Significant Factors of Bridge Deterioration

Task 2 Report: Data and Maintenance Record Review

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Introduction

The first section of this 2nd Task Report describes the bridge data and variables used for the statistical analysis. The second section explains the process used to identify bridge maintenance activity and the two sources of bridge groups that were considered. The third section summarizes the statistical analysis methods and is followed by the results (Section 4) and discussion (Section 5). The final section of the Task Report concludes with a Summary and Recommendations. The overall objective of this report is to identify the significant factors and data groups that will be used in a general condition rating (GCR) analysis within BrM for Task 3 of this research.

1 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), as well as 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 1 and were divided into smaller bridge groups to be evaluated for the potential influence of multiple variables on bridge deterioration.

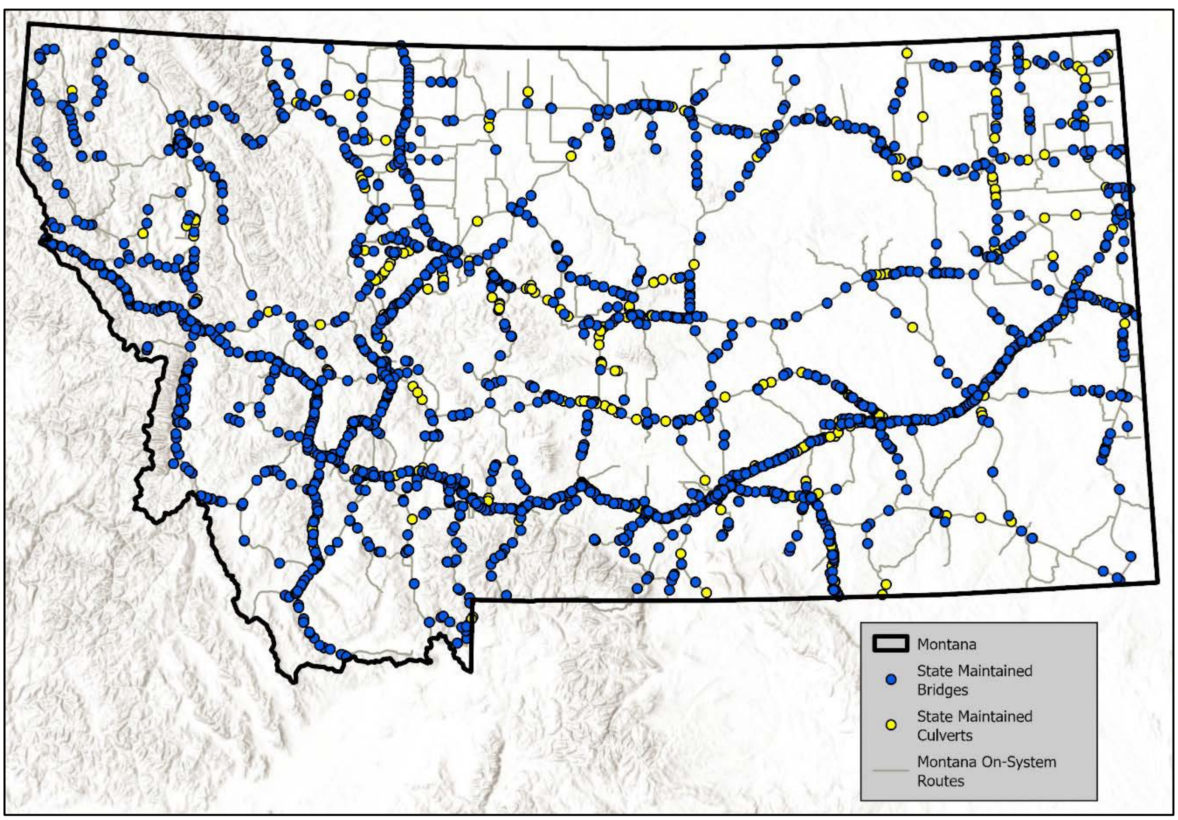


Figure 1: State maintained bridges and culverts in Montana.

1.1 Bridge Groups

The statistical analysis focuses on concrete bridge deck deterioration of 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).

<u>Maintenance District</u>

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 2.

