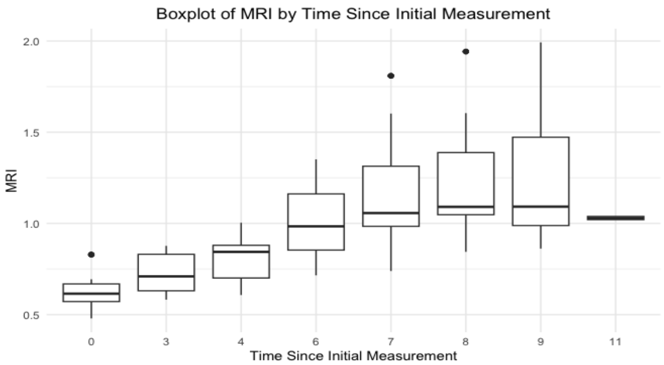

Figure 1: Descriptive Statistics of IRI in Dry-Non-Freeze Zone Using SPS-1 Experiment Data

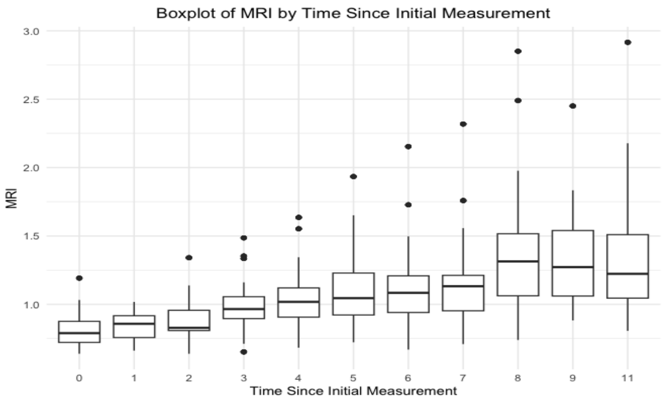

Figure 2: Descriptive Statistics of IRI in Wet-Freeze Zone Using SPS-1 Experiment Data

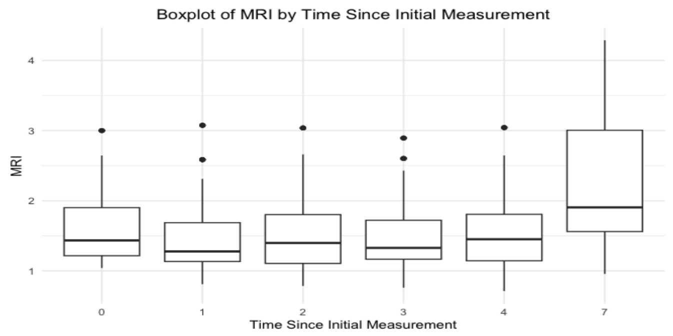

Figure 3: Descriptive Statistics of IRI in Wet-Freeze Zone Using SPS-3 Experiment Data

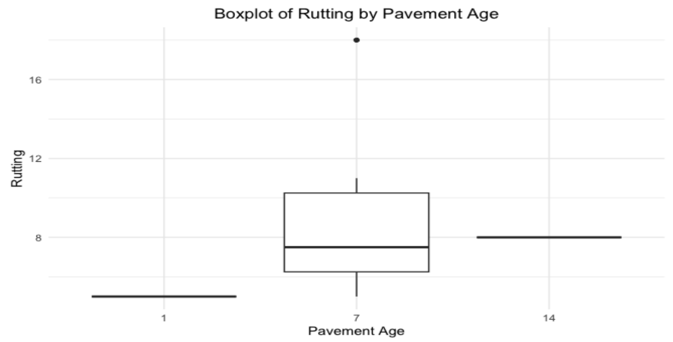

Figure 4: Descriptive Statistics of Rutting in Dry-Non-Freeze Zone Using SPS-1 Experiment Data

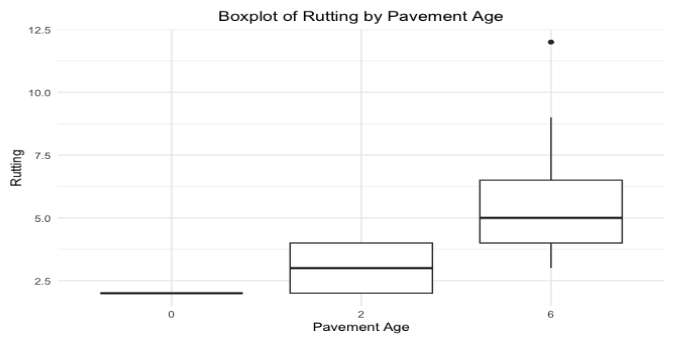

Figure 5: Descriptive Statistics of Rutting in Wet-Freeze Zone Using SPS-1 Experiment Data

7. METHODOLOGY

This research developed two types of models i.) Multiple Linear Regression ii.) Logistic Regression

7.1 Multiple Linear Regression

The objective of linear regression is to determine the relationship between one or more independent variables (X) with the dependent variable (Y). A linear regression that contains more than one variable is called multiple linear regression (Rahman et al., 2017). Statistical software R was used to develop Multiple Linear Regression Model.

