FINAL REPORT

Enhancement of AASHTOWare Bridge Management for Florida's Bridge Inspection and Asset Management

Contract No. BED30 TWO 977-10

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SI* (MODERN METRIC) CONVERSION FACTORS

APPROXIMATE CONVERSIONS TO SI UNITS

SYMBOL	WHEN YOU KNOW	MULTIPLY BY	TO FIND	SYMBOL
		LENGTH		
in	Inches	25.4	millimeters	mm
ft	Feet	0.305	meters	m
yd	Yards	0.914	meters	m
mi	Miles	1.61	kilometers	km

SYMBOL	WHEN YOU KNOW	MULTIPLY BY	TO FIND	SYMBOL
		AREA		
in^2	Square inches	645.2	square	mm^2
ft^2	Square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square	km^2

SYMBOL	WHEN YOU KNOW	MULTIPLY BY	TO FIND	SYMBOL
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
NOTE: volumes greater than 1000 L shall be shown in m^3				

SYMBOL	WHEN YOU KNOW	MULTIPLY BY	TO FIND	SYMBOL
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or	Mg (or "t")

SYMBOL	WHEN YOU KNOW	MULTIPLY BY	TO FIND	SYMBOL
		TEMPERATURE (exact degrees)		
°F	Fahrenheit	5 (F-32)/9 or (F-	Celsius	°C

SYMBOL	WHEN YOU KNOW	MULTIPLY BY	TO FIND	SYMBOL
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2

SYMBOL	WHEN YOU KNOW	MULTIPLY BY	TO FIND	SYMBOL
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square	6.89	kilopascals	kPa

*SI is the symbol for the International System of Units. Appropriate rounding should be made to comply with Section 4 of ASTM E380. (Revised March 2003).

APPROXIMATE CONVERSIONS FROM SI UNITS

SYMBOL	WHEN YOU KNOW	MULTIPLY BY	TO FIND	SYMBOL
		LENGTH		
mm	millimeters	0.039	inches	in
m	Meters	3.28	feet	ft
m	Meters	1.09	yards	yd
km	kilometers	0.621	miles	mi

SYMBOL	WHEN YOU KNOW	MULTIPLY BY	TO FIND	SYMBOL
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	Hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2

SYMBOL	WHEN YOU KNOW	MULTIPLY BY	TO FIND	SYMBOL
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	Liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3

SYMBOL	WHEN YOU KNOW	MULTIPLY BY	TO FIND	SYMBOL
		MASS		
g	Grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or	1.103	short tons (2000	T

SYMBOL	WHEN YOU KNOW	MULTIPLY BY	TO FIND	SYMBOL
		TEMPERATURE (exact degrees)		
°C	Celsius	1.8C+32	Fahrenheit	°F

SYMBOL	WHEN YOU KNOW	MULTIPLY BY	TO FIND	SYMBOL
		ILLUMINATION		
lx	Lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl

SYMBOL	WHEN YOU KNOW	MULTIPLY BY	TO FIND	SYMBOL
		FORCE and PRESSURE or STRESS		
N	Newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per	lbf/in^2

*SI is the symbol for the International System of Units. Appropriate rounding should be made to comply with Section 4 of ASTM E380. (Revised March 2003).

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16. Abstract
Following its adoption of the new AASHTO Bridge Element Inspection Manual, the Florida Department of Transportation (FDOT) has been collecting bridge element condition data in order to use the AASHTO's Bridge Management (BrM) software. Now, to aid the Department in satisfying the various federal requirements and prepare for anticipated changes at the national level in the bridge inspection and management standards, the FDOT needs to re-calibrate the core BrM models and tools, including the element deterioration models, risk models, the translator model, and cost models.

This study has developed deterioration models for forecasting bridge element condition within the analytical framework of the BrM and explored the revision of the FDOT's environmental classification scheme for its bridge inventory. Considering the natural and man-made hazards that are unique to Florida, risk models were developed by estimating at each bridge location, the likelihood of occurrence of the hazard, the likelihood of service disruption, and costs of the associated consequences. To enable conversion of bridge element condition data to the FHWA's NBI ratings, a new NBI Translator was developed, with the focus on five bridge components: deck, superstructure, substructure, culvert, and channel. Finally, in response to the decreasing availability of cost data for bridge maintenance, repair and rehabilitation (MR&R) activities, this study developed unit costs based on the available historical costs (bridge work orders and the bid unit prices) and also formulated a methodology for developing crew-based cost estimates.

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Executive Summary

The primary objective of this research is to assist the Department in its implementation of the AASHTOWare Bridge Management (BrM) software. Prior efforts, including a 2014 study served as a transitional effort to enable the Department to maintain the full decision support functionality of its bridge management system during the migration from the AASHTO CoRe Element Manual and Pontis to the new 2015 AASHTO Element Inspection Manual and AASHTOWare Bridge Management software. Since the 2014 study, three cycles of bridge element inspection data have been collected. The Department has been gathering these element inspection data under its newest revised Field Guide (revised February 2016) since October of 2016.

With the new data, it is now necessary to re-calibrate the core BrM models and tools, including the element deterioration models, risk models, the translator model, and cost models. This enhancement will aid the Department in satisfying the various federal requirements and prepare for anticipated changes at the national level in the bridge inspection and management standards.

Environmental classification and development of deterioration models

The initial task on the research project developed an updated set of forecasting models for bridge element condition for FDOT's implementation of BrM. Within the analytical framework of BrM, and using valid statistical methods based on existing bridge inspection and maintenance data, with expert judgement where necessary, the task provided the following data products: median transition times among element condition states; environment factors that correspond to the classification of elements; Weibull shaping parameters used by BrM to regulate the pace of the onset of deterioration in its forecasting model; protection factors to model the influence of the condition of deck wearing surfaces and element protective coatings on the rate of deterioration of substrate elements; and Markov transition probabilities of the improvement in condition expected from common preservation, rehabilitation, and reconstruction activities that may be planned with the assistance of BrM. The methodologies and results of the analysis are presented in this report and implemented in the accompanying Excel spreadsheet files which include a set of SQL statements that can be executed on FDOT's production database as a quick means of entering the parameters into BrM, and details on developing the Weibull shaping parameters.

The research also included a subtask to develop and refine the FDOT's BrM environmental classification scheme for its bridge inventory. Due to non-definitive results from the subtask because of identified limitations and lack of data, the findings from the task are reported separately in a different chapter of this report. The environmental subtask report recommends some specific changes in the methodology used by the engineer to classify elements, based on the information presented in the report. One of the limitations identified in the environmental subtask is the lack of data for non-bridge structures, and that some of the specific environmental data needed are not readily available for all structures, e.g., chloride tests, offsets to splash zone, etc.

In BrM, each element on each bridge is already classified in one of the three environmental classes that FDOT already uses, i.e., 2, 3, or 4. This report describes the methodology for developing Markov models that vary by environment and reports the results. This methodology depends on having a specific environmental class for every element on all 36,449 active structures, since it is necessary to develop models for all of them. BrM has default environment factors of 1.5, 1.0, and 0.7, but in Task 1 new values were developed for these three numbers. The results obtained, 1.04, 1.20, and 0.80, are not very satisfactory, and that is one reason why it is worthwhile to consider making changes in how FDOT defines its element classification. However, the effort in the subtask to develop environmental classification could not recommend a new classification for each of the elements on all 36,449 active structures.

Review and enhance BrM Risk Models

Considering the natural and manmade hazards that are unique to the state of Florida, this research task utilized the bridge parameters available in BrM as much as possible, to incorporate the effect of the risks due to these hazards into the FDOT BMS BrM. The study considered the following natural hazard scenarios: Hurricane Categories 1, 2, and 3; Hurricane Categories 4 and 5; Flood; Scour; Wildfire; and Tornado, while the manmade hazard scenarios were Overheight collision (bridges with vertical underclearances less than 13.5 ft.); Overheight collision (bridges with vertical underclearances greater than or equal 13.5 ft.); and vessel impact.

The methodology of the risk model involved estimating at each bridge location, the likelihood of occurrence of the hazard, the likelihood of service disruption, and costs of the associated consequences. Considering the bridge inventory, these estimates are utilized to compute the expected risk cost (social cost of risk), vulnerability index and utility for each bridge. BrM will use this information to prioritize risk mitigation and replacement projects. Hurricanes and other natural hazards are challenging to accurately predict, but this study utilized the historical records of the events at bridge locations, along with Geographic Information System (GIS) and other appropriate methodologies, to estimate the likelihoods of occurrence. Historical and documented costs, with necessary assumptions were used to compute the costs of consequences for each hazard scenario.

Four performance criteria were identified for Florida bridges to include recovery costs, safety, mobility, and environmental sustainability. During the study, focus was on three of the criteria, ignoring safety as most natural hazards in Florida occur with advance warning and managed vehicular traffic, to reduce traffic safety consequences. For manmade hazards, traffic safety may be of concern but their evaluation and incorporation into the BMS risk model would be complicated and outside the scope of the current study. Recovery costs include the costs of minor or major repairs, and replacement after the hazard occurrence. Mobility costs include the costs of the required detour in terms of the time of travel and vehicle operating costs, while the environmental sustainability cost is the emission damage cost associated with driving during this detour.

The estimated likelihoods of occurrence at state-maintained bridge locations under the hazard scenarios were relatively low for most cases but a bit relatively higher for hurricanes, scour, wildfire, overheight collisions (vertical underclearance <13.5 ft.), and vessel impact. The sum of social cost of risks computed for the state-maintained bridge inventory indicated the following order among the hazard scenarios (descending): scour, hurricane categories 1, 2, and 3; wildfire; flood; hurricane categories 4 and 5; overheight collision (clearance <13.5 ft.); vessel impact; overheight collision (clearance <= 13.5 ft.); and tornado. The risk utility computed for each bridge in the state-maintained inventory indicated that most bridges (about 94%) have utility values between 90 and 100, while only a very few bridges (15) have values less than 60. The lower values would increase the priority of those bridges for risk-mitigating activity. The BrM implementation was recommended through creation of a field for *risk utility* in the BrM *userbrg* table to contain the risk utility values for each bridge as computed from this study. A simple Microsoft Excel spreadsheet was also developed to contain summaries of the likelihoods and consequence costs for each hazard scenario, as well as an interactive user interface to view and compute the social cost of risks, vulnerability index and utility for each bridge in the state-maintained inventory.

Development of an improved NBI Translator

The primary objective was to develop a tool that can accurately convert data from bridge element inspection to the Federal Highway Administration (FHWA)'s National Bridge Inventory (NBI) data format, which the FHWA utilizes for important decision making on funding the bridge maintenance, repair and replacement projects nationwide. It was desired to make the developed tool easy-to-use as well as exploring new advanced techniques in data science, utilizing the bridge parameters available in BrM as much as possible.

The study considered many more explanatory variables extracted from the BrM database and NBI records than all the previous efforts to develop the NBI Translator, with the focus on five bridge components: deck, superstructure, substructure, culvert, and channel. The three methodologies explored are listed as follows: multiple linear regression, multinomial logistic regression, and Artificial Intelligence (AI), specifically, machine learning. It was discovered that considering more pertinent bridge attributes (age, ownership, structure type, etc.) and element data (primary element health index, percentages in condition states, etc. and similar data on defects, secondary, protection elements) improved the accuracy of the translated ratings. In addition to the typical NBI ratings (0 to 9), the Generalized NBI ratings, defined as the FHWA's ratings of Good, Fair, and Poor, which are aggregation of specific NBI ratings for each category, were also modeled in the Translator tool. Overall, the models showed better accuracy for the Generalized NBI ratings than for the regular NBI ratings. Best predictions were obtained in almost all the bridge components for those at the rating of 7 in the regular NBI ratings and Good for the Generalized NBI ratings. The predictions at the NBI ratings 8 and 9 were reasonable but at ratings 0 to 4, there were large errors, though it should be noted that the FDOT state-maintained bridge inventory for these lower ratings (0 to 4) are very low.

The multiple linear regression and the machine learning models of the NBI Translator indicated in many of the scenarios that the important explanatory variables, i.e., contributing most to the prediction, included the primary element health index, percentage of the primary element in state 4, percentage of the primary element defects in state 4, and age. The results from the multinomial logistic regression were slightly more accurate than those of the multiple linear regression but the latter will be much easier to understand and implement. The machine learning also produced good results, and the accuracies on some bridge components are better than those from the linear and logistic regression models. The main shortcomings of the machine learning models are that some of the models will require extremely high number of explanatory variables, some as high as 40 variables, and also the deployment of the models will be challenging due to its MATLAB development platform. It is recommended that the multiple linear regression models be deployed for the FDOT BrM Translator models, as they will be coded as linear functions of the already-existing element and bridge data in the database. For future research, it is suggested that more studies be conducted on a bridge inventory that are predominantly bridges in the lower NBI ratings, i.e., less than 5. It is also recommended that as the machine learning technology become more accessible in terms of common platforms, easily-deployable models be developed.

New cost estimating models for bridge MR&R activities

Due to the recent lack of bridge cost data at FDOT, and also with no mechanism for collecting specifically, bridge maintenance, repair and rehabilitation (MR&R) activities, this research task investigated: 1) how to utilize the available historical costs (e.g., bridge work orders and the bid unit prices) to develop bridge MR&R cost estimates; and 2) formulate a methodology for developing crew-based cost estimates, using typical crew data and production rates.

Bridge MR&R activities costs were extracted from the FDOT's Maintenance Management System (MMS) database, based on Bridge Work Order Library (BWOL) reports, linked using the Bridge IDs, to some pertinent fields in the BrM Bridge Table, such as bridge length, deck area, etc. The resulting data indicated activities measured in units per area (SF) of the bridge. The study was based on the MMS activity definition in the Maintenance Cost Handbook, where the units of measures were mostly Man Hour (MH), except for the following activities: Bridge Deck Joint Repair (LF); Bridge Deck Maintenance and Repair (SF); and Bridge Rail Maintenance and Repair (LF). The statewide annual fiscal year reports generated from the MMS database also provided some valuable information regarding the costs and labor efforts (MH) expended annually. The MMS activity list was expanded where possible by filter of the data, to identify some more specific activities such as "Clean and repair slope protection." Estimates of labor effort (MH) per SF deck area were combined with average costs per MH from the statewide annual MMS reports, to derive estimates of various activities, in terms of dollar per bridge SF deck area. This approach will enable FDOT to estimate unit costs of bridge MR&R activities using the data currently available.

The second approach involves the analyses of FDOT's historical bid costs, which are collected and published annually, covering all pay items used on FDOT construction bids. The most recent reports were downloaded (Excel files) and each pay item record in the data was classified to identify respective bridge MR&R activity, including cathodic protection, clean and maintain slope protection, etc. A mapping structure was established between the listed bridge MR&R activities and the pay items, for classification of the data; this will be useful for future processing of FDOT historical bid reports. The consumer price indexes were used to adjust the estimated unit cost for each bridge activity, to the Year 2024 dollars.

Lastly, a crew-based approach was presented where for bridge MR&R activities, the crew (required labor and equipment) can be selected, and the information on costs and crew daily production rate, are used to estimate the installation (labor and equipment) costs. The materials costs can then be added to complete the cost estimates. The use of RS Means Cost data was demonstrated as a useful source for implementing the crew-based cost estimates of bridge MR&R activities. The study utilized the materials and crew data for bridge MR&R activities from the FDOT Bridge Maintenance Reference Manual to develop an Excel spreadsheet for the crew-based cost estimating methodology.

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1. Introduction and background

The Moving Ahead for Progress in the 21st Century (MAP-21) Act and the more recent Fixing America's Surface Transportation (FAST) Act were enacted by the U.S. Congress to address many of the national concerns on the management of the national network of highways and bridges. To satisfy bridge owner needs and the MAP-21 requirements, AASHTO in 2013 approved a new bridge element inspection manual, which was updated in 2015 as the AASHTO Manual for Bridge Element Inspection. The Department started in 2014 to implement the AASHTOWare Bridge Management System or BrM to support network-level and project-level decision making in the headquarters and district offices. BrM has helped the Department's effort to improve the quality of asset management information provided to decision makers. The credibility and usefulness of this information is also essential for satisfaction of the requirements of the Government Accounting Standards Board Statement 34 (GASB 34) regarding the reporting of capital assets, and the Federal MAP-21 requirements for performance management and development of asset management plans.

The risk-based Transportation Asset Management Plan (TAMP), also a federal requirement, outlines the processes that the Department uses to improve or preserve the condition and performance of the National Highway System (NHS) pavement and bridge assets. The plan includes asset inventory, consideration of financial planning and investment strategies, as well as life cycle cost and risk management analyses. BrM provides the primary input for the highway bridge data necessary to develop the TAMP.

Like most states, Florida DOT had been using a customized version of the 1997 AASHTO CoRe Element Guide and has developed its inspection data, deterioration models, cost models, and other preservation analysis capabilities using the 1997 specifications. Towards the implementation of the new AASHTO Manual, Florida DOT developed a set of Bridge Management Elements, consistent with the FHWA and AASHTO requirements, to address elements not covered in the new FHWA regulations that FDOT requires. The new AASHTO Manual made many significant changes to the 1997 AASHTO CoRe Element Guide. Pursuant to the requirements of MAP-21, FHWA mandated national adoption of a portion of the AASHTO Manual, known as the National Bridge Elements for inspection of bridges on the National Highway System starting October 2014.

Florida DOT sponsored and conducted research from 2014 to 2016, through outside experts, to convert and adapt all of its prior bridge management preservation analysis models and software tools to fit the new manuals and data. This study has revised the existing methodology for computing the bridge health index (BHI) by investigating various approaches to assigning state weights and element importance weights. A list of recommended element weights was presented to FDOT as well as a methodology for calculating the BHI. A revised list of preservation actions was formulated to be compatible for use in the BrM software, based on the description of bridge elements, their condition states, and various levels and extents of defects in the FDOT Bridge Inspection Guide. New transition times for deterioration between states were developed to enhance the migration of the Pontis deterioration model to the BrM software. The action effectiveness model was revised, based on the new bridge element inspection manual. Based on historical costs and some assumptions, preservation unit costs and other cost parameters were provided as necessary to run the BrM software. Finally, the research team developed the migration of preservation benefits and optimization results to the BrM software and performed the necessary enhancements to the Project Level Analysis Tool to support decision making at FDOT.

Based on this 2014 study, it was identified that the BrM implementation would still require some additional work. Since the Department was just getting started with the new inspection process, which was further refined in 2015, it did not have solid data to calibrate models for the new analysis structure. The quantitative model parameters developed in 2014 were meant to be temporary until sufficient data were collected to enable statistical modeling.

1.1. Project objective and research tasks

On this project, the Department engaged the assistance of experts in bridge management to help it further with the implementation of the AASHTOWare Bridge Management (BrM) software. The 2014 study mentioned above can be viewed as a transitional effort to enable the Department to maintain the full decision support functionality of its bridge management system and the Project Level Analysis Tool during the migration from the AASHTO CoRe Element Manual and Pontis to the new 2015 AASHTO Element Inspection Manual and AASHTOWare Bridge Management software. Through some resourceful use of some old and new resources, the study was able to create a migration path for the FDOT health index, deterioration model, preservation cost and effectiveness models, and life cycle cost analysis so all the tools will work correctly with the new data and systems.