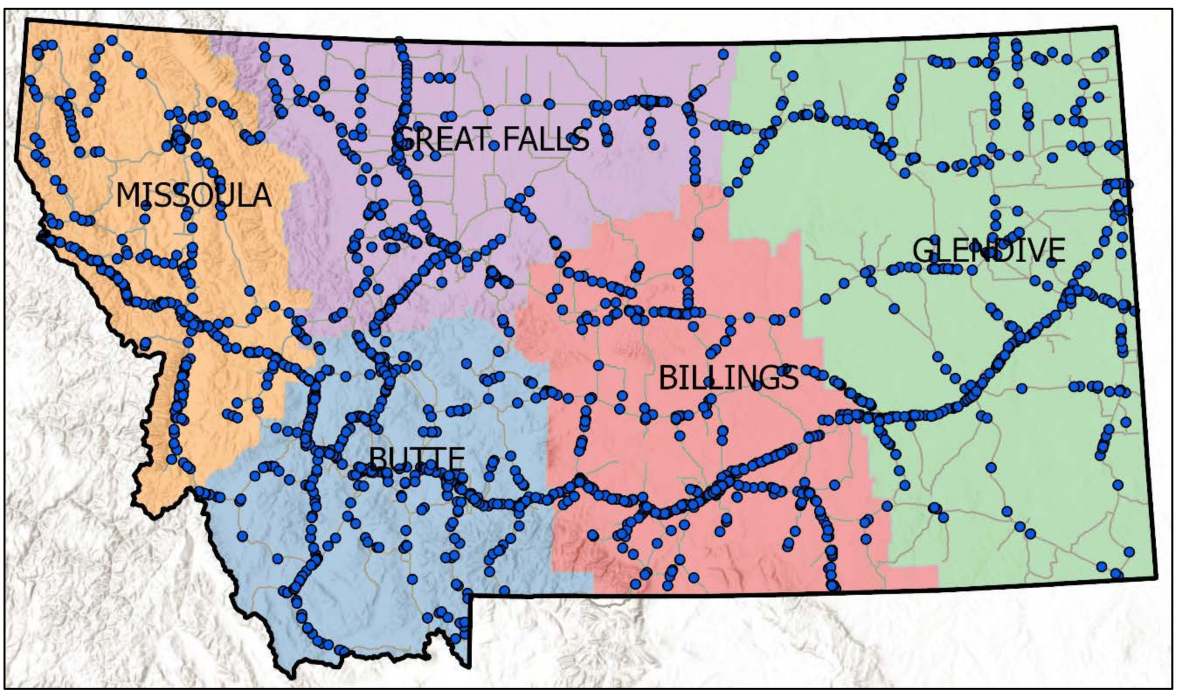


Figure 2: State maintained bridges within MDT maintenance districts.

<u>Superstructure Material</u>

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 3.

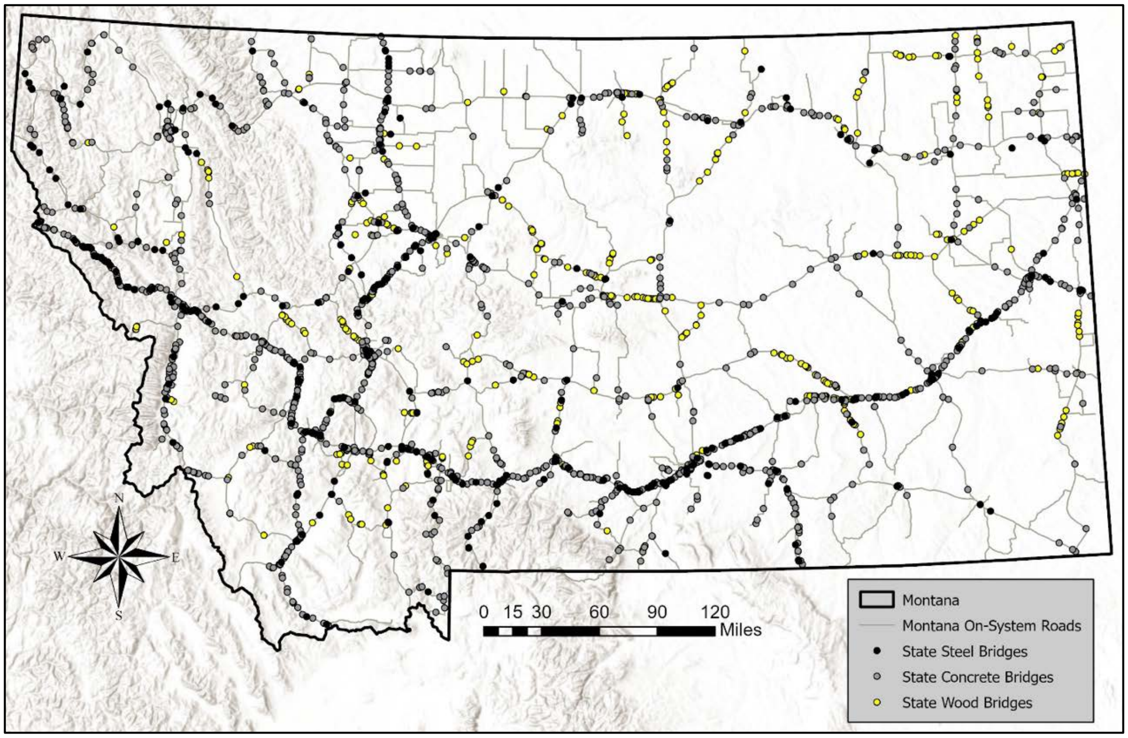


Figure 3: State maintained bridges by main structure material.

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 4. The larger traffic volumes and higher truck traffic on the instate routes, shown in Figure 5, has historically resulted in a higher allocation of bridge deck maintenance and rehabilitation funding to interstate bridges. To investigate the effect of this maintenance activity, 50 randomly selected interstate bridges were evaluated and are discussed in Section 2.2.

Highline Route

The Highline route shown in Figure 6 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. Features of the bridges along the Highline route, including the maintenance district, super structure material, functional class, and bridge age are shown in Figure 7.