The assumptions (Keith, 2019) of multiple linear regression are as follows:

1. A linear relationship exists between the dependent variable and the independent variables.

2. It is required to draw each observation independently from the population. This means that the errors for each observation are independent from those of others.

3. There should be a constant dispersion for each observation of the independent variables around the regression line. This property is referred to as homoscedasticity.

4. The errors are normally distributed.

5. Any of the independent variables should not be influenced by the dependent variable.

6. The independent variables are measured without any error.

7.2 Logistic Regression

A logistic regression is a special case of multiple regression where the response variable (also known as dependent variable) has only two outcomes (Ahmed et al. 2022). Statistical software R was used to develop Logistic Regression Model. Mathematically, it is expressed as:

$$\ln\left(\frac{P_n(i)}{1-P_n(i)}\right) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \dots\dots\dots + \beta_n x_n$$

$$\frac{P_n(i)}{1-P_n(i)} = \exp(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots\dots + \beta_n x_n)$$

$$P_n(i) = \frac{\exp(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n)}{1+\exp(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n)}$$

where,

$P_n(i)$ = probability of choosing a category

β_0 = intercept

x_n = predictor variables

β_n = coefficients of the corresponding variables

8. RESULTS AND DISCUSSIONS

Tables 4 to 10 present the results from multiple linear regression models for predicting the International Roughness Index (IRI) and rutting, and logistic regression models for predicting alligator cracking. In the multiple linear regression models, variable transformation of the outcome variable IRI and Rutting was conducted by applying logarithm. The Backward Elimination method was employed to refine these regression models. Variables that were not statistically significant were systematically excluded, resulting in models that incorporate only those factors that significantly impact the predictions.

8.1 IRI PREDCITION MODEL RESULTS

Table 4 shows that the initial IRI, time since initial measurement, and surface layer thickness were statistically significant variables for the IRI prediction model in the Dry-Non Freeze zone. Variables such as Base Layer Thickness, Annual Average Daily Truck Traffic (AADTT), and Equivalent Single Axle Load (ESAL) were not found to be significant. The model achieved an R^2 value of 0.68.

The analysis showed that initial IRI and time since initial measurement both have positive coefficient estimates, consistent with findings from the literature; the IRI increases with initial roughness and time, reflecting expected pavement deterioration. Conversely, the coefficient estimate for surface layer thickness is negative, aligning with engineering logic that thicker surface layers result in slower pavement deterioration. The regression results support this logical interpretation, demonstrating a clear relationship between these variables and pavement quality.

Table 4: IRI prediction model for Dry-Non-Freeze Zone (SPS – 1 experiment)

Variable	Estimate	Std. Error	t value	Pr (>t)
(Intercept)	0.229585	0.086357	2.659	0.0094 **
Initial IRI	0.653241	0.117359	5.566	3.2e-07 ***
Time Since Initial Measurement	0.038623	0.003270	11.811	< 2e-16 ***
Surface Layer Thickness	-0.02947	0.007919	- 3.72	0.00036***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 0.09107 on 82 degrees of freedom
Multiple R-squared: 0.6843, Adjusted R-squared: 0.6728
F-statistic: 59.25 on 3 and 82 DF, p-value: < 2.2e-16

Tables 5 and 6 detail the IRI prediction models for the Wet Freeze Zone using data from the SPS-1 and SPS-3 experiments. The initial IRI, time since initial measurement and base layer thickness were identified as statistically significant variables in both cases. Conversely, other variables, including surface thickness, were found to be statistically insignificant. The insignificance of surface thickness in these models could be attributed to several factors. In Wet Freeze zones, conditions such as freezing temperatures and moisture penetration may cause pavement deterioration more than surface thickness. Most importantly, the freeze-thaw cycles typical of such climates can lead to accelerated material degradation and structural failures, less influenced by the surface layer's thickness than other factors. The R^2 of the models are 0.63 and 0.70, respectively.

