

1 **Deterioration Models for Flexible Pavements in the Pacific Northwest Using the Long-**  
2 **Term Pavement Performance (LTPP) Database**

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18

1 **ABSTRACT**

2 Prediction of pavement performance deterioration is crucial for effective transportation  
3 infrastructure management and maintenance planning. This study focuses on developing deterioration  
4 models for flexible pavements in the Pacific Northwest, leveraging the extensive data available in the  
5 InfoPave Long-Term Pavement Performance (LTPP) tool. Specifically, historical records of International  
6 Roughness Index (IRI) measurements are analyzed to understand the performance degradation patterns of  
7 flexible pavements over time. Utilizing Kaplan-Meier (K-M) survival time analysis (reliability analysis),  
8 we investigate the survival probabilities of flexible pavements based on IRI measures identified by the  
9 federal measures over varying time intervals. By analyzing these survival curves, we aim to derive  
10 deterioration models that accurately estimate the percentage of flexible pavements surviving within  
11 specified IRI thresholds over time and identify trends in deterioration patterns affected by parameters  
12 such as maintenance treatments, average annual daily truck traffic, number of freeze and thaw cycles,  
13 average temperature, and the presence of cracking. The developed models provide valuable understanding  
14 into the deterioration trends of the Pacific Northwest's flexible pavements and offer predictive tools for  
15 infrastructure asset managers to optimize maintenance strategies and allocate resources efficiently on the  
16 network level. This research contributes to the advancement of pavement management practices by  
17 utilizing robust statistical methods to analyze large-scale longitudinal flexible pavement performance data  
18 to enhance the resilience and durability of transportation infrastructure.

19  
20 **Keywords:** International Roughness Index, Deterioration Models, Flexible Pavement, Infrastructure  
21 Resilience, LTPP.

# 1 INTRODUCTION

2 Approximately 94% of the paved roads in the United States are surfaced with asphalt,  
3 underscoring the critical role these structures play in national infrastructure and daily life. The integrity  
4 and functionality of pavements are paramount not only for efficient transportation systems but also for  
5 road safety. Each year, the American Society of Civil Engineers (ASCE) evaluates the state of U.S.  
6 infrastructure, revealing significant concerns related to road conditions. For instance, the 2009 report  
7 highlighted that out of 41,059 motor vehicle fatalities, approximately 14,000 were attributable to poor  
8 road and highway conditions. Furthermore, these adverse road conditions also contributed to over 2.49  
9 million injuries [1]. Studies further indicate that 15% to 18% of traffic accidents occur on wet pavements,  
10 which are often exacerbated by poor pavement conditions.

11 The importance of robust pavement management systems is increasingly recognized at the  
12 national level. The Moving Ahead for Progress in the 21st Century (MAP-21) federal transportation  
13 legislation mandates U.S. state highway agencies to develop performance-based approaches in their  
14 pavement management decision-making processes [2]. This legislative framework supports the need for  
15 continuous improvements in pavement evaluation and maintenance strategies, emphasizing the  
16 significance of long-term data collection and analysis for informed decision-making. In the broader  
17 economic context, road transportation is integral to the functioning of societies, influencing between 10%  
18 and 20% of the Gross Domestic Product (GDP). Roads facilitate personal mobility, including access to  
19 services, goods, and leisure, making the reliability of these transport pathways crucial for the economic  
20 stability and growth of nations [3]. Given these stakes, it becomes imperative to invest in research that  
21 seeks to extend the life of pavements and enhance their safety features through improved performance  
22 deterioration models and maintenance practices.

23 The Long-Term Pavement Performance (LTPP) program [4], initiated by the Federal Highway  
24 Administration (FHWA), has provided an invaluable database for pavement research, enabling the  
25 development and validation of numerous predictive models across various studies. This comprehensive  
26 collection of data spans hundreds of pavement sections and includes detailed information on pavement  
27 structure, performance, and environmental conditions, making it a cornerstone for advanced pavement  
28 deterioration and performance modeling. Recent studies illustrate the diversity and depth of analysis  
29 possible with LTPP data. For example, Jia et al. [5] utilized the LTPP data to develop a novel framework  
30 for characterizing the transverse profile shapes of rutting on asphalt pavements. Their approach, which  
31 integrates data acquisition, profile adjustment, categorization, and indicator analysis, demonstrates the  
32 utility of LTPP data in enhancing our understanding of specific distress mechanisms such as rutting.  
33 Similarly, Younos et al. [6] employed data from 89 LTPP sections to develop multi-input performance  
34 prediction models based on the Pavement Condition Index (PCI), highlighting the dataset's role in  
35 validating comprehensive pavement condition assessments. Further extending the application of LTPP  
36 data, Karam and Noorvand [7] focused on modeling the rutting potential in asphalt concrete subjected to  
37 repeated traffic loads, particularly in high-temperature environments. Their predictive model incorporates  
38 materials properties, traffic, and climatic data from the LTPP InfoPave database, showcasing the  
39 versatility of LTPP data in addressing region-specific pavement issues.

40 In addition to predictive modeling, Luo et al. [8] explored the effectiveness of preventive  
41 maintenance (PM) treatments using Specific Pavement Studies (SPS-3) data from the LTPP program.  
42 Their study evaluates the short-term impacts of various PM treatments on pavement performance, thereby  
43 contributing to more effective maintenance strategies. Moreover, the integration of advanced analytical  
44 techniques with LTPP data continues to expand. Li et al. [9] demonstrated the use of machine learning  
45 (ML) methods to predict the modulus of asphalt concrete layers, employing LTPP data to train and test  
46 their models. This approach not only enhances the accuracy of mechanical empirical rehabilitation  
47 analysis but also provides tools for managing pavement networks without extensive direct testing data.  
48 The research by Kaloop et al. [10] underscores the predictive capabilities enabled by LTPP data through  
49 the development of an IRI prediction model using Gaussian Process Regression and Locally Weighted  
50 Polynomials. Their work emphasizes the role of LTPP data in refining performance indicators critical to

1 pavement management. Zhang and Wang [11] and Khan et al. [12] have further broadened the scope of  
2 LTPP data utilization by incorporating geospatial and decision tree analyses to explore the impacts of  
3 environmental factors and traffic loads on pavement performance, and by employing experimental design  
4 techniques to analyze data-driven pavement design strategies. Through these diverse applications, the  
5 LTPP data continues to be a pivotal resource in advancing the field of pavement engineering, providing a  
6 robust foundation for developing reliable, region-specific deterioration models that address the unique  
7 challenges faced by pavement infrastructures across different geographic and climatic conditions. This  
8 research builds on previous research to improve the capabilities of pavement deterioration modeling  
9 specifically in the Pacific Northwest by leveraging the LTPP dataset in conjunction with innovative  
10 analytical methodologies.