Since the 2014 study, three cycles of bridge element inspection data have been collected. The Department has been gathering these element inspection data under its newest revised Field Guide (revised February 2016) since October of 2016. This marked the point when the inspection process started to use AASHTOWare Bridge Management release 5.2.2, and decision support functionality transitioned to the new version of the Project Level Analysis Tool. The Pontis software was retired at that point. In this time frame, several opportunities and requirements have emerged, including the following: an improved understanding of bridge element systems; an ability, for the first time, to start to separate the various deterioration processes, such as corrosion and cracking, by mining the new defect elements; the uniformity of element and condition state definitions in the new manual which will simplify some areas of data analysis, particularly element interactions; new steps have been taken in risk analysis, such as NCHRP Project 20-07(378), completed in summer of 2016, that may be implementable in Florida; and the finalization of new federal regulations for performance measures and Transportation Asset Management Plans in 2017.

With the new data, it is now necessary to re-calibrate the core BrM models and tools, including the element deterioration models, risk models, cost models, and the translator model. This enhancement will aid the Department in satisfying the various federal requirements and prepare for anticipated changes at the national level in the bridge inspection and management standards.

The following research tasks were established in order to accomplish the project objective: environmental classification and development of deterioration models; review and enhance BrM Risk Models; development of an improved NBI Translator; and new cost estimating models for bridge MR&R activities.

1.1.1. Environmental classification and development of deterioration models

In 2010 FDOT developed a deterioration model based on 14 years of CoRe Element data. One of the tasks on the 2014 study used a migration probability matrix, based on changes in element and condition state definitions, to convert the 2010 model into a form that is compatible with the 2016 Field Guide. Although the results are reasonable, the migration is based on judgment rather than statistical analysis. The new inspection process is more detailed than the old one, so a new statistical analysis of inspection data under the new Field Guide should yield much better models. In fact, much of the justification for the new inspection process has been to improve deterioration modeling. Two inspection cycles are necessary, at a minimum, to develop Markovian deterioration models. Now the Department has the inspection data needed. Any analysis to estimate new transition times should also quantify element interactions by estimating protection factors based on protective element condition. Environment factors and action effectiveness models can also be estimated in the same process. Also, FDOT established bridge elements' environmental classification under its implementation of Pontis. With the new BrM implementation, it may be necessary to refine this classification. FDOT Structures and Materials offices have some published criteria (based for example, on exposure to chloride) that would be useful in developing an environmental classification scheme.

1.1.2. Review and enhance BrM Risk Models

The Risk factor associated with a bridge is an important variable in the internal working computation in BrM. Currently, BrM maximizes Total Utility computed based on the multi-objective concept, to evaluate and forecast potential outcomes of bridge decision making. It does this by ranking projects using the change in utility relative to cost. The Total Utility is calculated based on a weighted average of scores on five variables: Condition; Life Cycle Cost; Safety; Mobility; and Risk. While the first four factors are typically obtained from already established data, the Risk factor may need to be configured by the agency to suit the predominant types of risks in their jurisdiction. For example, Alaska configured its system to account for seismic risks and impacts to the fish migrations. Louisiana tried to accommodate exposure to wave actions, while Kentucky included specific types of accidents (sideswipes, running off the road left or right, and side impacts), and Hawaii considered shoreline erosion as a type of risk.

It would be therefore be valuable for FDOT to configure its Risk factor input into the BrM Utility. In 2013, FDOT completed a study on using risk models for its BMS, with Pontis being the BMS at the time (Sobanjo and Thompson 2013). The FDOT TAMP's Risk Register also considers some specific types of risks in its computation. Another pertinent research report is the short study titled "Assessing Risk for Bridge Management" that was conducted for the AASHTO Standing Committee on Highways, through the National Cooperative Highway Research Program (NCHRP) Project 20-07, Task 378 (Thompson et al. 2017). Starting with these referenced research methods and documents, important types of risks will be identified, and a methodology will be developed to make the risk data usable in BrM for the Risk factor computation.

The likelihood of extreme events can be geographically related to bridge locations, while the likelihood and consequences of transportation service disruption can be assigned based on specific bridge attributes such as deteriorated condition, vertical underclearance, available detour length, etc. These three factors (extreme event likelihood, likelihood of disruption, and consequence of disruption) with consideration of the relative weights of the structure and hazard scenarios, are used to compute the risk utility (ranging from 0 to 100), as well as the social costs associated with the risk.

1.1.3. Development of an improved NBI Translator

The widespread changes in condition state definitions in the new inspection manual have biased the calculation of NBI condition ratings, so they no longer closely match the NBI ratings produced by inspectors. In general, the condition state definitions used in the new manual do tend to increase the likelihood of states 1 and 2, and reduce the likelihoods of states 3 and 4, especially for the elements having the biggest impact on NBI ratings for superstructures and substructures. This pattern is evident in the migration probability matrix developed in the 2014 study.

In order to meet the needs of upcoming federal requirements, there is also a need for the forecasting of the probability of Good and Poor overall condition ratings for each bridge, which can be aggregated over the inventory to evaluate asset management performance targets. Recalibration of this model will need to rely on field-collected element data, preferably dual inspections where the inspector has determined the element conditions and the NBI rating. It may be necessary to take defects into account, although the reliability of these data is still unknown. To forecast NBI ratings, a multinomial choice model could produce a probability of each NBI value, from which the most likely value would be selected.

1.1.4. New cost estimating models for bridge MR&R activities

Historical costs on specific bridge maintenance, repair and rehabilitation (MR&R) activities are not being collected by FDOT anymore. Based on the past studies by FDOT involving bridge costs, a methodology can be developed to estimate needed costs of bridge MR&R, based on: Historical-based cost estimates: Trnsport Bid data, linked to the bridge ID, and crew-based cost estimates: using typical crew data and production rates. It has been successfully demonstrated in prior studies that historical bid cost data can be analyzed to estimate the costs for some bridge MR&R activities. The major limitation was linking the bid data to specific bridge IDs; this is not done in AASHTO's Trnsport, the computer system utilized in assembling the bid cost data. But some key features of the bid data can be captured to enable such connection.

Historical bid cost data will be useful but will also need the necessary adjustment by both location and time indexes. Crew-based cost estimating is the methodology employed by contractors in developing detailed cost estimates for competitive bids. Driven by the production rate of a selected crew, the methodology involves first getting direct cost estimates of material, labor, equipment, and subcontract, if any. Markups and overheads are then added to obtain the eventual bid unit cost estimates. The main fundamental principle in the methodology is that the daily cost of a task divided by the crew's daily production rate will yield an estimate of the task's unit cost. A popular cost manual, the RS Means Cost Manual, has such methodology for buildings and highway construction projects, but none specifically for bridge new construction or maintenance and repair work. Prior FDOT studies have indicated some typical in-house crew production rates at FDOT, as well as overhead rates. Several FHWA and FDOT publications will provide basic data on the type and costs of materials needed. The results from the estimating methods described above will be imported and made compatible with the BrM MR&R activities.

1.2. Report organization

This report begins with a brief introduction and description of research objectives and tasks as already presented in this section. Next, sections 2 and 3 present the results from the first main research task, i.e., environmental classification and development of deterioration models. While section 2 focused on the deterioration model, section 3 discussed the environmental classification. The separate sections were used due to the inconclusive but pertinent results from section 3, including suggestions on how to improve the results. In section 4, the efforts on research task 2 (review and enhance BrM Risk Models) are reported, showing a comprehensive consideration of several natural and man-made hazards that the Florida bridges are vulnerable to. Next in section 5, development of an improved NBI Translator (research task 3) is presented, involving the application of conventional statistical approaches and machine learning methods. Lastly, in section 6, the results of the effort on developing new cost estimating models for bridge MR&R activities (research task 4) are presented. For the convenience of reading, each section has its own list of cited references at the end of the section. Appendixes A, B, C and D provide additional results from the study.

2. Element deterioration models

The Florida Department of Transportation began gathering bridge element condition data as part of its routine biennial inspections in the late-1990s, implementing the AASHTO CoRe Element Guide (AASHTO 1998) for use with its AASHTOWare Pontis bridge management system. Over time the Department augmented its bridge inspection process to incorporate the specialized elements of movable bridges, to add elements that are of particular maintenance concern in Florida (such as pile jackets, drainage systems, fenders, dolphins, and seawalls), and to add non-bridge structures such as sign supports, high-mast light poles, mast arms, and certain retaining walls (FDOT 2008).

Using its element inspection standards, the Department conducted innovative research to develop its own deterioration models, action cost and effectiveness models, and decision support tools for life cycle cost analysis and risk analysis at the project level and program level. In particular, FDOT has a statistically rigorous bridge deterioration model that it uses for many purposes in planning of bridge work (Sobanjo and Thompson 2011).

As many states gained experience with the element inspection process, a number of potential improvements were identified. Among them were:

- A more precise definition of the specific types of defects that are considered in condition state assessments;
- Separate assessment of certain types of protective systems from their underlying elements, especially deck wearing surfaces, coating systems, and cathodic protection systems;
- Standardization of the number of condition states possible for each element.

An initial version of a new Guide Manual was adopted in 2010 (AASHTO 2011), and was revised as an official AASHTO Manual shortly thereafter (AASHTO 2013). FDOT prepared its own version of this manual, containing its agency-defined elements, the next year (FDOT 2014).

At that point FDOT engaged a consultant to migrate its previous condition forecasting models to be compatible with the new element and condition state definitions. Since no data had yet been gathered under the new definitions, a migration model was prepared based on expert judgment about the effects of the changes in definitions (Sobanjo and Thompson 2016). This was meant as a stop-gap measure to enable the use of the AASHTOWare Bridge Management software while inspection data in the new format were gathered over subsequent years.

AASHTO published revisions to its Manual for Bridge Element Inspection in 2015 (AASHTO 2022), and FDOT began data collection using this version on 1 Dec 2015 (FDOT 2019). As of September 2023 FDOT's BrM database had nearly seven years of inspection data under the new manual, providing three consecutive inspections for most of its structures. With this much data, it became feasible to update the BrM forecasting models using statistical methods. The present study has, as part of its scope, to produce the updated models, in a form convenient for loading the data into the BrM software. The Scope of Services calls for the following data:

- Median transition times among element condition states for all elements defined in FDOT's bridge inspection process, including agency-defined elements, compatible with BrM's Markov model.

- Environment factors that correspond to the classification of elements, provided by bridge inspectors to represent the aggressiveness of climate and operating conditions for each element of each bridge.
- Weibull shaping parameters used by BrM to regulate the pace of the onset of deterioration in its forecasting model.
- Protection factors to model the influence of the condition of deck wearing surfaces and element protective coatings on the rate of deterioration of substrate elements.
- Markov transition probabilities of the improvement in condition expected from common preservation, rehabilitation, and reconstruction activities that may be planned with the assistance of BrM.

All of these data products are developed using valid statistical methods based on existing bridge inspection and maintenance data gathered since December of 2015, where possible, using older models and expert judgment where necessary to ensure full coverage and useful planning functionality of BrM.

2.1. Data gathering and processing

FDOT provided on 12 Sep 2023 a backup file of its production BrM database, containing its entire history of bridge element inspections up to the preceding day. The file was in a format compatible with Microsoft SQL Server and with AASHTOWare Bridge Management release 6 and above. The researcher created a copy of the production database by restoring to a local computer running Microsoft SQL Server Developer Edition. The data were provided under a confidentiality agreement.

Contained within the database were 43,758 bridges and non-bridge structures, of which 36,449 had been inspected since 1 Dec 2015. Based on correspondence with FDOT it was noted that the Custodian column of the Bridge table was used to identify bridges maintained by FDOT. When a bridge is closed or demolished, it remains in the database but is reassigned to notional district '09' and in most cases is no longer inspected. For the present study these bridges were excluded. State-maintained and non-state-maintained bridges were all used in the analysis, though for certain purposes, such as identification of preservation treatments, only state-maintained bridges could be considered.

2.1.1. Element inspection data

FDOT uses the standard element numbering scheme defined in the AASHTO Manual for all AASHTO-defined elements. It has an additional 66 agency-defined elements, all numbered in the 8000-series. Most of these elements relate to components of movable bridges, but some also describe supporting structures for lighting and traffic control devices unrelated to bridges, and auxiliary elements, such as slope protection and wingwalls, that are associated with bridges and require inspection and maintenance. Only the standard AASHTO element 510 is used for deck wearing surfaces, but FDOT has four agency-defined elements to distinguish different types of steel protective coatings, instead of the AASHTO-standard element 515. The database also contains other element definitions corresponding to defects, deprecated smart flags, and various administrative flags. These are not modeled in BrM and were excluded from the analysis.

When inspecting a bridge element, the inspector considers four condition states, where state 1 is like-new condition and state 4 is so deteriorated that a structural review is warranted. The condition state is based on a listing of possible defects to be considered, which defects typically relate to the physical process of deterioration and potential corrective actions. Table 2.1, reproduced from the FDOT Field Guide, shows the condition state definitions for concrete decks.

The inspector reports the condition of each element by estimating the percentage of the element observed to be in each of the possible condition states. Software used by the inspector provides the means of entering the data, comparing with previous inspections, and ensuring validity of the input. Table 2.2 shows an example of the data resulting from an element-level bridge inspection. The BrM database redundantly stores element conditions as quantities by condition state, in addition to percentages by state. For the present study, the percentages in Table 2.2 are recomputed from quantities to ensure consistency, since the quantity data are often more precise than the percentages.

The purpose of a deterioration model is to predict conditions at any point in the future, in the format of Table 2.2, based on conditions from a previous inspection or a previous forecast. The analytical framework of AASHTOWare Bridge Management uses a Markov model, which employs a simple matrix of transition probabilities to forecast the change in condition from one year to the next. This model is described mathematically in the next section.

Table 2.1. Concrete deck condition states

DECK

Defect	Condition State 1	Condition State 2	Condition State 3	Condition State 4
	GOOD	FAIR	POOR	SEVERE
Delamination/ Spall/ Patched Area (1080)	None	Delaminated. Spall 1 in. or less deep or less than 6 in. diameter. Patched area that is sound.	Spall greater than 1 in. deep or greater than 6 in. diameter. Patched area that is unsound or showing distress. Does not warrant structural review.	The condition warrants a structural review to determine the effect on strength or serviceability of the element or bridge; OR a structural review has been completed and the defects impact strength or serviceability of the element or bridge.
Exposed Rebar (1090)	None	Present without measurable section loss.	Present with measurable section loss that does not warrant structural review.	
Exposed Prestressing (1100)	None	Present without section loss	Present with section loss that does not warrant structural review.	
Cracking (PSC) (1110)	Insignificant cracks or moderate width cracks that have been sealed.	Unsealed moderate width cracks or unsealed moderate pattern or map cracking.	Wide cracks or heavy pattern or map cracking.	
Efflorescence/ Rust Staining (1120)	None	Surface white without build-up or leaching without rust staining.	Heavy build-up with rust staining.	
Abrasion/Wear (PSC/RC) (1190)	No abrasion or wearing.	Abrasion or wearing has exposed coarse aggregate but the aggregate remains secure in the concrete.	Coarse aggregate is loose or has popped out of the concrete matrix due to abrasion or wear.	
Distortion (1900)	None	Distortion not requiring mitigation, or distortion mitigated.	Distortion that requires mitigation, but does not warrant structural review.	
Damage (7000)	Not applicable	The element has impact damage. The specific damage caused by the impact has been captured in condition state 2 under the appropriate material defect entry.	The element has moderate damage caused by vehicular or vessel impact. The specific damage caused by the impact has been captured in condition state 3 under the appropriate material defect entry.	The element has severe damage caused by vehicular or vessel impact. The specific damage caused by the impact has been captured in condition state 4 under the appropriate material defect entry.

DECK

Table 2.2. Example of element condition data

		Percent in each condition state			
No	Element	State1	State2	State3	State4
12	Re Concrete Deck	61%	30%	8%	0%
107	Steel Opn Girder/Beam	41%	51%	8%	0%
113	Steel Stringer	53%	35%	12%	0%
120	Steel Truss	33%	34%	33%	0%
152	Steel Floor Beam	38%	40%	22%	0%
205	Re Conc Column	83%	14%	3%	0%
215	Re Conc Abutment	81%	15%	4%	0%
234	Re Conc Pier Cap	84%	15%	1%	0%
304	Open Expansion Joint	81%	8%	5%	7%
311	Moveable Bearing	38%	43%	16%	3%
330	Metal Bridge Railing	71%	17%	8%	4%
510	Wearing Surfaces	72%	16%	11%	1%
515	Steel Protective Coating	44%	25%	16%	16%

A Markov model is a cross-sectional model, able to compute forecasts by incrementally combining estimates of the change in condition from year to year over any period of time. Estimation of the transition probability matrix of the model is performed by summarizing the actual past changes in condition recorded in inspections, from one inspection to the next, on a large set of bridge elements encompassing all of the possible conditions. This makes it possible to develop useful deterioration models for the entire life cycle of bridges even if the inspection database does not extend back in time for the entire long lifespan of most bridges. FDOT's inventory has examples of bridge elements in every stage of their lives from brand-new to very old, experiences which can be combined to give a full picture of a lifetime of bridge deterioration.

2.1.2. Element inspection pairs

To develop a cross-sectional model, the fundamental unit of analysis is the inspection pair, consisting of two element inspections spaced at the typical interval of two years apart, two successive inspections in the format of Table 2.2. The mathematical process of estimating the transition probability matrix is a matter of finding the parameters that are most likely to explain the changes in condition observed in the inspection pairs.

From one inspection to the next, the condition of each element on each bridge may change. Condition is made worse by time, weather, traffic, pollution, and operating conditions such as saltwater spray. These factors promote physical and chemical processes that may increase the severity of material defects, or increase the extent of defects at any given severity level.

Counter-acting this normal deterioration and its impacts, the agency applies preservation actions intended to either improve condition, or at least slow the rate of deterioration. While deterioration can be observed every year, preservation actions occur infrequently, often at intervals of 10-30 years or more.

In order to estimate statistical models of deterioration, it is necessary to separate the effect of deterioration from the effect of agency actions. These effects are not directly measured, but must be deduced from a limited amount of information in two snapshots of condition spaced 2 years apart, plus any available evidence of agency actions that may have been performed in between the two snapshots. Figure 1.1 shows the problem schematically. If an agency action occurred on the element between 2013 and 2015, then the percent of the element observed to be in state 3 in 2015 may be due to a combination of normal deterioration from states 1, 2, or 3; and the effect of agency action in improving parts of the element which may previously have been in states 2, 3, or 4.