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 6. Additional bridge groups organized by deck material and type and precipitation will be created in Task 3, General Condition Rating Analysis, to evaluate their influence on bridge deterioration.

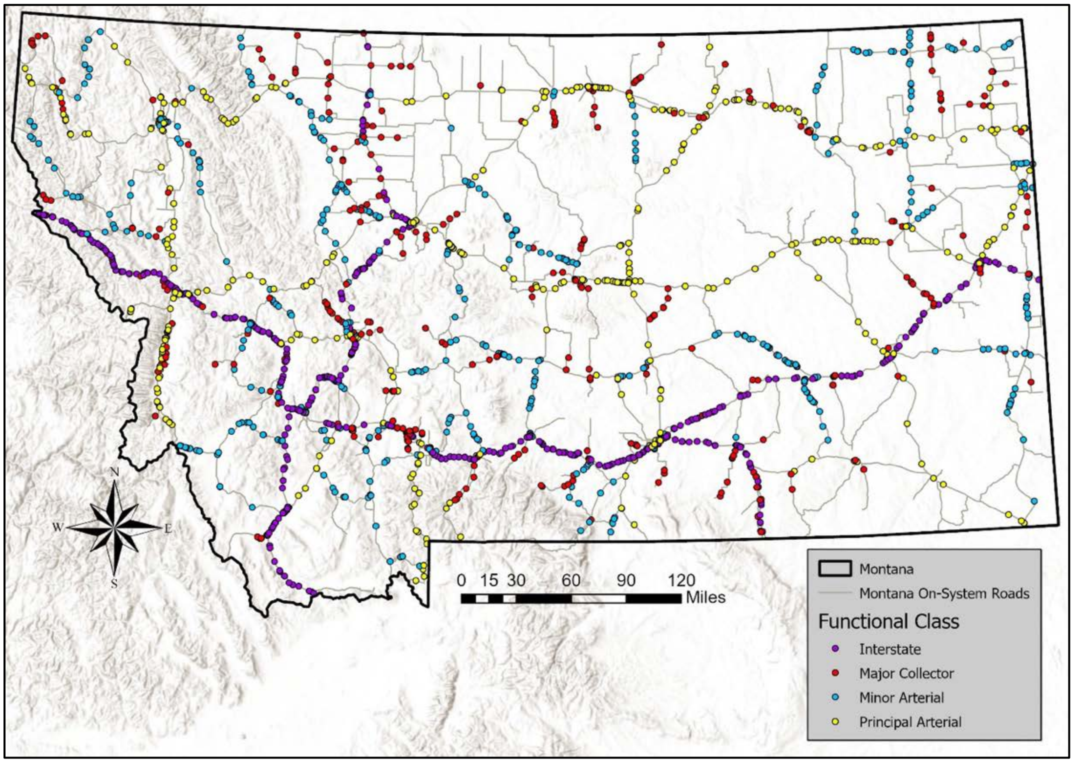


Figure 4: State maintained bridges by functional class.

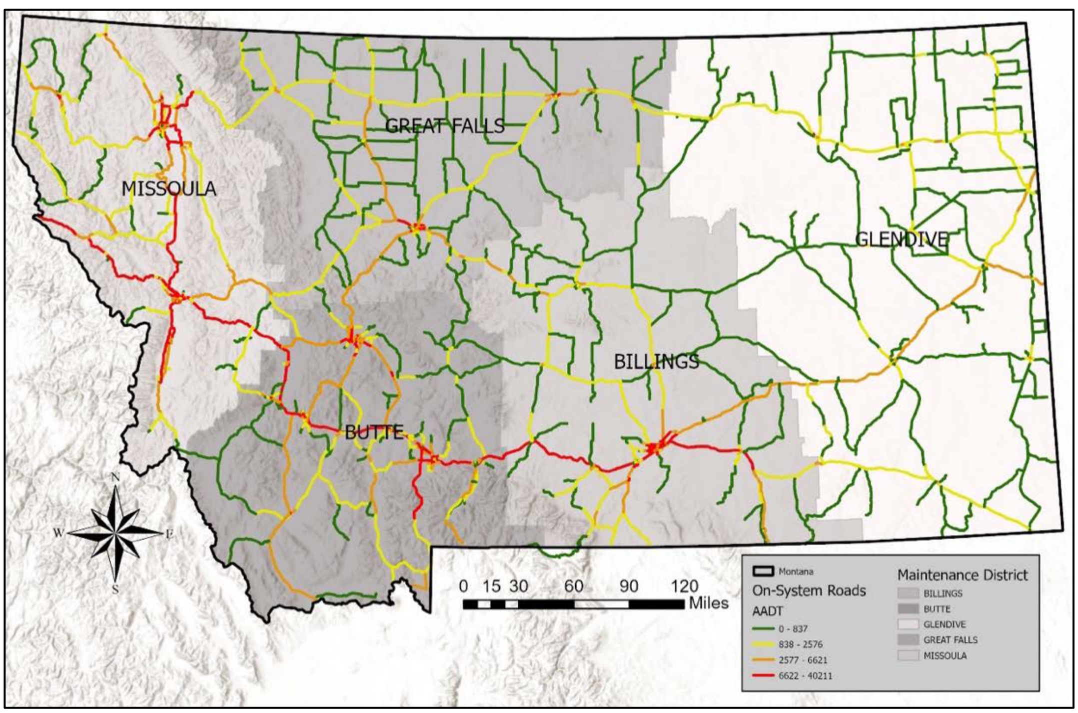


Figure 5: AADT for ranges in five maintenance districts.