## 11 **Literature Review**

13 The development of pavement deterioration prediction models is a crucial aspect of pavement  
14 management, enabling engineers and policymakers to make informed decisions regarding maintenance,  
15 rehabilitation, and overall infrastructure planning. A rich history of research utilizing various  
16 methodologies showcases the advancements and challenges in this field. One of the key performance  
17 indicators in pavement management is the IRI, which serves as a primary metric for evaluating pavement  
18 condition and ride quality. Kaloop et al. [10] developed a sophisticated IRI prediction model using  
19 Gaussian Process Regression and Locally Weighted Polynomials. This model utilized multiple variables  
20 from the LTPP data, including pavement age, initial IRI, and various distress indicators, demonstrating the  
21 complexity of factors influencing IRI. Beyond IRI, the Pavement Condition Index (PCI) has also been a  
22 focal point of study. Younos et al. [6] proposed multi-input performance prediction models based on PCI,  
23 using observations from specific pavement studies within the LTPP database. This approach highlights the  
24 utility of comprehensive datasets in developing reliable predictive models without maintenance  
25 influences. Justo-Silva et al. [3] provided a broader perspective by reviewing various modeling techniques  
26 used in pavement performance prediction. They emphasized the stochastic nature of pavement  
27 deterioration and the need for complex deterministic or probabilistic models, offering guidelines for  
28 future model development.

29 The integration of ML techniques has brought a new dimension to pavement deterioration  
30 modeling. Baykal et al. [13] utilized ensemble ML algorithms, including decision trees and boosting  
31 methods, to estimate IRI based on age, traffic loads, and structural parameters. Similarly, Liu et al. [14]  
32 applied ML to improve asphalt mix design, thereby enhancing pavement performance by predicting IRI  
33 values from the LTPP data. Innovative approaches have also been employed to overcome data variability  
34 challenges. Piryonesi and El-Diraby [15] segmented LTPP data into smaller, more cohesive groups based  
35 on location and functional class, which significantly improved model accuracy. This method underscores  
36 the importance of considering geographical and functional diversities in pavement analysis. Furthermore,  
37 the use of gene expression programming (GEP) by Imam et al. [16] to predict PCI from IRI exemplifies  
38 the novel application of genetic algorithms in pavement modeling, providing a fresh perspective on the  
39 relationship between different performance metrics. Also, the work by Tamagusko and Ferreira [17]  
40 systematically reviews ML models for predicting IRI, highlighting the transition towards more data-  
41 driven, accurate, and efficient modeling approaches in pavement management. Their synthesis of current  
42 methodologies provides valuable insights into the capabilities and future directions of pavement  
43 deterioration modeling.

44 Kaplan-Meier (K-M) survival analysis, traditionally used in medical research to estimate the  
45 survival time of patients, has found innovative applications in the field of pavement engineering. This  
46 nonparametric method provides a powerful tool for analyzing the survival probabilities of pavement  
47 systems over time, enabling researchers to better understand how various factors influence pavement  
48 longevity and performance [18]. In the realm of pavement research, K-M survival analysis is particularly  
49 useful for evaluating how long pavement remains in acceptable condition before reaching failure or  
50 requiring significant maintenance interventions. This approach allows for the estimation of median

1 survival times and the development of survival probability curves for various pavement distresses. A  
2 notable application of this method was presented by Hatoum et al. [19], who utilized K-M survival  
3 analysis to study the performance of flexible pavements. Their research focused on assessing the impacts  
4 of using reclaimed asphalt pavement (RAP) versus virgin materials on the fatigue life of asphalt  
5 pavements. By examining test sections extracted from the LTPP program, the study developed separate  
6 fatigue survival curves for pavements constructed with RAP and those with virgin materials. This analysis  
7 not only tested the equality of survival probabilities between the two materials but also highlighted the  
8 significant effect of vehicle overloading on pavement deterioration. Moreover, the study explored the  
9 influence of combined factors such as environmental conditions, pavement materials, and traffic loads on  
10 pavement performance. Through nonparametric and parametric survival analyses, Hatoum et al. [19]  
11 identified the most significant subset of risk factors (covariates) affecting pavement longevity. This  
12 involved developing K-M survival probability curves for multiple pavement distresses, comparing their  
13 failure probabilities, and determining the median survival time for each type of distress.

14 The utilization of K-M survival analysis in this context demonstrates its versatility and value in  
15 pavement engineering. It provides a robust framework for analyzing time-to-event data, offering a clearer  
16 understanding of the durability and performance of pavement systems under various stressors. This  
17 approach not only aids in the predictive modeling of pavement deterioration but also supports the  
18 development of more sustainable, cost-effective, and environmentally friendly solutions in road  
19 construction. By integrating K-M survival analysis into pavement research, this study enhances the  
20 methodological toolkit available to engineers and researchers, enabling more precise predictions of  
21 pavement life and more informed decision-making in pavement management. This research utilizes these  
22 techniques to further investigate the survival probabilities of flexible pavements in the Pacific Northwest,  
23 aiming to develop detailed models that reflect the unique environmental and operational conditions of the  
24 region.

25 The study of pavement performance and deterioration modeling is enriched by a diverse array of  
26 research contributions that collectively advance our understanding and management of pavement systems.  
27 Among the significant works in this field, the research by Medina et al. [20] stands out for its innovative  
28 approach to correlating the IRI with the PCI. Their study established a relationship between these two  
29 critical indices using a concept analogous to the time-temperature superposition principle known in  
30 materials science, which they adapted as the time-deterioration superposition principle for pavements.  
31 Medina et al. [20] focused on the practical aspect of pavement management, particularly under the  
32 constraints of budget and resource availability that vary significantly across different jurisdictions.  
33 Recognizing that IRI data collection is more affordable and frequent compared to detailed pavement  
34 distress surveys, their study aimed to leverage the more readily available IRI data to infer PCI. This  
35 approach is particularly beneficial for agencies with limited resources, enabling them to maintain  
36 effective pavement management practices without the extensive data collection costs associated with  
37 comprehensive distress surveys. The analysis used data from the LTPP InfoPave database, focusing on  
38 flexible pavements within network samples from Arizona, California, and Wisconsin. Their findings  
39 revealed a robust correlation between the changes in IRI and PCI over time, with coefficients of  
40 determination ranging from 0.71 to 0.85. These results not only demonstrate the efficacy of the proposed  
41 modeling approach but also establish a set of general threshold limits for IRI that can serve as  
42 benchmarks for assessing pavement condition across various networks.

43 This research is relevant to the current study as it illustrates a successful application of  
44 deterioration modeling techniques that combine multiple performance indices, providing a comprehensive  
45 view of pavement condition. Furthermore, the use of a time-deterioration superposition principle suggests  
46 a novel methodology that can be adapted and expanded upon in other contexts, including the Pacific  
47 Northwest, where specific regional conditions such as climate and traffic patterns may influence  
48 pavement performance differently. This study aims to contribute to this vital area by developing reliable  
49 models for predicting the deterioration of flexible pavements in the Pacific Northwest. Utilizing the LTPP  
50 data, this research seeks to innovate in the modeling of pavement degradation, addressing unique regional

1 challenges such as varying climate conditions and traffic patterns. By enhancing our understanding of  
2 pavement life cycles and deterioration processes, the findings from this study are expected to inform and  
3 refine pavement management strategies, leading to safer, more durable roads.