In the present study a table of element inspection pairs was created in the researcher's copy of the BrM database using an SQL query. The query accomplishes several important tasks:

- Matches each possible pair of inspections of each element, ensuring that the two inspections in each pair are spaced two years apart, give or take 6 months. The query also ensures that both inspections in a pair belong to the same bridge, structure unit, inspection, element, and environment; and that both inspections show the same total quantity of the element. The first inspection of each pair is denoted X, and the second one Y. Any given element inspection can be used by more than one pair as either the X or the Y inspection.
- Classifies the change in condition between the two inspections. If the quantities in each condition state are exactly the same for all four states, then the pair is classified as unchanged. If there is any improvement from any state to any better state, then the pair is classified as improved, indicating that work may have been done on the bridge. In all other cases, the pair is classified as deteriorating.
- For protective elements (wearing surfaces and coatings), matches them with their substrate element and then notes, for each substrate element, the identity and condition of its protector.
- Classifies each bridge as being on or off the state highway system based on the bridge.custodian field.
- Ensures that the data set includes only the appropriate inspection dates, districts, and elements as discussed above.
- Ensures valid data for other items used in various parts of the analysis.

The table of inspection pairs contains 532,592 records, which can be summarized as in Table 2.3.

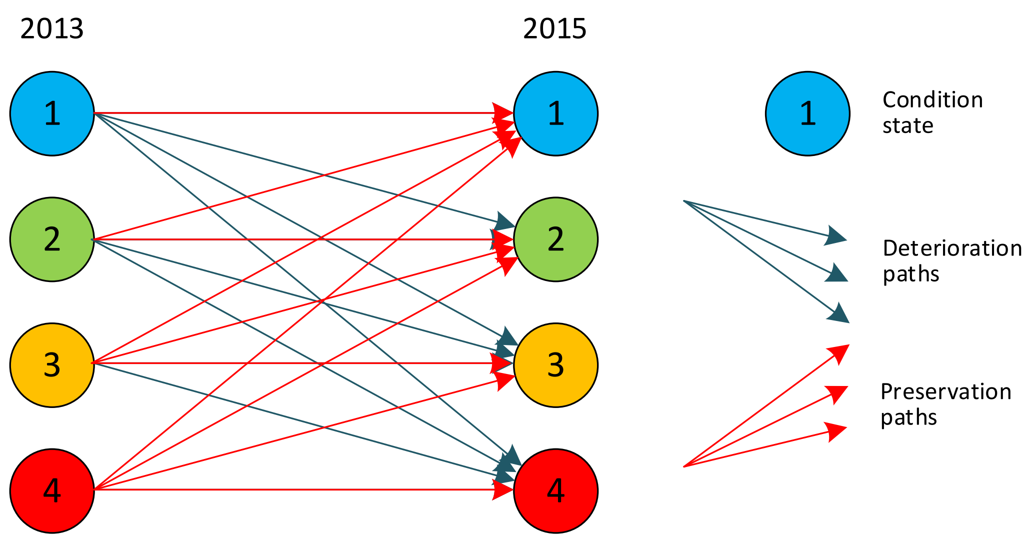


Figure 2.1. Changes in condition between two element inspections

Table 2.3. Population summary of inspection pairs table

Classification (Chg)	Statewide	FDOT-maintained
-1 (deteriorated)	100,475	59,902
0 (stayed same)	371,918	206,119
1 (improved)	60,199	36,804
Total	532,592	302,825

The following SQL query produces the inspection pairs table:

```
select ey.PON_ELEM_INSP_GD as Ey_GD,ex.PON_ELEM_INSP_GD as Ex_GD,
 bx.BRIDGE_ID,su.STRUNITKEY as SU,ed.ELEM_KEY,vd.ENVKEY,
 bx.Dist,bx.NHS,bx.SHS,bx.NBI,bx.SvOn,bx.SvU,
 ey.iDate as yDate,ey.Q1/ey.Q as yFrac1,ey.Q2/ey.Q as yFrac2,ey.Q3/ey.Q as yFrac3,ey.Q4/ey.Q as yFrac4,
 ex.iDate as xDate,ex.Q1/ex.Q as xFrac1,ex.Q2/ex.Q as xFrac2,ex.Q3/ex.Q as xFrac3,ex.Q4/ex.Q as xFrac4,
 ex.PElem,iif(ex.PCond is null,0.0,ex.PCond) as PCond,
 iif(ey.Q1=ex.Q1 and ey.Q2=ex.Q2 and ey.Q3=ex.Q3,0,iif(ey.Q1<=ex.Q1 and ey.Q1+ey.Q2<=ex.Q1+ex.Q2
  and ey.Q1+ey.Q2+ey.Q3<=ex.Q1+ex.Q2+ex.Q3,-1,1)) as Chg
into ElemPair
from STRUCTURE_UNIT su, PON_ELEM_DEFS ed, PON_ENVT_DEFS vd,
(select e.PON_ELEM_INSP_GD,e.INSPEVNT_GD,e.BRIDGE_GD,e.STRUCTURE_UNIT_GD,e.PON_ELEM_DEFS_GD,e.PON_ENVT_DEFS_GD,
 cast(i.INSPDATE as Date) as iDate, year(i.INSPDATE) as iYr,
 e.ELEM_QTYSTATE1 as Q1,e.ELEM_QTYSTATE2 as Q2,e.ELEM_QTYSTATE3 as Q3,e.ELEM_QTYSTATE4 as Q4,
 e.ELEM_QTYSTATE1+e.ELEM_QTYSTATE2+e.ELEM_QTYSTATE3+e.ELEM_QTYSTATE4 as Q
from PON_ELEM_INSP e, INSPEVNT i
where e.INSPEVNT_GD=i.INSPEVNT_GD and e.ELEM_QTYSTATE1+e.ELEM_QTYSTATE2+e.ELEM_QTYSTATE3+e.ELEM_QTYSTATE4>0
) ey,
(select e.PON_ELEM_INSP_GD,e.INSPEVNT_GD,e.BRIDGE_GD,e.STRUCTURE_UNIT_GD,e.PON_ELEM_DEFS_GD,e.PON_ENVT_DEFS_GD,
 cast(i.INSPDATE as Date) as iDate, year(i.INSPDATE) as iYr,
 e.ELEM_QTYSTATE1 as Q1,e.ELEM_QTYSTATE2 as Q2,e.ELEM_QTYSTATE3 as Q3,e.ELEM_QTYSTATE4 as Q4,
 e.ELEM_QTYSTATE1+e.ELEM_QTYSTATE2+e.ELEM_QTYSTATE3+e.ELEM_QTYSTATE4 as Q,
(select max(p.ELEM_KEY) from PON_ELEM_INSP p,PON_ELEM_DEFS pd
 where p.PON_ELEM_DEFS_GD=pd.PON_ELEM_DEFS_GD and pd.ELEM_PROTECT_SYS='Y' and p.INSPEVNT_GD=e.INSPEVNT_GD
  and p.ELEM_QTYSTATE1+p.ELEM_QTYSTATE2+p.ELEM_QTYSTATE3+p.ELEM_QTYSTATE4>0
          and p.PARENT_PON_ELEM_INSP_GD=e.PON_ELEM_INSP_GD
 ) as PElem,
(select iif(sum(p.ELEM_QTYSTATE1+p.ELEM_QTYSTATE2+p.ELEM_QTYSTATE3+p.ELEM_QTYSTATE4)<=0,0,
  sum(p.ELEM_QTYSTATE1+2.0/3.0*p.ELEM_QTYSTATE2+1.0/3.0*p.ELEM_QTYSTATE3)
  /sum(p.ELEM_QTYSTATE1+p.ELEM_QTYSTATE2+p.ELEM_QTYSTATE3+p.ELEM_QTYSTATE4))
 from PON_ELEM_INSP p,PON_ELEM_DEFS pd
 where p.PON_ELEM_DEFS_GD=pd.PON_ELEM_DEFS_GD and pd.ELEM_PROTECT_SYS='Y' and p.INSPEVNT_GD=e.INSPEVNT_GD
          and p.ELEM_QTYSTATE1+p.ELEM_QTYSTATE2+p.ELEM_QTYSTATE3+p.ELEM_QTYSTATE4>0
          and p.PARENT_PON_ELEM_INSP_GD=e.PON_ELEM_INSP_GD
 ) as PCond
from PON_ELEM_INSP e, INSPEVNT i, PON_ELEM_DEFS d
where e.INSPEVNT_GD=i.INSPEVNT_GD and e.PON_ELEM_DEFS_GD=d.PON_ELEM_DEFS_GD
 and i.INSPDATE>='2015-12-01' and (d.ELEM_KEY<1000 or (d.ELEM_KEY>=8000 and d.ELEM_KEY<9000))
 and e.ELEM_QTYSTATE1+e.ELEM_QTYSTATE2+e.ELEM_QTYSTATE3+e.ELEM_QTYSTATE4>0
) ex,
(select bi.BRIDGE_GD,bi.BRIDGE_ID,bi.Dist,bi.NHS,bi.SHS,bi.NBI,bi.SvOn,bi.SvU
from
(select b.BRIDGE_GD,b.BRIDGE_ID,
b.DISTRICT as Dist,
(select max(r.NHS_IND) from roadway r where r.BRIDGE_GD=b.BRIDGE_GD
 and r.ON_UNDER=(select min(rr.ON_UNDER) from roadway rr where rr.ON_UNDER>='1' and rr.BRIDGE_GD=b.BRIDGE_GD)) as NHS,
iif(b.CUSTODIAN in ('1','01','11','21'),1,0) as SHS,
iif(b.NBISLEN='Y',1,0) as NBI,
iif(b.SERVTYPON<'0' or b.SERVTYPON is null,'0',b.SERVTYPON) as SvOn,
iif(b.SERVTYPUND<'0' or b.SERVTYPUND is null,'0',b.SERVTYPUND) as SvU
from BRIDGE b
where b.DISTRICT<'09'
) bi
) bx
```

```
where ey.BRIDGE_GD=ex.BRIDGE_GD and bx.BRIDGE_GD=ex.BRIDGE_GD
  and ey.STRUCTURE_UNIT_GD=ex.STRUCTURE_UNIT_GD and ey.STRUCTURE_UNIT_GD=su.STRUCTURE_UNIT_GD
  and ey.PON_ELEM_DEFS_GD=ed.PON_ELEM_DEFS_GD and ey.PON_ENVT_DEFS_GD=vd.PON_ENVT_DEFS_GD
  and ey.PON_ELEM_DEFS_GD=ex.PON_ELEM_DEFS_GD and ey.PON_ENVT_DEFS_GD=ex.PON_ENVT_DEFS_GD
  and ey.Q=ex.Q and datediff(day,ex.iDate,ey.iDate)>1.5*365.25 and datediff(day,ex.iDate,ey.iDate)<2.5*365.25
```

2.1.3. Activity data

Activity data from the FDOT Maintenance Management System (MMS) were provided in the firm of Excel files for each district, on 19 Sep 2023. A set of PDF files of contract data was also provided, but these files contained very few bridge identifiers. They were not used in the deterioration model but may be useful in later tasks for the cost model. The MMS focuses on small projects undertaken by FDOT forces and day labor.

The Excel files were combined, extracting three columns: completion date (compdate), activity code (act), and bridge identifier (bridgeno). The rows were then filtered to remove invalid data in any of the three columns, and dates before 1 Dec 2015. The results were pasted into a new database table called Activity.

Table 2.4 summarizes the 53,125 rows in the table. It can be seen that some important categories of preservation are not covered, including deck overlays and painting. Larger rehabilitation and partial reconstruction projects, typically performed by contractors, also are not included. Naturally, bridges that are maintained by agencies other than FDOT are not addressed.

Table 2.4. Summary of MMS activity codes

Activity	Description	Count
521	Large & overlane sign maintenance and repair	19
805	Bridge deck joint repair	9,685
806	Bridge deck maintenance and repair	10,760
810	Bridge rail maintenance and repair	3,743
825	Superstructure maintenance and repair	4,203
845	Substructure maintenance and repair	16,177
859	Channel maintenance	2,423
861	Bridge electrical maintenance	2,018
865	Movable bridge mechanical maintenance	1,862
869	Movable bridge structural maintenance	2,235
	Total	53,125

Most of the activity codes can be associated with specific groups of elements to which they are applicable. For example, activity 805 should be associated with the condition of expansion joint elements. A table called Applicable was created to associate activity codes with elements, making it possible to query the database for all activity records potentially associated with a bridge element.

It is useful to gain an understanding of the relationship between inspection dates and activity completion dates, with the understanding that often the information gathered in a bridge inspection is what triggers a work order for repairs. Figure 1.2 is a histogram showing the time lag from the date of an inspection to the completion date of an activity following that inspection. The vast majority of work orders are completed near the middle of the two-year inspection cycle.

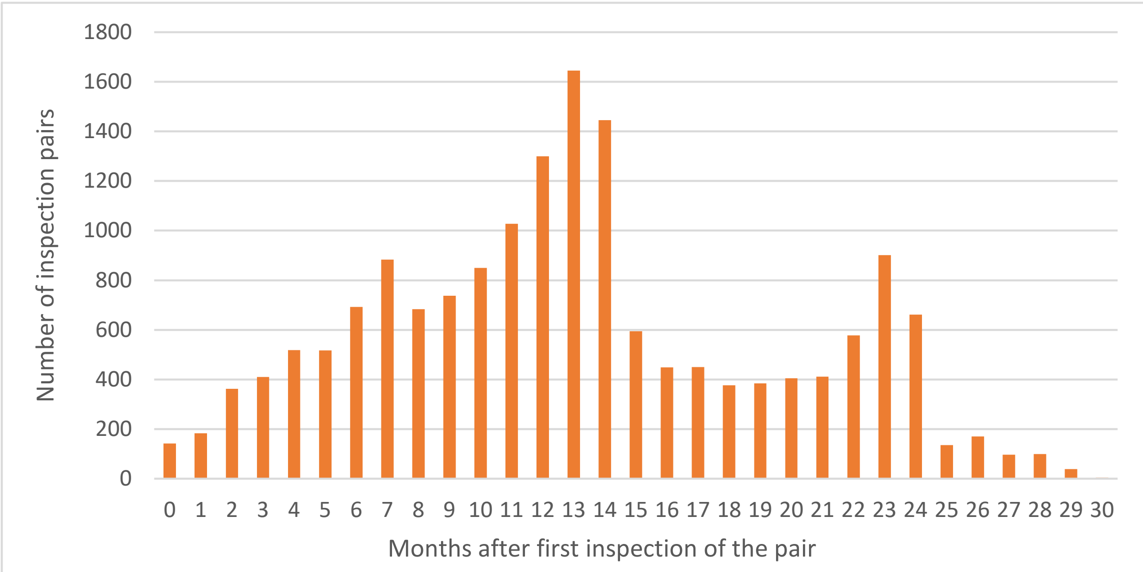


Figure 2.2. Time lag between inspection date and activity completion date

This histogram is produced by the following query:

```
select xMonth,count(*) as Cnt from (
select *,round(xActDays/30,0,0) as xMonth from (
select * from (
select BRIDGE_ID,SU,ELEM_KEY,ENVKEY,Chg,yDate,xDate,
datediff(day,p.xDate,(select max(Act.WorkDate) from Activity Act,Applicable App where Act.ActCat=App.ActCat and Act.Bridge_ID=p.BRIDGE_ID
and App.Elem_Key=p.ELEM_KEY and Act.WorkDate<=p.yDate)) as xActDays,
datediff(day,p.yDate,(select min(Act.WorkDate) from Activity Act,Applicable App where Act.ActCat=App.ActCat and Act.Bridge_ID=p.BRIDGE_ID
and App.Elem_Key=p.ELEM_KEY and Act.WorkDate>=p.xDate)) as yActDays
from ElemPair p
) x
where Chg=1 and not (xActDays is null) and xActDays>=-365 and ((yActDays is null) or yActDays>365 or xActDays>0)
) xx
) xxx
group by xMonth
order by xMonth
```

While the relationship between inspections and activities is compelling, the MMS data set gives an incomplete picture of work accomplishment as it relates to element condition, for the following reasons:

- Much of the work that takes place on Florida bridges is done under contracts, which rarely specify the bridge and element which were acted upon. Therefore a large fraction of observed condition improvements cannot be correlated to recorded work activities.
- Work recorded in the MMS is classified by an activity code which gives a general idea of the type of work performed, which is often potentially applicable to multiple elements on the bridge, even if only one of the elements actually was repaired. Therefore there are a significant number of activity records that do not correspond to an improvement in condition.
- Repair work typically takes place within 14 months after an inspection, after which there is time for further deterioration on other parts of the bridge before the next inspection. This again contributes to the number of activity records that do not correspond to an improvement in condition.

- Inspectors are provided with the results of the previous inspection, and asked to update the report with any changes in condition that may have occurred. This helps to reduce the potential for random error in condition state quantities. Repairs on a limited extent of an element might not be noticed, especially if they were performed under contract and not recorded in the MMS. An element's condition might be recorded as unchanged in such cases even if an activity did take place.

It can generally be assumed that elements which improved in condition over an inspection interval, probably had some action taken on them to cause the improvement. In some cases, the change in condition may be random error, but the investigation in (Sobanjo and Thompson 2011) found that random error was responsible for only a small fraction of these cases. For the present study, it is assumed that all improvements in condition signal that work has taken place.

For element inspection pairs having unchanged condition, it is likely that some fraction had work done, which either did not change condition, or was offset by subsequent deterioration. Activities that do not change condition are very likely to be small repairs or maintenance that would be done by FDOT forces and logged in the MMS. Based on researcher experience with other data sets having more complete coverage of activities, it was assumed that 55% of the unchanged inspection pairs did not have repair activity associated with them (Boadi et al 2022). About half of the remainder on the Florida state highway system had activities recorded in the MMS, with the remainder as unrecorded activity. All activity on non-FDOT structures was unrecorded.

2.2. Element deterioration models in BrM

Bridge element deterioration in BrM is modeled using a Markov Chain, modified using a Weibull model to limit the onset of deterioration as a means of improving realism of planning results. It is assumed that in any given year, conditions of any unit of an element can change by at most one condition state. The methodology was described as a "one-step" model in previous Florida research (Sobanjo and Thompson 2011), where it was developed and validated. The model was later tested by others and was ultimately built into AASHTOWare Bridge Management.

2.2.1. Markov deterioration models

A Markov model assumes that the probability of making a transition from one condition state to another depends only on the initial state, and not on age, past conditions, or any other information about the element. Thus, the model is expressed as a simple matrix of probabilities (Table 2.5).

Table 2.5. Example deterioration model

From	To state 1	State 2	State 3	State 4
State 1	93.6	6.4	0.0	0.0
State 2		92.0	8.0	0.0
State 3			91.1	8.9
State 4				100.0

All amounts in percent

In Table 2.5, the rows are condition states at the beginning of the year, and the columns are condition states one year later. A cross-sectional model like this is especially useful for structures whose lives can extend to 50-100 years or more, where a full time series data set is not obtainable.

Using a Markov model, conditions in any future year can be predicted by simple matrix multiplication. Mathematically, the matrix multiplication for Markovian prediction, when no maintenance action is taken, looks like this:

$$y_k = \sum_j x_j p_{jk} \text{ for all } k \tag{1}$$

where x_j is the probability of being in condition state j at the beginning of the year; y_k is the probability of being in condition state k at the end of the year; and p_{jk} is the transition probability from j to k. This computation can be repeated to extend the forecast for additional years. For example, Table 2.6 shows 20 years of this matrix multiplication.