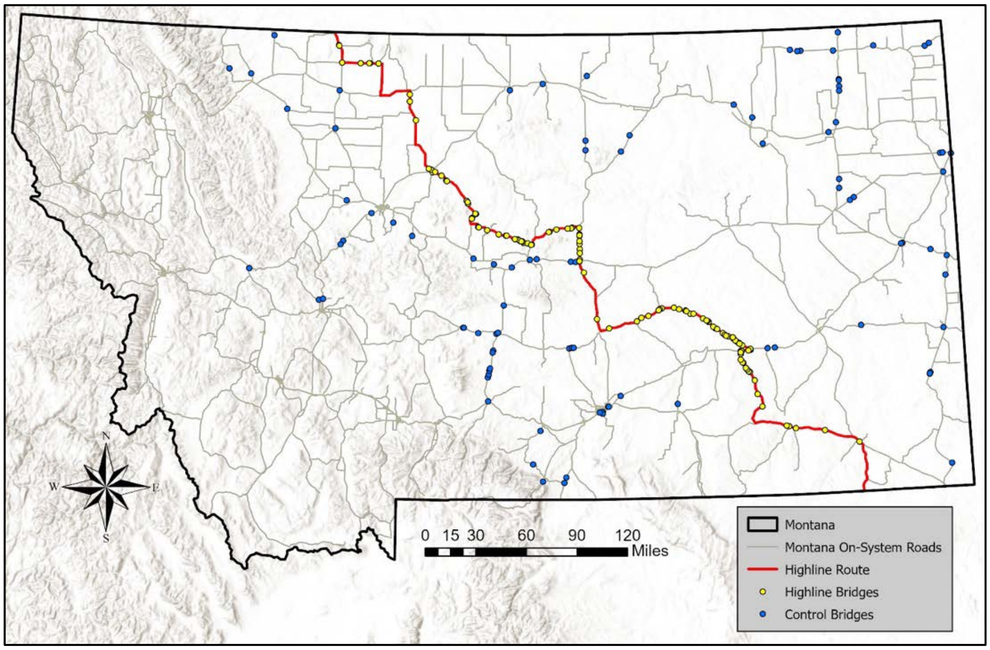
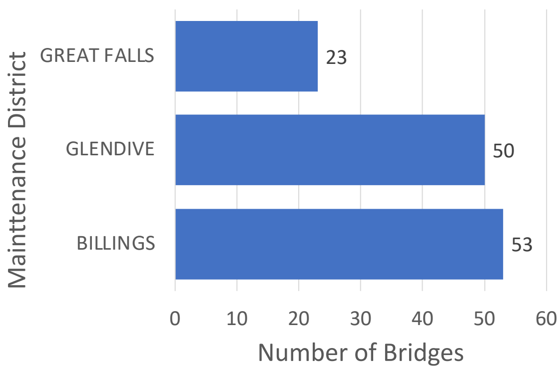
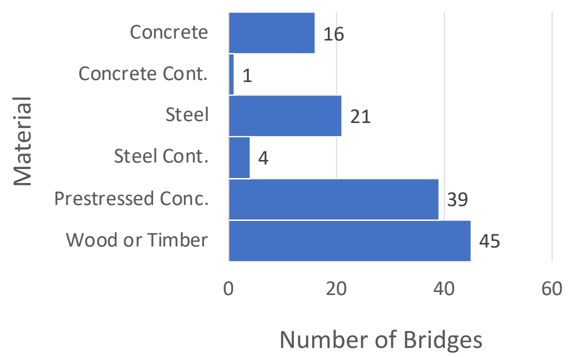


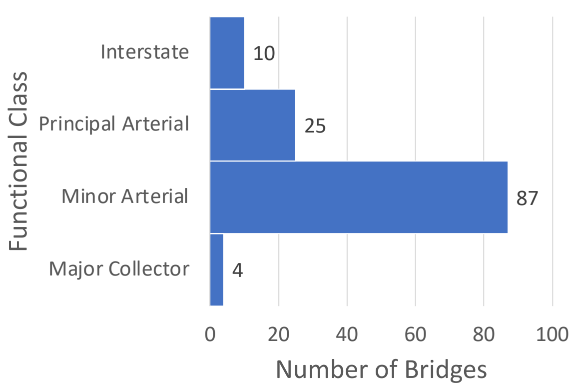
Figure 6: Highline route.