## 4 5 **METHODS**

6 The data used in this study were obtained from the InfoPave LTPP tool, a comprehensive  
7 database that offers a wealth of pavement performance data across various geographical regions in the US  
8 and Canada. Our focus was on flexible pavement sections in the Pacific Northwest, covering the states of  
9 Wyoming, Oregon, Idaho, Montana, and Washington. To narrow down our scope, we applied a filter for  
10 flexible pavement surface types within the Pacific Northwest states, resulting in the selection of 137  
11 sections distributed as follows: 23 sections in Wyoming, 15 sections in Oregon, 24 sections in Idaho, 38  
12 sections in Montana, and 37 sections in Washington. From the Pavement Structure and Construction tab,  
13 we obtained records of asphalt concrete (AC) surface treatments for the selected sections. The  
14 Performance tab provided us with data on AC distresses and Analysis Ready IRI datasets, which are key  
15 indicators of pavement condition and degradation over time. Traffic data, including truck volumes and  
16 Traffic Summary Statistics, were sourced from the Traffic tab. This data offers insights into the levels of  
17 truck traffic volumes affecting the pavements in the study area. Additionally, temperature data was  
18 collected from the Climate tab, which helps us understand the environmental factors influencing  
19 pavement performance with time.

20 Our study focused on data recorded over time, specifically examining IRI data for 129 out of the  
21 total 137 sections from the years 1989 to 2021. It is important to note that no IRI records were found for  
22 any section in the year 2006. This longitudinal data allowed us to track changes in pavement condition  
23 and develop models of deterioration trends. By utilizing this comprehensive dataset, we were able to  
24 perform a detailed analysis of flexible pavement performance in the Pacific Northwest region,  
25 contributing valuable insights into the long-term durability and resilience of transportation infrastructure  
26 in the region.

27 The data preparation process began with the identification of the number of record years for each  
28 pavement section. Sections with fewer than five years of recorded data were filtered out, resulting in a  
29 subset of 97 sections suitable for further analysis. This approach ensured the inclusion of sections with  
30 sufficient historical data to observe trends over time. Once the dataset was filtered, the remaining data  
31 were sorted chronologically from oldest to newest records, ensuring consistency in the timeline of each  
32 section. We aligned the corresponding independent variables, which included Annual Average Daily  
33 Truck Traffic (AADTT), the number of freeze and thaw cycles, average temperature, percentage of  
34 alligator cracking, length of transverse cracking, and length of longitudinal cracking. The maintenance  
35 history of each section was obtained from the LTPP data field reference guide and categorized according  
36 to predefined categories. This categorization facilitated a more systematic analysis of the impact of  
37 maintenance treatments on pavement performance. During data preparation, we encountered instances  
38 where discontinuities occurred in the dataset. These were cases where specific independent variables were  
39 not recorded in the same year as the corresponding IRI values. Such inconsistencies were addressed by  
40 cleaning the data and removing records with incomplete information, ensuring a high-quality and  
41 consistent dataset for subsequent analysis. By following this data preparation process, we achieved a  
42 comprehensive, cleaned, and filtered dataset ready for use in our analysis. This approach allowed for  
43 accurate modeling of flexible pavement deterioration patterns while taking into account the various  
44 factors influencing pavement performance over time.

45 To investigate the deterioration of flexible pavements over time, we adopted K-M survival time  
46 analysis, also known in engineering as reliability analysis or time to failure analysis. This statistical  
47 approach examines the incidence and timing of events, specifically the changes in IRI measures identified  
48 by federal standards over time. The K-M method is a nonparametric maximum likelihood estimator,  
49 commonly employed to estimate survival probabilities of pavement sections transitioning between  
50 different condition ratings. This method is particularly suitable for discontinuous data, as it can handle

1 variability in the intervals between recorded observations and the occurrence of events. The K-M  
 2 methodology calculates survival probabilities over time and provides insights into the expected lifespan  
 3 of flexible pavements under different conditions. The analysis produces survival curves, which show the  
 4 proportion of pavement sections that remain within specified IRI thresholds over time. These curves  
 5 allow us to assess the rate of deterioration and identify key factors influencing pavement performance.  
 6 Reliability data can be calculated using the K-M estimator by Equation 1.

$$\hat{S}(t) = \prod_{j:t_j \leq t} \left(1 - \frac{d_j}{n_j}\right) \text{ for } t_1 \leq t \leq t_k \quad (1)$$

7 where

8  $\hat{S}(t)$  is the K-M estimator,

9  $d_j$  is the number of sections for which the event occurred (transitioned to the lower condition) at time  $t_j$ ,

10  $n_j$  is the number of sections at risk of event at time  $t_j$ , and

11  $t_1$  and  $t_k$  are the boundary for  $k$  distinct event times

12  
 13 One limitation of the K-M method is the reduction in the quantity of available data when time-  
 14 blocking is used for analysis. Time-blocking, which involves dividing data into intervals based on specific  
 15 factors (e.g., era of construction), can lead to a loss of information and reduced sample sizes. Despite this  
 16 drawback, the K-M estimator remains a powerful tool for analyzing time-to-event data and uncovering  
 17 trends in flexible pavement performance.

18 We developed two K-M models to investigate the survivability of flexible pavement sections. The  
 19 first K-M model was designed to study the survival probability of flexible pavement sections classified as  
 20 being in good condition according to the federal standards, which is defined as having an IRI value of less  
 21 than 95 in/mi. This model provided insights into the expected lifespan of pavements that maintained a  
 22 high level of quality. The second K-M model was performed to investigate the survival probability of  
 23 flexible pavement sections classified as being in good or fair condition according to the federal standards,  
 24 which is defined as having an IRI value of less than 170 in/mi. This broader range allowed us to explore a  
 25 wider spectrum of pavement conditions and how they influence longevity. In both models, we considered  
 26 the maintenance history of each section to determine the potential impact of surface treatments on the rate  
 27 of IRI deterioration over time. By examining how maintenance treatments affected the slope of the K-M  
 28 curves, we were able to identify potential points of change where specific treatments may have helped to  
 29 slow down the deterioration process. Overall, K-M survival time analysis provides a robust framework for  
 30 assessing the reliability and deterioration patterns of flexible pavements in the Pacific Northwest. By  
 31 leveraging this approach, we can derive meaningful insights into pavement lifespan and develop  
 32 predictive models to support infrastructure management and maintenance planning.

33 Multiple regression analysis is a statistical technique employed in this study to explore the  
 34 relationship between the dependent variable and multiple independent variables. Specifically, it is used to  
 35 analyze the relationship between the IRI, and various independent variables such as AADTT, the number  
 36 of freeze-thaw cycles, average temperature, percentage of alligator cracking, length of transverse  
 37 cracking, and length of longitudinal cracking. Forward stepwise regression, a subset of multiple  
 38 regression, begins with an empty model and sequentially adds variables. At each step, the variable that  
 39 most significantly enhances the model, typically measured by the increase in R-squared, is included. This  
 40 process continues until no additional variables significantly contribute to the model's predictive power.  
 41 The general equation for a multiple regression model is given in Equation 2, while Equation 3 was  
 42 adopted in our study.