It is possible to derive transition probabilities if the median number of years between transitions is known. Often this is an easier way to develop a deterioration model from expert judgment. It also provides a convenient means of computing, storing, and reporting transition probabilities derived from historical inspection data. If it takes t years for 50% of a population of elements to transition from state j to state $k=j+1$, and no other transitions are possible, then the one-year transition probabilities are:

$$p_{jj} = 0.5^{(1/t)} \text{ and } p_{jk} = 1 - p_{jj} \tag{2}$$

So if it takes a median of 12 years to transition from state 1 to state 2, then the probabilities after one year are 94.39% for state 1 and 5.61% for state 2, as shown in the upper left of the Table 2.6 example.

The rightmost column of Table 2.6 also demonstrates the use of a health index as a way of summarizing condition at any point in time. To compute the health index, start with the percent in state 1, add 2/3 of the percent in state 2, and 1/3 of the percent in state 3. (Add none for state 4.) An element in best condition therefore has a health index of 100 and in worst condition has a health index of zero.

2.2.2. Onset of deterioration

AASHTOWare Bridge Management enhances the Markov model by allowing the transition probability from state 1 to state 2 to be variable with age. This accounts for the observation that certain elements, when newly constructed, tend to remain in excellent condition for a considerable length of time before the onset of deterioration. A special type of survival probability model known as a Weibull model provides a good approximation of this effect. The Weibull curve has the following functional form:

$$y_{1g} = \exp\left(-\left(g/\alpha\right)^{\beta}\right) \tag{3}$$

where y_{1g} is the state probability of condition state 1 at age (year) g, if no intervening maintenance action is taken between year 0 and year g; β is the shaping parameter, which determines the initial slowing effect on deterioration; and α is the scaling parameter, calculated as:

Table 2.6. Example of long-range condition forecasting

Deterioration (From state → To state)					
	1 → 2	2 → 3	3 → 4		
Med Years	12.0	60.0	100.0		
Same-state	94.39%	98.85%	99.31%		
Next-state	5.61%	1.15%	0.69%		
Years after inspection	Percent state 1	Percent state 2	Percent state 3	Percent state 4	Health index
Year	Pct1	Pct2	Pct3	Pct4	Health
0	100.0%	0.0%	0.0%	0.0%	100.00
1	94.4%	5.6%	0.0%	0.0%	98.13
2	89.1%	10.8%	0.1%	0.0%	96.34
3	84.1%	15.7%	0.2%	0.0%	94.63
4	79.4%	20.3%	0.4%	0.0%	93.00
5	74.9%	24.5%	0.6%	0.0%	91.44
6	70.7%	28.4%	0.9%	0.0%	89.94
7	66.7%	32.0%	1.2%	0.0%	88.51
8	63.0%	35.4%	1.6%	0.0%	87.13
9	59.5%	38.6%	2.0%	0.0%	85.81
10	56.1%	41.4%	2.4%	0.0%	84.55
11	53.0%	44.1%	2.8%	0.1%	83.34
12	50.0%	46.6%	3.3%	0.1%	82.17
13	47.2%	48.9%	3.8%	0.1%	81.05
14	44.5%	50.9%	4.4%	0.1%	79.97
15	42.0%	52.9%	4.9%	0.2%	78.93
16	39.7%	54.6%	5.5%	0.2%	77.93
17	37.5%	56.2%	6.1%	0.2%	76.97
18	35.4%	57.7%	6.7%	0.3%	76.04
19	33.4%	59.0%	7.3%	0.3%	75.14
20	31.5%	60.2%	7.9%	0.4%	74.27

$$\alpha = \frac{t}{(\ln 2)^{1/\beta}} \tag{4}$$

where *t* is the median transition time from state 1 to state 2, from the Markov model as calculated above.

Figure 1.3 shows the form of the Weibull curve, for four different values of the shaping parameter *β*, with *t*=20. A shaping parameter of 1 is mathematically equivalent to a Markov model, featuring the rapid onset of deterioration. A shaping parameter of 2 introduces a delay, and higher values postpone significant deterioration even longer.

Note that all the curves in Figure 1.3 intersect in 20 years at a probability of 0.5, since the Markovian transition time is the same in all cases.

The Weibull curve can also be used in reverse, to calculate an equivalent age if the fraction in condition state 1 is known. This is useful if earlier preservation work has been done on the bridge, such that it behaves as though younger than its actual age. To calculate equivalent age:

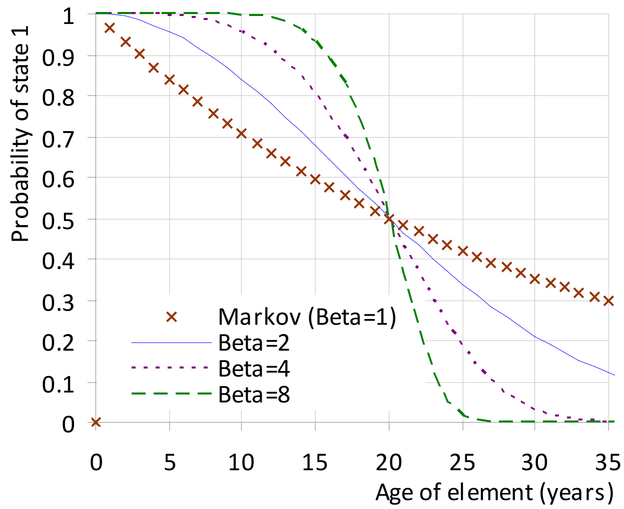


Figure 2.3. Comparison of shaping parameters

$$g' = \alpha \times 10^{\wedge}\left(\frac{\log(-\ln(y_1))}{\beta}\right) \tag{5}$$

Then the forecast percent in state 1 in the following inspection is computed using Equation 3 with *g*=*g'*+2.

2.2.3. Effect of protective systems

The AASHTO Manual for Bridge Element Inspection provides special elements for recording the condition of common types of protective systems, specifically deck wearing surfaces, steel coatings, concrete coatings, and other concrete protective systems. Each of these has four condition states, which would interact with the four condition states of the substrate elements that they protect.

The developers of AASHTOWare Bridge Management took advantage of the decision to avoid two-state transitions and presented the Markov deterioration model as merely a median transition time. They defined a new quantity called the protection factor, which summarizes the full effect of all possible element interactions that affect a given element at a given point in time. This protection factor may increase the median years to transition, thus slowing deterioration. It is applied like this:

$$\acute{M}_i = M_i \times PF \tag{6}$$

where $\acute{M}_i$ is the adjusted median years to transition from state *i* to state *i*+1; M_i is the default median years to transition from state *i* to state *i*+1; PF is the protection factor for the element.

For protecting element P, the protection factor PF is calculated as follows:

$$PF = PP_P \times (F_{P1} + 2/3 \times F_{P2} + 1/3 \times F_{P3}) \tag{7}$$

Where PP_P is the protection parameter for protecting element *P*; and F_{PS} is the fraction of element *P* in state s.

PP_P is a parameter indicating how much of its full protection element P gives when it is in a given condition. The protection factor is normally greater than 1.0.

Under the conventions used in BrM, Markov median transition times are always estimated under the assumption that protective systems are absent or, if present, that they are fully deteriorated. A calculation similar to the health index is used as a way to summarize the condition of protecting elements, and this is multiplied by a single protection parameter for each protecting element to yield the protection factor, which then increases the median transition time.

The protection afforded by a protecting element causes a year-to-year change in the transition probabilities affecting the substrate. For example, as a wearing surface deteriorates, the rate of deterioration of the substrate deck increases. For the Markov model, a new set of transition probabilities is computed for each year of age, based on the forecast condition of the protecting element. For the Weibull model, the transition probability from state 1 to state 1 for each year is computed as follows:

$$P_{11} = \exp(-(\mathrm{g} / \alpha)^{\beta} + ((\mathrm{g}-1) / \alpha)^{\beta}) \quad (8)$$

Where *g* is the age and all other symbols are the same as above for the Weibull model. Then the transition probability from state 1 to state 2 is $p_{12} = 1 - p_{11}$.

2.2.4. Environment factors

AASHTOWare BrM stores median transition times undifferentiated by environment, and then provides a separate table with four environment factors to represent each of the four allowed environment classifications for elements. FDOT uses three of these four categories. Environment factors affect transition times in the same way as protection factors *PF* in the equations above. These separate factors are multiplied together to yield a total protection factor to be used in computing an adjusted transition time.

2.3. Estimation of deterioration models

Quantitative parameters of the model are developed using an algebraic calculation from element inspection pair data developed as described above, using only the inspection pairs that deteriorated in condition, plus a fraction of those that remained unchanged. The latter fraction represents elements that did not receive any work during the inspection interval but nevertheless did not deteriorate. Variations on the same methodology are also used to estimate protection parameters and environment factors. The shaping parameter, being used in a more complex non-linear equation, is estimated using a maximum likelihood technique.

2.3.1. Markov model estimation methodology

AASHTOWare Bridge Management stores its deterioration models in the form of transition times, the median number of years to make a transition from each condition state to the next one. Then equation 2 (above) is used to calculate transition probabilities before using them in equation 1 for forecasting. The estimation process works in reverse, determining first the transition probability matrix, and then converting probabilities to transition times using the inverse of equation 2, as follows:

$$t = \frac{\log(0.5)}{\log(p_{jj})} \quad (9)$$

Since bridges deteriorate slowly, not much happens in just one year. If p_{13} and all other matrix elements non-adjacent to the diagonal are assumed to be zero, as in Table 2.5 above, then it is a *one-step* transition matrix. Previous Florida research developed an algebraic method to estimate one-step transition probabilities from inspection data (Sobanjo and Thompson 2011). To set up the estimation of a one-step matrix, the prediction equation is defined as follows:

$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \end{bmatrix} = \begin{bmatrix} p_{11} & p_{12} & 0 & 0 \\ & p_{22} & p_{23} & 0 \\ & & p_{33} & p_{34} \\ & & & p_{44} \end{bmatrix}^2 \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} \tag{10}$$

The element inspection vectors [*Y*] and [*X*] are spaced two years apart, but the transition probability matrix [*P*] is expressed for a one-year transition. Hence, it is applied twice. Writing out the individual equations necessary to calculate [*Y*] results in:

$$y_1 = x_1 p_{11} p_{11} \tag{11}$$

$$y_2 = x_1 p_{11} p_{12} + x_1 p_{12} p_{22} + x_2 p_{22} p_{22}$$

$$y_3 = x_1 p_{12} p_{23} + x_2 p_{22} p_{23} + x_2 p_{23} p_{33} + x_3 p_{33} p_{33}$$

$$y_4 = x_2 p_{23} p_{34} + x_3 p_{33} p_{34} + x_3 p_{34} p_{44} + x_4 p_{44} p_{44}$$

Since the sum of each row in [*P*] must be 1.0, the following additional equations apply:

$$p_{12} = 1 - p_{11}; \qquad p_{23} = 1 - p_{22}; \qquad p_{34} = 1 - p_{33} \tag{12}$$

The vectors [*X*] and [*Y*] can be computed from the database of inspection pairs to describe the combined condition of the element before and after, summed over all inspection pairs contributing to each model. The following query was used to accomplish this:

```
select d.ELEM_KEY,d.ELEM_LONGNAME,d.Group1,d.Group2,
(select count(*) from ElemPair p where p.ELEM_KEY=d.ELEM_KEY and p.Chg=1) as Impr,
(select sum(p.yFrac1) from ElemPair p where p.ELEM_KEY=d.ELEM_KEY and p.Chg=1) as yImpr1,
(select sum(p.yFrac2) from ElemPair p where p.ELEM_KEY=d.ELEM_KEY and p.Chg=1) as yImpr2,
(select sum(p.yFrac3) from ElemPair p where p.ELEM_KEY=d.ELEM_KEY and p.Chg=1) as yImpr3,
(select sum(p.yFrac4) from ElemPair p where p.ELEM_KEY=d.ELEM_KEY and p.Chg=1) as yImpr4,
(select sum(p.xFrac1) from ElemPair p where p.ELEM_KEY=d.ELEM_KEY and p.Chg=1) as xImpr1,
(select sum(p.xFrac2) from ElemPair p where p.ELEM_KEY=d.ELEM_KEY and p.Chg=1) as xImpr2,
(select sum(p.xFrac3) from ElemPair p where p.ELEM_KEY=d.ELEM_KEY and p.Chg=1) as xImpr3,
(select sum(p.xFrac4) from ElemPair p where p.ELEM_KEY=d.ELEM_KEY and p.Chg=1) as xImpr4,
(select count(*) from ElemPair p where p.ELEM_KEY=d.ELEM_KEY and p.Chg=0) as Same,
(select sum(p.yFrac1) from ElemPair p where p.ELEM_KEY=d.ELEM_KEY and p.Chg=0) as ySame1,
(select sum(p.yFrac2) from ElemPair p where p.ELEM_KEY=d.ELEM_KEY and p.Chg=0) as ySame2,
(select sum(p.yFrac3) from ElemPair p where p.ELEM_KEY=d.ELEM_KEY and p.Chg=0) as ySame3,
(select sum(p.yFrac4) from ElemPair p where p.ELEM_KEY=d.ELEM_KEY and p.Chg=0) as ySame4,
(select sum(p.xFrac1) from ElemPair p where p.ELEM_KEY=d.ELEM_KEY and p.Chg=0) as xSame1,
(select sum(p.xFrac2) from ElemPair p where p.ELEM_KEY=d.ELEM_KEY and p.Chg=0) as xSame2,
(select sum(p.xFrac3) from ElemPair p where p.ELEM_KEY=d.ELEM_KEY and p.Chg=0) as xSame3,
(select sum(p.xFrac4) from ElemPair p where p.ELEM_KEY=d.ELEM_KEY and p.Chg=0) as xSame4,
(select count(*) from ElemPair p where p.ELEM_KEY=d.ELEM_KEY and p.Chg=-1) as Detr,
(select sum(p.yFrac1) from ElemPair p where p.ELEM_KEY=d.ELEM_KEY and p.Chg=-1) as yDetr1,
```

```
(select sum(p.yFrac2) from ElemPair p where p.ELEM_KEY=d.ELEM_KEY and p.Chg=-1) as yDetr2,
(select sum(p.yFrac3) from ElemPair p where p.ELEM_KEY=d.ELEM_KEY and p.Chg=-1) as yDetr3,
(select sum(p.yFrac4) from ElemPair p where p.ELEM_KEY=d.ELEM_KEY and p.Chg=-1) as yDetr4,
(select sum(p.xFrac1) from ElemPair p where p.ELEM_KEY=d.ELEM_KEY and p.Chg=-1) as xDetr1,
(select sum(p.xFrac2) from ElemPair p where p.ELEM_KEY=d.ELEM_KEY and p.Chg=-1) as xDetr2,
(select sum(p.xFrac3) from ElemPair p where p.ELEM_KEY=d.ELEM_KEY and p.Chg=-1) as xDetr3,
(select sum(p.xFrac4) from ElemPair p where p.ELEM_KEY=d.ELEM_KEY and p.Chg=-1) as xDetr4
from PON_ELEM_DEFS d
where d.ELEM_KEY<1000 or (d.ELEM_KEY>=8000 and d.ELEM_KEY<9000)
order by d.ELEM_KEY
```

The result of this query forms the basis of the Elements table in the Excel file "Deterioration model.xlsx". This table then contains the formulas for deriving the Markov model. The system of seven equations and seven unknowns can be solved algebraically for the elements of [*P*]. First find p_{11} from equation 11, then find p_{12} from equation 12, then p_{22} and p_{23}, and so on in a simple sequence.

A complication arises because the equations are second-order polynomials in p_{ii}, so it is necessary to use the quadratic equation to find the roots. For example, the equation for p_{33} is:

$$p_{33} = \frac{-b \pm \sqrt{b^2 - 4ac}}{2a} \tag{13}$$

$$a = x_3; \qquad b = x_2 p_{23}; \qquad c = x_1 p_{12} p_{23} + x_2 p_{22} p_{23} - y_3$$

Each same-state transition probability p_{ii} is constrained to be in the range from 0 to 1 exclusive. Even though the quadratic equation finds two roots, in practice only zero or one root are in the necessary range. The final equations for the same-state probabilities are:

$$p_{11} = \sqrt{y_1/x_1} \tag{14}$$

$$p_{12} = 1 - p_{11}$$

$$p_{22} = \frac{-x_1 p_{12} + \sqrt{(x_1 p_{12})^2 - 4 \times x_2 \times (x_1 p_{11} p_{12} - y_2)}}{2 \times x_2}$$

$$p_{23} = 1 - p_{22}$$

$$p_{33} = \frac{-x_2 p_{23} + \sqrt{(x_2 p_{23})^2 - 4 \times x_3 \times (x_1 p_{12} p_{23} + x_2 p_{22} p_{23} - y_3)}}{2 \times x_3}$$

$$p_{34} = 1 - p_{33}$$

$$p_{44} = 1$$

2.3.2. Grouping of models and Markov results

The algebraic method of estimating a one-step Markov model is very efficient in its use of data. The earlier Florida research found that the model typically requires at least 500 inspection pairs to produce a reliable model, which is less than what would be required for common statistical fitting methods such as linear regression. Even so, many of the elements defined in the Florida manual do not have so many inspection pairs available. For example, the table of inspection pairs described above has only 37 records for element 147, Steel Main Cables. In fact, most of the elements have populations under 500. A way to accommodate these uncommon elements is to group them with similar elements that are more common and are expected to have similar deterioration rates.

Table 2.7 shows one scheme for aggregating elements into fairly coarse groups of similar elements. In most cases the populations are large and the resulting Markov transition times, computed as in the preceding section, are mostly reasonable. Table 2.8 is a somewhat finer-grained scheme where some of the groups are reasonable but some are too small and the results less reasonable. Table 2.9 shows the assignment of each element to each grouping scheme, and the element-level results where possible. Blank cells did not have enough occurrences to estimate a reliable model.

