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Research

SIGNIFICANT FACTORS OF BRIDGE DETERIORATION

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Final Report

December 2024

prepared for

THE STATE OF MONTANA DEPARTMENT OF TRANSPORTATION

in cooperation with

THE U.S. DEPARTMENT OF TRANSPORTATION
FEDERAL HIGHWAY ADMINISTRATION

December 2024

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16. Abstract Bridges structures deteriorate over time due to various factors. Understanding the factors that affect bridge deterioration rates is necessary for state agencies to maintain the safety and functionality of bridges during their design service life. To improve deterioration modeling in Montana, significant factors affecting bridge deterioration were evaluated within the Montana Department of Transportation's Bridge Management (BrM) software. The research improves existing deterioration curves established in Phase 1 of this research by considering different bridge groups, variables, NBI component-level data, and maintenance activities. Statistical analysis results from two regression models identified maintenance district, bridge age, and deck surface type as the top three significant variables that influence bridge deterioration in Montana. A procedure was established using BrM's general condition rating (GCR) analysis to estimate the number of bridges that are in good, fair, and poor condition over selected time periods. Two deterioration profiles were evaluated. Future research is needed to continue modeling within BrM to further implement analytical tools using the significant bridge groups and variables from this research to support MDT's bridge maintenance management.		
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1. Introduction

1.1 Background

Bridges structures deteriorate over time due to various factors such as environmental conditions, traffic loads, and age. Understanding the factors that affect bridge deterioration rates is necessary for state agencies to maintain the safety and functionality of bridges during their design service life.

The Phase 2 research described in this report responds to the Federal Highway program's initiative to use state-based deterioration models to forecast bridge maintenance activity. These models were developed during Phase 1, *Development of Deterioration Curves for Bridge Elements in Montana*. To address the Federal Highway's initiative and to improve deterioration modeling in Montana, significant factors affecting bridge deterioration were identified and evaluated within the Montana Department of Transportation's Bridge Management (BrM) software.

The objective of the research was to identify significant factors that have the highest influence on bridge deterioration in Montana. The expected outcome is to reliably determine the timing and type of work events that will reduce maintenance/rehabilitation expenditures and increase the service life of bridge structures. The proposed research improves deterioration curves by evaluating contributing factors, NBI component-level data, and maintenance activities using methodologies from the literature to extend these approaches for climate, construction, maintenance, or bridge management practices in Montana.

1.2 Summary of Work

The Literature Review (Section 2) of this Report reviews the new Specification for National Bridge Inventory (SNBI) and documents the new span types, bridge types, and materials for recording bridge component conditions that will be available for deterioration modeling in 2026. Published research identifying bridge characteristics that influence deterioration rates are summarized.

The Significant Factors Data and Maintenance Records Review (Section 1) summarizes the bridge data available from the Montana Department of Transportation and establishes bridge groups and variables used for the statistical analysis. An overview of the statistical analysis methods is described, followed by an evaluation of maintenance data available along the Highline route and 50 interstate bridges. Results of the preliminary analysis are presented.

Based on input from bridge engineers at MDT, a refined analysis (Section 4) was completed by removing the least significant and adding new bridge groups and variables. A discussion of the performance indicators and results of the two regression models is included.

The General Condition Rating (GCR) analysis (Section 5) with the Bridge Management software environment was used to produce Time-in-State reports and Good-Fair-Poor forecasting using bridge groups and variables identified in Section 4. Results of the GCR analysis are reported. A summary and conclusions of the research are presented in Section 6.

2. Literature Review

The objective of the literature review was to provide an efficient starting point to identify and quantify the influence of deterioration factors using Montana bridge inspection data and inspection records. The selected literature was intended to represent the environment, traffic, and maintenance practices in Montana.

The literature review includes a summary of the new span types, bridge types, and materials included in the new Specification for National Bridge Inventory (SNBI) followed by a summary of the published literature related to bridge characteristics that influence deterioration rates.

2.1 Specification for the National Bridge Inventory

The Specification for the National Bridge Inventory (SNBI) provides the framework and requirements for reporting highway bridge condition data for the National Bridge Inventory (NBI). The SNBI will replace the *Recording and Coding Guide for the Structure Inventory and Appraisal of the Nation's Bridges* (Coding Guide). The SNBI includes new designations for bridge components (decks, superstructures, substructures), materials (type, age, condition), and performance (load capacity, structural integrity, safety).

2.1.1 Span Material

The span material designates materials used for the bridge superstructure such as girders, beams, trusses, arches, and pipes. The span material is no longer a written description and is reported using the new SNBI codes that were expanded from 10 to 29 different materials shown in Table 1. Descriptions and examples can be found in Section B.SP.04 of the SNBI (FHWA, 2022).

Table 1: Comparison of the old NBI span materials and the new SNBI span material description and codes.

Old NBI Span Materials	New SNBI Span Materials (B.SP.04)	
Description	Code	Description
Aluminum, wrought iron, or cast iron	A01	Aluminum
	I01	Iron - cast
	I02	Iron - wrought
Concrete	C01	Reinforced concrete - cast-in-place
Concrete continuous	C02	Reinforced concrete - precast
Prestressed concrete	C03	Prestressed concrete - pre-tensioned
Prestressed concrete continuous	C04	Prestressed concrete - cast-in-place post-tensioned
	C05	Prestressed concrete - precast post-tensioned
	CX	Concrete - other
	F01	FRP composite - aramid fiber
	F02	FRP composite - carbon fiber
	F03	FRP composite - glass fiber
	FX	FRP composite - other
Masonry	M01	Masonry - block
	M02	Masonry - stone
	P01	Plastic - polyethylene
	PX	Plastic - other
Steel	S01	Steel - rolled shapes
Steel continuous	S02	Steel - welded shapes
	S03	Steel - bolted shapes
	S04	Steel - riveted shapes
	S05	Steel - bolted and riveted shapes
	SX	Steel - other
Wood or timber	T01	Timber - glue laminated
	T02	Timber - nail laminated
	T03	Timber - solid sawn
	T04	Timber - stress laminated
	TX	Timber - other
Other	X	Other

2.1.2 Span Types

The span type defines the superstructure system of the bridge and similar to the span material, will be reported using the new codes that were expanded from 23 to 43 designations shown in Table 2. Additional information and examples for coding span types can be found in Section B.SP.06 of the SNBI (FHWA, 2022).

Table 2: Comparison of the old NBI span types and the new SNBI span type descriptions and codes.

Old NBI Span Type	New SNBI Span Type (B.SP.06)	
Description	Code	Description
Arch - deck	A01	Arch - under fill without spandrel
Arch - thru	A02	Arch - open spandrel
	A03	Arch - closed spandrel
	A04	Arch - through
	A05	Arch - tied
Box beam or girders (single or spread)	B01	Box girder/beam - single
Box beam or girders (multiple)	B02	Box girder/beam - multiple adjacent
	B03	Box girder/beam - multiple spread
Segmental box girder	B04	Box girder/beam - segmental
Frame (except frame culverts)	F01	Frame - three-sided
Culvert (include frame culverts)	F02	Frame - four-sided
	F03	Frame - K-shaped
	F04	Frame - delta-shaped
Stringer/multi-beam or girder	G01	Girder/beam - I-Shaped adjacent
Stayed girder	G02	Girder/beam - I-Shaped spread
Tee beam	G03	Girder/beam - tee-beam
	G04	Girder/beam - inverted tee-beam
	G05	Girder/beam - double-tee adjacent
	G06	Girder/beam - double-tee spread
Channel beam	G07	Girder/beam - channel adjacent
	G08	Girder/beam - channel spread
Girder and floor beam system	G09	Girder/beam - girder & floor beam
	G10	Girder/beam - through girder
	GX	Girder/beam - other
Suspension	L01	Cable - suspension
	L02	Cable - cable-stayed
	L03	Cable - extradosed
	LX	Cable - other
Movable lift	M01	Movable - vertical lift
Movable - bascule	M02	Movable - bascule
Movable - swing	M03	Movable - swing
	MX	Movable - other
	P01	Pipe - rigid
	P02	Pipe - flexible
Slab	S01	Slab - solid
	S02	Slab - voided
Truss - deck	T01	Truss - deck
Truss - thru	T02	Truss - through
	T03	Truss - pony
Orthotropic	X01	Other - railroad flat car
Tunnel	X02	Other - ferry transfer
Mixed types	X03	Other - floating
Other	X	Other

2.1.3 Deck Material and Type

Expanded designations for deck material and type in the SNBI are shown in Table 3. Descriptions and examples for coding bridge deck material and type, are found in Section B.SP.09 of the SNBI (FHWA, 2022).

Table 3: Comparison of the old NBI deck material and type to the new SNBI deck material and type descriptions and codes.

Old NBI Deck Material and Type	New SNBI Deck Material and Type (B.SP.09)	
Description	Code	Description
Not applicable	0	None
Aluminum	A01	Aluminum
Concrete cast-in-place	C01	Reinforced concrete - cast-in-place
Concrete precast panel	C02	Reinforced concrete - precast
	C03	Prestressed concrete - pre-tensioned
	C04	Prestressed concrete - cast-in-place post-tensioned
	C05	Prestressed concrete - precast post-tensioned
	CX	Concrete
	F01	FRP composite - aramid fiber
	F02	FRP composite - carbon fiber
	F03	FRP composite - glass fiber
	FX	FRP composite - other
Open grating	S01	Steel - open grid
Closed grating	S02	Steel - filled or partially filled grid
Steel plate (includes orthotropic)	S03	Steel - plate
	S04	Steel - orthotropic
Corrugated steel	S05	Steel - corrugated
	SX	Steel - other
Wood or timber	T01	Timber - glue laminated
	T02	Timber - nail laminated
	T03	Timber - solid sawn
	T04	Timber - stress laminated
	TX	Timber - other
Other	X	Other

2.1.4 Summary

The new SNBI designations provide more specific descriptions of the bridge superstructure, decks, and materials which will enable a more granular analysis of bridge component deterioration. Forty-three designations under the old system are now represented by 96 new codes. The initial NBI data submittal using the SNBI will likely create inconsistent or conflicting condition data in the short-term, however the long-term benefit of monitoring deterioration of more specific bridge components and materials will be realized through more efficient bridge maintenance and rehabilitation operations.

2.2 Review of Published Literature

The objective of the literature review was to identify significant factors and methods used by other departments of transportation and researchers that influence the deterioration rates of bridges. Several investigations have considered the factors shown in Table 4 to predict bridge component deteriorations more accurately.

Table 4: Significant factors investigated by other researchers.

Category	Deterioration factor
Current bridge condition	Age
	Current NBI rating
	Maintenance history
Design	Design load
	Rebar protection
	Deck/structure material
	Structure type
	Wearing surface
Geometry	Deck/structure length
	Deck/structure width
	Deck/structure area
	Number of spans
	Roadway width
	Bridge skew
Service conditions	Average daily traffic
	Average daily truck traffic
	Functional class
	Service under the bridge
Environment	District/location
	Climate
	Number of cold/hot days
	Number of freeze-thaw cycles
	Precipitation

Many of the papers focus on the statistical methods and analyses used to evaluate and identify deterioration factors. Other researchers focused on factors that caused overall bridge deterioration and others limited their study to the deterioration of a single bridge element. The deterioration component and researchers are shown in Table 5.

Table 5: Deterioration components considered by researchers.

Deterioration component	Researcher
Steel coatings	Rahman et al., 2023
Concrete decks	Kong et al., 2022 Phares, Liu and Abdalla, 2022 Manafpour et al., 2018 Huang, 2010 Huang et al., (2010) Kim and Yoon, 2010 James, Zimmerman and McCreary, 1987
Concrete bridges	Srikanth and Arockiasamy, 2021
General	Ilbeigi and Ebrahimi Meimand, 2020 Moomen et al., 2017
Superstructure	Hasan and Elwakil, 2019 Veshosky et al., 1994

2.2.1 *Steel Coatings*

Analyzing Coating Conditions of Steel Bridges: A Data-Driven Approach

Rahman et al. (2023) used machine learning-based regression models with historical inspection data for steel girder/beam elements to predict the coating conditions of steel bridges in Florida. The analytical models estimated the bridge features that had the highest importance related to coating failure. Both the decision tree and random forest regression models predicted similar feature importance. The study's conclusions identified the mean absolute errors of the models and their applicability to other bridge elements. The results from their random forest regression models are shown Figure 1.

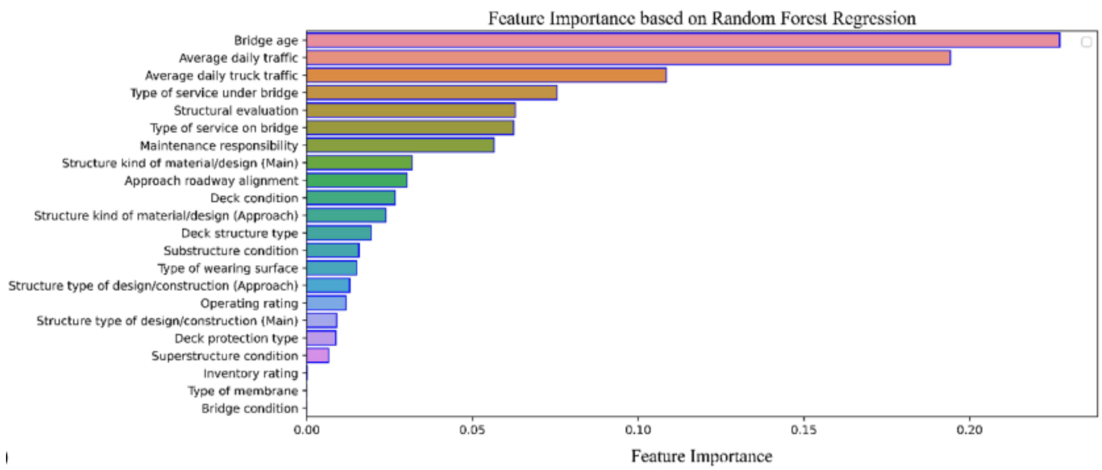

Figure 1: Feature importance by applying random forest regression (Rahman et al., 2023).

2.2.2 *Concrete bridge decks*

Bridge Deck Deterioration: Reasons and Patterns

Kong et al., (2022) investigated factors influencing the deterioration of concrete decks using a Shapley additive explanation (SHAP) machine learning framework. An XGBoost model was trained to perform binary classifications of heavily imbalanced datasets to classify bridges less than 20 years old with poor/fair deck conditions and older bridges (30-40 years old) with good deck conditions from the national bridge inventory database. Features identified as important to the deterioration of concrete bridge decks were wearing surface, structure width, ADT, number of snow days, span length, and ADTT. Conversely, bituminous and epoxy overlay wearing surfaces were highly associated with relatively old bridges with good deck conditions. Features identified as important to the deterioration of concrete bridge decks are shown in Figure 2.

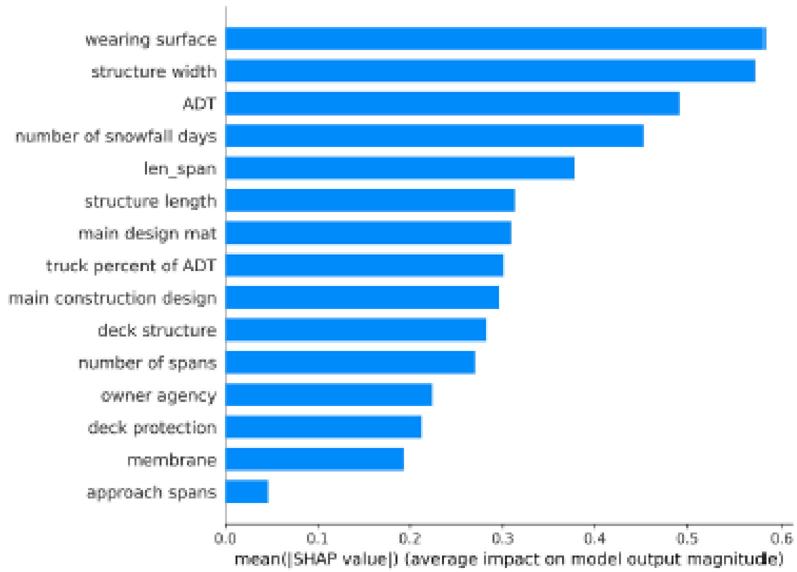

Figure 2: Feature importance based on SHAP values (Kong et al., 2022).

Investigation of the Causes of Transverse Bridge Deck Cracking

Phares et al., (2022) investigated transverse cracking in concrete bridge decks that initiated in the early stages of a bridge service life. Accelerated reinforcement corrosion, concrete deterioration, and increased maintenance costs were the motivation for their study. Observations for transverse deck cracking related to six bridge parameters are summarized in Table 6.

Table 6: Research observations from Phares et al., (2022).

Bridge Parameter	Observation
Location	Southwest and east Iowa had a higher propensity for deck cracking
Girder type	Precast, pretensioned concrete beams showed a higher chance of deck cracking than steel beam bridges
Cement type	Type 1 and IP (Portland-pozzolan) cement showed a higher chance of deck cracking compared to that for Type 2 cement
Concrete type	High performance concrete (HPC) bridge decks showed a higher chance of cracking compared to non-HPC bridge decks.
Bridge age	Bridges constructed between 1960 and 1980 showed a higher chance of deck cracking.
Evaporation during placement	Higher evaporation rates from six recorded concrete bridge deck placements resulted in a higher chance of deck cracking.

Bridge Deck Cracking Evaluation

Research by Nelson et al., 2021 included a field inspection, materials testing, and analytical modeling of Montana bridges to diagnose and recommend actions to mitigate the causes of transverse cracking in bridge decks. Based on studies completed by nine other State Departments of Transportation (including Montana in 2016) likely causes of bridge deck cracking were grouped into five different factors with their effect on cracking shown in Table 7. Effects from concrete mixture design, concrete strength, and construction practices are consistent with observations from Phares et al., 2022 for their parameters cement type, concrete type, and evaporation during placement (Table 6).

Table 7: Summary of Factors affecting bridge deck cracking, adapted from Nelson et al., 2021.

Factor	Effect on Bridge Deck Cracking
Concrete mixture design	• Thermal and autogenous shrinkage are influenced by cement type; using Type II cements can help reduce thermal stresses, while using fly ash and slag can reduce both thermal stresses and shrinkage stresses. Finely ground cements, such as Type III cements, may increase heat of hydration and associated thermal stresses. • Using high volume of coarse aggregates with low coefficient of thermal expansion can reduce both shrinkage and thermal stresses. • Reducing paste content can reduce thermal stresses. • Conflicting recommendations have been provided in the literature regarding recommended w/cm. Some researchers recommend a minimum w/cm of 0.40, while others recommend a maximum of 0.40. Recommending a minimum w/cm of 0.40 ignores the potential for increased autogenous shrinkage at these ratios.
Concrete strength	• High strength concrete has a greater tendency to crack due to its higher modulus of elasticity (i.e., larger stresses associated with thermal or shrinkage strains). • Modulus of elasticity develops faster than tensile strength for the first 3 to 5 hours after initial set of the concrete.
Restraint conditions	• Restraint is greatest in interior spans (due to intermediate supports) and at integral abutments (due to fixed-end conditions). • Simply-supported or pin connections can reduce crack tendency. • Curved girders and skew can increase restraint.
Element design	• Cracking increases when girders provide more stiffness than the deck. This includes designs with thin decks (< 8.5 inches), composite steel plate girders, wide flanges, and cross framing. Larger spacing and thicker decks can reduce crack tendency. • Concrete girders can provide less restraint than steel girders due to their lower coefficient of thermal expansion. • Offsetting the top and bottom transverse reinforcing bars can reduce the risk of full-depth crack formation. • Increased cover will increase crack widths but will reduce crack frequency.
Construction practices	• Practices that limit evaporation from freshly placed concrete surfaces can reduce the potential for early plastic shrinkage cracking. • Mechanical vibration can close plastic shrinkage cracks; however, roller screeding may increase the risk of cracking due to local increases in near-surface paste content. • Large temperature variations during placement can exacerbate thermal stresses.