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_k X_k + \epsilon \quad (2)$$

44 where

45  $Y$  is the dependent variable,

46  $X_1, X_2, \dots, X_k$  are the independent variables,

1  $\beta_0$  is the intercept,  
2  $\beta_1, \beta_2, \dots, \beta_k$  are the coefficients of the independent variables, and  
3  $\epsilon$  is the error term, representing unexplained variation.  
4

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \epsilon \quad (3)$$

5 where  
6  $Y$  is the dependent variable (IRI value),  
7  $X_1$ : AADTT,  
8  $X_2$ : number of freeze and thaw cycles,  
9  $X_3$ : average temperature,  
10  $X_4$ : percent of alligator cracking,  
11  $X_5$ : length of transverse cracking,  
12  $X_6$ : length of longitudinal cracking,  
13  $\beta_0$  is the intercept,  
14  $\beta_1, \beta_2, \dots, \beta_6$  are the coefficients of the independent variables, and  
15  $\epsilon$  is the error term, representing unexplained variation.  
16

17 Using forward stepwise regression facilitates the modeling process by incrementally selecting the  
18 most influential variables, providing a practical approach to identifying key factors affecting pavement  
19 roughness, especially when dealing with numerous potential predictors. This method is advantageous for  
20 ensuring that only statistically significant variables are retained in the final model, thereby enhancing  
21 model efficiency and interpretability. For the modeling and analysis, RStudio software was used. The  
22 models were run on a workstation equipped with an Intel(R) Xeon(R) CPU E3-1245 v5 @ 3.50 GHz  
23 processor and 16.0 GB of RAM, running Windows 10 Education. This setup provided the necessary  
24 computational power and environment to handle the data effectively and perform the analyses efficiently.  
25

## 26 RESULTS

27 In this study, we developed two K-M models to investigate the survivability of flexible pavement  
28 sections in the Pacific Northwest, using different criteria for pavement condition based on IRI values.  
29

### 30 Pavements in Good Condition (IRI < 95 in/mile)

31 The first model focused on the survival probability of flexible pavements considered to be in  
32 good condition (i.e., IRI value less than 95 in/mile). Figure 1 shows the K-M survival curve for this  
33 condition threshold demonstrates an initial high survival probability that gradually declines over time.  
34 The survival probability remains fairly stable in the early years, indicating good performance of the  
35 pavement sections initially. However, there is a noticeable change in the slope of the survival curve  
36 around the 5-year mark, where the survival probability begins to decrease at a faster rate, suggesting a  
37 significant deterioration in pavement quality over time. The smoothed survival curve, Figure 2, further  
38 highlights these changes, showing a more gradual but consistent decline in survival probability after  
39 approximately 5 years.

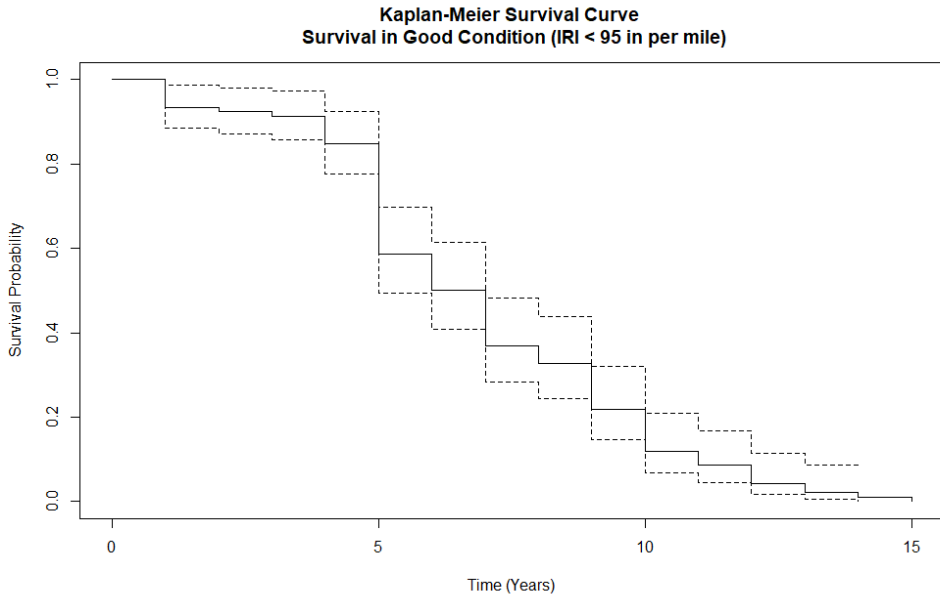


Figure 2: Survival probability in good condition (IRI < 95 in/mile)

1

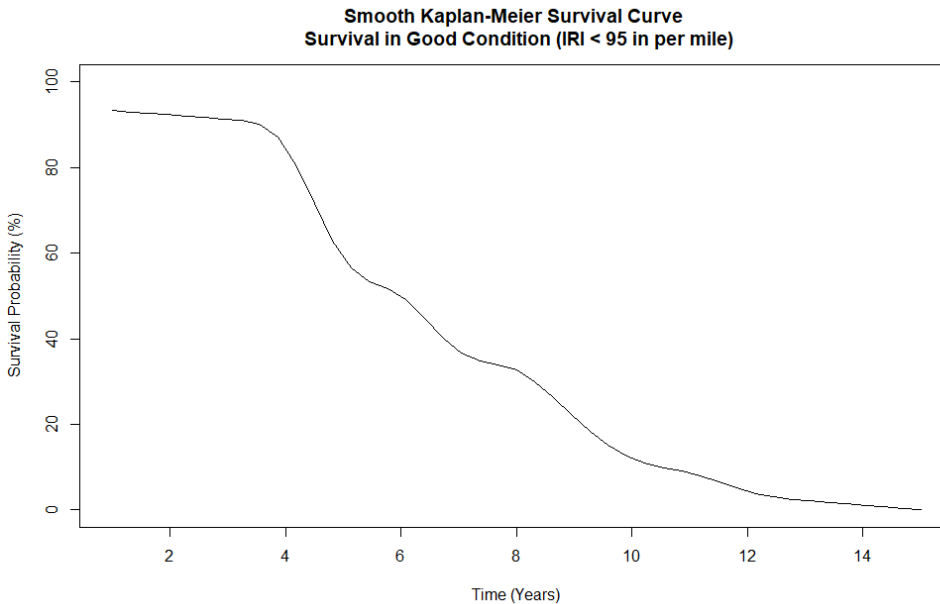


Figure 1: Smoothed survival probability in good condition (IRI < 95 in/mile)

2 **Pavements in Good or Fair Condition (IRI < 170 in/mile)**

3 The second model examined pavements categorized under good or fair condition (i.e., IRI value  
 4 less than 170 in/mile). Figure 3 shows the survival curve, for this broader condition range, starts with a  
 5 higher initial survival probability compared to the stricter good condition model. The curve exhibits a  
 6 slower rate of decline in the initial years, but similar to the first model, a noticeable change in slope  
 7 occurs around the 10-year mark. This indicates that while pavements may remain in fair condition for a  
 8 longer period, they eventually begin to deteriorate more rapidly.