Table 2.7. Groups of elements and the number of inspection pairs and resulting transition times in each group (scheme 1)

Model ID and name		Population	Transition times (years)		
			1->2	2->3	3->4
Dk	Deck	16,303	32	8	26
WS	Deck wearing surface	13,354	61	4	46
Dr	Deck drainage system	1,351	4	2	2
Jt	Expansion joints	17,482	12	4	2
Ra	Railings	22,397	40	15	19
AS	Approach slabs	12,565	135	7	20
SP	Superstructure - prestressed	8,363	131	2	116
SR	Superstructure - reinforced	914	31	5	139
SS	Superstructure - steel	4,983	17	2	247
ST	Superstructure - timber	1,193	11	22	2
Co	Coating	30,918	29	4	2
Br	Bearings	16,096	17	2	630
UP	Substructure - prestressed	9,903	12	4	93
UR	Substructure - reinforced	59,629	46	6	58
US	Substructure - steel	4,359	13	4	23
UT	Substructure - timber	5,938	6	13	12
UM	Substructure - MSE	3,321	131	3	11
Pr	Slope protection	10,432	84	10	13
Mo	Movable bridge elements	14,253	5	4	9
TC	Traffic control supports	34,081	13	3	27
Ch	Channel	17,196	3	11	24

Table 2.8. Groups of elements and the number of inspection pairs and resulting transition times in each group (scheme 2)

Model ID and name		Population	Transition times (years)		
			1->2	2->3	3->4
DkC	Deck - cast in place	8,590	28	7	
DkP	Deck - precast	3,121	54	4	10
DkS	Deck - steel	980	48	16	44
DkT	Deck - timber	733	10	18	4
DkZ	Slab	2,878	36	9	180
WS	Deck wearing surface	13,354	61	4	46
Dr	Deck drainage system	1,351	4	2	2
JtS	Expansion joints - sealed	16,215	12	4	2
JtO	Expansion joints - open	1,267	15	5	11
RaC	Railing - concrete	13,358	47	21	52
RaM	Railing - metal	3,619	34	10	13
RaO	Railing - other	5,421	30	14	15
AS	Approach slab	12,565	135	7	20
SP	Superstructure - prestressed	8,363	131	2	116
SR	Superstructure - reinforced	914	31	5	139
SSS	Superstructure - steel - sheltered	3,166	30	5	273
SSX	Superstructure - steel - exposed	1,817	9	1	234
ST	Superstructure - timber	1,193	11	22	2
CoS	Steel coating	9,613	22	3	2
CoO	Weathering steel or other	535	51	6	3
CoG	Galvanized coating	20,651	33	7	1
CoC	Concrete coating	119	132	2	13
BrE	Bearings - elastomeric	10,458	46	3	439
BrM	Bearings - movable	3,338	6	2	747
BrF	Bearings - fixed	2,300	7	2	836
UP	Substructure - prestressed	9,126	11	4	98
UR	Substructure - reinforced	38,403	59	6	33
US	Substructure - steel	3,288	15	4	48
UT	Substructure - timber	4,243	5	17	9
UCV	Substructure - concrete culvert	3,628	7	8	256
UW	Substructure - concrete wall	19,906	52	6	92
USV	Substructure - steel culvert/wall	839	8	4	9
UTW	Substructure - timber wall	1,520	8	8	18
UM	Substructure - marine	2,196	14	2	68
PrR	Slope protection - concrete	3,807	98	4	4
PrO	Slope protection - other	6,625	77	12	26
MoM	Movable bridge mechanical	3,425	4	5	30
MoS	Movable bridge structural	1,984	3	3	77
MoH	Movable bridge hydraulic	553	3	9	3
MoE	Movable bridge electrical	5,547	7	3	3
MoF	Movable bridge facilities	1,512	10	3	15
MoT	Movable bridge traffic control	1,233	4	8	2
TCV	Traffic control verticals	11,031	37	16	6
TCH	Traffic control horizontals	10,580	26	27	6
TCF	Traffic control foundations	12,470	5	2	45
Ch	Channel	17,196	3	11	24

Table 2.9. Assignment of elements to groups, with population and computed transition times

Element number and name		Grouping schemes		Population	Transition times (years)		
		1	2		1->2	2->3	3->4
12	Reinforced Concrete Deck	Dk	DkC	8590	28	7	
13	Prestressed Concrete Deck	Dk	DkP	4			
15	Prestressed Concrete Top Flange	Dk	DkP	239	142	6	
16	Reinforced Concrete Top Flange	Dk	DkP	340	118	24	
28	Steel Deck With Open Grid	Dk	DkS	491	96	42	
29	Steel Deck with Concrete Filled Grid	Dk	DkS	385	32	2	
30	Steel Deck Corrugated/Orthotropic/Etc.	Dk	DkS	104	51	149	16
31	Timber Deck	Dk	DkT	694	9	18	4
38	Reinforced Concrete Slab	Dk	DkZ	2878	36	9	180
54	Timber Slab	Dk	DkT	40			
60	Other Deck	Dk	DkP	6			
65	Other Slab	Dk	DkZ	1			
102	Steel Closed Web/Box Girder	SS	SSS	310	23	7	40
104	Prestressed Concrete Closed Web/Box Girder	SP	SP	494	21	3	
105	Reinforced Concrete Closed Web/Box Girder	SR	SR	13			
106	Other Closed Web/Box Girder	SS	SSX	2			
107	Steel Open Girder/Beam	SS	SSS	2207	27	5	454
109	Prestressed Concrete Open Girder/Beam	SP	SP	7799	184	2	93
110	Reinforced Concrete Open Girder/Beam	SR	SR	773	34	5	120
111	Timber Open Girder/Beam	ST	ST	1175	11	21	1
112	Other Open Girder/Beam	SS	SSX	2			
113	Steel Stringer	SS	SSS	649	54	5	
115	Prestressed Concrete Stringer	SP	SP	0			
116	Reinforced Concrete Stringer	SR	SR	24			
117	Timber Stringer	ST	ST	5			
118	Other Stringer	SS	SSX	0			
120	Steel Truss	SS	SSX	414	6	1	126
135	Timber Truss	ST	ST	0			
136	Other Truss	SS	SSX	2			
141	Steel Arch	SS	SSX	17			
142	Other Arch	SR	SR	1			
143	Prestressed Concrete Arch	SP	SP	0			
144	Reinforced Concrete Arch	SR	SR	88			
145	Masonry Arch	SR	SR	0			
146	Timber Arch	ST	ST	0			
147	Steel Main Cables	SS	SSX	37			
148	Secondary Steel Cables	SS	SSX	44			
149	Other Secondary Cable	SS	SSX	0			
152	Steel Floor Beam	SS	SSX	1170	9	1	257
154	Prestressed Concrete Floor Beam	SP	SP	70			
155	Reinforced Concrete Floor Beam	SR	SR	15			
156	Timber Floor Beam	ST	ST	2			
157	Other Floor Beam	SS	SSX	0			
161	Steel Pin and Pin & Hanger Assembly or both	Br	BrM	188	1		
162	Steel Gusset Plate	SS	SSX	128	13	1	
202	Steel Column	US	US	54			
203	Other Column	UR	UR	6			
204	Prestressed Concrete Column	UP	UP	35			
205	Reinforced Concrete Column	UR	UR	4450	35	5	49
206	Timber Column	ST	ST	11			
207	Steel Tower	SS	SSX	2			
208	Timber Trestle	ST	ST	0			
210	Reinforced Concrete Pier Wall	UR	UR	1277	12	5	
211	Other Pier Wall	UR	UR	0			
212	Timber Pier Wall	UT	UT	0			
213	Masonry Pier Wall	UR	UR	2			

Table 2.9. (continued). Assignment of elements to groups, with population and computed transition time

Element number and name		Grouping schemes 1	Grouping schemes 2	Population	Transition times (years) 1->2	2->3	3->4
215	Reinforced Concrete Abutment	UR	UR	16661	71	5	97
216	Timber Abutment	UT	UT	1237	8	18	9
217	Masonry Abutment	UR	UR	5			
218	Other Abutments	UR	UR	38			
219	Steel Abutment	US	US	54			
220	Reinforced Concrete Pile Cap/Footing	UR	UR	1427	26	12	387
225	Steel Pile	US	US	804	9	4	29
226	Prestressed Concrete Pile	UP	UP	8773	11	4	95
227	Reinforced Concrete Pile	UR	UR	1407	11	6	10
228	Timber Pile	UT	UT	1716	4	14	11
229	Other Pile	US	US	4			
231	Steel Pier Cap	US	US	459	24	4	45
233	Prestressed Concrete Pier Cap	UP	UP	131	30	4	
234	Reinforced Concrete Pier Cap	UR	UR	13129	131	8	108
235	Timber Pier Cap	UT	UT	1290	6	23	4
236	Other Pier Cap	UR	UR	2			
240	Steel Culvert	US	USV	406	7	3	5
241	Reinforced Concrete Culvert	UR	UCV	3626	7	8	256
242	Timber Culvert	UT	UTW	0			
243	Other Culvert	US	USV	35			
244	Masonry Culvert	UR	UCV	2			
245	Prestressed Concrete Culvert	UP	UP	3			
300	Strip Seal Expansion Joint	Jt	JtS	1345	5	13	8
301	Pourable Joint Seal	Jt	JtS	13210	13	3	2
302	Compression Joint Seal	Jt	JtS	1016	6	3	4
303	Assembly Joint With Seal	Jt	JtS	645	7	8	3
304	Open Expansion Joint	Jt	JtO	532	20	6	21
305	Assembly Joint Without Seal	Jt	JtO	339	17	10	14
306	Other Joint	Jt	JtO	396	10	2	7
310	Elastomeric Bearing	Br	BrE	10458	46	3	439
311	Movable Bearing	Br	BrM	2398	7	2	861
312	Enclosed/Concealed Bearing	Br	BrM	6			
313	Fixed Bearing	Br	BrF	2300	7	2	836
314	Pot Bearing	Br	BrM	716	6	24	82
315	Disk Bearing	Br	BrM	24			
316	Other Bearing	Br	BrM	6			
320	Prestress Concrete Approach Slab	AS	AS	5			
321	Reinforced Concrete Approach Slab	AS	AS	12561	136	7	20
330	Metal Bridge Railing	Ra	RaM	3619	34	10	13
331	Reinforced Concrete Bridge Railing	Ra	RaC	13358	47	21	52
332	Timber Bridge Railing	Ra	RaO	314	6	26	12
333	Other Bridge Railing	Ra	RaO	5099	34	12	16
334	Masonry Bridge Railing	Ra	RaO	8			
510	Wearing Surfaces	WS	WS	13354	61	4	46
515	Steel Protective Coating	Co	CoS	44			
520	Concrete Reinforcing Steel Protective System	Mo	MoE	393	140	3	4
521	Concrete Protective Coating	Co	CoC	119	132	2	13
8097	PS Conc Slab (Hybrid)	Dk	DkP	129	30	2	
8098	Conc Deck on PC Panel	Dk	DkP	256	20	9	
8099	PS Conc Slab (Sonovoid)	Dk	DkP	2147	57	2	6
8199	External Post Tensioning Duct	Mo	MoS	93			
8207	Hollow Core Pile	UP	UP	184	11	4	
8290	Channel	Ch	Ch	17196	3	11	24
8298	Pile Jacket Bare	US	US	1913	18	4	72
8386	Fender Dolphin System Metal Uncoated	US	UM	110	2	0	179
8387	Fender Dolphin System Prestressed Concrete	UP	UM	777	20	1	43

Table 2.9. (concluded). Assignment of elements to groups, with population and computed transition time

Element number and name		Grouping schemes		Popu-lation	Transition times (years)		
		1	2		1->2	2->3	3->4
8388	Fender Dolphin System Reinforced Concrete	UR	UM	6			
8389	Fender Dolphin System Timber	UT	UM	175	4	2	22
8390	Fender Dolphin System Other Material	US	UM	122	9	4	
8393	Bulkhead/Seawall Any Material	UR	UM	1006	15	2	154
8394	Abutment Slope Protection Reinforced Concrete	Pr	PrR	3807	98	4	4
8395	Abutment Slope Protection Timber	UT	UTW	398	9	9	12
8396	Abutment Slope Protection Other Material	Pr	PrO	6625	77	12	26
8397	Drainage System Metal Coated	Dr	Dr	261	4	2	2
8398	Drainage Sytem Other Material	Dr	Dr	1090	4	1	3
8474	Metal Wall	US	USV	398	8	6	706
8475	Wingwall/Retaining Wall Reinforced Concrete	UR	UW	15826	46	7	165
8476	Wingwall/Retaining Wall Timber	UT	UTW	1122	8	8	23
8477	Wingwall/Retaining Wall Other Material	UR	UW	759	33	6	34
8478	Mechanically Stabilized Earth Wall	UM	UW	3321	131	3	11
8480	Mast Arm Foundations	TC	TCF	413	6	1	4
8481	Metal Mast Arm Vertical Member	TC	TCV	361	11	3	3
8483	Rein Conc Mast Arm Vertical Member	TC	TCV	3			
8484	Metal Mast Arm Horizontal Member	TC	TCH	365	15	11	4
8487	Overlane Sign Structure Horizontal Member Metal Co	TC	TCH	10215	27	32	14
8488	Overlane Sign Structure Vertical Member Metal Coat	TC	TCV	9680	50	39	11
8489	Overlane Sign Structure Foundation	TC	TCF	11457	5	2	622
8491	RC Overlane Sign Vertical	TC	TCV	371	30	3	
8496	High Mast Light Pole	TC	TCV	615	4	21	
8499	High Mast Light Pole Foundations	TC	TCF	600	7	4	15
8516	Painted Steel	Co	CoS	9568	21	3	2
8517	Weathering Steel	Co	CoO	260	108	10	4
8518	Galvanized Steel	Co	CoG	20651	33	7	1
8519	Other Steel Coatings	Co	CoO	275	30	4	3
8540	Open Gearing	Mo	MoM	496	1	8	63
8541	Speed Reducers	Mo	MoM	450	3	8	23
8542	Shafts	Mo	MoM	448	13	19	7
8543	Shaft Bearings and Shaft Couplings	Mo	MoM	444	5	10	453
8544	Brakes	Mo	MoM	439	4	6	7
8545	Emergency Drive and Back Up Power System	Mo	MoE	470	6	3	1
8546	Span Drive Motors	Mo	MoE	410	6	17	
8547	Hydraulic Power Units	Mo	MoH	209	2	9	4
8548	Hydraulic Piping System	Mo	MoH	211	2	16	
8549	Hydraulic Cylinders/Motors/Rotary Actuators	Mo	MoH	133	3	5	3
8550	Hopkins Frame	Mo	MoS	143	3	6	3
8560	Span Locks/Toe Locks/Heel Stops/Tail Locks	Mo	MoM	529	1	4	57
8561	Live Load Shoes/Strike Plates/Buffer Cylinders	Mo	MoM	552	3	4	25
8562	Counterweight Support	Mo	MoS	558	5	2	39
8563	Access Ladder & Platforms	Mo	MoF	1032	11	3	29
8564	Counterweight	Mo	MoS	626	3	3	
8565	Trunnion/Straight and Curved Track	Mo	MoS	562	2	4	
8570	Transformers & Thyristors	Mo	MoE	454	314		
8571	Submarine Cable	Mo	MoE	482	8	4	2
8572	Conduit & Junction Boxes	Mo	MoE	1082	4	2	19
8573	Programmable Logic Controllers	Mo	MoE	291	13	2	
8574	Control Console	Mo	MoE	508	4	2	2
8580	Navigational Light System	Mo	MoE	1458	5	3	1
8581	Operator Facilities	Mo	MoF	480	9	4	3
8582	Lift Bridge Specific Equipment	Mo	MoM	36			
8583	Swing Bridge Specific Equipment	Mo	MoM	32			
8590	Resistance Barriers	Mo	MoT	150	2	6	
8591	Warning Gates	Mo	MoT	522	4	14	2
8592	Traffic Signal	Mo	MoT	562	8	5	1

2.3.3. Expert review

All of these results are computed and tabulated in the file “Deterioration model.xlsx” delivered with this report. In the Elements worksheet, the researcher has judged, for each element, which of the three schemes appears to be most reasonable. This can be found in column AV of the worksheet. The Graphs worksheet provides a visualization of the models resulting from the various grouping schemes, to enable quick comparison (Figure 1.4).

In some cases it is evident that condition state 4 is rarely used by inspectors, resulting in very long transition times. This occurs most often with superstructure and bearing elements, and may stem from inspectors’ reluctance to recommend structural review, or unrecorded repair actions. It may also occur because advanced section loss is not always in a location where structural integrity is compromised. While these results are an exact calculation from the available data, the transition times into state 4 in some cases may be too long to be reasonable for planning purposes. The planning models in BrM may produce more useful results if these transition times into state 4 are made shorter. The researcher has suggested some more reasonable times in column BB.

Column AV, and columns AZ to BB, are provided to enable FDOT experts to review and, if necessary, correct any of these judgment-based decisions. The final model, incorporating all corrections, is in columns BC to BE. Column BF creates a series of SQL queries that can then be used to enter the results into the pon_mod_deter table of the BrM database.

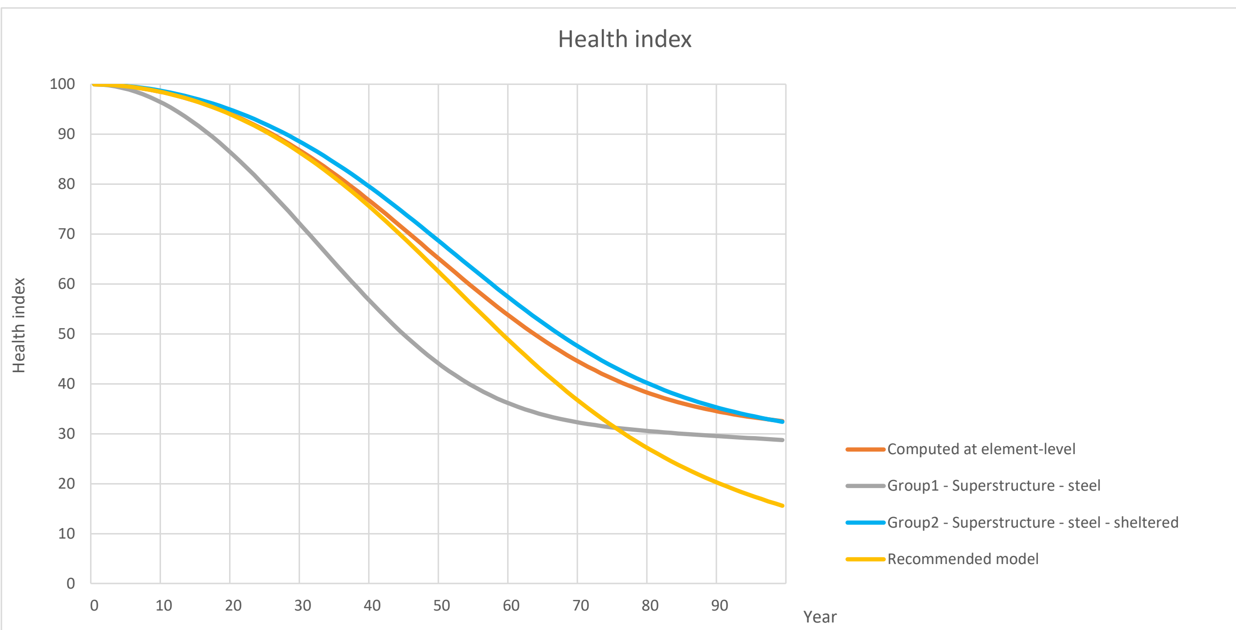


Figure 2.4. Visualization of deterioration models (example for element 107 - Steel Open Girder/Beam)

2.3.4. Shaping parameter

Equation 3 above uses a shaping parameter β to regulate the onset of deterioration, to account for elements that, when new, usually do not start to deteriorate right away. Ideally such models would be estimated using time series data, but the 2015 AASHTO manual is too recent to support a time series methodology. The 2011 Florida research found an alternative approach that takes advantage of the fact that the shaping parameter focuses on bridges in near-new condition, when it is unlikely that the agency would need to perform any repair work on them. For this situation it can be assumed that the onset of deterioration follows a survival probability model where it is only necessary to know the age of the element at the time its condition is observed. There is no closed-form methodology to compute the shaping parameter, but it can be estimated using a maximum-likelihood fitting technique. Research performed more recently for a Midwest pooled-fund study (Boadi et al 2022) produced a somewhat simpler estimation methodology, which is used here.