Stochastic Analysis and Time-Based Modeling of Concrete Bridge Deck Deterioration

Manafpour et al., (2018) investigated stochastic analysis for time-based modeling of concrete bridge deck deterioration using Markov chain models. The investigation assessed the effectiveness of preventive maintenance strategies by incorporating the stochastic deterioration processes of bridge decks into the decision-making process. The researchers developed a time-based Markov chain model to predict the transition probabilities of different deck states for bridges with different characteristics. Based on the model, a cost-benefit analysis was conducted to evaluate various preventive maintenance strategies. The study concluded that the model could effectively predict the deck's deterioration process and support cost-effective maintenance decision-making.

Artificial Neural Network Model of Bridge Deterioration

Huang (2010) used a statistical analysis to identify significant factors that influenced deterioration and developed an application model for estimating the future condition of bridges. Based on data derived from historical maintenance and inspection records of concrete decks in Wisconsin, the study identified 11 significant factors (county, district, design load, deck length, deck area, number of lanes, functional class, ADT, environment, degree of skew, number of spans) and developed an artificial neural network (ANN) model to predict associated deterioration.

Exploring the Deterioration Factors of RC Bridge Decks: A Rough Set Approach

Huang et al., (2010) investigated 29 bridge characteristics to determine their influence on reinforced concrete deck deterioration using the Rough Set Theory (RST) data mining technique. They grouped the factors into six common types and identified the factors causing the most significant impact using inspection data from 2,128 bridges in the Taiwan National Freeway System. The major factors contributing to two types of deterioration are shown in Table 8.

Table 8: Significant deterioration factors for RC bridge deck from Huang et al., (2010).

Deterioration Type	Significant Factor
Cracking	Peak monthly rainfall
	Max. rainy days in a month
	Type of girder material
	No. of lanes
	Expansion joints
	Type of pier
	Water crossing
	Design live load
Corrosion of Rebar	Area of main span deck
	Number of spans

Identifying Critical Sources of Bridge Deterioration in Cold Regions through the Constructed Bridges in North Dakota

Kim and Yoon (2010) studied the source of bridge deck deterioration in cold regions using condition ratings from 2,801 concrete decks inspected between 2006-2007. Their unique approach combined multiple regression and geographic information system technology to evaluate physical, material, and environmental factors associated with the condition of existing bridge decks. The most significant parameter contributing to bridge deterioration was the year built, followed by ADT and the type of structural system. Decks on major interstate highways had lower condition ratings than other decks. The presence of water was also found to be critical to the deterioration in cold regions, and steel bridges were the most vulnerable bridge type in cold regions.

Effects of Overloads on Deterioration of Concrete Bridges

James et al., (1987) investigated the interaction between physical damage from wheel loads and other damage mechanisms through a field study that documented the variation in cracking across the width of a bridge deck. Control structures with similar supports, age, construction, and traffic characteristics were used to compare the damage levels due to heavy truck traffic on the test bridges that carried outbound traffic from several aggregate quarries. The differential heavy truck traffic from the quarries was estimated to be 180 vehicles per hour and was thought to have lasted for approximately 26 years. Results of their research are summarized in Table 9.

Table 9: Research observations from (James et al., 1987).

Parameter	Observation
Flexural cracking	May occur at tensile stresses below the assumed $7.5\sqrt{f'_c}$.
Crack density	Increased densities of longitudinal and transverse cracking were observed in the overloaded concrete bridge decks.
Bridge type	Bridges supported by steel girders are more susceptible to progressive overload-induced damage than decks on prestressed concrete girders.

2.2.3 Concrete bridges

Remaining Service Life Prediction of Aging Concrete Bridges Based on Multiple Relevant Explanatory Variables

Srikanth and Arockiasamy (2021) studied explanatory variables using multivariate regression analysis based on the ordinary least square's technique. NBI data from 1992 to 2013 were used to develop the deterioration models. Conclusions from the investigation of eight variables organized into two categories are shown in Table 10.

Table 10: Explanatory variables considered by Srikanth and Arockiasamy (2021).

Category	Explanatory variable	Conclusions
Operation-related	Age	Deterioration rate varies with age during the service life of concrete bridge components. Bridges nearing their design life service life are more sensitive to faster deterioration.
	ADT	The effect of ADT on deterioration rate varies across different bridge components
	Functional class	Concrete bridge decks in urban locations deteriorate faster than rural areas.
Structure-related	Area of main span deck	Larger deck areas of the main span increase the deterioration rate of reinforced concrete bridge decks. Prestressed deck slabs were not affected.
	Number of spans	Deterioration increases with the number of spans and is attributed to an increase in number of joints
	Skewness	No statistically significant influence on bridge deterioration
	Wearing surface	Reduces deterioration rate, especially in concrete solid slab bridges
	Continuity of spans	No statistically significant influence on bridge deterioration

2.2.4 General

Statistical Forecasting of Bridge Deterioration Conditions

Ilbeigi and Ebrahimi Meimand (2020) performed statistical forecasting of bridge deterioration conditions using historical data of more than 28,000 bridges in Ohio from 1992 to 2017. Results of the ordinal regression analysis identified the explanatory variables for operation- and structure-related categories shown in Table 11. Truck ADT was not found to be statistically significant. Results of the validation and forecasting process showed that the model has a significantly high prediction power, and the forecasted transitions were statistically identical with actual transitions at a 1% significance level.

Table 11: Statistically significant variables from an ordinal regression analysis performed by Ilbeigi and Ebrahimi Meimand (2020).

Category	Explanatory Variable
Operation-related	Age
	ADT
	Deck area
	Current Condition
	Age from reconstruction
Structure-related	Area of main span deck
	Number of spans
	Skewness
	Wearing surface
	Continuity of spans

Bridge Deterioration Models to Support Indiana's Bridge Management System

Moomen et al., (2017) modeled families of curves representing deterioration models for bridge deck, superstructure, and the substructure for Indiana's bridge management system. Deterministic and probabilistic models were used to investigate traffic volume, truck traffic, design type, and climatic conditions on bridge deterioration rates. Conclusions from their investigation are shown in Table 12.

Table 12: Research observations from Phares et al*.,* (2022).

Parameter	Observation
Climate variables	Freeze index, number of freeze-thaw cycles, and average precipitation were found to influenced bridge deck and substructure deterioration more than the superstructure.
Traffic loading	Concrete deck deterioration was much more sensitive to traffic
Location	General deterioration differences across maintenance districts in Indiana were observed, but the differences were not consistent.

2.2.5 Superstructure

Stochastic regression deterioration models for superstructure of prestressed concrete bridges in California

Hasan and Elwakil (2019) studied the effect of non-periodic maintenance on NBI condition ratings. They identified the variables affecting superstructure deterioration and built models for predicting the superstructure condition. Their literature review identified a suite of variables shown in Table 13 have been previously studied and were identified as significant factors for bridge deterioration. Using NBI data from California, models were built to predict the superstructure condition of slab, stringer, multibeam or girder, T-beam, and box beam or girder structure types using regression technique and Monte Carlo simulations. Age and ADT were identified as significant factors for increasing the rate of bridge deterioration. Span length, structure length, deck width, high degree of skew, ADTT, and roadway width were also associated with higher superstructure deterioration rates.

Table 13: Significant factors in bridge deterioration research identified by Hasan and Elwakil (2019).

Significant Variables	Kim & Yoon (2010)	R. Y. Huang et al. (2010)	Y. H. Huang (2010)	Moomen et al. (2017)	Manafpour et al. (2018)	Hasan & Elwakil (2019)	Ilbeigi & Meimand (2020)
Age of bridge	x	x		x		x	x
Current NBI rating	x			x			x
Maintenance history				x			
Design load	x		x				
Degree of skew			x			x	
Type of rebar protection					x		
Deck/structure length		x	x		x	x	x
Deck/structure width	x	x				x	
Deck/structure Area		x	x				x
Deck/structure material	x			x			x
Structure type	x				x		x
Number of spans	x	x			x		
Type of wearing surface				x	x		
Roadway width						x	
Average daily traffic	x	x	x			x	
Average daily truck traffic	x			x		x	
Functional class			x	x	x		
Service under the bridge	x			x			
District/location			x		x		
Environment		x	x				
Number of cold/hot days	x			x			
Number of freeze-thaw cycles				x			
Precipitation	x	x					

Comparative Analysis of Bridge Superstructure Deterioration

Veshosky et al., (1994) selected homogeneous groups of bridges with similar structural material and type, maximum span length, maintenance responsibility, and other factors to evaluate superstructure deterioration. A regression analysis was used to estimate deterioration rates for homogeneous groups of steel and prestressed concrete bridges. Age and ADT were included as independent variables and superstructure condition ratings were the dependent variable. Statistical problems due to the multicollinearity of ADTT with ADT resulted in ADTT being excluded from the analysis. The bridge sample included 10,053 steel and 5705 prestressed concrete bridges built after 1950. Results of the investigation found no statistically significant differences in the rates of deterioration of steel and prestressed concrete bridge superstructures. Age and ADT were the primary determinants of superstructure deterioration.

2.3 Literature Review Summary

Several significant factors influencing the deterioration of bridges were identified from published research. Some of the research focused on statistical methods and analyses to evaluate and identify deterioration factors, while other researchers focused on historical condition ratings using NBI data. The studies summarized in this review considered the general deterioration of bridge components in addition to specific deterioration of steel coatings, concrete bridge decks, concrete bridges, and the deterioration of superstructure members. The analytical tools used by researchers included data-driven approaches, machine learning frameworks, data mining techniques, and statistical analyses. A summary of the factors considered or identified by at least two of the researchers included in this literature review are shown in Figure 3.

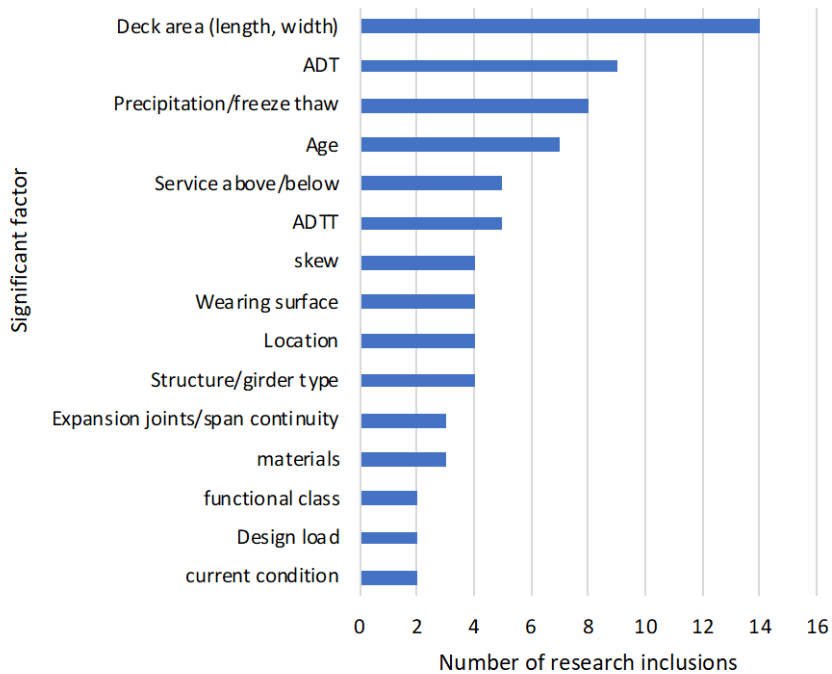

Figure 3: Significant factors considered by researchers.

3. Significant Factor Data and Maintenance Records Review

The overall objective of the Significant Factors Data and Maintenance Records Review was to identify the significant factors and data groups to use in a general condition rating (GCR) analysis within the Bridge Management Software (BrM). The influence of different bridge groups and variables was assessed using the MDT National Bridge Inventory (NBI) condition rating data from 2022.

Two statistical regression models were used to investigate selected bridge groups and model variables. A preliminary analysis described in this section considered five bridge groups and 28 variables to characterize their influence on bridge deterioration in Montana.

An overview of the statistical analysis methods is described in this section. Maintenance data that was reviewed is also presented, however these data were not implemented in the regression analysis. Bridge groups and variables used in the preliminary analysis are described, followed by a discussion and preliminary results.

3.1 Statistical Analysis Methods

Two regression models were used to evaluate significant factors of bridge deterioration by identifying hidden relationships between the NBI deck ratings and different variables. General Linear (GL) and Random Forest (RF) regression models assigned numerical values to the selected variables and quantified and ranked their impact on NBI deck rating. The regression analysis estimates the relationship between independent variables (factors) and dependent variables (NBI deck rating). The results determine the strength (large or small coefficients) and direction (positive or negative) of the relationship. The magnitude of the coefficients can indicate the importance of each independent variable in explaining the variation of deterioration. Regression models also provide statistical tests (p-values) that can be used to identify the significance of individual or categorical variables. This helps determine whether the relationships observed are likely to be genuine or have occurred by chance. NBI ratings from the 2022 inspection year used.

All statistical analyses were conducted in the program *R* (R Core Team, 2023). For each model group considered, 80% of the NBI deck ratings were randomly selected and used as a training dataset. The remaining 20% of the bridges were used as a validation dataset to calculate the statistical performance indicators. Details of the GL and RF regression models are described below.

3.1.1 Generalized Linear Models

All variables were included in the generalized linear regression model during the first analysis iteration. Subsequent iterations considered only the most significant variables with the smallest p-values (minimized extreme observations). Insignificant variables were removed until all p-values were less than 0.05. For the preliminary analysis, the number of variables remaining for each bridge group model ranged from 4 to 12, from the original 28 variables considered.

Two statistical parameters, or performance indicators, assessed the accuracy of the predicted NBI values from the GL model. The first was the adjusted R-squared (R^2), which is an R^2 value adjusted by the number of predictors in the model. The adjusted R^2 indicates how much of the variation in the dependent variable (i.e., NBI concrete deck rating) is explained by the independent variables in the regression model. Larger adjusted R^2 values (between 0 and 1) indicate less variation in the dependent variable and indicates a better predictor of future outcomes. The second performance indicator for the GL model is the root mean squared error (RMSE). The RMSE measures the average difference between values predicted by a model and the actual value. It provides an estimate of how accurate the model is and how well it can predict the independent variable. The RMSE is measured in the same units as the target variable. The lower the RMSE, the more accurate the predicted variable is.

3.1.2 Random Forest Regression Models

Random Forest (RF) regression models are a type of machine learning algorithm that is efficient at identifying patterns in complex datasets (Iranitalab and Khattak, 2017; Schlögl *et al.*, 2019). and are commonly used in traffic safety studies. The RF model was created by using the selected variables to build a decision tree for each sample that identified the best performing predictors. The results of each RF model were averaged across all models created. Each tree uses an out-of-bag sample of data, making the predictor variables more accurate across a wide range of datasets.

Five hundred decision trees were created for each of the selected bridge groups with six random variables selected for each tree. To identify important variables in the RF models the percent increase in mean-squared error (MSE) was used through each iteration of the 500 decision trees. Larger percentage increases in MSE indicate more important variables, and negative values indicate the variables are creating a less accurate model.

Two statistical parameters, or performance indicators, assessed the accuracy of the predicted NBI values from the RF models. The first indicator was the mean of the squared residuals (MSR). The MSR accounts for the dispersion of actual and estimated values from the regression model and is the sum of the squared differences between the actual and estimated values divided by the number of observations. The MSR is different than the MSE described above, which is a direct comparison for the prediction error between the actual and estimated observations. The lower the value of MSR, the better the regression model is at explaining the data. The second performance indicator was the percentage of variance explained (Pseudo-R^2). The Pseudo- R^2 value is used for regression models when it is not possible to compute a single R^2 value. This statistic is most useful when comparing competing models for the same data, i.e., all the decision trees in an RF model. The model with the largest Pseudo- R^2 value is the best performing model according to this measurement. A summary of the performance indicators used for each model are shown in the Table 14 below.

Table 14: Statistical model performance indicators.

Model	Performance Indicator	Performance Indicator
General Linear (GL)	Adjusted R^2	Root Mean Squared Error (RMSE)
Random Forest (RF)	Pseudo R^2	Mean of Squared Residuals (MSR)

3.2 Maintenance Data

Three sources of maintenance data were investigated: (1) BrM, (2) the National Bridge Inventory (NBI) inspection data, and (3) electronic sources available through MDT's Maintenance Management System (MMS). The Highline route was selected for an initial review of maintenance data because of the large number of permitted trucks that travel the route and the relatively comprehensive electronic data available in BrM. A second search of maintenance data information was performed on 10 interstate bridges randomly selected from each maintenance district (50 total bridges).

3.2.1 Highline Route Maintenance

BrM Rehab Data

The BrM rehabilitation data field was used to search for the presence of maintenance data for bridges on the Highline route. A few upgrades and rehabs were found, but the records did not include direct information about the type of maintenance. There were two challenges in using this Highline Route data for maintenance modelling. First, 80% of the Highline Route bridges did not have Rehab data in BrM, and second, most of rehabilitations for the bridges with data available were related to railing or approach work when cross-referenced with the project plans.

NBI Inspection Data

A second approach to find relevant maintenance data was to specifically target bridges with a sudden increase in inspection rating. Using NBI component-level inspection data for the Highline Route, jumps and drops in rating over time were identified to select individual bridges and timeframes for a more focused maintenance records search. This approach did not directly show maintenance within BrM related to the bridges, as most increases and decreases were not accompanied by rehabilitation or maintenance information.

The physical maintenance file folders for bridges with an identified inspection rating jump were also searched. These folders only included records such as construction plans and inspections. Physical records located in MDT's Information Services Division records were also pulled for three bridges with an inspection rating jump. Data located in these records included paper records dating mostly to the installation of the bridges, such as handwritten engineer's notes and tables from the 1950's but it could not be traced specifically to maintenance activity.

Maintenance Management System Data

A third source reviewed for potential maintenance data was MDT's Maintenance Management System (MMS). A spreadsheet that documented maintenance information during the past 6 years for State roadways was valuable because it identified specific bridges and categorized the work as Superstructure, Substructure, or Deck improvements. The MMS data showed the general category, work hours, and cost involved in the work, though it did not show the specific type of maintenance performed. Additional information on the specific bridge element being maintained in greater detail was found by cross-referencing the MMS work log with Inspections report files and work candidates' information in BrM.

For the six years of data available from the MMS spreadsheet, only 17% of the bridges were on the Highline route were included. This small sample during the past six years was not a confident indicator of maintenance over longer periods of time. The information within MMS could be useful in the future as the dataset increases and if it is expanded to include the specific maintenance activity completed.

3.2.2 *Interstate Bridge Maintenance*

Based on discussions with the technical panel, a possible explanation for the low volume of traffic served by the Highline Route may be a factor in the lack of maintenance data available. To compare the maintenance data available on the Highline route, a similar search was done on a dataset of 50 interstate bridges that included 10 bridges from each maintenance district.