Table 5: IRI prediction model for Wet Freeze Zone (SPS – 1 experiment)

Variable	Estimate	Std. Error	t value	Pr (>t)
(Intercept)	0.284946	0.074141	3.843	0.000155 ***
Initial IRI	0.523170	0.066962	7.813	1.70e-13 ***
Time Since Initial Measurement	0.024069	0.001931	12.463	< 2e-16 ***
Base Layer Thickness	- 0.00591	0.001465	- 4.034	7.36e-05 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 0.09723 on 242 degrees of freedom
Multiple R-squared: 0.6325, Adjusted R-squared: 0.628
F-statistic: 138.8 on 3 and 242 DF, p-value: < 2.2e-16

Table 6: IRI prediction model for Wet Freeze Zone (SPS – 3 experiment)

Variable	Estimate	Std. Error	t value	Pr (>t)
(Intercept)	0.138296	0.097086	1.424	0.157
Initial IRI	0.410344	0.039385	10.419	< 2e-16 ***
Time Since Initial Measurement	0.026553	0.004989	5.322	4.2e-07 ***
Base Layer Thickness	0.013247	0.006002	2.207	0.029 *

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 0.1257 on 134 degrees of freedom
Multiple R-squared: 0.7036, Adjusted R-squared: 0.697
F-statistic: 106 on 3 and 134 DF, p-value: < 2.2e-16

8.2 RUTTING PREDICTION MODEL RESULTS

Tables 7 and 8 present the rutting prediction models for the Dry-Non-Freeze Zone and Wet-Freeze Zone, respectively. In the Dry-Non Freeze Zone, pavement age, surface layer thickness, and base layer thickness were identified as statistically significant variables. The coefficient estimate for pavement age is positive, which aligns with literature findings and logically suggests that rutting increases as pavements age. Conversely, the coefficients for surface and base layer thickness are negative, indicating that thicker pavements exhibit less rutting deterioration. The model achieves a high R^2 value of 0.90, indicating a good explanation of the variance in rutting by the included variables. As rutting can indicate pavement structural failure, traffic variables such as Equivalent Single Axle Load (ESAL) and Annual Average Daily Truck traffic (AADTT) should be statistically significant. Still, these variables were not statistically significant in this model, which could be due to the protective effect of the pavement structure in the Dry-Non-Freeze Zone, where robust surface and base layers effectively distribute the load and mitigate the impact of traffic loads on rutting. As such, variations in ESAL and AADTT might not significantly influence rutting when the pavement structure is sufficiently resilient.

From the rutting prediction model developed for the Wet-Freeze Zone, it was found that pavement age and Equivalent Single Axle Load (ESAL) are statistically significant variables. The model demonstrates a moderate R^2 value of 0.64. The significance of pavement age and ESAL in this model can be attributed to their direct impact on pavement wear and deterioration. Age is critical as older pavements typically show more signs of rutting due to cumulative stress and material fatigue over time. ESAL, representing the traffic load, directly influences the rate at which rutting occurs; higher traffic volumes and heavier loads accelerate the deformation of the pavement surface. Interestingly, surface and base layer thickness were not statistically significant variables in this model for the Wet-Freeze Zone. The probable reason could be that in environments subjected to freeze-thaw cycles, temperature fluctuations, and moisture ingress might have a more pronounced impact on the structural condition of pavement than its thickness. Freezing water can expand and cause damage to the pavement material, and repeated cycles can exacerbate this effect. In such scenarios, the material composition and quality, along with drainage and subgrade conditions, might play more significant roles than simply the thickness of the surface and base layers in mitigating rutting.

Table 7: Rutting prediction model for Dry-Non-Freeze Zone (SPS – 1 experiment)

Variable	Estimate	Std. Error	t value	Pr (> t)
(Intercept)	4.68681	0.57782	8.111	0.00126 **
Age	0.07873	0.02273	3.464	0.02572 *
Surface Layer Thickness	- 0.23625	0.04590	-5.147	0.00676 **
Base Layer Thickness	- 0.09939	0.02443	-4.069	0.01524 *

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 0.1759 on 4 degrees of freedom
Multiple R-squared: 0.9044, Adjusted R-squared: 0.8327
F-statistic: 12.61 on 3 and 4 DF, p-value: 0.01658

Table 8: Rutting prediction model for Wet Freeze Zone (SPS – 1 experiment)

Variable	Estimate	Std. Error	t value	Pr (> t)
(Intercept)	- 4.792e+00	2.029e+00	- 2.362	0.03444 *
Age	1.469e-01	4.090e-02	3.592	0.00328 **
ESAL	9.404e-05	3.448e-05	2.727	0.01727 *

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 0.3391 on 13 degrees of freedom
Multiple R-squared: 0.639, Adjusted R-squared: 0.5835
F-statistic: 11.51 on 2 and 13 DF, p-value: 0.001329