The general framework for maximum likelihood estimation can be described in the following steps:

1. Prepare a table containing one row per element inspection pair or per observation, containing the age and the observed outcome as the fraction in condition state 1.
2. Add to each row of the table a computation to forecast the outcomes using the unknown model parameters to be estimated.
3. Provide an initial guess of the unknown model parameters. In each row of the table compare the observed outcome against the forecast outcome, using a formula known as a log likelihood function.
4. Iteratively adjust the unknown model parameters until the total log likelihood function is maximized.

The data set needed for step 1 can be produced from the table of element inspection pairs described above, using an SQL query. For example, the following query was used for deck elements up to 30 years of age, limited to bridges that did not exhibit any improvement in condition.

```
select p.BRIDGE_ID,Year(p.yDate) as yYr,Year(p.yDate)-b.YEARBUILT as Age,p.yFrac1
from ElemPair p,PON_ELEM_INSP i,bridge b,PON_ELEM_DEFS d
where p.Ey_GD=i.PON_ELEM_INSP_GD and i.BRIDGE_GD=b.BRIDGE_GD and i.PON_ELEM_DEFS_GD=d.PON_ELEM_DEFS_GD
  and b.YEARBUILT>=1993 and not (b.YEARBUILT is null) and d.Group1='Dk'
  and p.yDate=(select max(pp.yDate) from ElemPair pp where pp.BRIDGE_ID=p.BRIDGE_ID)
  and (select count(*) from ElemPair pp where pp.BRIDGE_ID=p.BRIDGE_ID and pp.Chg=1)=0
order by p.BRIDGE_ID
```

The result set from this query was copied to a spreadsheet table in the file “Weibull models.xlsx”. Equation 3 was then used to compute a predicted fraction in state 1. An initial guess of the shaping parameter was obtained from the 2011 Florida research, and the unknown scale parameter was initially calculated from equation 4.

In step 3, the log likelihood function is a measure of the relative deviation of each observation between the forecast and the observed outcome. It is expressed as a negative number, so maximizing it is a process of finding parameters that move the total log likelihood closer to zero. A body of statistical theory exists for using the log likelihood function to evaluate the explanatory power of a model and to compare two or more alternative models. The log likelihood function is:

$$LLike = y_1 \times \ln(\tilde{y}_1) + (1 - y_1) \times \ln(1 - \tilde{y}_1) \qquad (15)$$

where y_1 is the observed fraction in condition state 1, and $\tilde{y}_1$ is the predicted fraction in state 1 as computed using equation 3.

In step 4, the iterative search for the maximum likelihood model parameters is conducted using the generalized search algorithm in Excel's Solver.

Separate worksheets are provided in the file "Weibull models.xlsx" for groups of elements that are expected to share the same shaping parameter. Table 2.10 shows the results of this analysis. Because the population of newer elements is smaller than what is available for the Markov model, it is necessary to use coarser groups in order to have a sufficient number of observations. In the case of movable bridge elements, very few of these have been built since 2011, so there were not enough observations to support this type of model. In those cases, the results of the 2011 research were used instead. Some of the models yielded shaping parameters of less than 1.0. This was judged to be unrealistic, so it was decided instead to use the Markov model without the Weibull refinement, equivalent to a shaping parameter of 1.0.

The shaping parameter results were copied into the "Deterioration model.xlsx" file so they can be entered into the pon_mod_deter table of the BrM database using the same SQL queries that are used for the Markov transition times.

Table 2.10. Weibull shaping parameter results

Element group	Population	Shaping parameter
Decks and slabs	807	1.7
Wearing surfaces	469	2.4
Expansion joints **	567	1.0
Railings **	1,008	1.0
Approach slabs **	1,008	1.0
Concrete super- and sub-structure	3,117	2.0
Steel super- and sub-structure	304	1.7
Timber super- and sub-structure	85	1.4
Coatings	7,255	1.7
Bearings	667	1.5
Mechanically-stabilized earth walls	371	1.6
Slope protection	389	1.9
Movable bridge mechanical *	1,652	1.6
Movable bridge structural *	548	4.1
Movable bridge electrical *	1,272	3.0
Movable bridge other *	457	1.1
Sign and lighting supports **	10,876	1.0
Channel **	500	1.0

* Results from Sobanjo and Thompson (2011).
** Rounded up to 1.0 to use the Markov model unmodified.

2.3.5. Protection parameter

As a part of creating element inspection pairs, described above, the SQL query also identified protective elements and computed their condition, for all substrate elements. It is straight-forward to compare elements whose protective systems are in like-new condition, with elements whose protective systems are in fully-deteriorated condition. This is done using the SQL query and formulas in the Auxiliary worksheet in "Deterioration model.xlsx". The methodology for the calculations is the same as for Markov transition times.

The analysis resulted in a protection factor of 1.96 for coatings and 4.11 for deck wearing surfaces. These results are entered into the pon_mod_deter table of the BrM database using the same SQL queries that are used for the Markov transition times.

2.3.6. Environment factor

Similar to protection factors, environment factors can be computed from inspection pairs using the same methodology as for transition times. This is done using the SQL query and formulas in the Auxiliary worksheet in “Deterioration model.xlsx”. The results are summarized in Table 2.11.

Table 2.11. Environment factor results

Environment	Factor
2 - Moderate	1.04
3 - Severe	1.20
4 - Extremely severe	0.80

2.3.7. Action effectiveness

The FDOT Maintenance Management System provides data on many of the smaller maintenance and repair actions that can be performed using FDOT forces and day labor. The data processing steps described above associate each activity record with a set of elements to which it may have been applied, and an observed improvement in condition helps to quantify the effect. It is not possible with the available data to trace a unit of element from its prior condition to the condition after treatment, but some approximations can be made to yield a reasonable estimate of treatment effectiveness probabilities. As a first step in deriving these approximations, it is possible to calculate the average improvement in condition into condition state 1 from worse conditions, for state highway bridges having activity records completed within the dates of the inspection pair. This is done using the following SQL query:

```
select d.Group1,count(*) as Cnt, sum((p.yFrac1-p.xFrac1)/(p.xFrac2+p.xFrac3+p.xFrac4))/count(*) as P234_1
from ElemPair p, PON_ELEM_INSP i, PON_ELEM_DEFS d
where p.Ey_GD=i.PON_ELEM_INSP_GD and i.PON_ELEM_DEFS_GD=d.PON_ELEM_DEFS_GD and p.Chg=1 and p.SHS=1 and p.yFrac1>p.xFrac1
and p.xFrac2+p.xFrac3+p.xFrac4>0
and (select count(*) from Activity Act,Applicable App where Act.Bridge_ID=p.BRIDGE_ID and Act.WorkDate>=p.xDate and
Act.WorkDate<=p.yDate and Act.ActCat=App.ActCat and App.Elem_Key=p.ELEM_KEY)>0
group by d.Group1
order by d.Group1
```

Similarly, it is possible to compute the improvement for elements starting in states 3 or 4, into state 1 or 2, from the following SQL query:

```
select d.Group1,count(*) as Cnt,
sum((p.yFrac1+p.yFrac2-p.xFrac1-p.xFrac2)/(p.xFrac3+p.xFrac4))/count(*) as P34_12
from ElemPair p, PON_ELEM_INSP i, PON_ELEM_DEFS d
where p.Ey_GD=i.PON_ELEM_INSP_GD and i.PON_ELEM_DEFS_GD=d.PON_ELEM_DEFS_GD and p.Chg=1 and p.SHS=1 and
p.yFrac1+p.yFrac2>=p.xFrac1+p.xFrac2 and p.xFrac3+p.xFrac4>0
and (select count(*) from Activity Act,Applicable App where Act.Bridge_ID=p.BRIDGE_ID and Act.WorkDate>=p.xDate and
Act.WorkDate<=p.yDate and Act.ActCat=App.ActCat and App.Elem_Key=p.ELEM_KEY)>0
group by d.Group1
order by d.Group1
```

If it can be assumed that the transition probability into state 1 is the same regardless of the starting state, then the quantities from these two queries can be used to derive action effectiveness probabilities. Any fraction that is not improved into a better condition state, remains in its starting state after the action. This approximation yields reasonable values for the elements addressed by MMS activities. Unfortunately, the MMS data does not address coatings, bearings, slope protection, or sign and light supports. It also does not clearly identify approach slabs. For these elements, it is necessary to borrow the results from another, similar element.

The calculations for this process can be found in the Effectiveness table of "Deterioration model.xlsx" and the results in Table 2.12. In the spreadsheet, columns P to U are provided to enable a reviewer to modify the transition probabilities using judgment. Something to keep in mind in reviewing and using these results is that some of the indicated transitions are unlikely to be used in the BrM models. Many of the elements do not have feasible repair treatments for condition state 4, for example.

Table 2.12. Action effectiveness probabilities for repair treatments

		Transition probabilities from-> to the indicated condition states								
Model	Name	2->1	2->2	3->1	3->2	3->3	4->1	4->2	4->3	4->4
Dk	Deck	0.5196	0.4804	0.5196	0.1293	0.3511	0.5196	0.1293	0.1293	0.2218
WS	Deck wearing surface	0.6972	0.3028	0.6972	0.1161	0.1867	0.6972	0.1161	0.1161	0.0705
Dr	Deck drainage system	0.7462	0.2538	0.7462	0.0000	0.2538	0.7462	0.0000	0.0000	0.2538
Jt	Expansion joints	0.5450	0.4550	0.5450	0.1808	0.2743	0.5450	0.1808	0.1808	0.0935
Ra	Railings	0.6339	0.3661	0.6339	0.0914	0.2747	0.6339	0.0914	0.0914	0.1833
AS	Approach slabs	0.5196	0.4804	0.5196	0.1293	0.3511	0.5196	0.1293	0.1293	0.2218
SP	Superstructure - prestressed	0.4643	0.5357	0.4643	0.1219	0.4139	0.4643	0.1219	0.1219	0.2920
SR	Superstructure - reinforced	0.1830	0.8170	0.1830	0.2197	0.5973	0.1830	0.2197	0.2197	0.3776
SS	Superstructure - steel	0.5462	0.4538	0.5462	0.0000	0.4538	0.5462	0.0000	0.0000	0.4538
ST	Superstructure - timber	0.1972	0.8028	0.1972	0.5125	0.2903	0.1972	0.5125	0.0000	0.2903
Co	Coating	0.6972	0.3028	0.6972	0.1161	0.1867	0.6972	0.1161	0.1161	0.0705
Br	Bearings	0.5795	0.4205	0.5795	0.0000	0.4205	0.5795	0.0000	0.0000	0.4205
UP	Substructure - prestressed	0.4324	0.5676	0.4324	0.0465	0.5212	0.4324	0.0465	0.0465	0.4747
UR	Substructure - reinforced	0.5502	0.4498	0.5502	0.0670	0.3828	0.5502	0.0670	0.0670	0.3157
US	Substructure - steel	0.5795	0.4205	0.5795	0.0000	0.4205	0.5795	0.0000	0.0000	0.4205
UT	Substructure - timber	0.7054	0.2946	0.7054	0.0000	0.2946	0.7054	0.0000	0.0000	0.2946
UM	Substructure - MSE	0.6853	0.3147	0.6853	0.0498	0.2649	0.6853	0.0498	0.0498	0.2151
Pr	Slope protection	0.5196	0.4804	0.5196	0.1293	0.3511	0.5196	0.1293	0.1293	0.2218
Mo	Movable bridge elements	0.8399	0.1601	0.8399	0.0185	0.1417	0.8399	0.0185	0.0185	0.1232
TC	Traffic control supports	0.5795	0.4205	0.5795	0.0000	0.4205	0.5795	0.0000	0.0000	0.4205
Ch	Channel	1.0000	0.0000	1.0000	0.0000	0.0000	1.0000	0.0000	0.0000	0.0000

FDOT does not have work accomplishment data for any of its contract projects that can clearly be associated with element conditions on specific bridges. It is simple enough to assume that element replacement actions yield 100% in condition state 1, but there is also an intermediate level of treatment, often in a category called "rehabilitation".

One way to get a handle on rehabilitation treatments is to assume that any amount of condition improvement past a certain threshold represents a possible rehab treatment, except for treatments that move condition entirely to state 1. A way to estimate the appropriate threshold is to tabulate histograms of condition improvements, comparing inspection pairs that have intervening activities, with those that have no activity. The elements that improved without a recorded activity might be rehab actions, if the improvement is large enough. Comparing the two histograms, the point where the no-activity histogram exceeds the yes-activity histogram, might be a reasonable threshold for identifying rehab actions and separating them from actions that are more likely to be repairs or smaller preservation work. This comparison is shown in the bottom table of the Effectiveness worksheet in the "Deterioration model.xlsx" file.

To quantify the amount of improvement, the amount of increase to state 1 or 2 is computed. The query to do this, for the yes-activity histogram, is

```
select Impr,count(*) as Cnt
from (
select 0.01 * round((p.yFrac1+p.yFrac2-p.xFrac1-p.xFrac2)*100,0,1) as Impr
from ElemPair p, PON_ELEM_INSP i, PON_ELEM_DEFS d
where p.Ey_GD=i.PON_ELEM_INSP_GD and i.PON_ELEM_DEFS_GD=d.PON_ELEM_DEFS_GD and p.Chg=1 and p.SHS=1 and p.yFrac1+p.yFrac2>p.xFrac1+p.xFrac2 and p.xFrac3+p.xFrac4>0
and (select count(*) from Activity Act,Applicable App where Act.Bridge_ID=p.BRIDGE_ID and Act.WorkDate>=p.xDate and Act.WorkDate<=p.yDate and Act.ActCat=App.ActCat and App.Elem_Key=p.ELEM_KEY)>0
) x
group by Impr
order by Impr
```

The no-activity histogram is the same except the final inequality is changed to equality, so the number of intervening activities is equal to zero:

```
select Impr,count(*) as Cnt
from (
select 0.01 * round((p.yFrac1+p.yFrac2-p.xFrac1-p.xFrac2)*100,0,1) as Impr
from ElemPair p, PON_ELEM_INSP i, PON_ELEM_DEFS d
where p.Ey_GD=i.PON_ELEM_INSP_GD and i.PON_ELEM_DEFS_GD=d.PON_ELEM_DEFS_GD and p.Chg=1 and p.SHS=1 and p.yFrac1+p.yFrac2>p.xFrac1+p.xFrac2 and p.xFrac3+p.xFrac4>0
and (select count(*) from Activity Act,Applicable App where Act.Bridge_ID=p.BRIDGE_ID and Act.WorkDate>=p.xDate and Act.WorkDate<=p.yDate and Act.ActCat=App.ActCat and App.Elem_Key=p.ELEM_KEY)=0
) x
group by Impr
order by Impr
```

If the difference between the two histograms is smoothed, the point where the two histograms cross is at a level where approximately 30% of the quantity in state 3 or 4, is improved to state 1 or 2. Any amount of improvement larger than 30%, but less than 90%, is then considered to be a rehab action. Using this method, the query for the probability into state 1 from all other condition states is:

```
select d.Group1,count(*) as Cnt, sum((p.yFrac1-p.xFrac1)/(p.xFrac2+p.xFrac3+p.xFrac4))/count(*) as P234_1
from ElemPair p, PON_ELEM_INSP i, PON_ELEM_DEFS d
where p.Ey_GD=i.PON_ELEM_INSP_GD and i.PON_ELEM_DEFS_GD=d.PON_ELEM_DEFS_GD and p.Chg=1 and p.SHS=1 and p.yFrac1>p.xFrac1 and p.xFrac2+p.xFrac3+p.xFrac4>0 and p.yFrac1+p.yFrac2-p.xFrac1-p.xFrac2>0.3 and not (p.yFrac1>=0.9 and p.xFrac4>=0.01)
and (select count(*) from Activity Act,Applicable App where Act.Bridge_ID=p.BRIDGE_ID and Act.WorkDate>=p.xDate and Act.WorkDate<=p.yDate and Act.ActCat=App.ActCat and App.Elem_Key=p.ELEM_KEY)=0
group by d.Group1
order by d.Group1
```

The probability for elements starting in states 3 or 4, into state 1 or 2, is:

```
select d.Group1,count(*) as Cnt, sum((p.yFrac1+p.yFrac2-p.xFrac1-p.xFrac2)/(p.xFrac3+p.xFrac4))/count(*) as P34_12
from ElemPair p, PON_ELEM_INSP i, PON_ELEM_DEFS d
where p.Ey_GD=i.PON_ELEM_INSP_GD and i.PON_ELEM_DEFS_GD=d.PON_ELEM_DEFS_GD and p.Chg=1 and p.SHS=1 and p.xFrac3+p.xFrac4>0 and p.yFrac1+p.yFrac2-p.xFrac1-p.xFrac2>0.3 and not (p.yFrac1>=0.9 and p.xFrac4>=0.01)
and (select count(*) from Activity Act,Applicable App where Act.Bridge_ID=p.BRIDGE_ID and Act.WorkDate>=p.xDate and Act.WorkDate<=p.yDate and Act.ActCat=App.ActCat and App.Elem_Key=p.ELEM_KEY)=0
group by d.Group1
order by d.Group1
```

The other effectiveness probabilities are developed in the same way as for repair actions. The resulting action effectiveness probabilities for rehabilitation are shown in Table 2.13.

Table 2.13. Action effectiveness probabilities for rehabilitation treatments

		Transition probabilities from-> to the indicated condition states								
Mode	Name	2->1	2->2	3->1	3->2	3->3	4->1	4->2	4->3	4->4
Dk	Deck	0.5193	0.4807	0.5193	0.3723	0.1084	0.5193	0.3723	0.0000	0.1084
WS	Deck wearing surface	0.8909	0.1091	0.8909	0.0743	0.0348	0.8909	0.0743	0.0000	0.0348
Dr	Deck drainage system	0.8056	0.1944	0.8056	0.0000	0.1944	0.8056	0.0000	0.0000	0.1944
Jt	Expansion joints	0.7330	0.2670	0.7330	0.1698	0.0972	0.7330	0.1698	0.0000	0.0972
Ra	Railings	0.7457	0.2543	0.7457	0.1592	0.0952	0.7457	0.1592	0.0000	0.0952
AS	Approach slabs	0.8757	0.1243	0.8757	0.1242	0.0001	0.8757	0.1242	0.0000	0.0001
SP	Superstructure - prestressed	0.9228	0.0772	0.9228	0.0619	0.0153	0.9228	0.0619	0.0000	0.0153
SR	Superstructure - reinforced	0.9228	0.0772	0.9228	0.0619	0.0153	0.9228	0.0619	0.0000	0.0153
SS	Superstructure - steel	0.7774	0.2226	0.7774	0.0000	0.2226	0.7774	0.0000	0.0000	0.2226
ST	Superstructure - timber	0.8615	0.1385	0.8615	0.0680	0.0705	0.8615	0.0680	0.0680	0.0025
Co	Coating	0.8277	0.1723	0.8277	0.0552	0.1171	0.8277	0.0552	0.0552	0.0618
Br	Bearings	0.7718	0.2282	0.7718	0.1665	0.0616	0.7718	0.1665	0.0000	0.0616
UP	Substructure - prestressed	0.6131	0.3869	0.6131	0.2024	0.1845	0.6131	0.2024	0.0000	0.1845
UR	Substructure - reinforced	0.7694	0.2306	0.7694	0.1413	0.0893	0.7694	0.1413	0.0000	0.0893
US	Substructure - steel	0.7411	0.2589	0.7411	0.1711	0.0878	0.7411	0.1711	0.0000	0.0878
UT	Substructure - timber	0.4971	0.5029	0.4971	0.1825	0.3204	0.4971	0.1825	0.1825	0.1379
UM	Substructure - MSE	0.8068	0.1932	0.8068	0.1481	0.0450	0.8068	0.1481	0.0000	0.0450
Pr	Slope protection	0.6971	0.3029	0.6971	0.2564	0.0465	0.6971	0.2564	0.0000	0.0465
Mo	Movable bridge elements	0.9075	0.0925	0.9075	0.0592	0.0333	0.9075	0.0592	0.0000	0.0333
TC	Traffic control supports	0.8982	0.1018	0.8982	0.0727	0.0292	0.8982	0.0727	0.0000	0.0292
Ch	Channel	1.0000	0.0000	1.0000	0.0000	0.0000	1.0000	0.0000	0.0000	0.0000

2.4. Discussion

Deterioration models developed as described in this report provide a close fit to actual changes in element condition that have occurred in the period from 1 Dec 2015 to 11 Sep 2023. Using these models in BrM entails an assumption that future changes in condition will follow the same patterns. While this is not an unreasonable assumption, there may be reasons why reasonable judgment might be applied.