The rehabilitation data available in BrM revealed 91 documents for 39 out of the 50 interstate bridges. Rehabilitation files for 84 of these bridges were isolated in BrM and used to create the repair categories shown in Figure 4. The Joint Repair category included modifying, replacement, and removal of bridge joints.

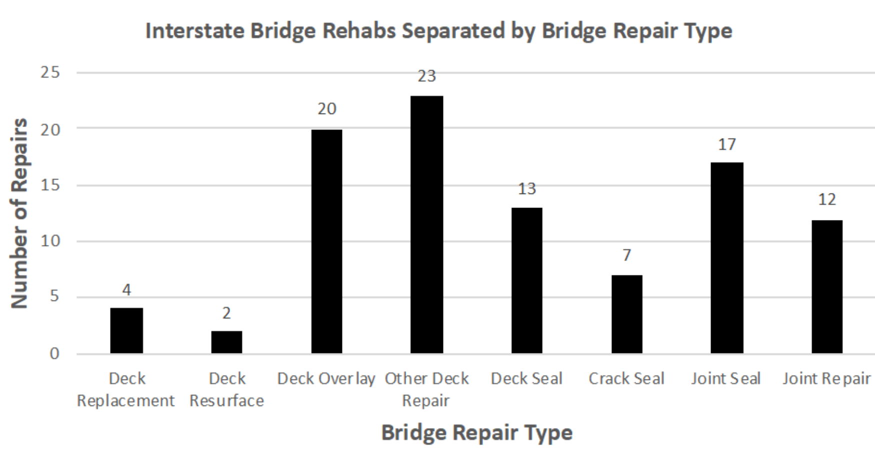

Figure 4: Frequency of bridge repair types across 50 interstate bridges.

To assess the effect of rehabilitations on the 50 interstate bridge decks, the NBI condition ratings made before and after the rehabilitation were collected. Figure 5 shows the rehabilitation year for bridges in each maintenance district which is color coded to represent the change in NBI rating. Rehabs before 1980 and after 2022 were excluded because past and future NBI ratings were not available. Fourteen bridge decks had an increase in NBI ratings the year following rehabilitation (green shading), five bridge decks had a lower NBI rating (red shading), and 28 bridge decks were rated the same (yellow shading) as the year before rehabilitation. The larger number of improved NBI ratings (14 vs 5) suggests the rehabilitations generally led to an increase or the same condition (28) in the year following the work.

NBI Inspection Deck Rating Change Following Rehabs

District	**Billings**													
Rehab Year	2015	2015	2001	1999	2001	2014	2015	1999	2014					
District	**Butte**													
Rehab Year	2009	2016	2014	1993	2003	2012	1993	2003	2012	1995	2005	2013		
District	**Glendive**													
Rehab Year	1991	2016												
District	**Great Falls**													
Rehab Year	1980	1998	2020	1993	2021	1994	2011	2000	1995	2002				
District	**Missoula**													
Rehab Year	2004	1991	1994	2018	1985	1994	2018	1995	2017	1994	1999	2012	1999	2004

Legend	-2	-1	-	+1	+2	NBI rating change

Figure 5: Positive, neutral, and negative NBI rating changes after rehabilitation.

The format, source, and variability in the maintenance data available limited its efficient and compatible inclusion with the statistical analysis. Therefore, maintenance data was not included in the GL and RF regression models.

3.3 Bridge Data

There are a total of 5,074 bridges and culverts across the state of Montana that are maintained by the Montana Department of Transportation (MDT), county, city, and township agencies. The analysis focused specifically on 2,966 structures maintained by MDT that includes 2,232 bridges and 734 culverts. The state-maintained structures can be seen in Figure 6 and were divided into smaller bridge groups to be evaluated for the potential influence of multiple variables on bridge deterioration.

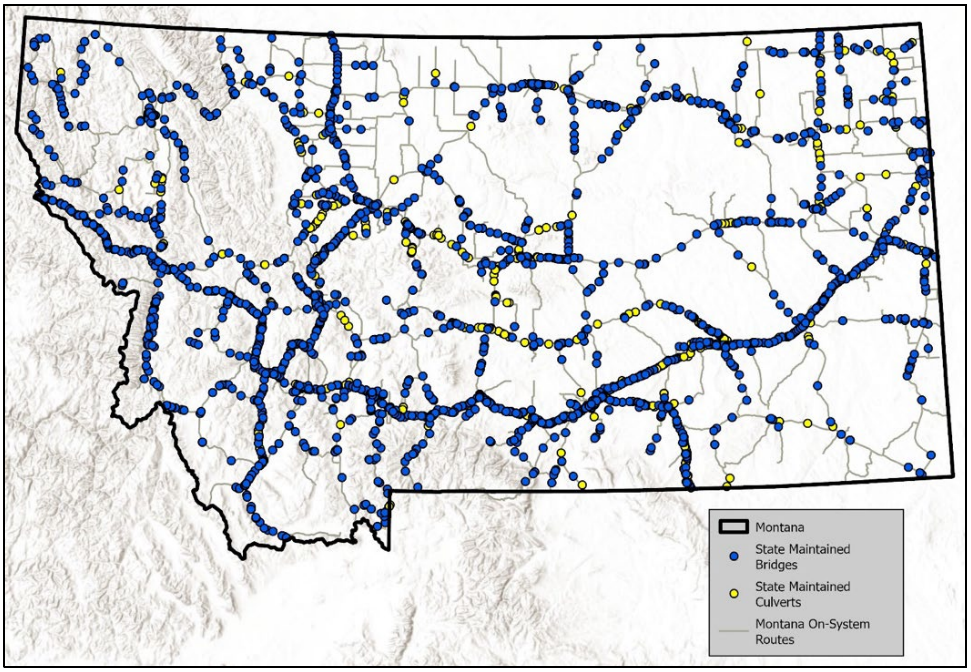

Figure 6: State maintained bridges and culverts in Montana.

3.4 Preliminary Bridge Groups

The preliminary statistical analysis focused on MDT-maintained bridges (*n* = 2,114). The bridges were organized into five groups: 1) maintenance district, 2) main structure material, 3) functional class, 4) the Highline route, and 5) a Highline control group. The groups were used to identify potential variations of the significant factors that influence bridge deck condition ratings. Identifying specific deterioration factors for each group will allow targeted and more representative analyses to be performed within MDT's Bridge Management System (BrM).

3.4.1 Maintenance District

Bridges were divided into maintenance districts to highlight the different environmental conditions across the state of Montana. The west side of Montana is mountainous with more dense forests and higher average yearly precipitation levels. The east side of Montana includes prairie landscapes with smaller and more sparsely distributed mountain ranges.

The number of MDT-maintained bridges are approximately the same for the five maintenance districts in Montana: Billings (*n* = 444), Butte (*n* = 493), Glendive (*n* = 414), Great Falls (*n* = 381), and Missoula (*n* = 382). The bridges in each maintenance district can be seen in Figure 7.

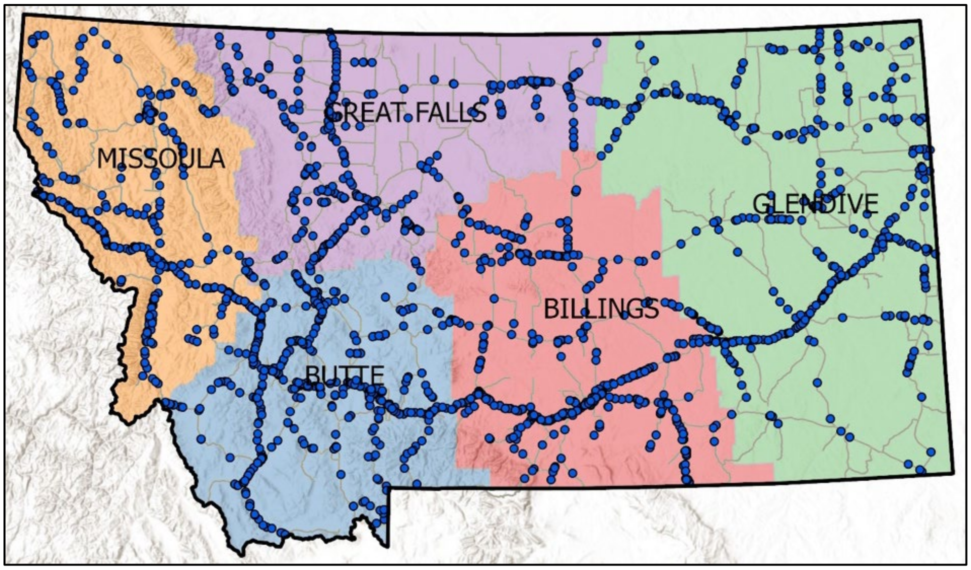

Figure 7: State maintained bridges within MDT maintenance districts.

3.4.2 Superstructure Material

Materials considered for the superstructure include concrete, steel, and wood. Out of the 2,114 bridges in the analysis, there are 1,452 made from concrete, 318 steel bridges, and 344 made from wood, or timber. The division of bridges by superstructure material can be seen in Figure 8.

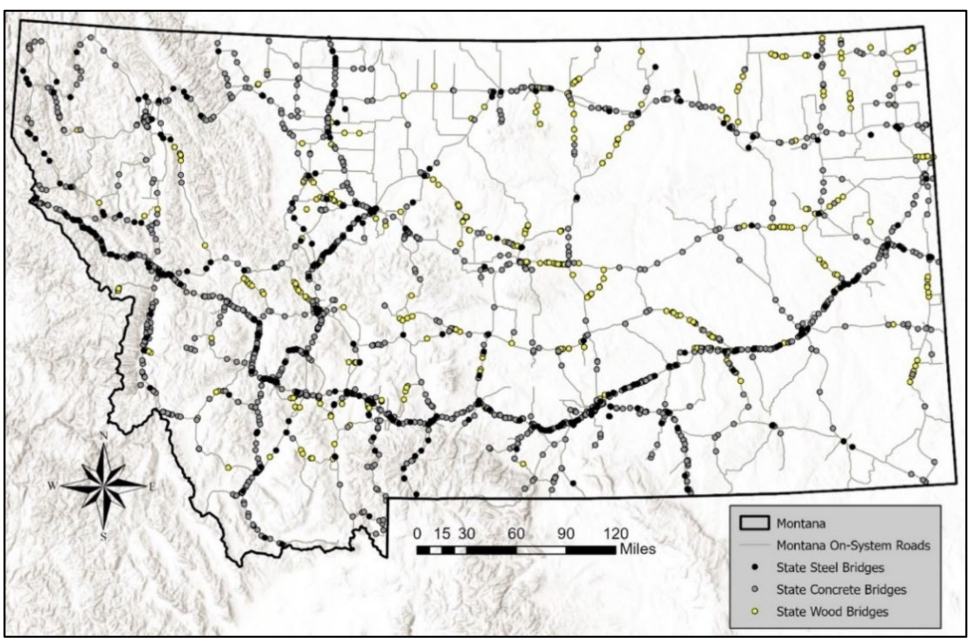

Figure 8: State maintained bridges by main structure material.

3.4.3 Functional Class

Four types of roads or functional classes were considered that are generally related to different traffic volumes. Interstates, for example, have controlled access points and carry the largest traffic volumes across all functional classes of roads. There are 805 bridges on interstate roads, 453 on major arterial roads, 483 bridges on minor arterials, and 373 on collector roads. The bridges divided by functional class can be seen in Figure 9. The larger traffic volumes and higher truck traffic on the instate routes, shown in Figure 10, has historically resulted in a higher allocation of bridge deck maintenance and rehabilitation funding to interstate bridges.

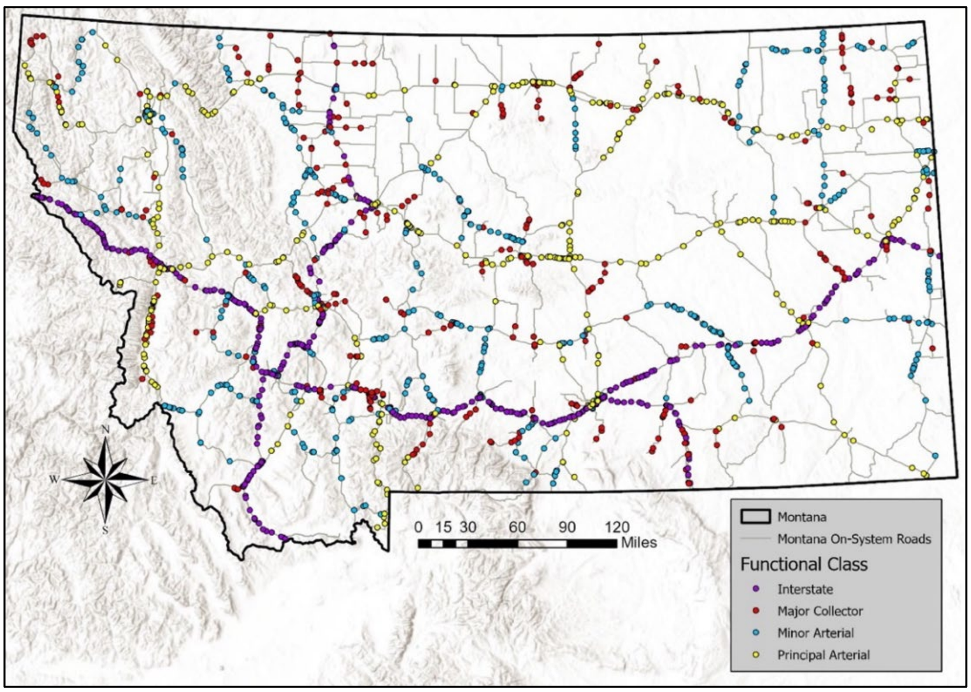

Figure 9: State maintained bridges by functional class.

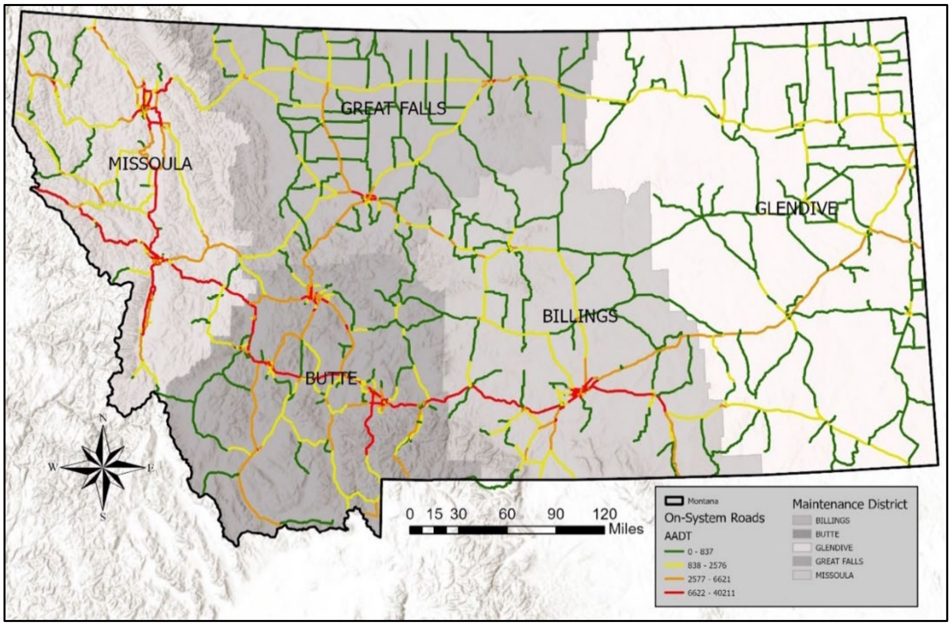

Figure 10: State maintained bridges' AADT in the five maintenance districts.

3.4.4 Highline Route

The Highline route shown in Figure 11 represents a common permitted route for oversize and/or overweight trucks and was selected as a bridge group to determine if the deterioration and/or maintenance activity on this route is different than the other bridge groups considered.

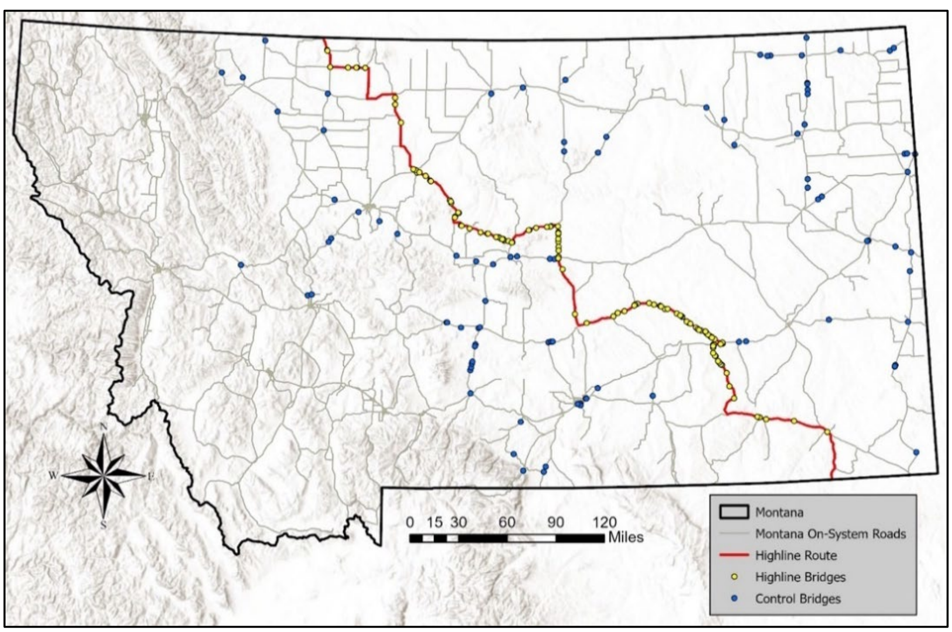

Figure 11: Highline route structures and control group used in preliminary analysis.

3.4.5 Highline Control Group

The bridges on the Highline route were compared to a control group of bridges that was created by randomly sampling an equal number of bridges in the same maintenance district and with the same functional class as the bridges along the Highline route. The Highline control bridges are also shown in Figure 11.

3.5 Preliminary Bridge Variables

For each of the bridge groups described above, 28 different bridge variables were used in the preliminary analysis as variables to assess changes in the NBI concrete bridge deck ratings. Variables were chosen based on the literature review (Section 2) of this research and their availability in BrM. The NBI data for the statistical analysis was recorded in 2022.

An initial analysis was performed to identify statistically insignificant variables that could be removed based on results of a correlation test. Four variables were removed, leaving five groups and 24 variables representing a combination of bridge design (e.g., design load, structure type, superstructure material, etc.), geometry (e.g., number of spans, maximum span length, deck area, etc.), service condition (e.g., average annual daily traffic [AADT], functional class, service under bridge, etc.), and location (e.g., district and county). The age of the bridge was calculated based on the year built or reconstruction date. Although age does not directly deteriorate a bridge, it is used as a time variable to determine how long a bridge has been exposed to an environment or has remained in each NBI condition. The estimated average annual daily truck traffic (AADTT) was calculated by multiplying the percentage of trucks from MDT's traffic volume data layer (counted or estimated) and the AADT. A summary of the numerical and categorical data variables for the 2,014 bridge decks that were evaluated in the preliminary statistical analysis can be seen in Table 15 and Table 16, respectively.

Table 15: Summary of numeric data variables.