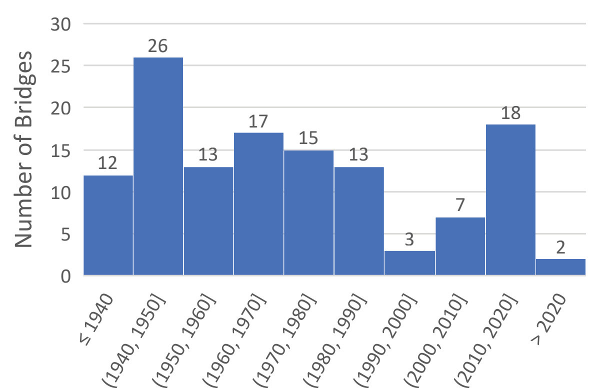
(a) Maintenance District



(b) Superstructure Material



(c) Functional Class



(d) Year Built or Reconstructed

Figure 7: Highline bridge characteristics.

1.2 Bridge Variables

For each of the bridge groups described above, 28 different bridge characteristics were used in the analysis as variables to assess changes in the NBI concrete bridge deck ratings. Variables were chosen based on the literature review performed in Task 1 of this research and their availability in BrM. The NBI data for the statistical analysis was recorded in 2022.

A preliminary analysis was performed to identify statistically insignificant variables that could be removed based on results of a correlation test. Four variables were removed, leaving 24 variables that represent 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 a given 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 statistical analysis can be seen in Table 1 and Table 2.

Table 1: 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

Freeze-thaw data were also reviewed as a factor that influences bridge deck deterioration. The datasets are difficult to quantify for several reasons, one of which was the different definitions used for a freeze-thaw cycle. As an alternative to freeze-thaw cycles, the number of days with recorded temperatures below 32°F were reviewed. The number of days that reached below 32°F in Choteau, Fergus, Liberty, Musselshell, Powder River, Rosebud, and Toole counties ranged from 90 to 109. This relatively small change was determined to be an unreliable factor to statistically estimate NBI bridge deck ratings. A second approach to include freeze-thaw cycles as a variable in the statistical analysis will be completed in Task 3 (General Condition Rating Analysis).

A second dataset reviewed to assess its influence on bridge deck deterioration was the quantity of deicer material applied to bridge decks. A preliminary review of the available deicer data identified analysis challenges because of the assumptions necessary to quantify deicer applied on the different bridges by Cities, Counties, or State agencies. As noted in Task 1 (Literature review) the influence of deicing materials used on bridge decks was not well documented. A second approach, however, has been identified and will be investigated in Task 3 of this research.

Table 2: 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

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).

2.1 Highline Route Maintenance

2.1.1 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.

2.1.2 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 a 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.

2.1.3 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.

2.2 Interstate Bridge Maintenance

Based on discussions with the technical panel, it was considered possible that 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 8. The Joint Repair category included modifying, replacement, and removal of bridge joints.

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 9 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.

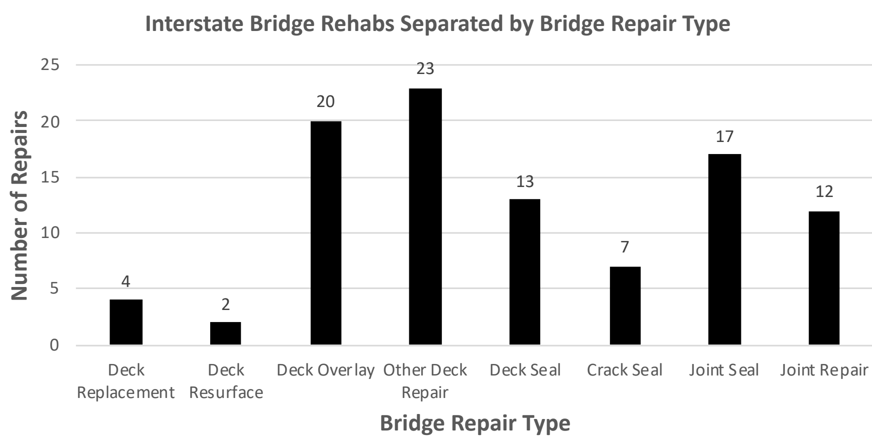


Figure 8: Frequency of bridge repair types across 50 interstate bridges.