1 The smoothed survival curve, Figure 4, for this model emphasizes a more pronounced and steady  
2 decline after the initial stable period, which correlates with increased deterioration rates as the pavement  
3 ages.

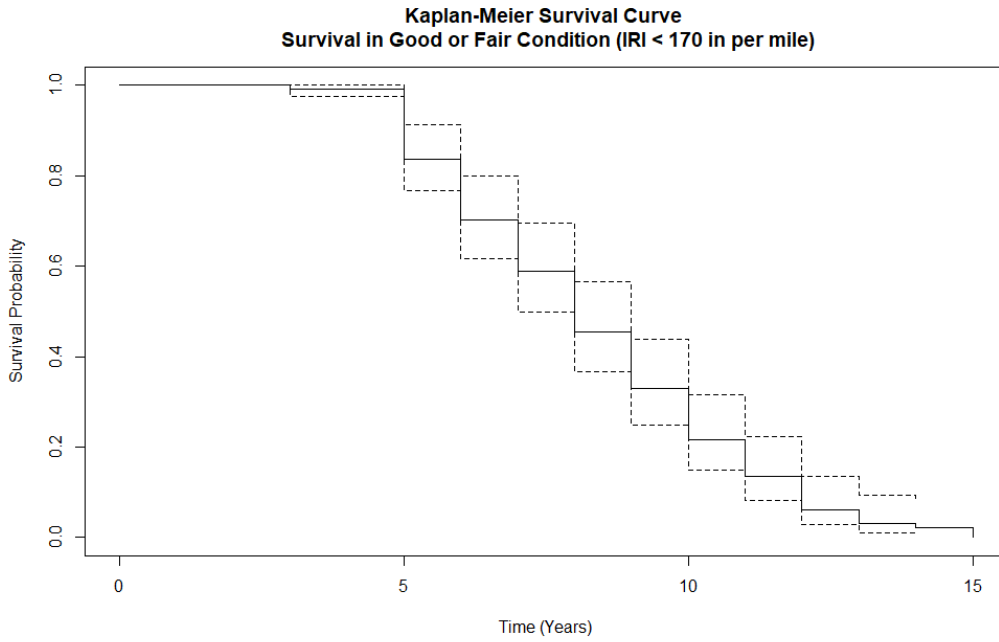


Figure 3: Survival probability in good or fair condition (IRI < 170 in/mile)

4

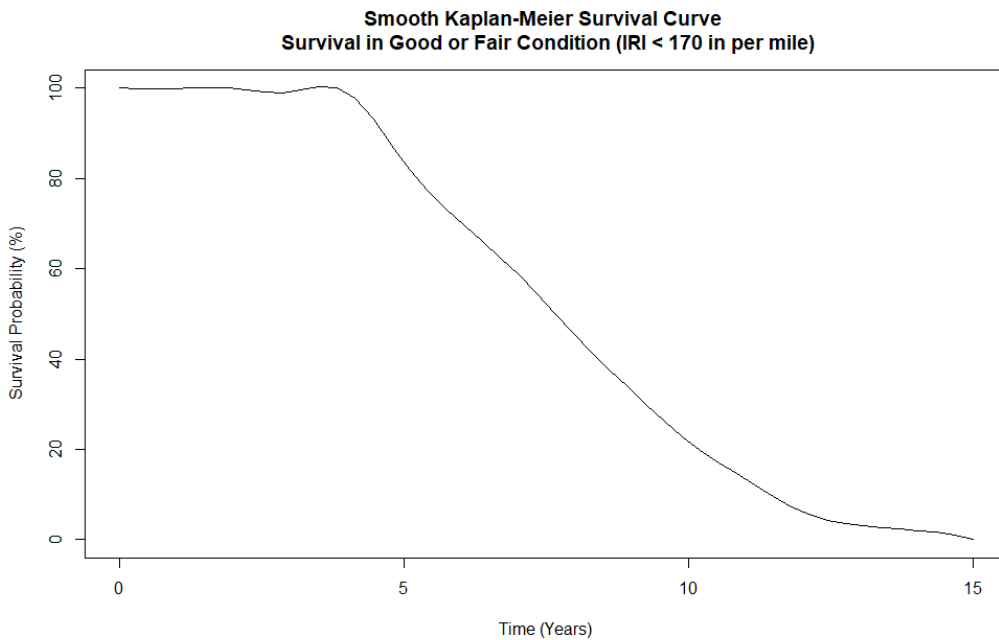


Figure 4: Smoothed survival probability in good or fair condition (IRI < 170 in/mile)

5

6

## 1 Analysis of Kaplan-Meier Survival Curves with Maintenance Interventions

2 Interestingly, at points where changes in the slope of the K-M curves are observed, corresponding  
3 maintenance history data indicates the application of surface treatments. These maintenance interventions  
4 appear to coincide with the changes in the rate of pavement deterioration, suggesting that timely  
5 maintenance could be effectively slowing down the deterioration process. Specifically, the points of slope  
6 change in both models seem to align with significant maintenance activities, which could be attributed to  
7 the retardation in the degradation of the IRI values over time. In the survival curve for pavement sections  
8 categorized as being in good condition, the treatments applied at the first 4 years of the pavement lifespan  
9 and at approximately 5, 7, 10, and 12 years appear to significantly alter the trajectory of the curve (Figure  
10 5). Prior to the treatment at 5 years, the curve shows a severe decline, suggesting a natural progression of  
11 deterioration. After each treatment, however, the rate of decline in survival probability noticeably slows,  
12 indicating that the treatments are effective in extending the pavement's lifespan in good condition. This is  
13 particularly evident after the second and third treatments at around 7 and 10 years, where the slope of the  
14 curve flattens, suggesting a pronounced retardation in deterioration.