Numerical Variable	Min.	Max.	Mean	Median	Std. Dev.
Number of Spans	1	33	3	3	2
Maximum Span Length (ft)	6	520	54	46	45
Deck Area (ft^2)	180	142,028	6,122	3,479	9,236
AADT	0	40,211	4,414	2,245	5,550
Age (yr)	1	103	49	52	21
Total Structural Length (ft)	6	2,122	146	92	200
Deck Width (ft)	15	312	34	36	25
AADTT	0	3,651	561	139	764
Bridge Skew (degree)	0	99	9	0	NA
Road Width (ft)	18	90	35	37	NA
Number of Lanes	2	6	2	2	NA
Speed on Bridge	25	80	69	70	NA

Table 16: Summary of categorical variables.

Variable	# of Categories	Names in Categories
District	5	Billings, Butte, Glendive, Great Falls, Missoula
County	56	All 56 counties in Montana
National Highway System	2	On NHS, not on NHS
Service Under Bridge	8	Creek, Drainage, Irrigation, Lake/Reservoir, Land, Railroad, River, Road
Functional Class	4	Interstate, Major Collector, Minor Arterial, Principle Arterial
Surface Type	3	Asphalt, Concrete, Unpaved
Urban Area	2	In Urban Area, Not in Urban Area
Design Load	10	HL-93, H-15, H-20, H-10, HS-15, HS-20, HS-20 + mod, ≥ HS-25, Other, Unknown
Bridge Material	8	Concrete, Concrete Continuous, P/S Conc. Continuous, P/S Concrete, Steel, Steel Continuous, Wood or Timber, Other
Bridge Design	13	Arch-Deck, Box Beam or Girders, Channel Beam, Culvert, Girder and Floor-beams, Segmental Box Girder, Slab, Stringer or Multi-Beam, Stringer/Girder, Tee Beam, Truss-Thru, Truss-Deck, Other
Deck Surface	8	Bituminous, Epoxy Overlay, Gravel, Integral Concrete, Latex Concrete or Similar, Low Slump Concrete, Monolithic Concrete, None
Deck Material	5	Concrete-Cast-in-Place, Concrete Precast Panel, Corrugated Steel, Wood or Timber, Other

3.6 Preliminary Analysis Results

Results of the Generalized Linear and Random Forest regression models are presented below.

3.6.1 Generalized Linear Model

Several significant factors were identified using the GL model for each data group. A summary of the significant variables identified in each model can be found in Table 17. The adjusted R^2 values for the models ranged from 0.128 for the steel bridge group to 0.500 for the highline bridge route. The RMSE for the GL model ranged from 0.424 for the Glendive district and 0.965 for the Highline Control group of bridges.

Table 17: Model performance for each group and significant variables identified in each model. Grey boxes indicate variables that were not included in the model.

Bridge Group Model	Number of Bridges	Adjusted R^2	RMSE	District	County	Age	Max Span Length	Structure Length	Deck Width	Deck Area	Bridge Over	Functional Class	Bridge Skew	AADT	AADTT	# of Lanes	Speed	Urban Area	Design Load	Bridge Material	Bridge Design	Deck Surface	Deck Material
Statewide	2,114	0.2189	0.6772	x		x	x		x	x	x	x		x	x				x			x	
Billings	444	0.2657	0.5845		x	x		x			x		x									x	
Butte	493	0.2614	0.6089			x			x			x		x	x		x	x	x	x		x	
Glendive	414	0.4299	0.4244		x	x	x			x		x					x		x			x	x
Great Falls	381	0.2952	0.8086		x	x	x			x		x					x		x			x	x
Missoula	382	0.2899	0.9362		x	x			x	x		x		x	x	x	x		x			x	x
Concrete	1,452	0.2553	0.6457	x		x			x	x	x	x		x	x		x		x			x	
Steel	318	0.1284	0.8613			x					x	x			x								
Wood	344	0.2680	0.4298	x						x				x									x
Interstate	805	0.2219	0.6097	x		x		x		x				x	x				x			x	
Major Arterial	453	0.2779	0.7421	x		x	x				x		x	x							x	x	
Minor Arterial	483	0.3011	0.7948	x		x		x	x	x	x						x		x		x	x	
Collector	373	0.2616	0.6078	x		x		x							x				x			x	
Highline Route	95	0.4996	0.7065	x				x		x										x		x	
Highline Control	95	0.3359	0.9650				x	x			x	x	x		x							x	

The final variables used in each model ($p < 0.05$) were different for each group. The smallest number of variables used was the wood bridges group, with four variables included. The Missoula district group had the largest number of variables with 12. The percentage of variables that represented each bridge group, or frequency, can be seen in Figure 12. District or county, age of the bridge, and deck surface were used in 80% of the models. The functional class was a significant variable in 72% of the models. The deck area and the bridge design load were in 60% of the models and AADTT was used in 54% of the models. All other variables were used in < 50% of the models.

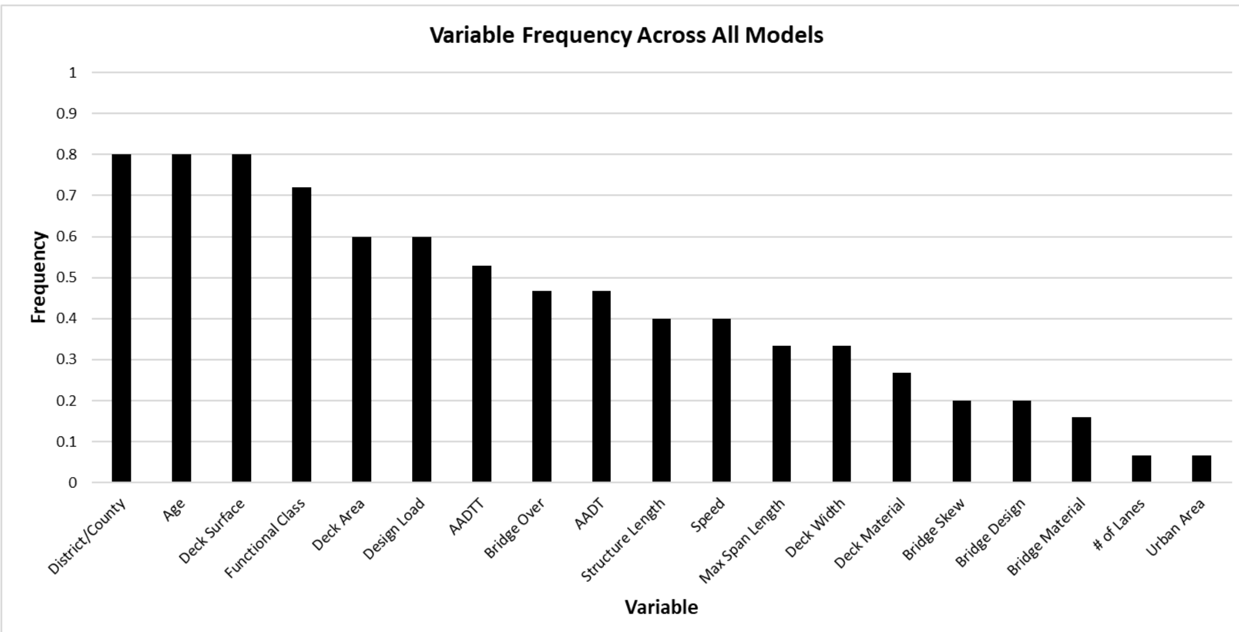

Figure 12: Frequency of variables used in the final models across all the groups.

To evaluate the GL model prediction accuracy for each bridge group, the average and standard deviations for the maintenance district, main structural material, and functional class are shown in with the adjusted R^2 and RMSE values for the statewide, Highline route, and Highline control groups. The R^2 values range from 0.217 when the bridges are grouped by the main structural material to 0.308 in the maintenance district group. The average RMSE ranged from 0.646 for the main structural material group to 0.689 for the functional class group shown in Table 18. Smaller standard deviations were calculated for both performance indicators in the functional class group.

Table 18: Performance indicator averages and standard deviation for the general linear models for each bridge group.

Bridge Groups	Adjusted R^2	RMSE
Statewide	0.219	0.677
Districts	0.308	0.673
Material	0.217	0.646
Functional Class	0.266	0.689
Highline Route	0.500	0.707
Highline Control	0.336	0.965

3.6.2 Random Forest Regression

A summary of the calculated percent increase of the mean-squared error (MSE) for all RF models can be found in Table 19. The most important variables, indicated by large percent MSEs are shaded green in Table 19. The least important variables are shaded red, and variables shaded in dark grey have a negative effect on the model's performance. The missing values shaded in light grey were not included in the original RF model. There are clear similarities between the statewide, districts, bridge material, and functional class bridge groups.

The mean of squared residuals shown in Table 19 represents the sum of the squared differences between the actual values and estimated values from the model. The least accurate model according to the MSR indicator was the wood bridge group with a MSR of 0.154. The most accurate model, with an MSR of 0.734 was the Highline control group of bridges. The Pseudo-R^2 values used to assess the performance of the competing RF models using the same data ranged from -0.033 (negative correlation) for the Highline bridges to 0.348 for the bridges located in the Billings District.

To evaluate the RF model prediction accuracy for each bridge group, the average MSE values are shown in Table 20 for the maintenance district, main structural material, and the functional class groups. The same color shading shown in Table 19 was used (most significant = dark green, least significant = red, light gray = variable not used, dark gray = decrease in MSE).

Table 19: Random Forest regression percent increase in mean squared error for all the model groups.

Bridge Group Model	Mean of Squared Residuals	Pseudo-R^2	District	County	Age	Max Span Length	Structure Length	Deck Width	Deck Area	Bridge Over	Functional Class	Bridge Skew	AADT	AADTT	# of Lanes	Speed	Urban Area	Design Load	Bridge Material	Bridge Design	Deck Surface	Deck Material
Statewide	0.428	0.292	52.0		36.1	23.3	21.8	26.7	22.6	15.3	13.9	3.8	21.5	22.3	0.1	11.3	6.9	17.0	19.2	4.6	26.9	13.9
Billings	0.259	0.348		26.0	22.8	10.8	14.2	11.3	15.0	14.2	4.3	5.5	7.4	10.1	-1.4	4.7	1.5	17.2	15.2	10.2	6.8	4.5
Butte	0.358	0.276		12.0	17.6	14.9	10.3	19.1	14.0	12.7	11.9	3.7	14.4	15.0	0.0	7.9	5.7	6.9	13.4	5.6	15.6	13.9
Glendive	0.237	0.340		8.3	10.9	10.7	12.6	10.8	13.7	7.1	1.0	0.8	10.6	7.9	1.0	9.3	0.7	5.0	7.1	2.2	16.3	9.4
Great Falls	0.595	0.241		8.1	16.7	15.2	14.6	14.5	12.6	2.7	4.5	-0.3	10.0	11.8	-0.5	8.4	0.9	13.5	7.5	7.6	15.7	4.9
Missoula	0.622	0.241		16.9	14.3	10.1	16.0	12.7	19.5	4.3	9.5	2.9	7.2	6.7	0.2	4.0	3.5	1.0	12.5	0.1	10.6	3.8
Concrete	0.427	0.318	47.4		34.3	17.3	23.9	19.7	24.2	11.8	9.9	5.5	18.2	17.3	-0.5	9.2	6.5	12.3	7.5	7.5	34.1	1.2
Steel	0.628	0.124	10.9		15.4	8.8	6.0	6.4	5.9	3.8	4.8	-1.3	2.6	6.7	1.5	-0.1	1.9	4.8	13.3	-3.5	2.4	1.1
Wood	0.154	0.287	28.7		7.6	8.2	9.0	3.2	10.3	5.4	10.0	-2.2	7.9	10.1	0.0	-0.4	0.0	8.2				0.0
Interstate	0.371	0.335	33.8		18.5	19.7	20.8	24.4	22.5	15.3		7.7	24.5	20.0	0.0	10.5	4.5	3.0	10.0	6.5	28.9	0.0
Major Arterial	0.413	0.292	21.0		19.1	14.5	12.3	10.3	14.8	9.4		0.9	10.9	10.6	0.2	8.4	1.5	6.3	14.6	2.4	5.2	4.3
Minor Arterial	0.508	0.264	20.2		18.1	15.3	12.5	10.2	11.1	4.8		-2.4	9.3	9.7	1.7	10.9	1.8	10.4	6.7	0.3	7.8	11.6
Collector	0.435	0.173	14.4		10.5	8.5	9.8	6.6	12.3	2.6		-0.5	3.4	2.8	0.0	0.8	1.0	9.4	10.5	4.5	6.0	5.8
Highline Route	0.483	-0.033	3.0		0.0	4.0	4.0	4.6	6.0	2.0	2.5	2.7	6.2	0.8	0.0	0.2	0.0	2.5	2.9	4.4	4.6	0.5
Highline Control	0.734	0.124	0.9		5.6	5.9	8.0	-1.4	10.0	1.9	-2.2	5.3	1.6	-1.1	0.0	-1.8	-0.3	4.2	5.1	-1.6	-0.8	4.0

Table 20: Average statistical measurements for the random forest models for each bridge group.

Bridge Group Model	Mean of Squared Residuals	Pseudo-R^2	District	County	Age	Max Span Length	Structure Length	Deck Width	Deck Area	Bridge Over	Functional Class	Bridge Skew	AADT	AADTT	# of Lanes	Speed	Urban Area	Design Load	Bridge Material	Bridge Design	Deck Surface	Deck Material
Statewide	0.428	0.292	52.0		36.1	23.3	21.8	26.7	22.6	15.3	13.9	3.8	21.5	22.3	0.1	11.3	6.9	17.0	19.2	4.6	26.9	13.9
District	0.414	0.289		14.2	16.5	12.3	13.6	13.7	15.0	8.2	6.2	2.5	9.9	10.3	-0.1	6.9	2.5	8.7	11.1	5.2	13.0	7.3
Material	0.403	0.243	29.0		19.1	11.4	13.0	9.8	13.4	7.0	8.2	0.7	9.6	11.4	0.4	2.9	2.8	8.4	10.4	2.0	18.3	0.8
Functional Class	0.432	0.266	22.4		16.5	14.5	13.9	12.9	15.2	8.0		1.4	12.0	10.7	0.5	7.7	2.2	7.3	10.4	3.4	12.0	5.4

The average and standard deviations for the pseudo- R^2 and MSR for the maintenance districts, main structural material, and functional class are shown in Table 20. The pseudo- R^2 values range from 0.243 when the bridges are grouped by the main material of the superstructure to 0.734 in the Highline control group. The average MSR values range from -0.033 for the Highline group to 0.432 for the functional class group. 0.646 for the main structural material group to 0.689 for the functional class group. The average MSR values and small standard deviation for the function class group suggests the RF regression model is a better predictor of NBI ratings for this group.

3.7 Discussion

The GL and RF regression models were used to determine which variables influence the NBI concrete deck ratings. Observations related to the bridge groups and variables considered, a comparison of the prediction indicators, and a final ranking of significant factors for the preliminary analysis are discussed below.

3.7.1 Highline Bridge and Control Groups

The bridge group with least accurate prediction capability based on the RSME performance indicator from the GL model and the pseudo R^2 value from the RF regression models was the Highline bridge group and the Highline control group. For the GL models, the Highline and Highline control group had the largest and least accurate RSME values of 0.965 and 0.707, respectively (Table 17). The poor performance indicators were also reflected in the RF regression models, with the Highline and Highline control group pseudo R^2 values of -0.033 and 0.124, respectively (Table 19). A simple interpretation of the negative value is that it is better to simply predict any sample as equal to the mean value. The poor performing model for this bridge group may be caused by the small number of bridges used in the model or that bridge deterioration for the Highline route is mainly influenced by a variable not included in the model. The Highline route was selected due to the high number of permitted trucks. It is possible the missing variable to model this bridge group could be the permitted truck traffic.

The two most accurate models from the GL models using the RMSE performance indicator were the Glendive District (RMSE = 0.424) with nine variables and the Wood Bridges group (RMSE = 0.430) that only used four variables. However, the Glendive District and Wood Bridges ranked 2nd and 8th most accurate, respectively, when using the Adjusted R^2 performance indicator. This comparison, in addition to the absent permitted truck traffic variable for the Highline group are examples of the importance of selecting influential variables rather than using as many variables as possible.

3.7.2 Regression Model Comparisons

Observations related to the performance indicators used for Generalized Linear and Random Forest Models and the results of the Highline Route are discussed below.

<u>Generalized Linear Models</u>

The calculated adjusted- R^2 values for the GL models are low (<0.5), which was expected due to the large number and overlapping influence different variables on bridge deterioration. The lack of consistency between the adjusted R^2 values for the bridge groups makes observations to the accuracy of the GL models using this performance indicator difficult (Table 18).

The RMSE performance indicator, however, did show some consistency between its values and standard deviations for the GL models. The average RMSE for each bridge group were approximately the same, ranging from 0.646-0.689 (Table 18). The standard deviation for the functional class bridge group was less than half the standard deviation for the other groups and suggests the NBI rating prediction was better explained by the functional class groups using the GL model.

Random Forest Models

There were similar differences between the performance measurements for the RF regression models. Based on the calculated averages and standard deviations, the results did not reveal a consistent improved prediction of NBI ratings in the model groups using the pseudo- R^2 and MSR performance indicators.

In general, considering the number of iterations and their adaptability to multiple datasets, the RF regression models may be a better predictor of NBI deck ratings. This observation is highlighted in the statewide bridge group analysis where the largest number of bridges produced the highest described variance compared to the other smaller bridge groups using the same variables in the model.

3.7.3 Significant Factor Rating

The statistical analyses identified several significant factors that influence the NBI condition ratings for bridge decks in Montana. The ranking of all variables using the average performance indicators for both the Generalized Linear and Random Forest regression models can be seen in Table 21. Maintenance district, bridge age, and deck surface are the three most influential variables identified by both the GL and RF model. Lower rankings varied between the two analyses which were averaged to approximate the influence of the remaining variables. Based on these averages, the next most influential variables are the bridge deck area, AADTT, structure length, functional class, design load, AADT, and deck width.

Table 21: Significant variable ranking for generalized linear and random forest models.

Model Type	District/County	Age	Deck Surface	Deck Area	AADTT	Structure Length	Functional Class	Design Load	AADT	Deck Width	Max Span Length	Bridge Over	Speed	Bridge Material	Deck Material	Bridge Design	Bridge Skew	Urban Area	# of Lanes
GLM	1	2	3	5	7	10	4	6	9	13	12	8	11	17	14	16	15	19	18
RF	1	2	3	4	8	6	13	11	9	5	7	12	14	10	15	16	18	17	19
Average Ranking	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19

4. Final Analysis

Based on the results from both regression models and input from bridge engineers at MDT, a refined analysis was performed. Statistically insignificant bridge groups and variables were removed, and one new bridge group and four new variables were added. The final analysis considered four bridge groups, and 21 variables compared with five bridge groups and 28 variables for the preliminary analysis.

The first revision to the data was to limit the bridge dataset to bridges with reinforced concrete decks. There are four types of deck materials identified in the structural asset data: concrete cast-in-place (n = 1,686), concrete precast panel (n = 39), corrugated steel (n = 3), and wood or timber (n = 344). Due to the low number of bridge decks made with precast concrete, corrugated steel, and the relatively low traffic volumes and maintenance expenditures on wood and timber bridges, the statistical analysis included only bridges with concrete cast-in-place decks. The smaller bridge dataset was intended to improve the statistical analysis results by considering a bridge element that receives a large percentage of MDT maintenance/rehabilitation resources.

The second refinement made to the data groups was to remove the Highline route and highline control route based on the inconclusive results obtained during the preliminary analysis. A new bridge group, deck overlay material (i.e. epoxy, bituminous, latex concrete) was added to the analysis.