8.3 ALLIGATOR CRACK PREDICTION MODEL RESULTS

Table 9 shows the result of logistic regression model for alligator crack prediction model. From the model results, it was found that pavement age, surface layer thickness, and AADTT are statistically significant variables. The co-efficient for the age variable is 0.647813, which indicates that as the pavement age increases by one year, the log odds of observing alligator cracking increase significantly, suggesting that older pavements are more likely to exhibit alligator cracking. The coefficient for Surface Layer Thickness is -0.739545, which indicates that an increase in surface layer thickness decreases the likelihood of alligator cracking, suggesting that thicker surface layers are protective against this type of damage. The negative coefficient for AADTT (Annual Average Daily Truck Traffic) in the logistic regression model, although statistically significant, is not logical, as it is expected that heavier traffic increases the likelihood of pavement damage such as alligator cracking. A possible interpretation can be that in areas with high truck traffic, pavements are often designed to higher specifications and may receive more frequent maintenance to accommodate the heavy loads. This enhanced structural condition could reduce the occurrence of alligator cracking despite higher traffic volumes. Roads with higher traffic and heavy trucks are generally designed with thicker or more robust pavement structures that effectively distribute the load across the surface. This design aspect could mitigate the impact of heavy traffic on the pavement's susceptibility to alligator cracking.

Table 9: Alligator crack prediction model for Dry-Non-Freeze Zone (SPS – 1 experiment)

Variable	Estimate	Std. Error	z value	Pr (> z)
(Intercept)	3.548840	1.115093	3.183	0.00146 **
Age	0.647813	0.132293	4.897	9.74e-07 ***
Surface Layer Thickness	-0.739545	0.179040	-4.131	3.62e-05 ***
AADTT (Annual Average Daily Truck Traffic)	-0.002954	0.001241	-2.380	0.01731 *

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
(Dispersion parameter for binomial family taken to be 1)
Null deviance: 189.51 on 138 degrees of freedom
Residual deviance: 100.28 on 135 degrees of freedom
AIC: 108.28

For the Alligator crack model development for Wet Freeze Zone, only pavement age variable was found to be statistically significant. The co-efficient for the age variable is 0.6824, which indicates that as the pavement age increases by one year, the log odds of observing alligator cracking increase significantly, suggesting that older pavements are more likely to exhibit alligator cracking.

Table 10: Alligator crack prediction model for Wet Freeze Zone (SPS – 1 experiment)

Variable	Estimate	Std. Error	z value	Pr (> z)
(Intercept)	-1.3150	0.6696	-1.964	0.04955 *
Age	0.6824	0.2029	3.363	0.00077 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
(Dispersion parameter for binomial family taken to be 1)
Null deviance: 60.579 on 51 degrees of freedom
Residual deviance: 43.212 on 50 degrees of freedom
AIC: 47.212
Number of Fisher Scoring iterations: 5

9. CONCLUSION

This research developed pavement performance prediction models for the International Roughness Index (IRI), Rutting, and Alligator cracking using the LTPP data in two different climate zones (i.e., Dry-Non Freeze zone and Wet Freeze zones). This research helped to understand the variables that affect the pavement performance in two different climate zones. By understanding the significant predictors of pavement deterioration, state department of transportation can schedule maintenance before severe deterioration occurs. Predictive models help prioritize maintenance and rehabilitation efforts by forecasting the future condition of pavement sections. In addition, this allows for strategic allocation of limited resources, ensuring that budgets are used efficiently to maintain road quality and safety.

The significant findings obtained from the above analysis are documented below:

- Initial IRI, time since initial measurement, and surface layer thickness are found to be important predictors for the IRI prediction model in the Dry-Non Freeze zone
- In Wet Freeze zones, initial IRI and time since initial measurement remain significant; however, base layer thickness rather than surface thickness plays a significant role, likely due to the dominant impact of freeze-thaw cycles over structural features.
- In the Dry-Non Freeze zone, pavement age and the thickness of surface and base layers are found to be statistically significant variables for the rutting prediction model, indicating that thicker pavements are less prone to rutting despite varying traffic loads.
- For the Wet-Freeze Zone, pavement age and ESAL are significant predictors, emphasizing the impact of aging and traffic load on rutting. Surface and base layer thicknesses are less impactful, possibly due to environmental conditions such as moisture and freeze-thaw effects.
- In the Dry-Non Freeze zone, pavement age, surface layer thickness, and AADTT significantly influence the occurrence of alligator cracking. Interestingly, higher AADTT does not increase cracking as expected, suggesting that roads subjected to heavier traffic may be better designed and maintained.
- In the Wet-Freeze Zone, only pavement age is a significant predictor for alligator cracking

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