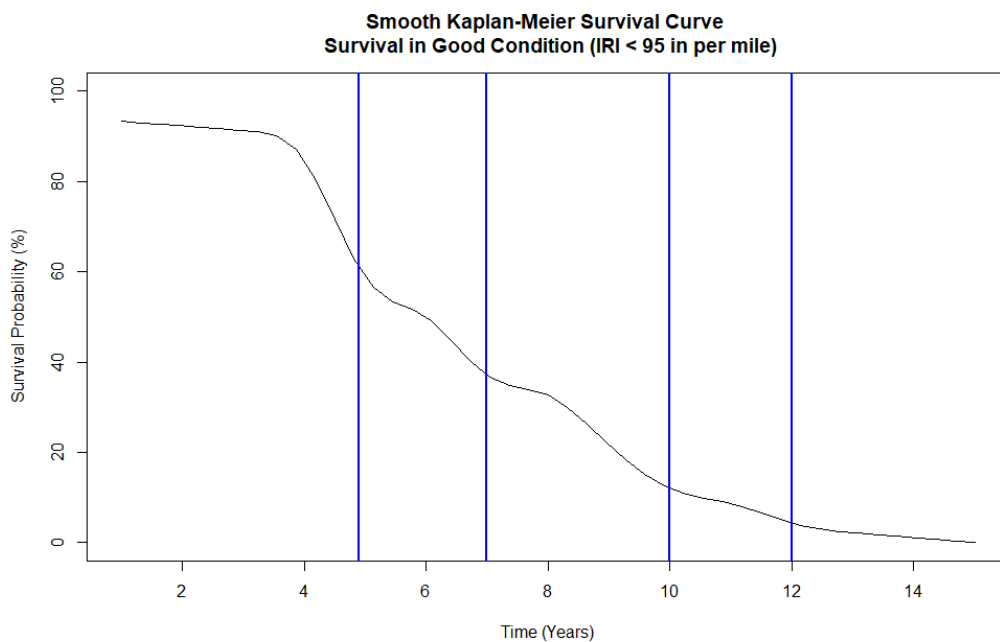


Figure 5: Maintenance interventions for pavements surviving in good conditions

15 For pavements maintained in good or fair condition, the treatments at the same points, the first 5  
16 years of the pavement lifespan and at around 7, 10, and 12 years, also show a marked impact on the  
17 survival probabilities. The curve initially declines steadily, but each maintenance intervention correlates  
18 with a noticeable deceleration in the rate of deterioration (Figure 6).

19 These findings suggest that proactive and strategic maintenance plays a crucial role in extending  
20 the lifespan of pavement sections and maintaining them within acceptable IRI thresholds. The analysis  
21 demonstrates the effectiveness of surface treatments in impacting pavement survival rates, providing  
22 valuable insights for transportation infrastructure management and planning. These results are discussed  
23 further in the subsequent sections to explore their implications for pavement management practices and to  
24 compare them with existing literature on pavement deterioration modeling.

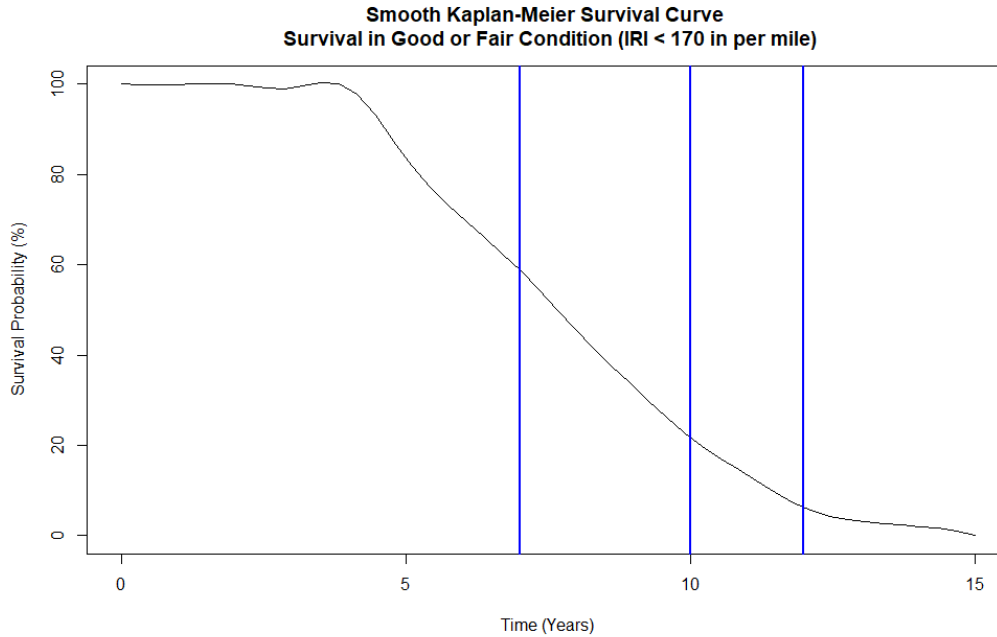


Figure 6: Maintenance interventions for pavements surviving in good or fair conditions

## 1 Regression Analysis

2 Our regression analysis aimed to explore the relationships between the IRI and a set of  
 3 independent variables to identify key factors influencing pavement performance. We used a linear  
 4 multiple regression model, as described in the methods section, and performed the analysis to select the  
 5 most suitable model for the data. Initial exploration of the correlation matrix revealed varying levels of  
 6 correlation between the independent variables and the response variable, IRI value, as shown in Figure 7.  
 7 Specifically, average temperature ( $X_3$ ), percentage of alligator cracking ( $X_4$ ), and length of longitudinal  
 8 cracking ( $X_5$ ) demonstrated a moderate to strong correlation with IRI. In contrast, annual average daily  
 9 truck traffic ( $X_1$ ), the number of freeze and thaw cycles ( $X_2$ ), and length of transverse cracking ( $X_6$ )  
 10 showed lower correlation with IRI. This observation was consistent with the scatterplot matrix, which  
 11 further corroborated the distinct relationships between IRI and specific independent variables.

12 Reducing the model by excluding variables with lower correlation could enhance its predictive  
 13 capability, providing insights that can guide maintenance strategies and infrastructure planning.  
 14 Performing the full model hypothesis test, we found that at least one factor significantly affected the IRI  
 15 value of flexible pavement sections. Testing for collinearity indicated that collinearity was not a concern  
 16 in our model. We continued with individual factor hypothesis testing, where the null hypothesis was that  
 17 each factor is not significant. The tests revealed that annual average daily truck traffic ( $X_1$ ) and length of  
 18 transverse cracking ( $X_6$ ) were not significant, as the null hypothesis was not rejected for these two factors.  
 19 Consequently, they were considered for removal from the model. Upon inspection of the adjusted R-  
 20 squared value, we found that 52.44% of the variation in IRI values could be explained by the relationships  
 21 between all the variables in the model. However, further analysis was conducted to optimize the model.  
 22 This included removing  $X_1$  and  $X_6$  and exploring potential model transformations to improve the  
 23 correlation and explanatory power of the model. These adjustments were pursued to enhance the model's  
 24 predictive capability and better capture the key factors influencing pavement deterioration. Assessment of  
 25 model assumptions was conducted to ensure the mean of residuals approximated zero (indicating  
 26 linearity), residuals followed a normal distribution, residuals were independent, and variance of residuals  
 27 was homogenous. Further examination of diagnostic plots confirmed that all model assumptions were

- 1 met. Several reduced models were tested to identify the most appropriate model, following a forward
- 2 stepwise analysis approach.