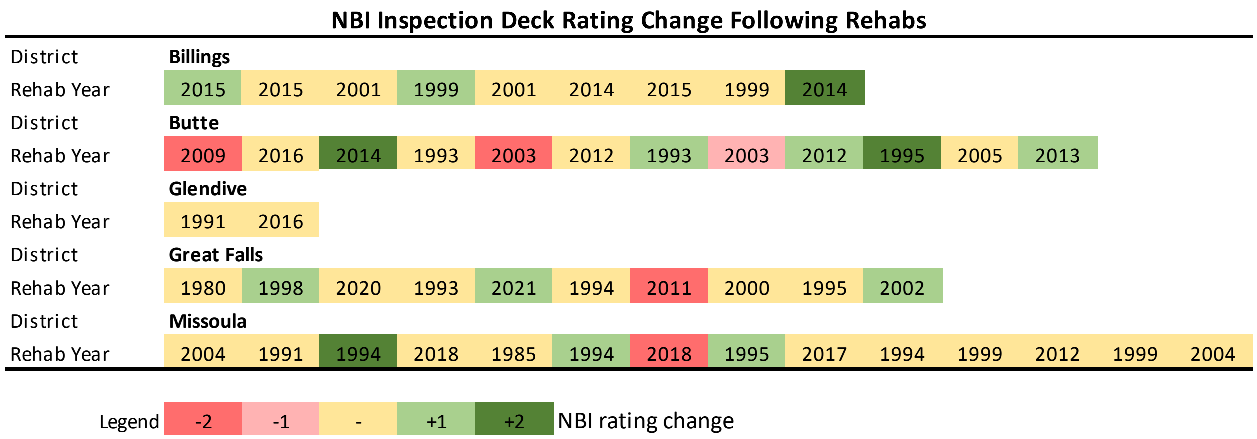


Figure 9: Positive, neutral, and negative NBI rating changes after rehabilitation.

3 Analysis Methods

Regression models were used to evaluate significant factors of bridge deterioration by identifying hidden relationships between the NBI deck ratings and 24 different variables. These methods assign numerical values to the selected variables and quantifies and ranks 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 described in Section 1.1, 80% of the NBI deck ratings were randomly selected and used as a training dataset. The additional 20% of the bridges were used as a validation dataset to calculate the statistical performance indicators. General Linear and Forest Regression models, described below, were used for the analysis.

3.1 Generalized Linear Models

Generalized linear (GL) regression models were used to evaluate the 24 variables shown in Table 1 and Table 2, for the five selected bridge groups. All variables were included during the first 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. The number of variables remaining for each bridge group ranged from four to 12 out of the 20 variables for the GL models.

Two statistical parameters, or performance indicators, were used to assess the accuracy of the predicted NBI values from the GL models. 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 used 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.

3.2 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 variables listed in Table 1 and Table 2 to build a decision tree for each sample to identify the best performing predictors. The results of each RF model are 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 five 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 signify that the variables are creating a less accurate model.

Two statistical parameters, or performance indicators were used to assess 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 3 below.

Table 3: Statistical model performance indicators.

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

4 Analysis Results

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

4.1 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 4. 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 4: Model performance for each group and significant variables identified in each model. Grey boxes indicate variables that were not included in the model.

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	0.219	0.677	x		x	x		x	x	x	x		x	x				x			x	
Billings District	444	0.266	0.585		x	x		x			x		x									x	
Butte District	493	0.261	0.609			x			x			x		x	x		x	x	x	x		x	
Glendive District	414	0.430	0.424		x	x	x			x		x					x		x			x	x
Great Falls District	381	0.295	0.809		x	x	x			x		x					x		x			x	x
Missoula District	382	0.290	0.936		x	x			x	x		x		x	x	x	x		x			x	x
Concrete Bridges	1,452	0.255	0.646	x		x			x	x	x	x		x	x		x		x			x	
Steel Bridges	318	0.128	0.861			x					x	x			x								
Wood Bridges	344	0.268	0.430	x						x				x									x
Interstate Bridges	805	0.222	0.610	x		x		x		x				x	x				x			x	
Major Arterial Bridges	453	0.278	0.742	x		x	x				x		x	x							x	x	
Minor Arterial Bridges	483	0.301	0.795	x		x		x	x	x	x						x		x		x	x	
Collector Bridges	373	0.262	0.608	x		x		x							x				x			x	
Highline Route Bridges	95	0.500	0.707	x				x		x										x		x	
Control Bridges	95	0.336	0.965				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 10. 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.

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 Table 5 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 (Table 5). Smaller standard deviations were calculated for both performance indicators in the functional class group.