The third revision made was the removal of insignificant variables identified in the preliminary analysis and the inclusion of four new variables: freeze-thaw cycles, rain precipitation, snow precipitation, and deicer application rate.

4.1 Final Bridge Groups

Using a new dataset of reinforced concrete decks and including a new bridge deck overlay material group results in different numbers of bridges evaluated in the statistical analysis. The four bridge groups considered in the final analysis are described below.

4.1.1 Maintenance Districts

Bridges were divided into maintenance districts to highlight the different environmental conditions across the state of Montana and specific effort put forward by each district. The number of bridges with reinforced concrete decks in each maintenance district are Billings (n = 348), Butte (n = 420), Glendive (n = 287), Great Falls (n = 282), and Missoula (n = 349).

4.1.2 Superstructure Materials

Bridge materials considered for the superstructure include concrete, steel, and wood. Out of the 1,686 bridges in the analysis, there are 1,366 made from concrete, 311 steel bridges, and 9 made from wood, or timber. Due to the low number of bridges with wood or timber superstructures, only concrete and steel superstructure materials were included in this analysis.

4.1.3 Functional Class

Bridges were also divided into functional class groups. Four types of road functional classes are identified in the MDT on-system routes: interstate (n = 799), major arterial (n = 237), minor arterial (n = 290), and collector roads (n = 360).

4.1.4 Bridge Deck Overlay Material

Five different surface type groups were considered for this analysis: bituminous (n = 210), epoxy overlay (n = 128), latex concrete or similar (n = 206), monolithic concrete (n = 814), and no additional surface (n = 311).

4.2 New Variables

The percentage of variables that represented the smallest number of bridge groups shown in Figure 12 (no. of lanes, urban area) were removed from the preliminary analysis because of their low statistical significance. In addition, because only reinforced concrete bridge decks were considered in the final analysis, the 'deck material' group in Figure 12 was also removed. Based on input from bridge engineers at MDT, four new variables were added to the analysis: 1) freeze-thaw cycles, 2) rain precipitation, 3) snow precipitation, and 4) deicer application rate. Latitude and longitude coordinates for each collection site were used from the station closest to each bridge. The final statistical analysis included 21 bridge variables that were used to predict NBI concrete bridge deck ratings. An updated summary of the 13 numerical variables can be seen in Table 22 and the eight categorical variables can be seen in Table 23. A description of the data used for the four new variables is described below.

Table 22: Summary of numeric data variables used in analysis.

Variable	Min.	Max.	Mean	Median	Std. Dev.
Age (yr)	1	102	46	51	18
Maximum Span Length (ft)	8	520	75	65	44
Total Structural Length (ft)	10	2,122	210	135	226
Deck Width (ft)	15	312	44	42	18
Deck Area (ft^2)	395	142,028	8,952	5,590	10,559
Average Annual Daily Traffic	0	40,211	5,177	3,141	6,080
Average Annual Daily Truck Traffic	0	3,651	632	155	815
Bridge Skew (degree)	0	99	10	0	14
Speed on Bridge (mph)	25	80	69	70	14
Average Freeze/Thaw Cycles (days)	5	187	116	118	30
Average Rain Precipitation (in)	0	43	14	13	7
Average Snow Precipitation (in)	0	169	10	6	17
Deicer Application (gal/ln-mi)	19	3,589	439	151	729

Table 23: Categorical variables used in the preliminary analysis.

Variable	Number of Categories	Names in Categories
District	5	Billings, Butte, Glendive, Great Falls, Missoula
County	56	All 56 counties in Montana
Service Under Bridge	8	Creek, Drainage, Irrigation, Lake/Reservoir, Land, Railroad, River, Road
Functional Class	4	Interstate, Major Collector, Minor Arterial, Principle Arterial
Design Load	10	HL-93, H-15, H-20, H-10, HS-15, HS-20, HS-20 + mod, ≥ HS-25, Other, Unknown
Bridge Material	8	Concrete, Concrete Continuous, P/S Conc. Continuous, P/S Concrete, Steel, Steel Continuous, Wood or Timber, Other
Bridge Design	13	Arch-Deck, Box Beam or Girders, Channel Beam, Culvert, Girder and Floor-beams, Segmental Box Girder, Slab, Stringer or Multi-Beam, Stringer/Girder, Tee Beam, Truss-Thru, Truss-Deck, Other
Deck Surface	8	Bituminous, Epoxy Overlay, Gravel, Integral Concrete, Latex Concrete or Similar, Low Slump Concrete, Monolithic Concrete, None

4.2.1 Freeze-Thaw Cycles

Yearly freeze-thaw cycles (FTCs) were estimated by counting each day where the daily minimum and maximum temperatures cross the 32°F ±1°F freezing threshold. FTCs occurring over periods of less than one day were not counted. The weather station data used to estimate FTCs included 64 weather stations and data recorded from 2000 to 2020. Years with less than 300 days of temperature data were excluded from the averages. The daily summaries for the weather stations were sourced from National Oceanic and Atmospheric Administration (NOAA) and the National Centers for Environmental Information (NCEI) archive. This method was inspired by the Great Lakes Integrated Sciences Assessments Center in their models of regional freeze-thaw cycles (GLISA, 2020). The freeze-thaw temperature locations were obtained from the stations shown in Figure 13.

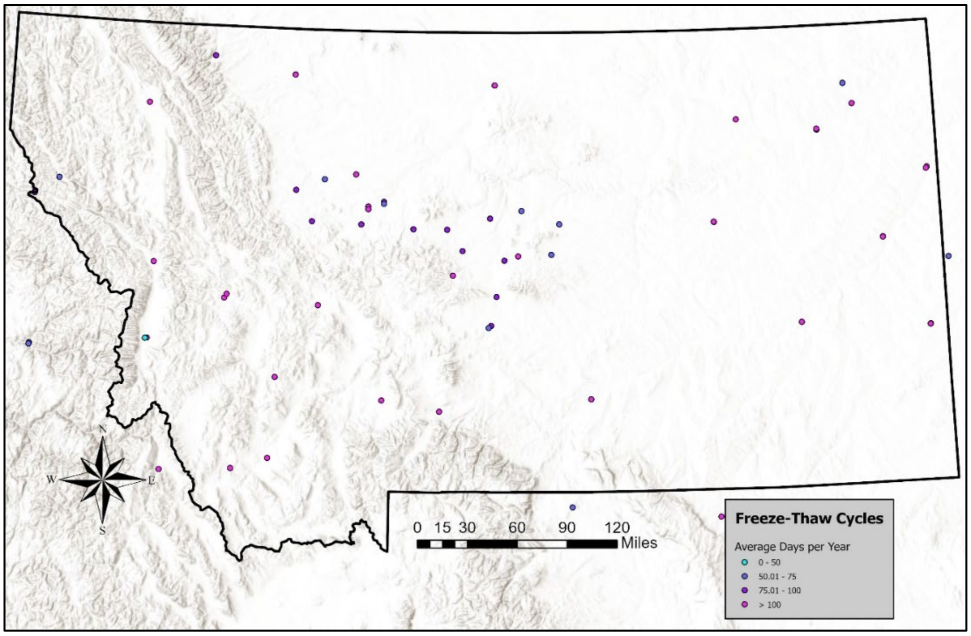

Figure 13: Stations used for the average days per year that experienced a freeze-thaw cycle.

4.2.2 Rain Data

Yearly rain precipitation estimates were created with data from weather stations in Montana, as well as nearby stations in bordering states and Canada, shown in Figure 14. Daily rain precipitation data from 221 weather stations was obtained from the NCEI online archive which was reduced to 164 by removing 57 stations with insufficient data. Yearly values for precipitation were created by averaging total precipitation daily values for each calendar year between 1935 and 2010.

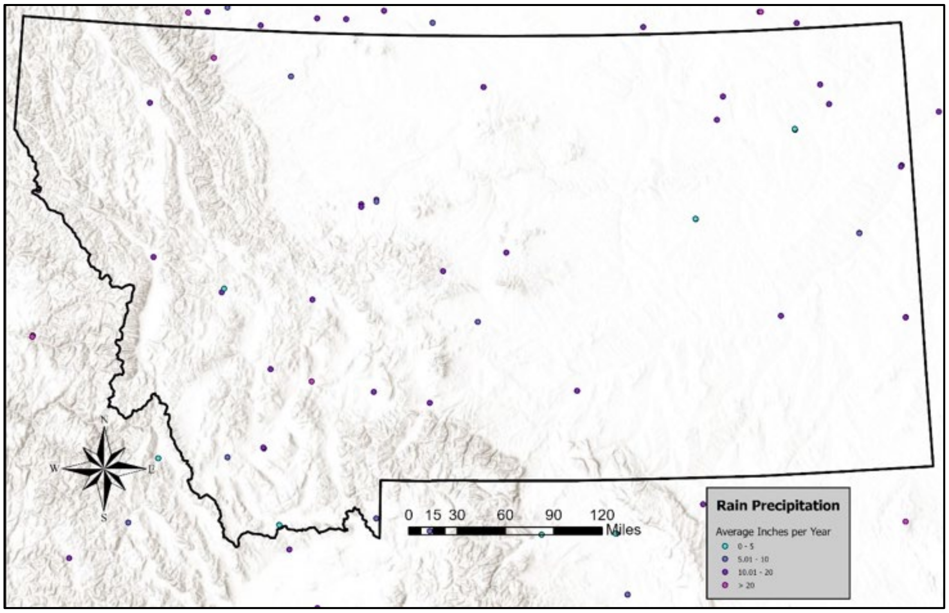

Figure 14: Rainfall data collection stations.

4.2.3 Snowfall Data

MDT provided a statewide dataset of information for snowfall, which was sourced from NOAA and the NWS. Total daily snowfall data was averaged for 733 weather stations to obtain yearly snowfall averages from 1876 to 2011. The distribution of snowfall recording stations is shown in Figure 15.

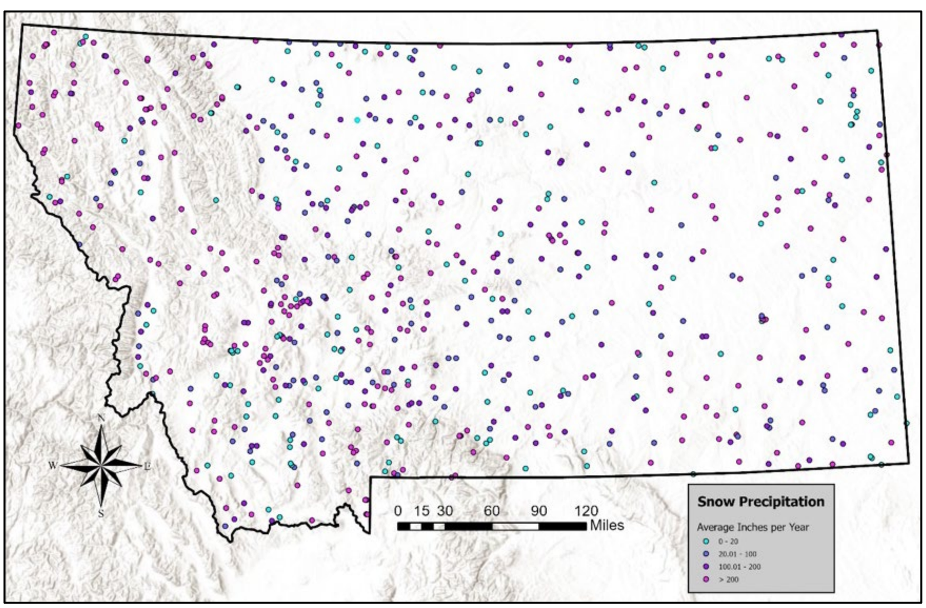

Figure 15: Snowfall data collection stations.

4.2.4 Deicer Application Rates

The influence of deicer materials on bridge deck deterioration was evaluating using the quantity of deicer applied to bridge decks. Deicer data described by gallons per lane-mile (gal/ln-mi) was obtained from the MDT Maintenance Department. It was assumed the deicer application rates shown in Figure 16 were the same for all bridges in the maintenance section.

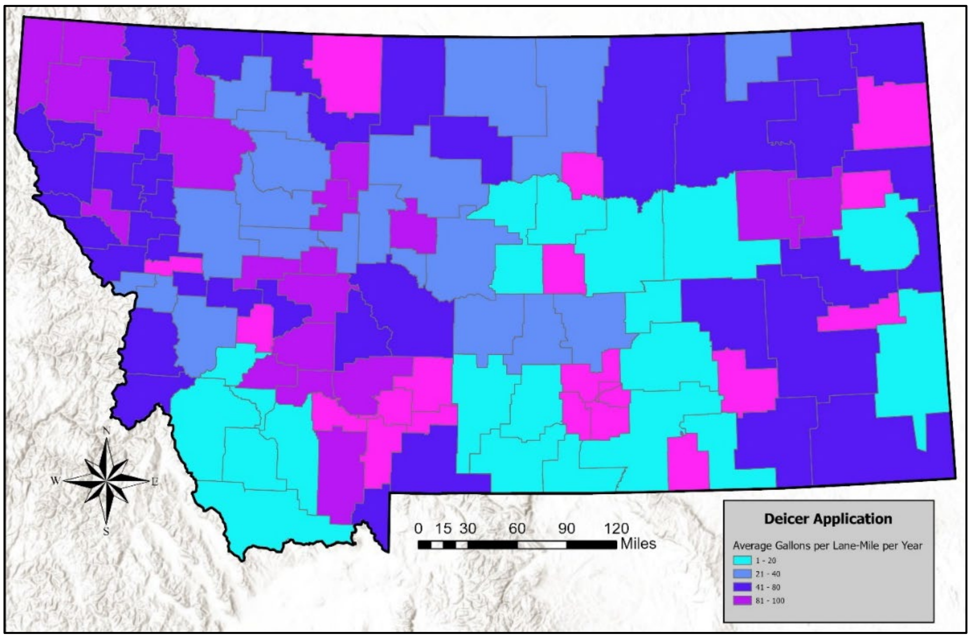

Figure 16: Deicer application rates by MDT maintenance sections.

4.3 Final Analysis Results

Results of the Generalized Linear regression models and Random Forest regression models using the final data groups and variables are presented below.

4.3.1 Generalized Linear Model

The percentage of variables that represented each bridge group, or frequency, can be seen in Figure 17. District or county and age of the bridge were identified as significant variables in over 90% of the models created, and deck surface type were included in over 80% of the bridge models. Snow precipitation was a significant variable in 52% of the bridge groups and functional class was significant in 45% of the bridge groups. All other variables were identified as significant in less than 35% of the bridge models created.

A more detailed summary of the significant variables identified using the GLM for each bridge group can be found in Table 24. Cells shaded grey indicate variables that were not included in the model. The adjusted R^2 values for the models ranged from 0.113 for the bridges in the Butte district and 0.356 for bridge decks with an epoxy overlay surface. The RMSE for the GL model ranged from 0.534 for the Glendive district and 1.11 for bridge decks with an epoxy overlay surface.

The final variables used in each model ($p < 0.05$) are identified with an 'x' in Table 24. The smallest number of significant variables identified was identified in the Billings and Glendive districts with four significant variables. Bridges with a concrete main span superstructure had the largest number of variables with 12.

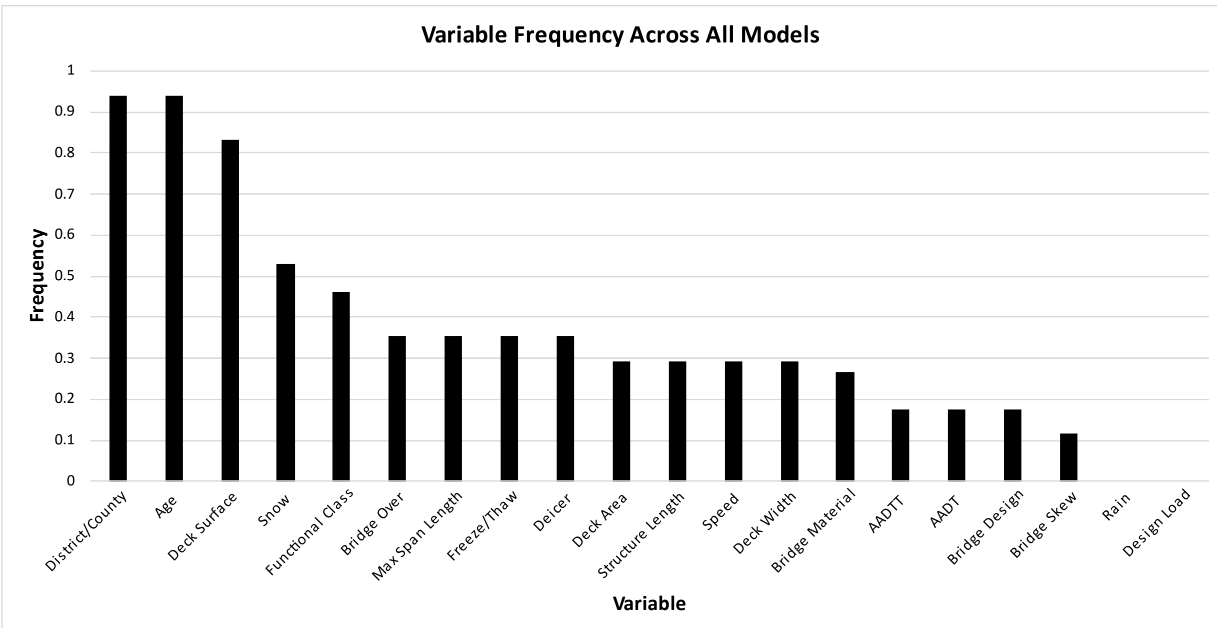

Figure 17: Frequency of variables used in the final models across all the groups.

Table 24: Model performance for each bridge group model and significant variables identified in each model.

Bridge Group Model	Number of Bridges	Adjusted R^2	RMSE	District	County	Age	Max Span Length	Structure Length	Deck Width	Deck Area	Bridge Over	Functional Class	Bridge Skew	AADT	AADTT	Speed	Design Load	Bridge Material	Bridge Design	Deck Surface	Freeze/Thaw	Rain	Snow	Deicer
Statewide	1,686	0.229	0.718	x		x	x		x	x										x			x	x
Billings	348	0.226	0.628			x	x				x									x				
Butte	420	0.113	0.669		x	x			x											x			x	
Glendive	287	0.306	0.534		x	x														x	x			
Great Falls	282	0.284	1.032		x	x	x					x		x						x				
Missoula	349	0.294	0.967		x	x	x		x			x				x		x	x	x				
Concrete	1,366	0.252	0.606	x		x	x	x	x		x	x				x			x	x			x	x
Steel	311	0.226	1.020	x		x					x	x							x		x			
Interstate	799	0.276	0.670	x		x		x		x	x			x	x			x		x			x	
Major Arterial	360	0.294	0.753	x		x		x			x												x	x
Minor Arterial	290	0.278	0.854	x		x		x		x						x				x	x			
Collector	237	0.249	0.724	x		x		x					x		x					x				
Bituminous	210	0.302	0.867	x		x										x		x			x		x	
Epoxy Overlay	128	0.356	1.114	x		x	x				x		x								x		x	x
Latex Concrete	206	0.321	0.775	x						x				x		x		x					x	
Mono. Concrete	814	0.231	0.737	x		x				x		x									x		x	x
No Additional	311	0.272	0.748	x		x			x			x												x

4.3.2 Random Forest Regression

A summary of the calculated percent increase of the mean-squared error (MSE) for all RF models can be found in Table 25. The most important variables, indicated by large percent MSEs are shaded green. The least important variables are shaded red, and unshaded variables with negative values have a negative effect on the model's performance. The missing values shaded in light grey were not included in the RF model because these variables overlapped with the bridge group.