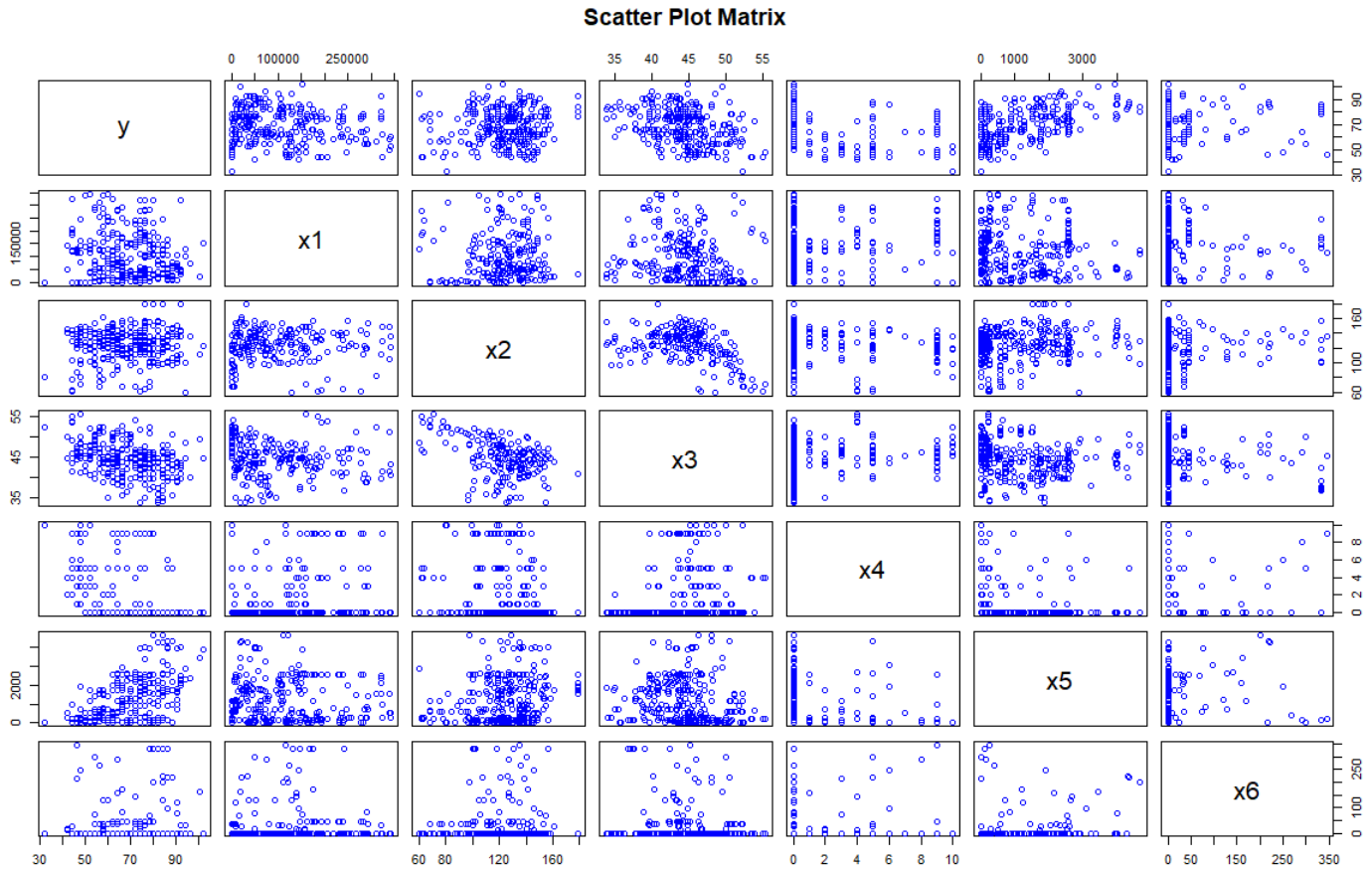


Figure 7: Full model scatter plot matrix

- 3 The selected model, excluding annual average daily truck traffic ( $X_1$ ) and length of transverse
- 4 cracking ( $X_6$ ), showed a slightly higher R-squared value of 55.28% compared to the full model and all
- 5 tested reduced models. Assessment of the selected model's assumptions was performed to ensure all
- 6 assumptions were met. Diagnostic plots further confirmed that all assumptions were met. As a result, the
- 7 chosen model is considered the most suitable for predicting IRI values based on the analyzed LTPP
- 8 dataset. The selected model for this study is shown in equation (4). This model, which omits  $X_1$  and  $X_6$ ,
- 9 optimally captures the key factors affecting pavement deterioration and serves as a valuable tool for
- 10 understanding and forecasting the condition of flexible pavement sections.

$$\hat{Y} = 174 - 13.82 \log(X_2) - 0.97 X_3 - 6.38 \log(X_4) + 0.006 X_5 \quad (4)$$

- 11
- 12 The "Predicted vs. Actual" plot illustrates the comparison between the predicted and actual (IRI)
- 13 values. The scatter plot, marked by a red line denoting perfect prediction alignment, reveals a general
- 14 concordance between the predicted and actual IRI measurements, thereby underscoring some predictive
- 15 accuracy of the model. However, the spread of data points around this line indicates notable prediction
- 16 variability. Particularly, the predictions are more consistent around the median IRI range, whereas
- 17 accuracy diminishes at the extremes, suggesting a potential underfitting issue where the model fails to
- 18 capture more complex or extreme data patterns. The lack of data points clustering tightly around the red
- 19 line further points to errors across the spectrum of IRI values, indicating room for model refinement or

- 1 enhancement through additional features or improved data quality to boost prediction accuracy, especially
- 2 for very low or high IRI values.

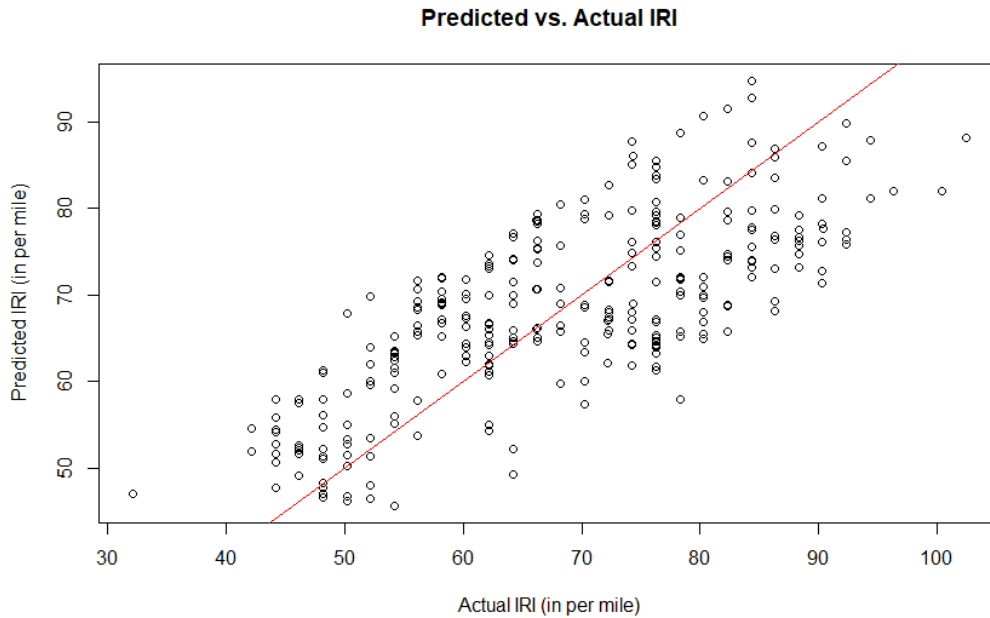


Figure 8: Predicted vs. Actual IRI (in\mile)