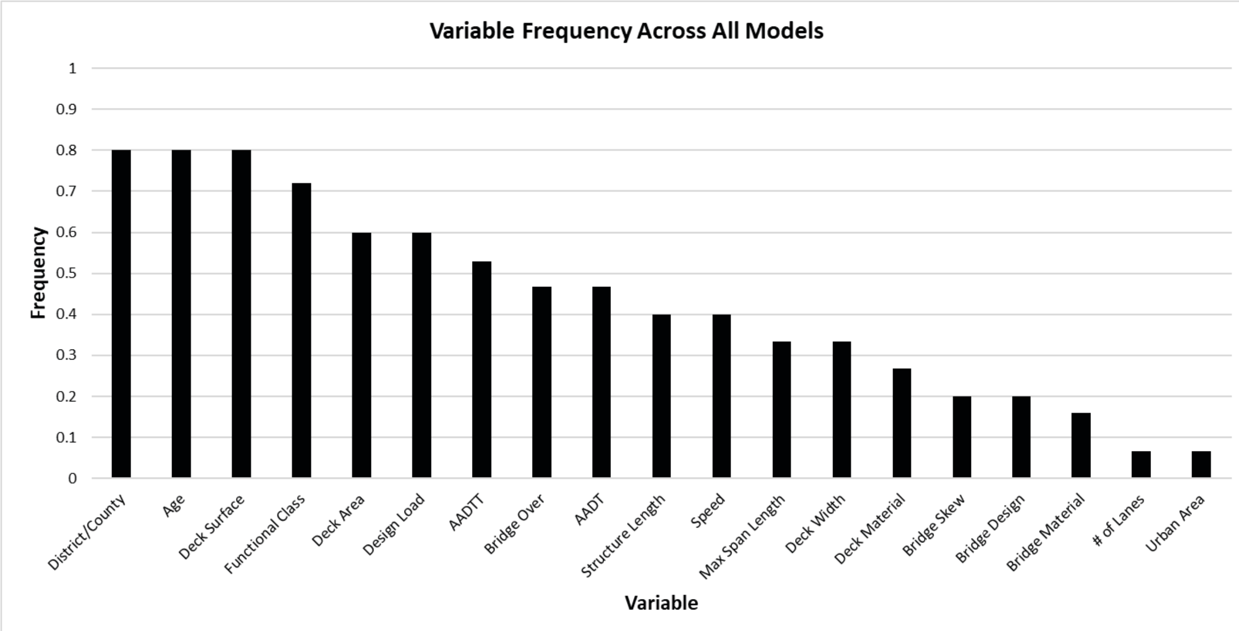


Figure 10: Frequency of variables used in the final models across all the groups.

Table 5: Performance indicator averages and standard deviation for the general linear models for each bridge group.

	Adjusted R^2		RMSE	
Bridge Groups	**Avg.**	**Std. Dev**	**Avg.**	**Std. Dev**
Districts	0.308	0.07	0.673	0.20
Material	0.217	0.08	0.646	0.22
Functional Class	0.266	0.03	0.689	0.09
	Adjusted R^2		RMSE	
Statewide	0.219		0.677	
Highline Route	0.500		0.707	
Highline Control	0.336		0.965	

4.2 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 6. The most important variables, indicated by large percent MSEs are shaded green in Table 6. The least important variables are shaded red, and variables shaded in dark grey 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 groups.

Table 6: Random forest regression statistical measurements for all the model groups.

Model	Mean of Squared Residuals (MSR)	Pseudo-R^2	Percent Increase in MSE: 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	3.77	21.5	22.3	0.09	11.3	6.87	17.0	19.2	4.61	26.9	13.9
Billings District	0.259	0.348		26.0	22.8	10.8	14.2	11.3	15.0	14.2	4.33	5.49	7.43	10.1	-1.42	4.72	1.52	17.2	15.2	10.2	6.81	4.53
Butte District	0.358	0.276		12.0	17.6	14.9	10.3	19.1	14.0	12.7	11.9	3.65	14.4	15.0	0.00	7.92	5.70	6.85	13.4	5.59	15.6	13.9
Glendive District	0.237	0.340		8.26	10.9	10.7	12.6	10.8	13.7	7.05	1.00	0.81	10.6	7.95	1.00	9.32	0.73	4.96	7.13	2.23	16.3	9.45
Great Falls District	0.595	0.241		8.09	16.7	15.2	14.6	14.5	12.6	2.73	4.48	-0.35	10.0	11.8	-0.53	8.36	0.89	13.5	7.47	7.64	15.7	4.86
Missoula District	0.622	0.241		16.9	14.3	10.1	16.0	12.7	19.5	4.30	9.51	2.86	7.20	6.69	0.19	4.02	3.53	0.97	12.5	0.07	10.6	3.78
Concrete Bridges	0.427	0.318	47.4		34.3	17.3	23.9	19.7	24.2	11.8	9.86	5.50	18.2	17.3	-0.46	9.21	6.50	12.3	7.46	7.46	34.1	1.23
Steel Bridges	0.628	0.124	10.9		15.4	8.78	6.01	6.37	5.89	3.80	4.76	-1.25	2.61	6.69	1.53	-0.12	1.93	4.79	13.3	-3.49	2.40	1.12
Wood Bridges	0.154	0.287	28.7		7.60	8.21	9.01	3.15	10.3	5.41	10.0	-2.24	7.85	10.1	0.00	-0.41	0.00	8.15				0.00
Interstate Bridges	0.371	0.335	33.8		18.5	19.7	20.8	24.4	22.5	15.3		7.66	24.5	20.0	0.00	10.5	4.55	3.02	9.99	6.47	28.9	0.00
Major Arterial Bridges	0.413	0.292	21.0		19.1	14.5	12.3	10.3	14.8	9.37		0.89	10.93	10.6	0.19	8.40	1.51	6.31	14.6	2.39	5.16	4.30
Minor Arterial Bridges	0.508	0.264	20.2		18.1	15.3	12.5	10.2	11.1	4.82		-2.40	9.27	9.66	1.66	10.9	1.77	10.4	6.67	0.27	7.85	11.6
Collector Bridges	0.435	0.173	14.4		10.5	8.52	9.78	6.55	12.3	2.59		-0.45	3.37	2.81	0.00	0.84	0.99	9.36	10.5	4.50	5.96	5.78
Highline Route Bridges	0.483	-0.033	2.98		0.01	3.99	3.97	4.56	5.98	2.01	2.50	2.67	6.22	0.79	0.00	0.23	0.00	2.49	2.85	4.40	4.58	0.49
Control Bridges	0.734	0.124	0.87		5.65	5.93	8.04	-1.39	9.98	1.88	-2.21	5.30	1.59	-1.10	0.00	-1.81	-0.27	4.24	5.05	-1.63	-0.80	3.98

The mean of squared residuals shown in Table 6 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 7 for the maintenance district, main structural material, and the functional class groups. For comparison, the MSE values are also shown for the statewide, Highline route, and Highline control groups. The same color shading shown in Table 6 was used (most significant = green, least significant = red).