To evaluate the RF model prediction accuracy for each bridge group, the average MSE values are shown in Table 26 for statewide, maintenance district, superstructure material, functional class, and deck surface groups. The same color shading shown in Table 19 was used (most significant = green, least significant = red).

Table 25: Random Forest regression percent increase in mean square error for all bridge group models.

Bridge Group Model	Mean of Squared Residuals	Pseudo-R^2	District	Age	Max Span Length	Structure Length	Deck Width	Deck Area	Bridge Over	Functional Class	Bridge Skew	AADT	AADTT	Speed	Design Load	Bridge Material	Bridge Design	Deck Surface	Freeze/Thaw	Rain	Snow	Deicer
Statewide	0.458	0.289	43.7	27.2	20.0	19.0	15.5	18.9	11.3	9.0	6.4	17.4	15.1	8.8	12.1	20.7	7.8	27.8	15.0	15.0	13.4	17.5
Billings	0.287	0.285		15.3	9.7	14.3	10.5	11.9	16.4	7.3	5.2	8.4	8.5	7.3	8.4	12.6	5.2	8.4	6.8	9.8	7.4	9.5
Butte	0.359	0.230		17.6	10.1	9.8	20.1	8.4	11.0	7.3	5.6	16.0	11.3	5.8	6.4	10.6	4.4	14.1	6.5	8.5	13.1	9.5
Glendive	0.258	0.176		15.6	10.6	9.6	10.6	8.7	-0.2	4.0	1.2	5.5	5.5	0.5	-0.2	8.1	4.9	11.4	5.4	5.5	8.7	4.8
Great Falls	0.656	0.259		12.5	17.6	9.8	7.7	9.9	4.4	8.0	3.9	9.4	9.9	6.9	11.4	10.8	4.5	10.3	2.1	7.8	4.2	7.2
Missoula	0.635	0.200		13.2	13.5	13.0	5.6	12.4	3.9	12.4	2.7	8.8	8.4	2.2	4.8	9.8	1.4	9.1	5.3	5.8	6.4	5.9
Concrete	0.414	0.324	47.2	25.9	18.7	15.3	19.0	18.7	13.8	11.9	6.5	19.9	17.2	10.7	11.2	6.0	6.5	29.7	16.8	15.5	16.4	20.3
Steel	0.620	0.099	12.2	9.2	6.6	6.7	7.0	4.4	3.3	3.0	0.8	4.5	6.0	0.7	4.5	7.6	5.4	9.3	2.4	-0.4	1.8	5.7
Interstate	0.339	0.346	28.0	20.2	18.3	17.3	17.1	17.9	13.6		8.1	21.9	17.7	9.1	4.3	11.6	7.3	24.7	16.2	17.4	14.8	20.8
Major Arterial	0.487	0.258	18.0	14.4	9.7	11.9	7.6	10.8	12.0		-0.9	9.3	4.1	2.9	3.0	8.6	-0.4	5.3	4.3	4.3	8.3	6.0
Minor Arterial	0.676	0.252	12.0	10.8	6.6	11.1	9.9	8.9	3.6		-0.7	7.7	7.0	6.2	5.7	5.4	2.6	4.2	6.4	2.0	4.1	17.0
Collector	0.504	0.139	14.5	6.7	0.7	6.8	5.4	7.6	2.6		1.0	6.8	7.1	-3.9	11.3	2.9	2.3	5.1	4.0	3.7	1.6	5.8
Bituminous	0.494	0.206	14.6	10.2	6.5	5.6	8.3	7.7	2.0	2.2	1.1	0.7	4.6	1.3	3.0	7.3	-0.9		2.4	3.2	5.6	4.1
Epoxy Overlay	0.447	0.134	11.1	11.0	6.0	7.6	7.9	7.6	4.1	2.0	3.8	4.2	2.5	1.8	1.0	5.5	0.4		4.1	3.8	2.5	5.5
Latex Concrete	0.553	0.229	19.1	6.8	10.9	6.8	9.6	7.0	7.0	2.1	1.0	3.7	8.2	3.3	-0.2	7.9	1.7		9.1	2.9	11.5	9.2
Mono. Concrete	0.445	0.306	32.7	22.8	15.6	18.4	14.9	16.4	8.3	7.5	3.2	13.1	13.1	5.8	5.8	11.9	3.8		14.9	9.0	9.9	17.6
No Additional	0.348	0.253	7.1	25.1	8.6	6.7	8.6	8.9	9.5	4.7	6.2	9.3	7.8	6.5	7.1	4.6	2.5		3.9	7.3	7.4	5.8

Table 26: Random Forest average percent increase in mean square error for each bridge group.

Bridge Group Model	Mean of Squared Residuals	Pseudo-R^2	District	Age	Max Span Length	Structure Length	Deck Width	Deck Area	Bridge Over	Functional Class	Bridge Skew	AADT	AADTT	Speed	Design Load	Bridge Material	Bridge Design	Deck Surface	Freeze/Thaw	Rain	Snow	Deicer
Statewide	0.458	0.289	43.7	27.2	20.0	19.0	15.5	18.9	11.3	9.0	6.4	17.4	15.1	8.8	12.1	20.7	7.8	27.8	15.0	15.0	13.4	17.5
Districts	0.439	0.230		14.8	12.3	11.3	10.9	10.2	7.1	7.8	3.7	9.6	8.7	4.6	6.1	10.4	4.1	10.6	5.2	7.5	7.9	7.4
Material	0.517	0.211	29.7	17.6	12.6	11.0	13.0	11.5	8.6	7.4	3.6	12.2	11.6	5.7	7.8	6.8	5.9	19.5	9.6	7.6	9.1	13.0
Functional Class	0.501	0.249	18.1	13.0	8.8	11.8	10.0	11.3	7.9		1.9	11.4	9.0	3.6	6.1	7.1	2.9	9.8	7.7	6.8	7.2	12.4
Deck Surface	0.458	0.225	16.9	15.2	9.5	9.0	9.9	9.5	6.2	3.7	3.0	6.2	7.3	3.7	3.4	7.5	1.5		6.9	5.3	7.4	8.4

4.4 Discussion

The GL and RF regression models were used to determine which variables had the highest influence on the NBI concrete deck ratings. There was a large variation in the statistical performance indicators of the two model types which are shown in Table 27. A comparison of the performance indicators for each model type, observations related to the significant variables, and results of the GCR analysis are discussed below.

4.4.1 Generalized Linear Regression Model

The calculated adjusted-R^2 values for the GL models are low (<0.5), which was expected due to the large number and overlapping influence that different variables have on bridge deterioration. The bridge group with least accurate prediction capability based on the RSME performance indicator was the deck surface group with an average RMSE of 0.848 (Table 27). These values show, on average, the deck surface group was the least accurate predicter of bridge deck NBI ratings.

Table 27: Comparison of statistical results for generalized linear and Random Forest regression models for each bridge group.

Bridge Group	GLM Adjusted-R^2	GLM RMSE	RF Pseudo-R^2	RF Mean of Squared Residuals
Statewide	0.229	0.718	0.289	0.458
Districts	0.244	0.766	0.230	0.439
Material	0.239	0.813	0.211	0.517
Functional Class	0.274	0.750	0.249	0.501
Deck Surface	0.296	0.848	0.225	0.458

Based on the results from the GLMs the most accurate model to predict deck NBI ratings is the statewide bridge group, but this model also has the lowest adjusted-R^2 value (Table 27). This means that overall, the variables do a poor job at explaining the variance in the model. This highlights the importance of breaking the bridges into more specific groups. The highest adjusted-R^2 value, and the bridge group model that is best fit from this data was the deck surface bridge groups (adjusted-R^2 = 0.296). Even though it is the best fit model for the bridge groups considered, the variables only explain 30% of the variation in NBI deck ratings that can be predicted from the selected variables.

4.4.2 Random Forest Regression Models

There were similar differences between the performance measurements for the RF regression models. Based on the calculated averages (Table 27) the results did not reveal a consistent improved prediction of NBI ratings in the model groups using the pseudo-R^2 and the Mean of Squared Residuals (MSR) performance indicators.

The bridge group with the least accurate prediction capability based on the MSR value from the RF regression models was the superstructure material group (MSR = 0.517). However, all the bridge groups had similar values, with MSR ranging from 0.439-0.517. These models generally have the same prediction accuracy, on average, to the GLM analysis. The percentage of the variance of the NBI deck ratings that can be explained by the selected variables are also similar to the GL models. The pseudo- R^2 values ranged from 0.211-0.289 (Table 27) with the largest value in the statewide bridge group. The RF analysis suggests that the bridge group best described by the selected variables is the statewide bridge grouping.

In general, considering the number of iterations and their adaptability to multiple datasets, the RF regression models may be a better representation of the performance of NBI deck rating predictor models and hold a higher weight to variable selection. This observation is highlighted in the statewide bridge group analysis where the largest number of bridges produced the highest described variance compared to the other smaller bridge groups using the same variables in the model.

4.4.3 New Variables

Including the additional variables (e.g., snow, rain, freeze-thaw, and deicer) and removing non-significant variables from the preliminary analysis (Section 1) did not meaningfully change the results of the final analysis nor did it change the significance of the top three previously identified variables. The significance ranking of the variables from both regression models in the final analysis can be seen in Table 28.

Table 28: Significant variable ranking for generalized linear and Random Forest models.

Model Type	District/County	Age	Deck Surface	Max Span Length	Bridge Over	Snow	Deck Area	Structure Length	Deicer	Deck Width	Freeze/Thaw	Functional Class	Bridge Material	AADT	AADTT	Speed	Rain	Bridge Design	Design Load	Bridge Skew
GLM	1	2	3	7	6	4	10	11	9	13	8	5	14	16	15	12	19	17	20	18
RF	1	2	3	4	6	12	6	5	8	7	13	17	10	9	11	18	14	19	16	20
Average Ranking	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20

Despite the revision to the bridge dataset, groups, and variables considered in the final analysis, the same top three significant variables were identified as those from the preliminary analysis: district/county, age of the bridge, and surface type. After the top three, the two regression models begin to vary. Considering the average values of the rankings between the two models, max span length and the feature the bridge crosses are ranked 4th and 5th most-significant variables. Out of the four new variables considered (freeze-thaw, rain, snow, and deicer), the average ranking for the variable snow was the highest at 6. Freeze-thaw cycles were ranked as the 11th most significant variable, on average, and rain precipitation was ranked 17th.

5. General Condition Rating Analysis

The final task of this research includes performing General Condition Rating (GCR) analyses within the Bridge Management (BrM) software. The overall objective was to a) quantify the influence of the selected variables for predicting National Bridge Inventory (NBI) deck ratings, b) use the results as input variables for a GCR analyses, c) and explore alternatives to integrate the results within the larger BrM optimization framework. Results of the General Condition Rating analysis performed within BrM are described, followed by results.

5.1 General Condition Rating Analysis

After identifying the significant variables from the regression models, MDT's asset management software, Bridge Management System (BrM), was used to conduct a General Condition Rating analyses (GCR). The GCR uses NBI component-level data to produce Time-in-State reports and Good-Fair-Poor forecasts.

5.1.1 Time-in-State Report

The first analysis completed through the GCR tool in BrM was the time-in-state report. The analysis considers a user-selected bridge group and calculates the number of years each bridge has remained in the nine NBI component-level condition ratings. The report provides the average years in a condition state with standard deviations based on the total surface area of bridges and by the number of bridges. Based on input from Mayvue Solutions, the average number of years in a condition state plus one standard deviation was selected for the WTI profile used for the Good-Fair-Poor optimization.

5.1.2 Good-Fair-Poor Forecast

A good-fair-poor forecast within BrM estimates the number of bridges that will be in a condition state in the future, given some level of repair and or maintenance expenditures. "Good" bridges have NBI component-level ratings from 7 to 9, indicating excellent to minor issues. "Fair" bridges include ratings from 5 to 6, with minor to moderate deterioration. "Poor" bridges are rated from 0 to 4 with advanced defects to imminent failure.

The good-fair-poor forecasts in BrM have an option for entering maintenance and/or repair types and frequencies to extend the number of years a bridge remains in the 'good' or 'fair' condition. For the GCR analysis described in this Report, no maintenance and/or repair strategies were implemented. Using the WTI profile obtained from the time-in-state report for each bridge group and each condition rating, zero-cost optimizations were run and forecast for 10-, 20-, 30-, 40-, and 50-year intervals. These forecasts were compared with the MDT deck profile to observe differences and compare with MDT's bridge repair practices and experience. The MDT deck profile was also created with time-in-state reports using different bridge datasets and/or different numbers of standard deviations added to the average times in a condition state.

5.2 Results

A procedure was established using BrM's general condition rating (GCR) analysis to estimate the number of bridges that are in good, fair, and poor condition over selected time periods. The analysis performed in this research used a zero-cost optimization to make predictions over a 100-year time period.

5.2.1 General Condition Rating Analysis

Bridge datasets for the GCR analysis were created within BrM using the same filters as the regression models described above. Only active bridges maintained by MDT with a concrete cast-in-place reinforced concrete deck were used for the GCR analysis.

Time-in-State Report

The BrM time-in-state reports are used to create a profile that is used for the good-fair-poor analysis. The results of the time-in-state reports can be seen in Table 29. For the WTI profile, the average number of years plus one standard deviation for each of the bridge groups is shown. Grey shaded values with bold text are values obtained from the time-in-state report. The unshaded '1' values for condition ratings 1-3 were used instead of the zero values generated by the analysis. Unshaded values for condition ratings 8 and 9 also produced zero values from the time-in-state report and were replaced with the values for the state-wide bridge group. Also shown in Table 29 are the median number of years in each condition state using the MDT Deck Profile.

Table 29: Median years in each NBI rating developed from the time-in-state reports (shaded) for each bridge group.

Bridge Group	Number of Bridges	NBI 9	NBI 8	NBI 7	NBI 6	NBI 5	NBI 4	NBI 3	NBI 2	NBI 1
MDT Deck Profile	1,890	10	4	28	20	22	11	10	10	10
Statewide	1,890	4	4	33	21	16	16	10	1	1
Billings District	400	4	3	37	24	23	13	1	1	1
Butte District	469	4	4	30	21	15	3	1	1	1
Glendive District	328	4	4	28	21	20	2	1	1	1
Great Falls District	323	4	5	33	27	21	20	1	1	1
Missoula District	370	4	4	30	18	10	16	10	1	1
Concrete Main Span	1,517	4	5	33	21	16	12	10	1	1
Steel Main Span	363	4	4	28	25	17	21	1	1	1
Interstate Roads	813	4	4	29	21	14	4	1	1	1
Major Arterial Roads	365	4	3	32	20	13	11	1	1	1
Minor Arterial Roads	297	4	6	31	25	17	16	10	1	1
Collector Roads	273	4	4	35	22	24	3	1	1	1
Bituminous Surface	286	4	6	36	21	17	25	1	1	1
Epoxy Overlay Surface	144	4	3	28	22	10	10	1	1	1
Latex Concrete Surface	223	4	3	27	20	12	6	1	1	1
Monolithic Concrete Surface	875	4	5	34	22	19	15	1	1	1
No Additional Surface	345	4	1	28	23	16	3	1	1	1

Good-Fair-Poor Analysis

Each of the bridge groups were analyzed using a no-cost Good/Poor optimization within BrM for the WTI and MDT GCR profiles. The results of the statewide analysis can be seen in Figure 18. The downward trends of the Good (green) and Fair (yellow) lines represent fewer bridges in these condition states over time because maintenance activity has been excluded. Conversely, the upward trend of the Poor (red) line increases because of the bridges moving into this condition state in the absence of maintenance activity (zero-cost). Similar plots for the bridge groups shown in Table 29 can be found in Appendix: Good-Fair-Poor Plots.

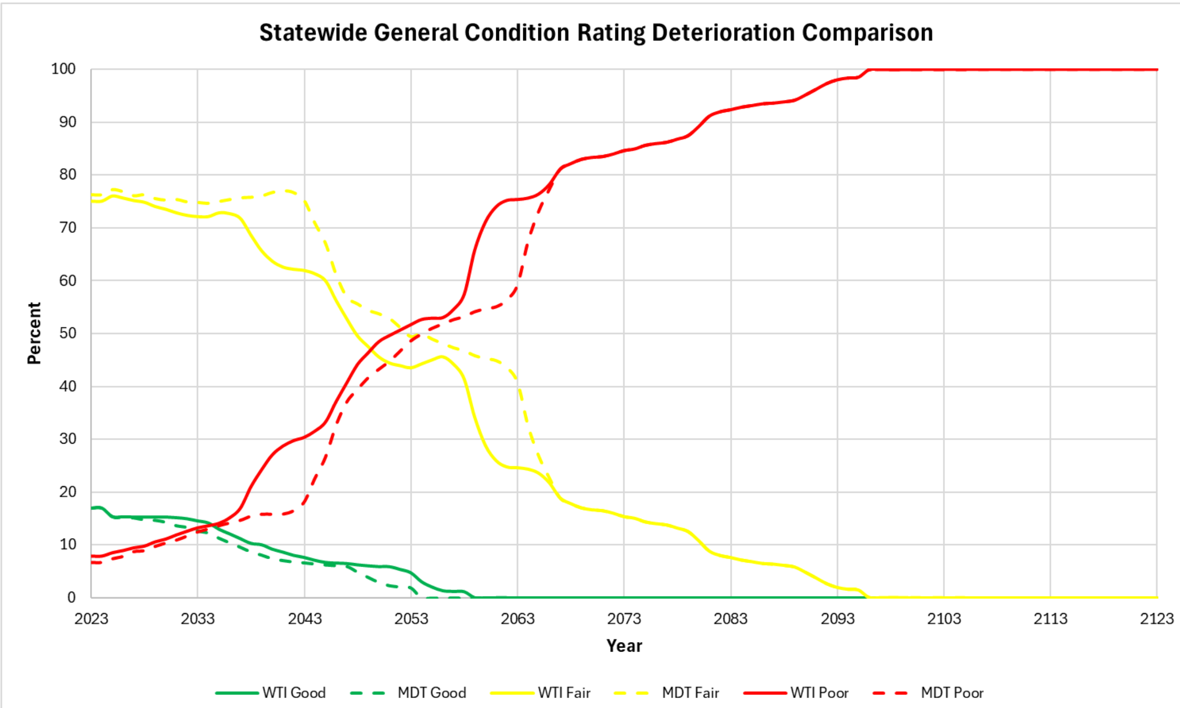

Figure 18: Good-fair-poor analysis comparison between default MDT Deck Profile and established WTI GCR deterioration values for the statewide bridge group.

One way to quantify the trends shown in the good-fair-poor analysis is to estimate the number of bridges in poor condition over 50 years. The good-fair-poor analysis estimates the percentage of bridges at each time step. The percentage estimates for the WTI and MDT profiles are displayed next to each other for each 10-year period in Table 30. The percentages in Table 30 were multiplied by the total bridge numbers in each bridge group and shown in Table 31.

Table 30: Estimates for the percentage of bridges in poor condition for bridge groups using WTI and MDT default GCR profiles.