### 3 DISCUSSION

4 The findings of our study provide valuable insights into the deterioration patterns and factors  
5 affecting the IRI of flexible pavements in the Pacific Northwest. By leveraging the LTPP data and  
6 employing advanced statistical methods such as K-M survival analysis and multiple regression, we have  
7 been able to assess the impact of different variables on pavement performance over time. Our survival  
8 analysis revealed the significance of IRI values in understanding pavement conditions and lifespan.  
9 Specifically, we assessed the survival probabilities of flexible pavement sections in both good and fair  
10 conditions according to federal measures, identifying trends in how various factors influence pavement  
11 longevity. This information is crucial for transportation infrastructure management and maintenance  
12 planning, particularly in achieving federal targets for interstate and non-interstate National Highway  
13 System (NHS) pavements. Our regression analysis further highlighted the key predictors of IRI values,  
14 such as average temperature, percentage of alligator cracking, and length of longitudinal cracking, while  
15 identifying less significant factors like annual average daily truck traffic (AADTT) and length of  
16 transverse cracking. This nuanced understanding of the most impactful variables aids in prioritizing  
17 maintenance strategies and interventions.

18 The “Predicted vs. Actual” plot demonstrated a general alignment between predicted and actual  
19 IRI values, indicating some predictive accuracy of the model. However, the spread of data points around  
20 the perfect prediction line suggests notable prediction variability, particularly at the extremes of the IRI  
21 range. This indicates potential underfitting issues and suggests a need for model refinement to capture  
22 more complex data patterns and improve prediction accuracy, especially for very low or high IRI values.  
23 The practical implications of our findings are substantial. For transportation agencies, understanding the  
24 key factors affecting pavement performance allows for targeted maintenance strategies, enabling the  
25 efficient allocation of resources to achieve federal and state targets. Specifically, the results can guide  
26 decisions to maintain pavement in good condition, thereby supporting the Federal Highway  
27 Administration’s (FHWA) targets of limiting poor conditions to less than 4% for Interstate pavements and  
28 less than 8% for non-Interstate NHS pavements.

1           However, our study has limitations that may impact the results. The analysis may be subject to  
2 data quality issues due to the diverse sources and time periods covered in the LTPP data. Furthermore, our  
3 models were based on available data and may not fully capture the complex interplay of variables  
4 affecting pavement deterioration. Future research could explore alternative modeling approaches or  
5 additional data sources to enhance the predictive power of models and address underfitting issues. The  
6 development of flexible pavement deterioration models in this study, using historical IRI measurements  
7 and the K-M survival analysis, contributes significantly to the existing body of knowledge. This approach  
8 aligns with the findings of Medina et al. [20], who successfully related PCI and IRI through advanced  
9 deterioration modeling techniques. However, unlike Medina et al., who primarily focused on empirical  
10 relationships between PCI and IRI, this study extends the methodology by incorporating survival analysis  
11 to provide a probabilistic estimation of pavement lifespans under varying environmental and traffic  
12 conditions. This probabilistic approach offers a more nuanced understanding of pavement behavior over  
13 time, which is crucial for regions like the Pacific Northwest where environmental conditions can  
14 significantly influence pavement performance. The use of survival analysis highlights how different  
15 maintenance strategies can extend pavement life, a critical consideration for optimizing resource  
16 allocation in pavement management.

17           Furthermore, the integration of ML techniques, as seen in the previous studies [10], [13], and  
18 [17], suggests a growing trend towards employing sophisticated analytical tools in pavement management  
19 systems. The current study's application of these techniques underlines their potential to enhance  
20 predictive accuracy and operational efficiency. However, it also brings to light the challenges associated  
21 with integrating such complex models into practical applications, such as the need for extensive training  
22 data and computational resources. Future research should focus on refining these models to improve their  
23 usability in real-world settings, potentially by simplifying the models or enhancing their computational  
24 efficiency. Additionally, the development of hybrid models that combine traditional statistical methods  
25 with ML could provide a balanced approach, maintaining predictive power while reducing complexity  
26 and resource demands. In conclusion, the insights gained from this study contribute to the body of  
27 knowledge on pavement performance and can inform more effective maintenance strategies. With  
28 ongoing research and development, transportation agencies can leverage these findings to enhance the  
29 resilience and durability of flexible pavements in the region.

## 30 **CONCLUSION**

31           Pavement deterioration prediction is essential for effective transportation infrastructure  
32 management and maintenance planning. This study successfully developed deterioration models for  
33 flexible pavements in the Pacific Northwest by utilizing extensive data from the InfoPave LTPP tool.  
34 Historical records of IRI measurements were analyzed to understand performance degradation patterns of  
35 flexible pavements over time. Through K-M survival analysis, we assessed the survival probabilities of  
36 flexible pavements based on IRI measures as defined by federal standards over varying time intervals.  
37 This approach allowed us to derive models that estimate the percentage of flexible pavements surviving  
38 within specified IRI thresholds over time, considering factors such as maintenance treatments, average  
39 annual daily truck traffic, freeze and thaw cycles, average temperature, and the presence of various forms  
40 of cracking. These models offer valuable insights into the deterioration trends of flexible pavements in the  
41 Pacific Northwest and provide predictive tools for infrastructure asset managers. By understanding these  
42 trends, managers can optimize maintenance strategies and allocate resources efficiently at the network  
43 level.

44           Future research could focus on refining predictive models to address underfitting and improve  
45 accuracy, particularly for very low or high IRI values. Incorporating additional data sources or exploring  
46 alternative modeling techniques could enhance the models' predictive power. Investigating the impact of  
47 other variables not covered in this study may also provide further insights into pavement performance. In  
48 practice, the findings can guide transportation agencies in optimizing maintenance strategies to improve  
49 the resilience and longevity of flexible pavements. By focusing on the most impactful variables and

1 targeting maintenance efforts accordingly, agencies can effectively allocate resources to achieve federal  
2 and state targets for pavement conditions. In conclusion, our study contributes to the body of knowledge  
3 on flexible pavement deterioration and provides practical guidance for transportation infrastructure  
4 management. Continued research and model development will further enhance our understanding of  
5 pavement performance and support the development of more effective maintenance strategies for the  
6 long-term durability of transportation infrastructure.  
7

### 8 **AUTHOR CONTRIBUTIONS**

9 The authors confirm contribution to the paper as follows: study conception and design: Lamei and  
10 Kassem; data collection: Lamei; analysis and interpretation of results: Lamei and Kassem; draft  
11 manuscript preparation: Lamei. All authors reviewed the results and approved the final version of the  
12 manuscript.

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