Table 7: Average statistical measurements for the random forest models for each bridge group.

Bridge Groups	Average Percent Increase in MSE: 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
Districts		14.2	16.5	12.3	13.6	13.7	15.0	8.20	6.24	2.49	9.92	10.3	-0.15	6.87	2.47	8.69	11.1	5.15	13.0	7.29
Material	29.0		19.1	11.4	13.0	9.76	13.4	7.02	8.22	0.67	9.57	11.4	0.36	2.89	2.81	8.42	10.4	1.99	18.3	0.78
Functional Class	22.4		16.5	14.5	13.9	12.9	15.2	8.01		1.43	12.0	10.7	0.46	7.66	2.21	7.26	10.4	3.41	12.0	5.42
	Percent Increase in MSE																			
Statewide	52.0		36.1	23.3	21.8	26.7	22.6	15.3	13.9	3.77	21.5	22.3	0.09	11.3	6.87	17.0	19.2	4.61	26.9	13.9
Highline Route Bridges	2.98		0.01	3.99	3.97	4.56	5.98	2.01	2.50	2.67	6.22	0.79	0.00	0.23	0.00	2.49	2.85	4.40	4.58	0.49
Control Bridges	0.87		5.65	5.93	8.04	-1.39	9.98	1.88	-2.21	5.30	1.59	-1.10	0.00	-1.81	-0.27	4.24	5.05	-1.63	-0.80	3.98

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 8 with the pseudo- R^2 and MSR values for the statewide, Highline route, and Highline control groups. 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.

Table 8: Performance indicator averages and standard deviation for the random forest regression models for each bridge group.

	Pseudo-R^2		MSR	
Bridge Groups	**Avg.**	**Std. Dev**	**Avg.**	**Std. Dev**
Districts	0.289	0.052	0.414	0.183
Material	0.243	0.104	0.403	0.238
Functional Class	0.266	0.069	0.432	0.057
	Pseudo-R^2		MSR	
Statewide	0.428		0.292	
Highline Route	0.483		-0.033	
Highline Control	0.734		0.124	

5 Discussion

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

5.1 Variables

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 5). 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 7). 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 number of variables in a model is not a function of its accuracy. Using too many variables may introduce overfitting of the model, which can be observed in the variance explained and prediction accuracy. 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.

5.2 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.

5.2.1 Generalized Linear Models

The calculated adjusted- R^2 values for the GL models method 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 and standard deviations for the bridge groups shown in Table 5 makes observations to the accuracy of the GL models using this performance indicator difficult.

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 5). The standard deviation for the functional class bridge group was less than half the standard deviations for the other groups and suggests the NBI rating prediction was better explained by the functional class groups using the GL model.

5.2.2 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.

5.3 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 shown in Table 5 and Table 8 for both the Generalized Linear and Random Forest regression models can be seen in Table 9. 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 9: Significant variable ranking for generalized linear and random forest models.

Model	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
	Significant Variable Ranking																		
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	7.5	8	8.5	8.5	9	9	9.5	10	12.5	13.5	14.5	16	16.5	18	18.5

6 Summary and Recommendations for BrM General Condition Rating Analysis (Task 3)

This task report used generalized linear and random forest regression models to evaluate the influence of an array of variables to predict NBI general condition ratings for bridge decks in Montana. These models were helpful in identifying significant variables. The predictive variables of district/county, bridge age, and surface type were identified as the top-3 significant variables in both models. The total bridge deck area and average annual daily truck traffic are the next two most significant variables on average.

Based on the results of the models, the bridges divided into maintenance district groups had more influence on the NBI deck ratings. It is the model where the most variance is explained by the selected variables, and the second most accurate model relative to the RMSE (0.673). The district does not directly deteriorate a bridge, but generally provides a location, just like age provides a timeframe. Within each district across Montana, there are differences with the environment, project management, bridge inspectors, and many other factors that are not recorded in bridge data records. Some of these differences will be evaluated in Task 3 of this research.

Task 3 of this research includes performing General Condition Rating (GCR) analyses within the Bridge Management (BrM) software. Some adjustment to the statistical models used in this Task report may be necessary to be compatible with the analyses available within BrM. For example, a second review of deicer application rates, precipitation, and freeze/thaw data will be included in the analysis. Additional bridge groups and differences identified in the maintenance district groups will be used to determine if deck surface and deck materials improve the accuracy of the models. Initial recommendations are to analyze bridge deck condition ratings based on maintenance districts and build five separate models using the top-ten variables selected from the RF regression. These variables will be used in the GL models to remove non-significant variables and develop coefficient estimates used within BrM. The final statistical models will be created after the details of the GCR are better understood.

7 References

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