Bridge Group	WTI 10 yrs	MDT 10 yrs	WTI 20 yrs	MDT 20 yrs	WTI 30 yrs	MDT 30 yrs	WTI 40 yrs	MDT 40 yrs	WTI 50 yrs	MDT 50 yrs
Statewide	13.3	12.5	30.4	18.1	51.7	48.6	75.4	59.2	84.6	84.6
Billings District	12	12	13.5	14.1	45.8	48.1	55.8	58.1	79.9	82.3
Butte District	5.5	4.8	24	7.7	50.7	43.4	80.5	58.3	91.3	90.6
Glendive District	12.4	11.5	21.3	15.6	48	47	76.2	60.8	93.2	93
Great Falls District	9.3	9.3	20.5	13.7	37.6	44.1	51.3	51.2	69.7	72.4
Missoula District	36.6	21.8	50	34.4	74	57.5	79.3	64	93	85.4
Concrete Main Span	7.8	6.5	22.5	10.1	44	41.3	71	51.8	82.7	82.7
Steel Main Span	21.7	21.5	39.5	30.3	59.6	59.6	70.3	70.3	87.4	87.4
Interstate Roads	8.4	7.7	26	13.9	53.6	48.4	77.3	62.6	89	87.2
Major Arterial Roads	17	13	38.5	19.6	50.6	47.3	73.2	53.1	83.4	81.4
Minor Arterial Roads	22.2	21.7	34.3	28.5	49.7	49.7	59.3	59.3	82.2	83.8
Collector Roads	14.1	14.1	16	16	47.7	48.6	58.1	55.6	81.5	85.4
Bituminous Surface	16.6	16.6	26.4	19.9	46.9	45.8	64.7	56.6	73.9	74.7
Epoxy Overlay Surface	23.9	14.4	35.7	25.4	57.7	50.9	70.2	61.6	84.9	81.2
Latex Concrete Surface	17.3	11.8	32.7	21.8	56.5	52.1	79.4	60.7	93.4	87.8
Mono. Concrete Surface	13.1	12.5	26.9	16.5	48.6	48.1	67.3	58.2	83.1	85.7
No Additional Surface	7	6.6	25	10	46.2	41.6	75.8	56.1	84.5	84.3

Table 31: Estimates for the number of bridges in poor condition state-wide using WTI and MDT default GCR profiles.

Bridge Group	WTI 10 yrs	MDT 10 yrs	WTI 20 yrs	MDT 20 yrs	WTI 30 yrs	MDT 30 yrs	WTI 40 yrs	MDT 40 yrs	WTI 50 yrs	MDT 50 yrs
Statewide	251	236	575	342	977	919	1425	1119	1599	1599
Billings District	48	48	54	56	183	192	223	232	320	329
Butte District	26	23	113	36	238	204	378	273	428	425
Glendive District	41	38	70	51	157	154	250	199	306	305
Great Falls District	30	30	66	44	121	142	166	165	225	234
Missoula District	135	81	185	127	274	213	293	237	344	316
Concrete Main Span	118	99	341	153	667	627	1077	786	1255	1255
Steel Main Span	79	78	143	110	216	216	255	255	317	317
Interstate Roads	68	63	211	113	436	393	628	509	724	709
Major Arterial Roads	62	47	141	72	185	173	267	194	304	297
Minor Arterial Roads	66	64	102	85	148	148	176	176	244	249
Collector Roads	38	38	44	44	130	133	159	152	222	233
Bituminous Surface	47	47	76	57	134	131	185	162	211	214
Epoxy Overlay Surface	34	21	51	37	83	73	101	89	122	117
Latex Concrete Surface	39	26	73	49	126	116	177	135	208	196
Mono. Concrete Surface	115	109	235	144	425	421	589	509	727	750
No Additional Surface	24	23	86	35	159	144	262	194	292	291

The values from Table 31 were added together by bridge group and are plotted in Figure 19. When comparing the number of bridges in poor condition for the MDT and WTI profiles, it is observed that the number of bridges in poor condition are generally the same at the start of the analysis, and after 50 years. The difference between the two profiles occurs near 20 and 40 years, where the MDT profile predicts fewer bridges moving to a poor condition.

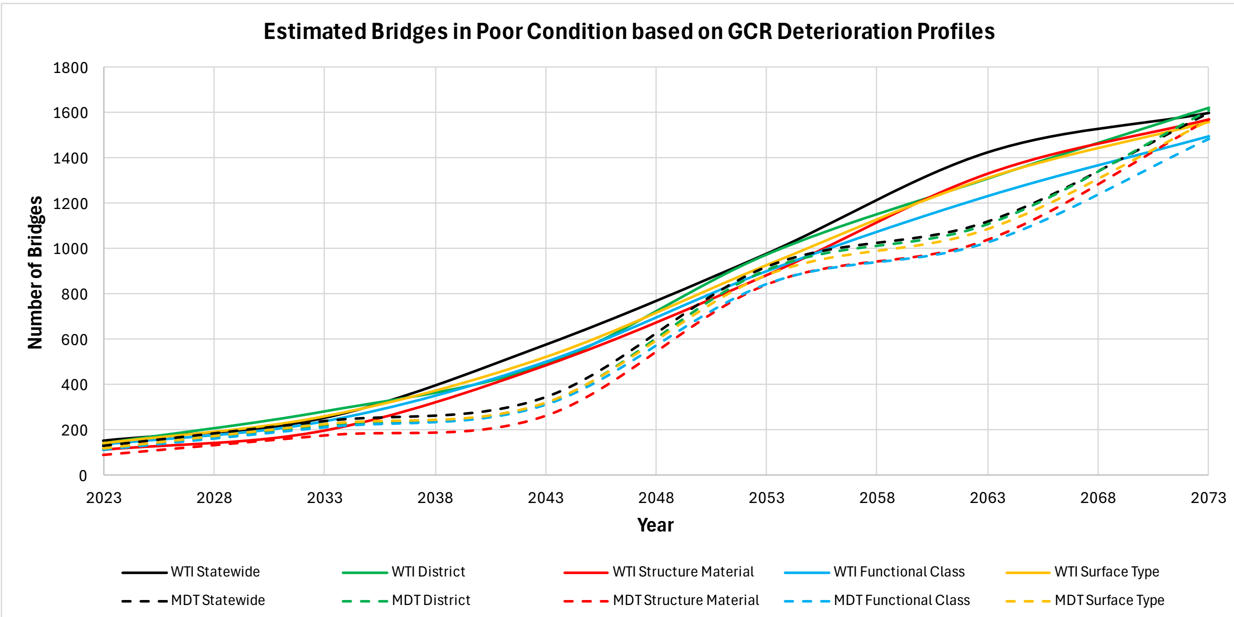

Figure 19: Estimated number of bridges in poor condition based on WTI and MDT GCR deterioration profiles based on no-cost optimizations.

6. Summary and Conclusions

This research project explored different factors and variables that contribute to the deterioration of Montana bridges. Combinations of bridge datasets, groups, and variables were analyzed using two different regression models to identify factors that had the largest influence on the National Bridge Inventory inspection ratings. A general condition rating (GCR) analysis within BrM using the most influential bridge groups was performed to forecast the number of bridges in good, fair, and poor condition using zero-cost optimizations. Two different analysis profiles were considered. Findings from the research are presented below:

- Very little maintenance data was identified on the Highline route and suggests special permitted vehicles are not contributing to higher levels of maintenance on this traffic corridor.
- A review of maintenance records for 50 interstate bridges identified deck overlay and joint seal as the top two documented repair activities.
- A review of the condition ratings after interstate maintenance activities indicates a larger number of improved NBI ratings (14 vs 5) and suggests the rehabilitations performed by MDT generally led to an increase or no change in condition rating in the year following the work.
- Statistically insignificant bridge groups and variables were removed and a refined analysis was completed that included one new bridge group (deck overlay) and 4 new variables (freeze-thaw, rain, snow, and deicer). The refined analysis results identified the same top three significant variables as the preliminary analysis.
- The Random Forest regression model may be a better representation of the performance of NBI deck rating predictor models and hold a higher weight to variable selection. This observation is highlighted in the statewide bridge group analysis where the largest number of bridges produced the highest described variance compared to the other smaller bridge groups using the same variables in the model.
- A procedure was established using BrM's general condition rating (GCR) analysis to estimate the number of bridges in good, fair, and poor condition over selected time periods. Zero-cost optimizations were completed using two different deterioration profiles. The WTI profile used the average transition time for each condition state plus one standard deviation.

Future research is needed to continue modeling within BrM to identify analytical tools that use the significant bridge groups and variables to help MDT bridge engineers make reliable and efficient maintenance decisions. This 3rd phase of research, BrM modeling and implementation, will complement earlier research (deterioration curves, significant factors) to complete a well-documented basis for maintenance resource allocation toward Montana's transportation infrastructure.

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8. Appendix: Good-Fair-Poor Plots

8.1 Maintenance District Plots

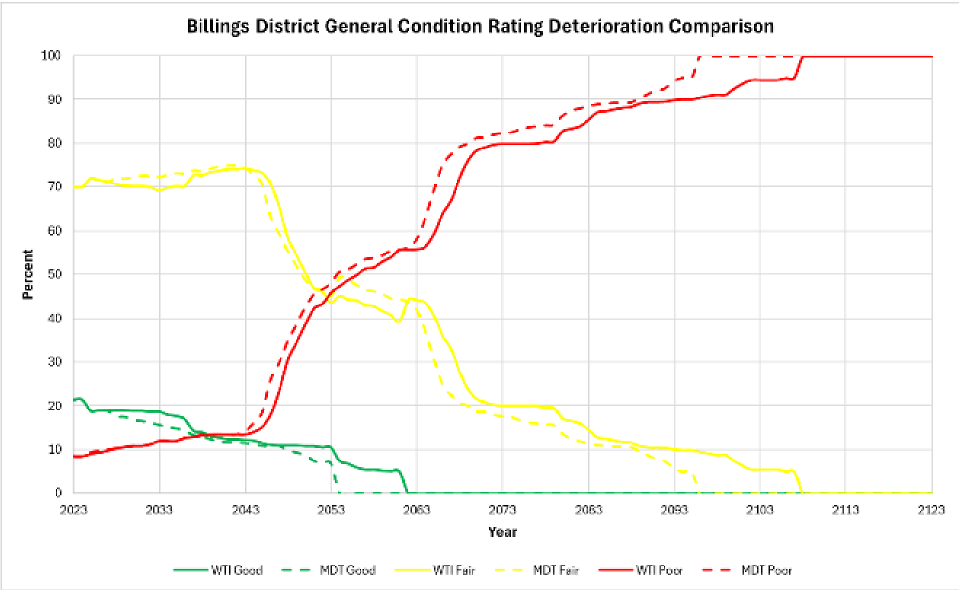

Figure 20: Good-fair-poor analysis comparison between default MDT Deck Profile and established WTI GCR deterioration values for the Billings maintenance district.

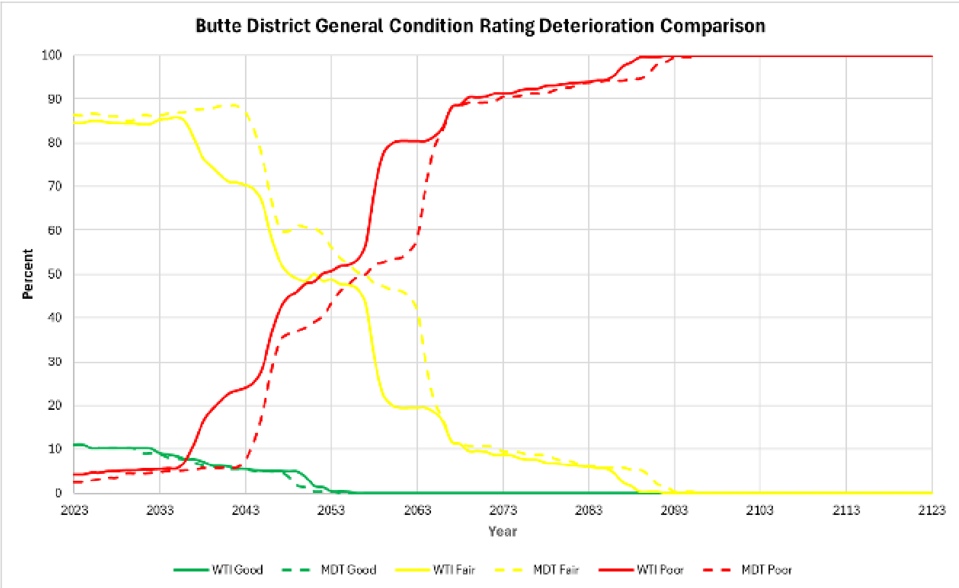

Figure 21: Good-fair-poor analysis comparison between default MDT Deck Profile and established WTI GCR deterioration values for the Butte maintenance district.

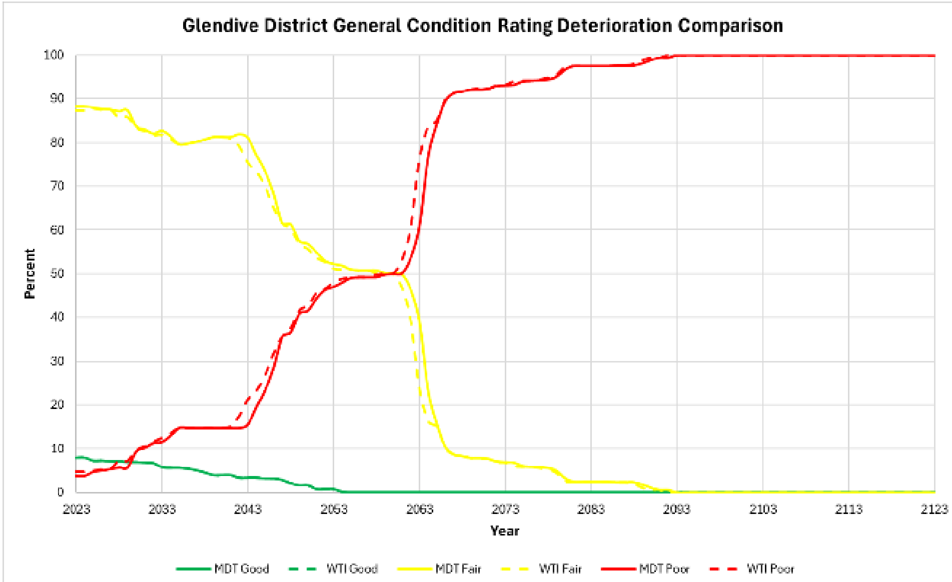

Figure 22: Good-fair-poor analysis comparison between default MDT Deck Profile and established WTI GCR deterioration values for the Glendive maintenance district.

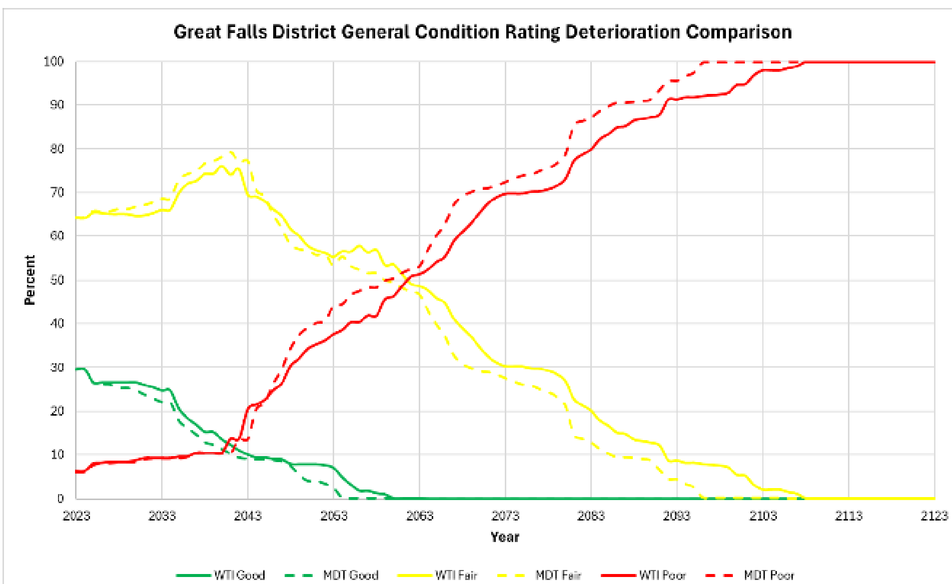

Figure 23: Good-fair-poor analysis comparison between default MDT Deck Profile and established WTI GCR deterioration values for the Great Falls maintenance district.

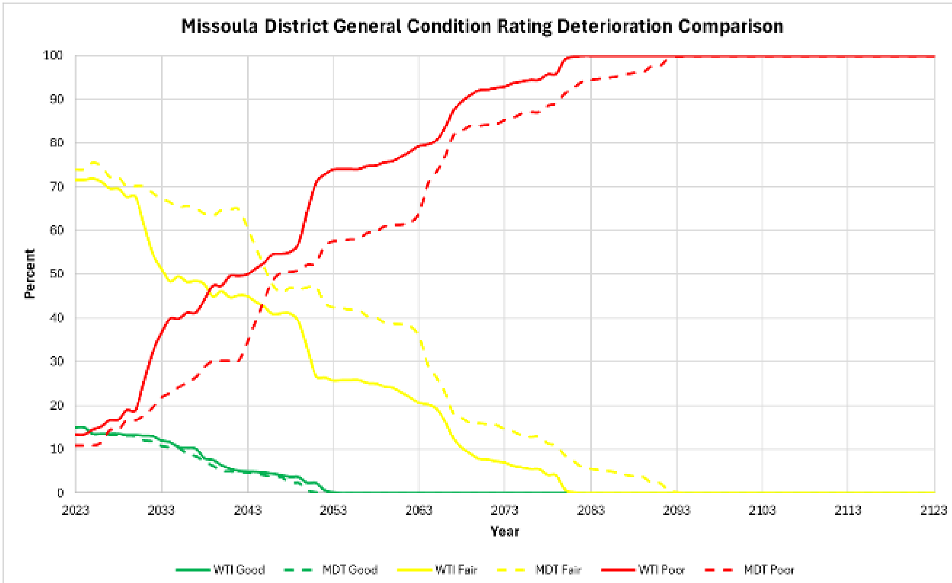

Figure 24: Good-fair-poor analysis comparison between default MDT Deck Profile and established WTI GCR deterioration values for the Missoula maintenance district.

8.2 Bridge Material Plots

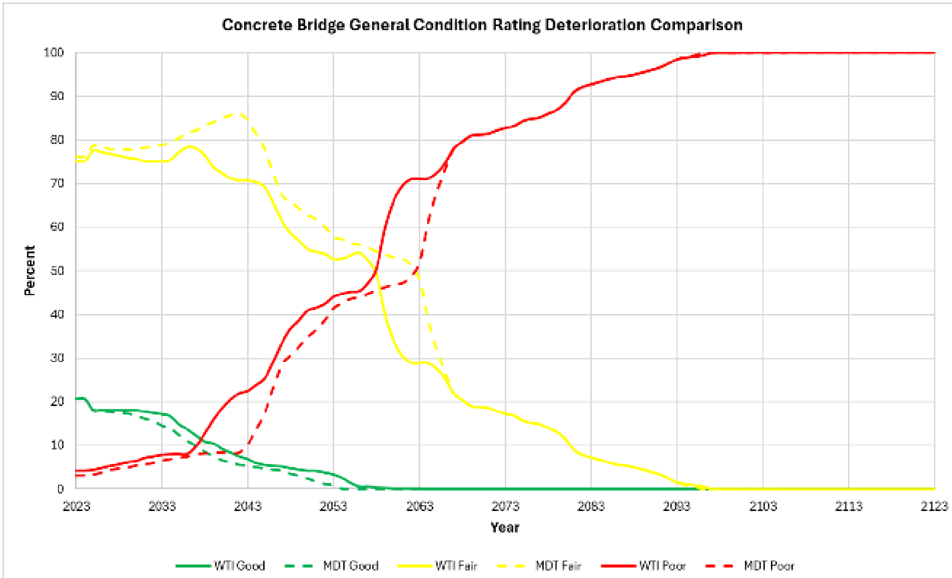

Figure 25: Good-fair-poor analysis comparison between default MDT Deck Profile and established WTI GCR deterioration values for the concrete bridge group.