Most importantly, BrM models tend to assume that elements deteriorate all the way to state 4 before there are significant consequences such as road user effects or the need to replace. The historical inspection data do not always follow this pattern. Especially with superstructure and bearing elements, there are very few instances of state 4. This may stem from inspectors' reluctance to recommend structural review, or may occur because advanced section loss is not always in a location where structural integrity is compromised. This characteristic of the data leads to unrealistically long transition times. The researcher has noted this problem in many other agencies using the 2015 and later AASHTO manuals. Some more reasonable transition times into state 4 have been suggested in the delivered spreadsheet.

The agency may have other reasons to expect future changes in deterioration rates, based on their knowledge of specific groups of bridges in the inventory. While over-riding the calculated models will cause future forecasts to deviate from past experience, this still may be a valid thing to do if it improves the expected accuracy or usefulness of the planning models in BrM.

2.5. References

AASHTO. AASHTO Guide for Commonly Recognized Structural Elements with 2002 and 2010 Interim Revisions. American Association of State Highway and Transportation Officials, 1998.

AASHTO. AASHTO Guide Manual for Bridge Element Inspection. American Association of State Highway and Transportation Officials, 2011.

AASHTO. AASHTO Manual for Bridge Element Inspection. American Association of State Highway and Transportation Officials, 2013.

AASHTO. AASHTO Manual for Bridge Element Inspection, 2nd Edition with 2022 Interim Revisions. American Association of State Highway and Transportation Officials, 2022. Available at https://store.transportation.org/Item/PublicationDetail?ID=4155.

Boadi, Richard, Paul Thompson, Pedro Serigos, Basak Bektas, and Gaowei Xu. Bridge Element Deterioration for Midwest States. Report WisDOT 0092-19-40. Federal Highway Administration Pooled-Fund Study TPF-5(432). 2022. Available at https://www.pooledfund.org/Document/Download?id=14072.

FDOT. Bridge Inspection Field Guide for Commonly-Recognized (CoRe) Elements. Florida Department of Transportation, 2008.

FDOT. Bridge Inspection Field Guide for National Bridge, Bridge Management, and Agency-Defined Elements. Florida Department of Transportation, 2014.

FDOT. Bridge Inspection Field Guide, National Bridge, Bridge Management, and Agency-Defined Elements. Florida Department of Transportation, 2019. Available at https://www.fdot.gov/maintenance/inspection.shtm.

Sobanjo, John O., and Paul D. Thompson. Enhancement of the FDOT's Project Level and Network Level Bridge Management Analysis Tools: Final Report. Florida Department of Transportation Contract BDK83 977-01, 2011. Available at https://rosap.ntl.bts.gov/view/dot/18692.

Sobanjo, John O., and Paul D. Thompson. Implementation of the 2013 AASHTO Manual for Bridge Element Inspection. Final Report. Florida Department of Transportation Contract BDK30-977-07, 2016. Available at https://rosap.ntl.bts.gov/view/dot/37491.

3. Environmental classification

The FDOT has established bridge elements' environmental classification under its implementation of Pontis. But with the new implementation of AASHTOWare Bridge Management (BrM), it was deemed necessary to refine this classification. This research includes the review and adoption of the FDOT Structures and Materials Office's published criteria on bridge environmental classification scheme (FDOT 2023). The FDOT's scheme is based primarily on the bridge's nearness to water bodies and the results of some tests, including exposure to chloride, sulfate, industrial facilities, etc. First, the documented experiences of other state DOTs are summarized, before describing the methodology of BrM's bridge element's environmental classification. Then the classification scheme approach is described and implemented for classifying Florida bridge elements into environmental classes.

In section 1 of this final report discussing the development of deterioration models, the existing system of environmental classification was used to try to develop environment factors for the bridge element deterioration model. The expected pattern would be that elements classified as "2 – Low" would have the slowest deterioration, and "4 – Severe" would be fastest. The results of that analysis, tabulated in Section 2.3.6 of this final report, did not find a clear pattern of slower deterioration in the "2- Low" category. This suggests that there is room for improvement in the way elements are classified. The following sections provide some additional insights and analysis that may help in re-evaluating environmental classifications so that their observed deterioration might be more consistent going forward.

3.1. Literature review

There are limited published efforts on developing environmental classification of bridges for the BrM. Wells (1994) developed an environmental classification scheme for implementation in Pontis for Virginia bridges, by considering through a survey of expert opinions, the influences of the climatic and operating practices, including average daily truck traffic (ADTT), annual freeze thaw cycles (F/T), and annual chloride applications. The survey responses were used to develop a simple regression model relating the environmental class (1 to 4), to the three independent variables mentioned above. While a good effort for Pontis, the approach will not be suitable to the current challenges in BrM, where the application of protection elements and detailed consideration of defects are incorporated into the element condition state definitions. Fick and Bell (2022) also presented an approach to determining the environmental factors for bridge elements in Montana, for each of five maintenance districts, in which the proportions of total deck areas in each condition state are reviewed relative to time to estimate the appropriate shape factor (b) for the Weibull distribution. The shape factors are then compared to that of a moderately deteriorating bridge as stated in BrM, to establish whether the rate of onset of deterioration is fast or slow. The environmental factors determined by Fick and Bell (2022) did not properly reflect the effects of maintenance and rehabilitation, and also ignored other adjustment factors such as those required for specific environments (local and global), and the protective elements.

According to the bridge inspection office manual, Oklahoma DOT described its assignment of environments for each bridge element into either of two categories as follows: Benign, when the bridge elements are not significantly affected by environmental factors or operation practices, and there is no mitigation of deterioration by past maintenance actions, or use of highly effective protective systems; and Severe, where environmental factors and practices contribute to rapid deterioration of the bridge element, with no protective elements or ineffective ones in place (ODOT 2022a).

Using the agency's functional classification, on-system bridge elements on DIV 1,3,4,5,7,8 (Interstate and NHS) and DIV 6 NHS/STP) roadways are placed in the severe category, while for the off-system bridges, elements in the ACOG (OKC metro), INCOG TULSA metro) or cities with population greater than or equal to 15,000 are placed in the severe category, and those bridge elements in cities with population less than 15,000 or remainder of ACCO are classified as benign. It was stated that salt usage on any bridge will automatically place the elements of that bridge in the severe category.

Examples of the specific environmental factors considered at ODOT includes the following: Timber Elements – high moisture content, pest infestation, ice flow impacts; Steel Elements – distance from salt air, water wet/dry cycles, exposure to corrosive soils and liquids; Concrete Elements – freeze-thaw cycles, tire chain wear, deck salting; Petroleum Based – high temperatures; Joints and Bearings – extreme temperature ranges; and Operating Practices – high traffic or truck volume, or both.

Virginia DOT defined four local environments with the option of adding two or three more (Springer 2017, Nasrollahi and Springer 2021). The four local environments were listed as follows: Environment 1: Continuous Superstructure Above; Environment 2: Link Slab Above / Deck Extension Above (midlife); Environment 3: Joint Above; Splash Zone; Directly Located in Brackish Environment; and Environment 4: Directly Located in Marine Environment. The approach proposed by Virginia DOT is very comprehensive in trying to establish their environment categories for the BrM; some of the Virginia DOT's concepts will be considered in the formulation of environments for the Florida BrM.

NJ DOT has also made a good effort in establishing its bridge BrM environmental classification scheme. It utilizes two of the BrM-defined environmental levels: Moderate and Severe levels, in which the moderate level represents the typical normal environment for New Jersey bridges, and severe level reflects those bridges exposed to saltwater (marine), brackish water ,and industrial environment (NJDOT 2015).

3.2. BrM bridge environmental classification scheme

The primary consideration in assigning environmental classes for bridge elements is identifying what enhances or reduces the elements' deterioration rates, based on their physical environment or the bridge design, construction, and maintenance practices. Florida, having a "long" shape geographically, and also significantly surrounded by the ocean on the sides, will be exposed to different climates in different regions, and have coastal areas. The regional factors may also indicate a non-homogenous situation for the state, with cases of harsh or moderate weather.

According to the BrM Technical Manual, factors are incorporated into the bridge deterioration model, to account for the external influences on the element deterioration rates, by making adjustments to the median transition times between the condition states, as follows:

$$f = f^E * f^F * f^M_{combined} \tag{1}$$

where,

- f = Adjustment Factor
- f^E = Environmental Factor
- f^F = Formula Factor estimated from a user-customized formula, and
- $f^M_{combined}$ = combined modifier factor for all Protective Systems

3.2.1. Environmental factors

There are four levels of environment defined by the BrM, through consideration of the environmental factors, operating practices, and the effectiveness of protective systems on the bridge elements (Table 3.1). The environment levels range from the Benign level, where there is no external influence on element deterioration rate and the protective systems are highly effective, to a Severe level, where external factors and ineffective protective systems enhances the rapid deterioration. In between these two extremes are the Low level, which is similar to the Benign level except that there may be external influences at the Low level, but the protective systems are very effective, and the Moderate level, where the effects of the external factors are considered normal.

Each environment class will have an environmental factor assigned to it. The default BrM values of environmental (adjustment) factors for each level are as follows: Benign (2.0); Low (1.5); Moderate (1.0); and Severe (0.7). This implies that the moderate environmental level does not need any adjustment to the transition times, but bridge elements in Severe environments will need to reduce the typical transition time by 30%, i.e., applying a factor of 0.70. Bridge elements will have their transition times increased twice and 1.5 times for Benign and Low environments, respectively. Figure 3.1 demonstrates the effects of each of the BrM default factors on computed bridge element's Health Index on the deterioration curve.

A review of the FDOT's structures design guidelines showed that the current approach to establishing environmental classes for its structures may be appropriate for assigning the environmental factor as required in the BrM. As reflected in Table 3.1, FDOT's guidelines suggest three categories instead of the four stated for the default in BrM. The adaptation of the FDOT guidelines will be presented in detail in this report.

Table 3.1. BrM definition of environment levels

Environment	Description	Recommended FDOT Environment[#]
1 -- Benign	Neither environmental factors nor operating practices are likely to significantly change the condition of the element over time, or their effects have been mitigated by the presence of highly effective protective systems.	
2 -- Low	Environmental factors, operating practices, or both either do not adversely influence the condition of the element, or their effects are substantially lessened by the application of effective protective systems.	1 -- Slightly aggressive
3 – Moderate	Any change in the condition of the element is likely to be quite normal as measured against the environmental factors, operating practices, or both that are considered typical by the agency.	2 -- Moderately aggressive
4 – Severe	Environmental factors, operating practices, or both contribute to the rapid decline in the condition of the element. Protective systems are not in place or are ineffective.	3 -- Extremely aggressive

[#] Based on the FDOT Structures Design Guidelines (FDOT 2023)

BrM uses its environmental classes in a somewhat different way from Pontis, in that the effect of protective system condition is explicit in the deterioration model for elements protected by coatings or wearing surfaces. FDOT's Project Level Analysis Tool (PLAT) also uses environmental classes in a way that is similar to Pontis and not compatible with BrM. As a result, the environment classification of a specific element on a specific bridge should not change as the condition of its coating or wearing surface changes. The reference to protective systems in the language of Table 3.1 should therefore be interpreted as describing distinctions in the type of protective element (e.g. lead paint vs. urethane or other paint formulations), or elements that have protective systems other than coatings or wearing surfaces. This is to avoid double-counting the effect of coating and wearing surface condition.

The absence of a coating or wearing surface on elements that normally have such elements (e.g. unpainted steel girders) also is reflected in the deterioration model already and should not be further considered in the environmental classification. In BrM, the deterioration rate of unpainted steel elements is calculated in the same way as painted steel having a fully deteriorated coating. Similarly, a bare concrete deck is modeled using the same deterioration rate as a deck having a fully-deteriorated wearing surface. These deterioration rates are developed in the Markov model estimation methodology described separately.

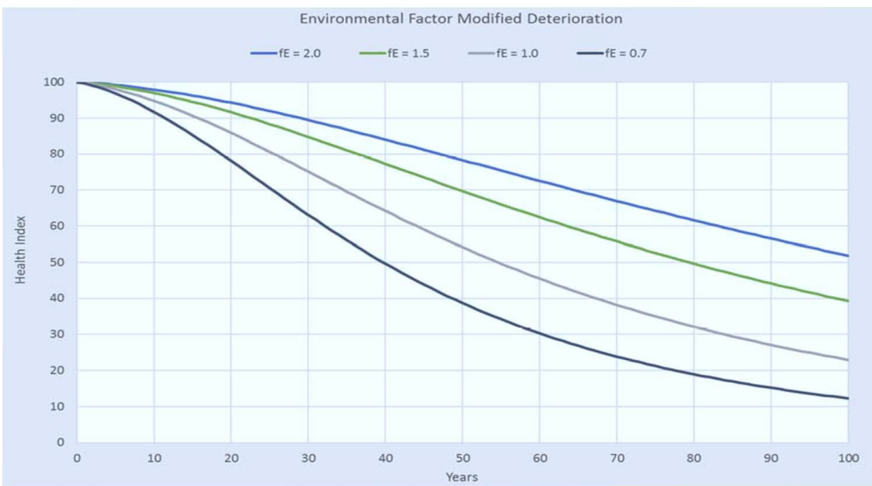


Figure 3.1. Modification of bridge deterioration based on environmental factors (NJDOT 2015).

3.2.2 FDOT's structures design guidelines

FDOT described specific instructions, at the design stage, for the environmental classification of bridges in Florida. The Geotechnical Engineer of Record is responsible for recommending the environmental classifications for all new bridge sites, and widenings. The bridge plans under "General Notes," will include the environmental classification for the superstructure and substructure based on the following classifications: 1. Slightly Aggressive; 2. Moderately Aggressive; and 3. Extremely Aggressive. It is indicated that the substructure will not be classified less severely than the superstructure.

Bridge components from the bearing upwards are considered the superstructure while those below the bearings are the substructure. The criteria for classifying bridge components are summarized in Figure 3.2 and Table 3.1. The first classification is to identify marine structures based on the vicinity to 2500 feet of water with more than 2000 ppm chloride content. Information on water's chloride content is available at FDOT in the Environmental database SharePoint.

Marine structures with chloride concentrations more than 6,000 ppm will have their superstructure and substructure classified as extremely aggressive. Any structure over water, with chloride concentrations of 2,000 to 6,000 ppm, will have the substructure classified as extremely aggressive. Superstructures which are located within the splash zone will be classified as extremely aggressive, while those above the zone will be classified as moderately aggressive. The splash zone is defined as “the vertical distance from 4-feet below MLW to 12-feet above MHW and/or areas subject to wetting by personal watercraft (e.g., jet skis) or other activities and features.” For marine structures not directly over water but with nearby water chloride concentrations of 2,000 to 6,000 ppm, the superstructure will be classified as moderately aggressive, and the substructure will be classified according to the criteria for non-marine structures.

The classification for non-marine structures is summarized in Table 3.1, showing a consideration of the environmental condition using measurements of pH, chloride content, sulfate content, and resistivity, for both water and soil. Bridges located within 2,500-feet of any coal burning industrial facility, pulpwood plant, fertilizer plant, or any other similar industry will have their superstructure classified as Moderately Aggressive, while all others will be classified as Slightly Aggressive.

For the Reinforced Concrete Panel MSE Wall, the Environmental Classification is stated as follows: “Based on wall proximity to 100-year flood plain of water with chloride content > 2,000 ppm, and Distance D to closest of SHWL shoreline to a body of water with chloride content above 2,000 ppm or to a source releasing air contaminants (coal burning industrial facility, pulpwood plant, fertilizer plant or similar industry).”

Requirements are provided for the use of uncoated weathering steel superstructures in terms of the vicinity (4 miles minimum away) to the coast or the intracoastal waterway (whichever is closer), and the vertical and horizontal clearances to water. If the structure is located over water with chloride content less than 6000 ppm, the superstructure must be at least 25 feet above the mean or normal high water. For structures adjacent to the water, and the chloride content of the water is less than 6000 ppm the minimum horizontal clearance should be at 25 feet from the water, and at least 100 feet clearance if the chloride content of the water is greater than or equal to 6000 ppm. FDOT has more detailed requirements described in the manual for the use of uncoated weathering steel superstructures, when located within 4 miles of the coast or the intracoastal waterway. These include ASTM tests on airborne salt deposition rate, average concentration for SO_2, and yearly average time of wetness (TOW). Restrictions on the vertical and horizontal clearances to water also apply as well as location of the steel superstructures above the splash zone.

The FDOT Engineer also has the option of taking representative cores to determine chloride intrusion rates for any superstructure within 2,500-feet of any major body of water containing more than 6,000-ppm chlorides. Based on core results (the chloride intrusion rate in lbs/cy/year at a depth of 2-inch), those with rates greater than or equal to 0.016 lbs/cy/year will be classified as Extremely Aggressive, while those less than 0.016 lbs/cy/year will be termed Moderately Aggressive.