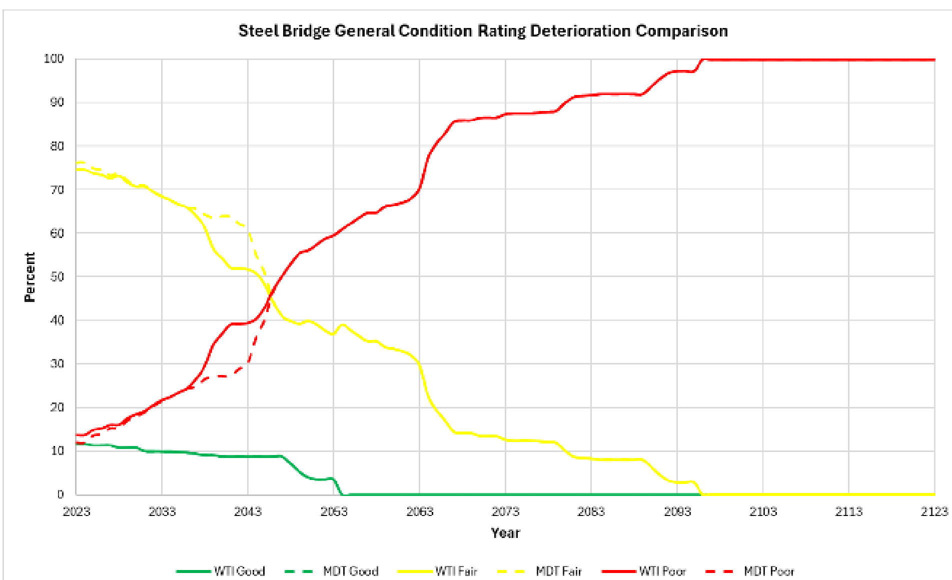

Figure 26: Good-fair-poor analysis comparison between default MDT Deck Profile and established WTI GCR deterioration values for the steel bridge group.

8.3 Functional Class Plots

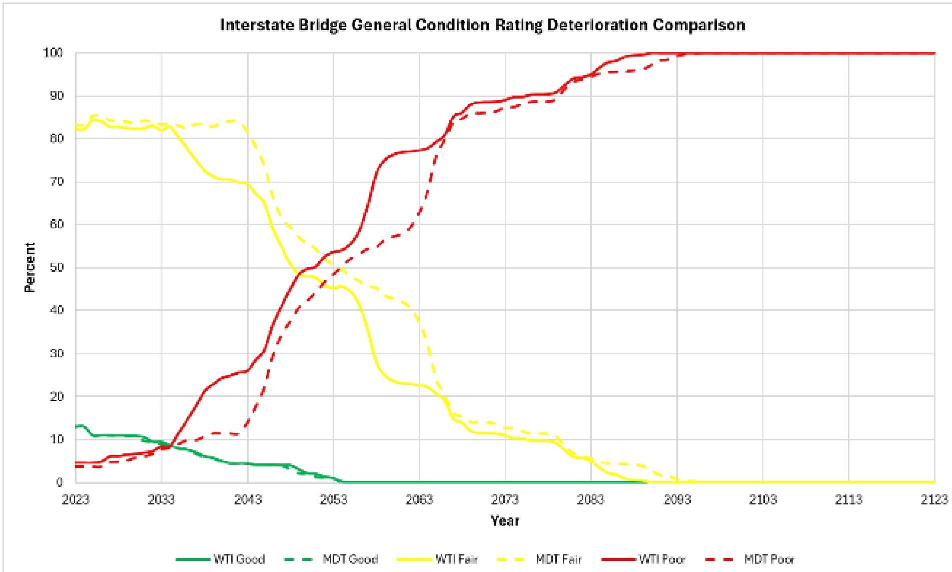

Figure 27: Good-fair-poor analysis comparison between default MDT Deck Profile and established WTI GCR deterioration values for the interstate bridge group.

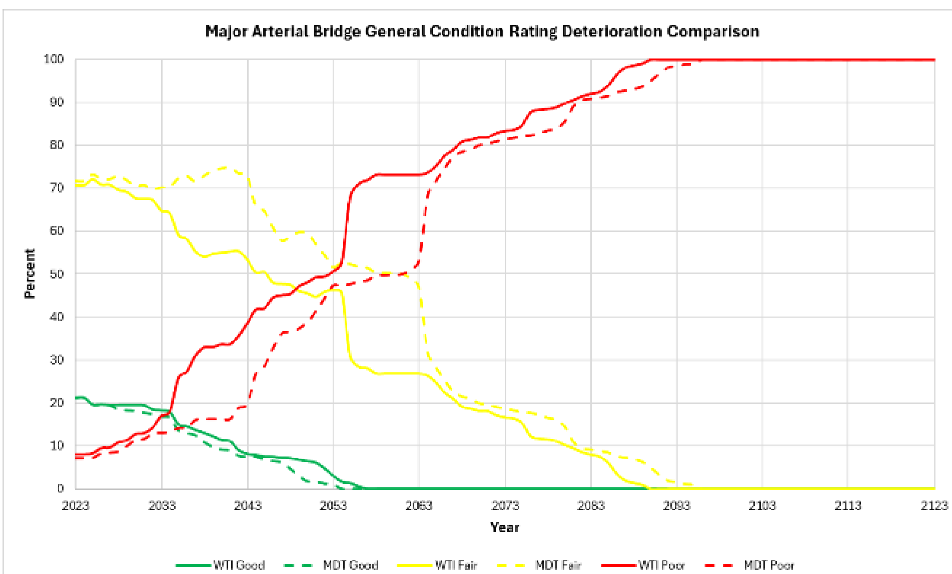

Figure 28: Good-fair-poor analysis comparison between default MDT Deck Profile and established WTI GCR deterioration values for the major arterial bridge group.

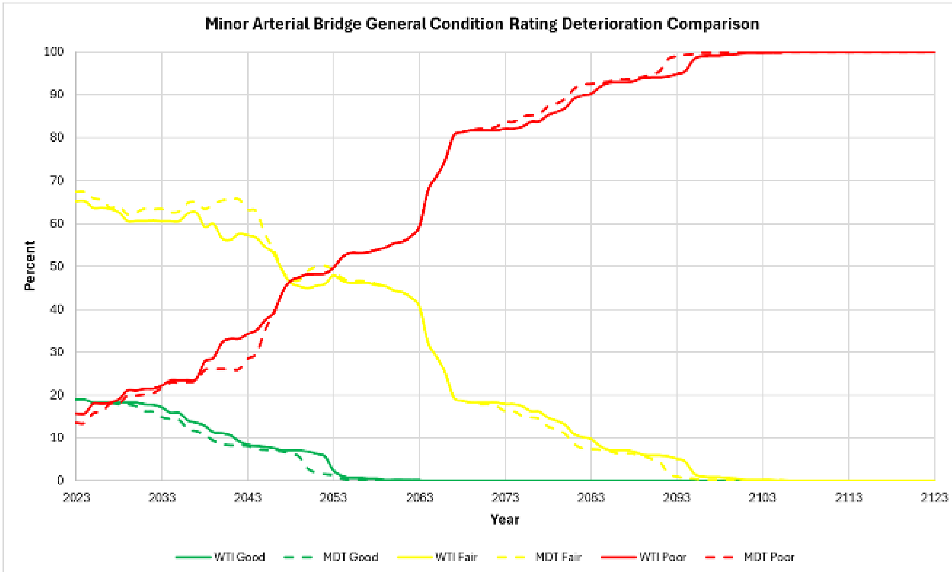

Figure 29: Good-fair-poor analysis comparison between default MDT Deck Profile and established WTI GCR deterioration values for the minor arterial bridge group.

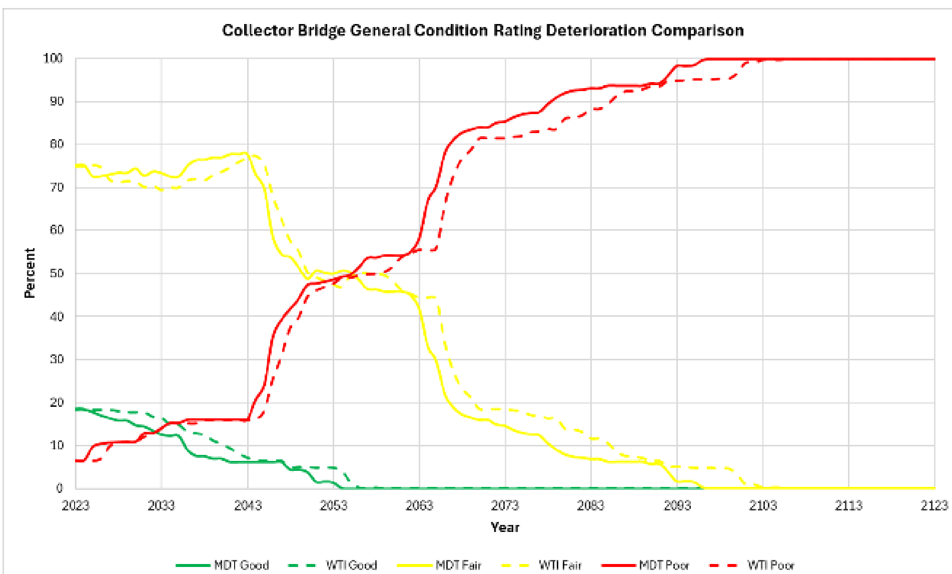

Figure 30: Good-fair-poor analysis comparison between default MDT Deck Profile and established WTI GCR deterioration values for the collector bridge group.

8.4 Surface Type Plots

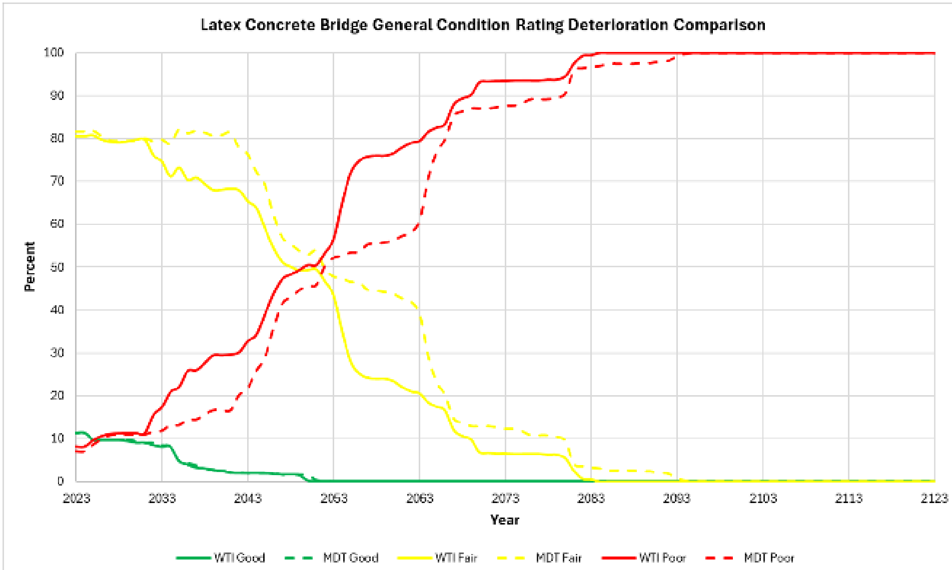

Figure 31: Good-fair-poor analysis comparison between default MDT Deck Profile and established WTI GCR deterioration values for the latex concrete bridge group.

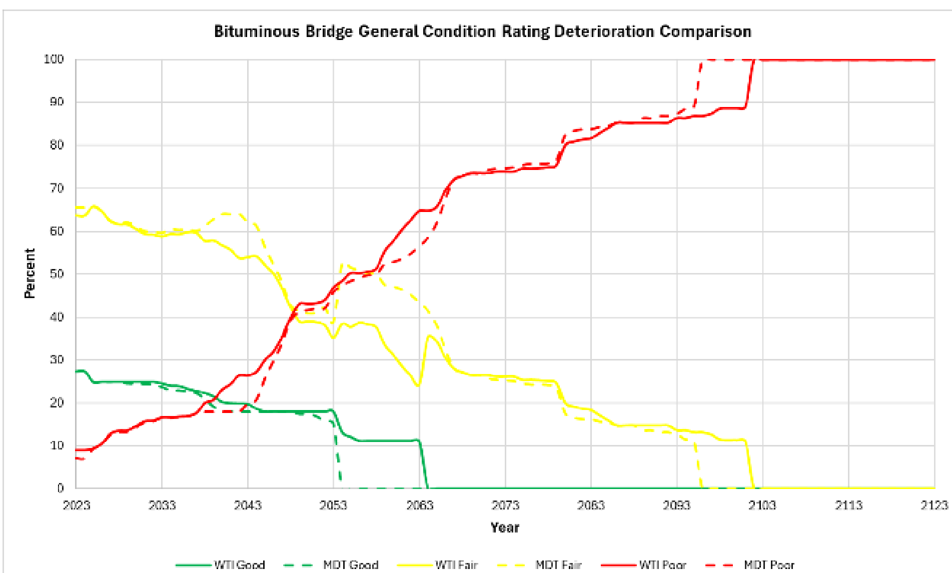

Figure 32: Good-fair-poor analysis comparison between default MDT Deck Profile and established WTI GCR deterioration values for the latex concrete bridge group.

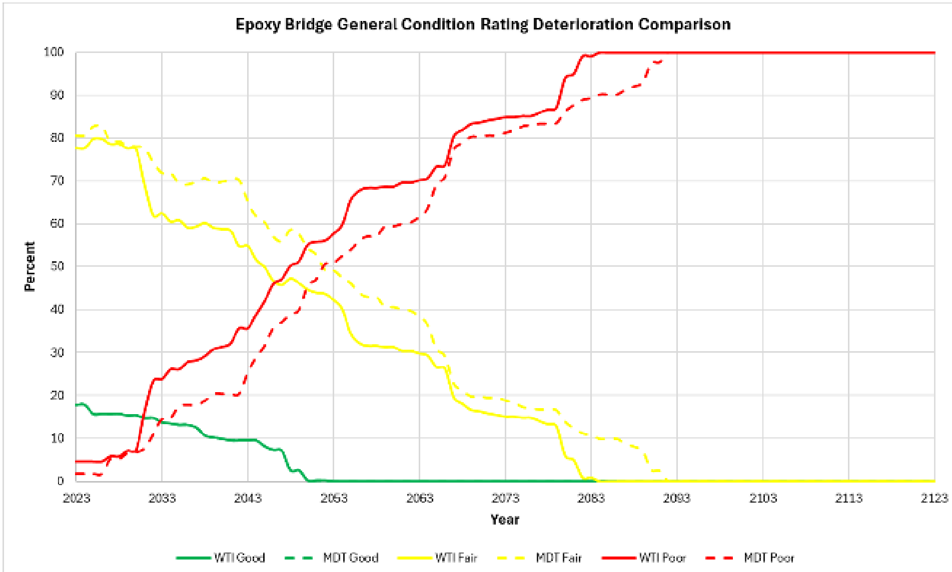

Figure 33: Good-fair-poor analysis comparison between default MDT Deck Profile and established WTI GCR deterioration values for the epoxy bridge group.

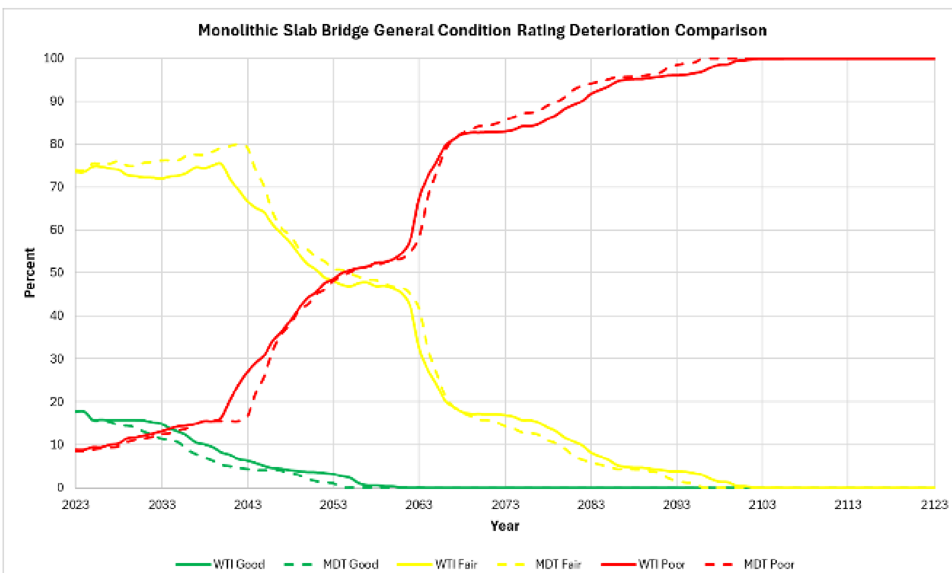

Figure 34: Good-fair-poor analysis comparison between default MDT Deck Profile and established WTI GCR deterioration values for the monolithic slab bridge group.

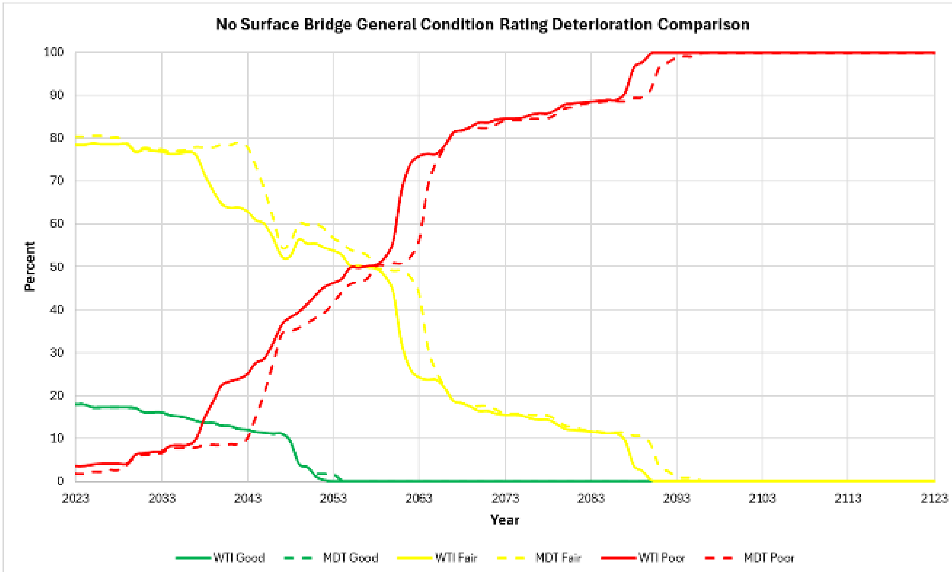

Figure 35: Good-fair-poor analysis comparison between default MDT Deck Profile and established WTI GCR deterioration values for the no surface bridge group.