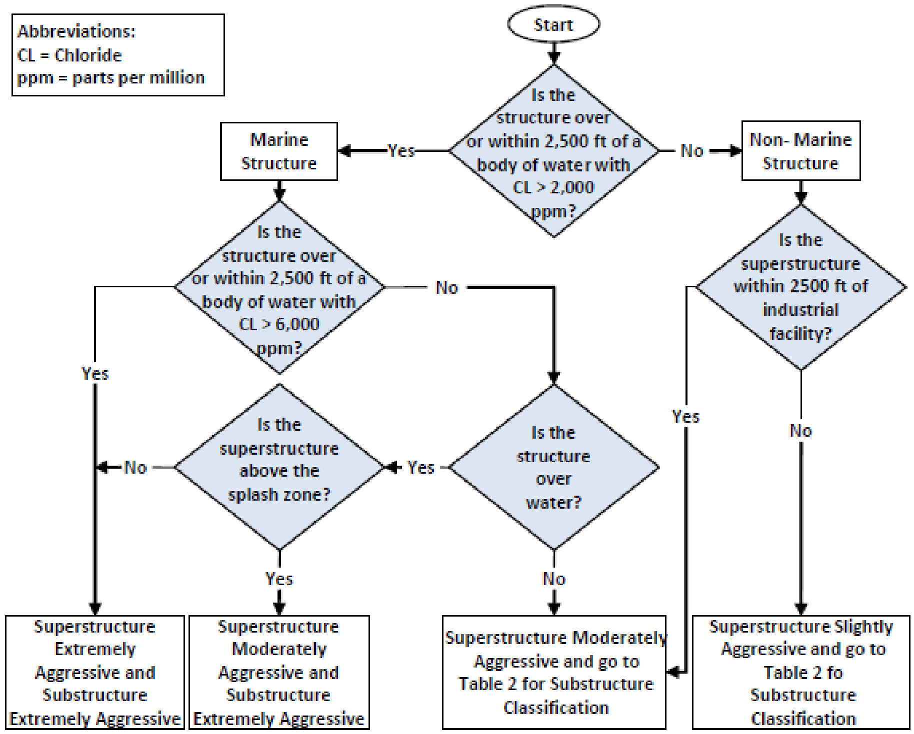


Figure 3.2. Flow Chart for Environmental Classification of Structures (FDOT 2023).

Table 3.2. Criteria for Substructure Environmental Classifications (FDOT 2023).

Classification	Environmental Condition	Units	Steel		Concrete	
			Water	Soil	Water	Soil
Extremely Aggressive (If any of these conditions exist)	pH		< 6.0		< 5.0	
	Cl	ppm	> 2,000		> 2,000	
	SO_4	ppm	N.A.		> 1,500	> 2,000
	Resistivity	Ohm-cm	< 1,000		< 500	
Slightly Aggressive (If all of these conditions exist)	pH		> 7.0		> 6.0	
	Cl	ppm	< 500		< 500	
	SO_4	ppm	N.A.		< 150	< 1,000
	Resistivity	Ohm-cm	> 5,000		> 3,000	
Moderately Aggressive	This classification must be used at all sites not meeting requirements for either slightly aggressive or extremely aggressive environments.					
pH = acidity ($-\log_{10}H^{+}$; potential of Hydrogen), Cl = chloride content, SO_4 = Sulfate content.						

3.2.3. Environmental factors for Florida bridges

The initial step in developing environmental factors for Florida bridges was a review and enhancement of the environmental classification scheme required in the FDOT Design Guide Guidelines, as it reflects the common practice in design, construction, and maintenance at the agency. The flow chart shown in Figure 3.2 was modified by expanding into a bigger flowchart (Figure 3.3) that incorporates the criteria shown in both Figure 3.2 and Table 3.2. The data used for implementing the process are summarized in Table 3.3, including the environmental test data and various pertinent GIS data layers.

The FDOT environmental data was refined and separated into two tables based on the material tested (water and soil). The reasons for eliminating records included the following: blank/wrong Structure No. (alphanumeric or with ?); missing test date; duplicate records (for bridge with multiple records for same test, keeping the most recent record); and blank chloride test data. The summary is as follows:

Original FDOT data: 8542 records (water test data: 7496; soil test data: 1011).
Data after refinement: 5390 records (water test data: 5130; soil test data: 260).

Geospatial analyses were performed using ESRI ArcGIS Pro Version 3.2. Non-proprietary GIS shapefiles were identified and downloaded for Florida Roadway Basemap Routes With Measures (FDOT), bridges (FDOT and FHWA BTS/NBI); Rivers (National Park Service); Lakes (Florida DEP); and Industrial facilities (US EPA). The industrial facilities layer was further refined to indicate that the facilities are operating and that the air emissions are classified as “major.” Two standalone tables were created from the FDOT Environment Data, or for the water tests and the other for soil tests.

The steps shown in Figure 3.3 were implemented using geospatial analyses. First, buffer layers of 2500 ft. were created in the GIS software around the features in rivers, lakes, and industrial facilities layers. Then each of the three buffer layers were spatially intersected with the FDOT bridge layer to identify pertinent bridges that are either over or within 2500 ft. of water, and also for those bridges within 2500 ft. range of industrial facilities. Starting with 9935 FDOT bridges, a merge was done with the FHWA BTS/NBI layer, reducing the data to 9510 bridges; the latter has the necessary information to classify the bridges as required later in the process. The resulting list of bridges over or within 2500 ft. of water also included coastal and riverine bridges as defined in the FDOT bridge database (*userbrdg* table in BrM was queried in the fieldname of *scrmode* using the codes M (Tidal/Riverine) and T (Tidal)).

It was observed that 2584 bridges are over water or within 2500 ft of water while 6926 are not. Combining the 9510 bridge records with the FDOT Environmental data indicated that 1039 bridges can be assigned to such environmental information as desired in the study. The next query identified 475 bridges as marine structures, i.e., over or near water where the chloride content of the water is greater than 2000 ppm, and 415 of these marine structures are close to water with chloride content greater than 6000 ppm. Following the flowchart in Figure 3.3, these 415 bridges will eventually be placed in the “Superstructure Extremely Aggressive” and “Substructure Extremely Aggressive” categories. Bridges over or near water, but with chloride content less than 2000 ppm, were identified, classified as non-marine structures, and added to the list of 6926 bridges which were not over or near water. Thus, there is a list of 7490 non-marine bridges. Figure 3.3 also shows these numbers of bridges at each step of the process.

The same query revealed 60 marine bridges having chloride content between 2000 ppm and 6000 ppm. Further evaluation of the 60 bridges included whether being directly over water and also checking the superstructure’s position relative to the splash zone. The NBI field Item for service under the bridge was used to identify the values as being 5 (Waterway), 6 (Highway-waterway), and 9 (Relief for waterway), confirming that they are all over water. In evaluating the splash zone vicinity, there was no data available specifically for this; the only relevant record available in the NBI was the Navigation Clearance (NBI Item

39), and these indicated 0's for the identified bridges. This means that the evaluation cannot be made due to limited data. The 60 bridges will be put into the "Substructure Extremely Aggressive" category but may be in either the "Superstructure Extremely Aggressive" or "Superstructure Moderately Aggressive" categories.

Next the non-marine bridges were evaluated based on the vicinity (2500ft.) of an industrial facility. Using an EPA GIS Layer of Florida industries and their air emissions attributes, facilities were selected to show ones that are "Operating" and have "Air major" emissions. The feature buffer layer was intersected with the non-marine structures, and it was observed that 160 bridges satisfy this criterion. These 160 bridges will be in the "Superstructure Moderately Aggressive" category while the remaining 7330 non-marine bridges that are not near industrial facilities, will be put in the "Superstructure Slightly Aggressive" category. All 7330 non-marine bridges were further evaluated for their substructure classifications.

The non-marine structures data were then merged with the FDOT Environmental data, showing a resulting data for 1943 bridges with the need information. Queries were written in the ArcGIS Pro (see Figure 3.4), using the NBI Item information on bridge material type to identify 1785 of the 1943 bridges as being concrete structures. Using the criteria specified in the FDOT Structures Design Manual, expressed in SQL queries, 196 and 560 concrete substructures were determined and listed to be in the "Substructure Extremely Aggressive" and Substructure Slightly Aggressive" categories, respectively. Similarly, 145 of the 1943 bridges were identified as steel substructures, with 41 bridges classified as "Substructure Extremely Aggressive" and 10 as "Substructure Slightly Aggressive." According to the criteria, the remaining 1029 concrete substructures and 94 steel substructures under the current evaluation, will be classified in the "Substructure Moderately Aggressive" category.

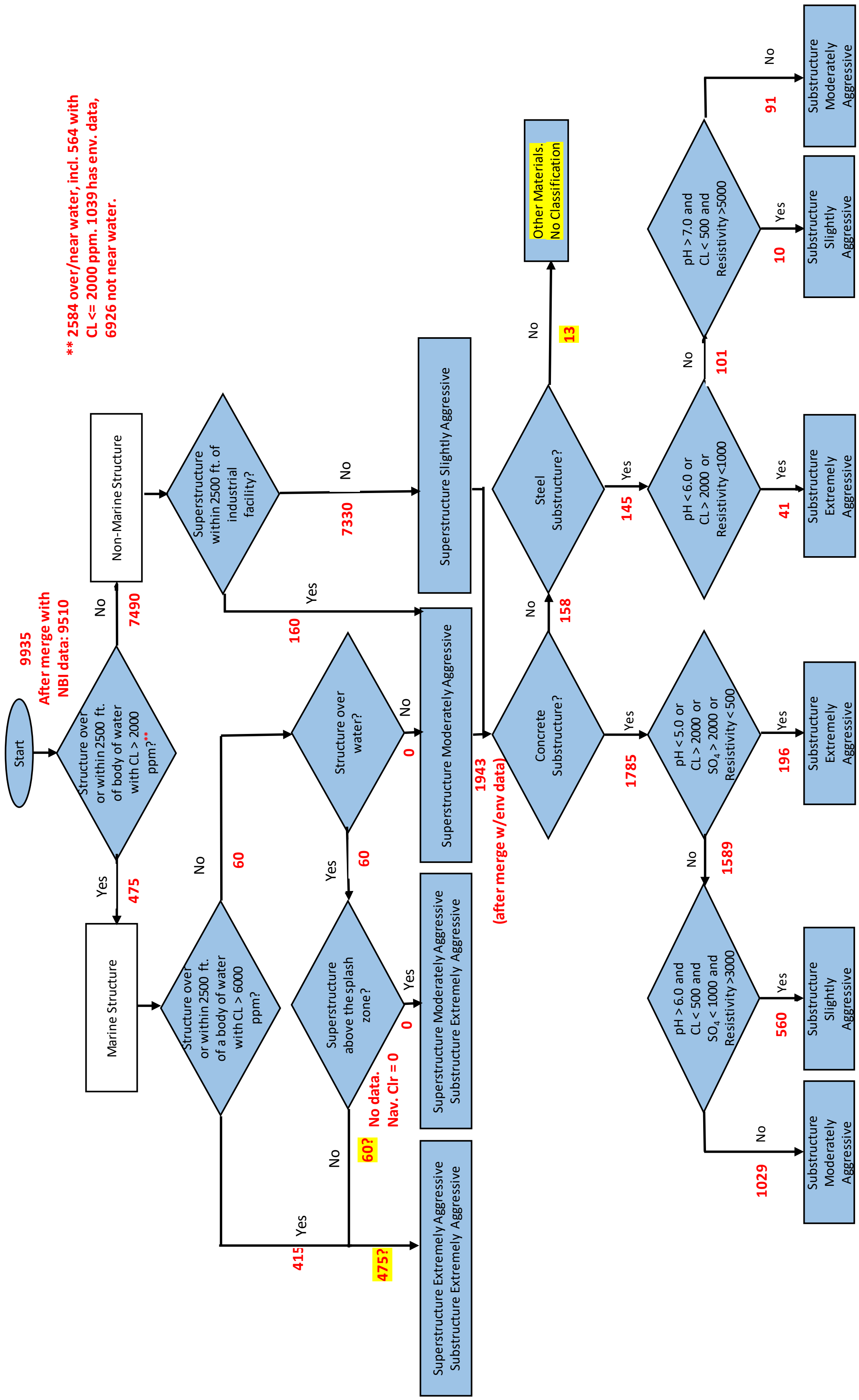


Figure 3.3. Criteria Flowchart for Substructure Environmental Classifications (Adapted and modified from FDOT 2023). (Number of bridge records indicated at each step of the process).

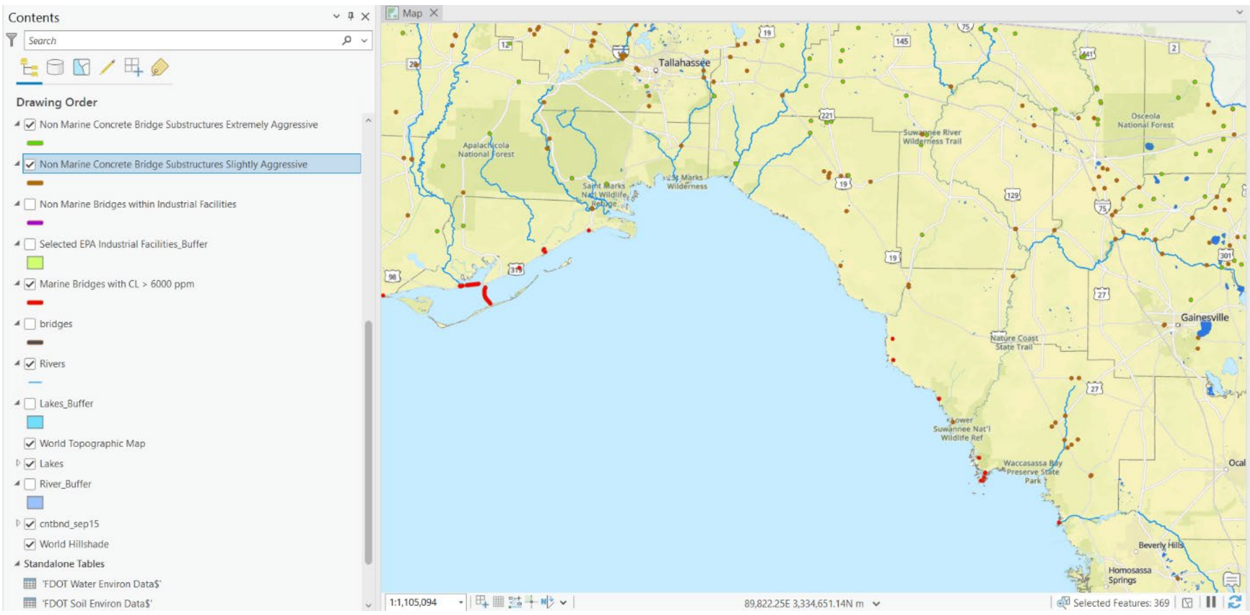
Table 3.3. Information on data and GIS Layers.

Name	Description
Bridges - 2023	Originators: Florida Department of Transportation, Transportation Data & Analytics Office (TDA). Metadata: https://www.fdot.gov/statistics/gis/default.shtm
Rivers - 2015	Originator: National Park Service, US Department of the Interior. Nationwide Rivers Inventory in Florida - November 2015. Metadata: http://www.esri.com/metadata/esriprof80.html.
US EPA Regulated Air Emissions Facilities (ICIS-AIR) in Florida - August 2023	This dataset contains an EPA Facility Registry Service (FRS) subset of facilities that link to the Integrated Compliance Information System for Air (AIR). Additional information on FRS is available at the EPA website https://www.epa.gov/enviro/facility-registry-service-frs.
National Bridge Inventory in Florida - June 2022	This dataset contains a subset of the National Bridge Inventory dataset as of June 15, 2022, from the Federal Highway Administration (FHWA) and is part of the U.S. Department of Transportation (USDOT)/Bureau of Transportation Statistics (BTS) National Transportation Atlas Database (NTAD). The data describes almost 13,000 of the bridges located on public roads, including Interstate Highways, U.S. highways, State and county roads, as well as publicly-accessible bridges on Federal and Tribal lands within the state of Florida. The Coding Guide is available at: https://doi.org/10.21949/1519105.
Florida Roadway Basemap Routes With Measures 2022	Originators: Florida Department of Transportation, Transportation Data & Analytics Office (TDA). The FDOT LRS Routes with Measures feature class is a weekly snapshot of the official FDOT LRS. It provides a spatial representation of roadways in RCI. Metadata: https://www.fdot.gov/statistics/gis/default.shtm.
Lakes Resource in Florida - 2022	This dataset is a polygon feature class representing the Watershed Monitoring Program's Large Lakes (features >= 10 hectares) and Small Lakes (features > 4 hectares and less than 10 hectares) in the State of Florida. Information regarding the lake features in the USGS NHD can be found at https://floridadep.gov/dear/watershed-services-program/content/about-florida-national-hydrography-dataset.
FDOT Environmental Data.	FDOT Materials Office.

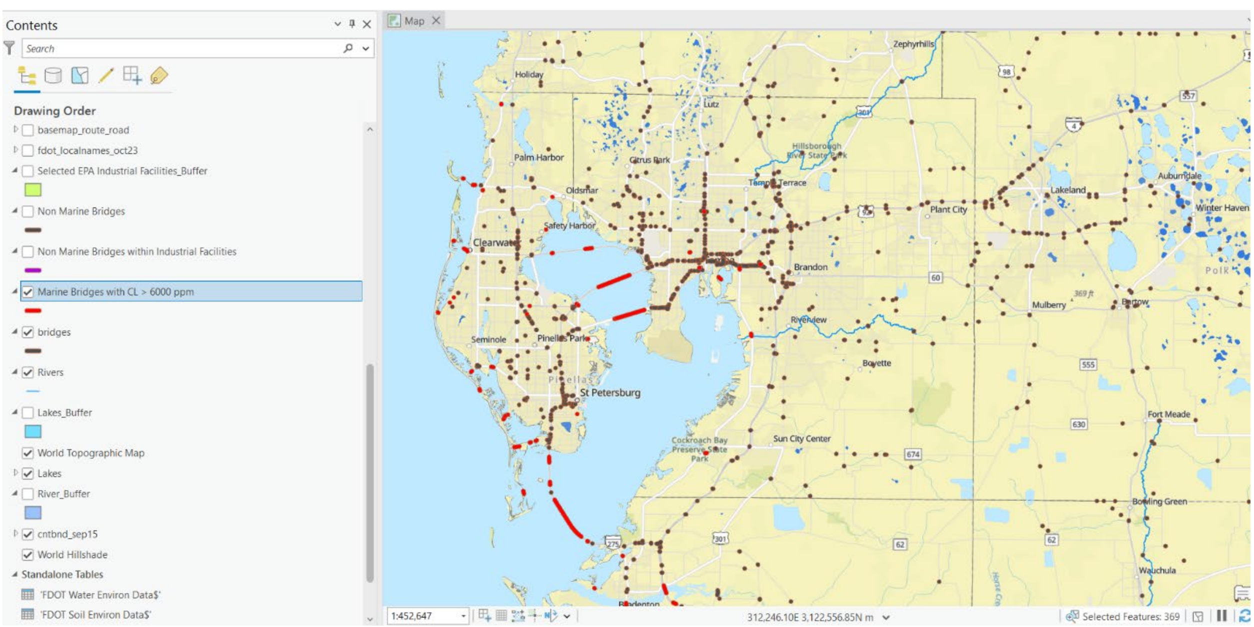
Identifying concrete bridges:
bts_bridge_jun22.STRUCTUR_2 = '1' Or bts_bridge_jun22.STRUCTUR_2 = '2' Or bts_bridge_jun22.STRUCTUR_2 = '5' Or bts_bridge_jun22.STRUCTUR_2 = '6'
Identifying concrete substructures in extremely aggressive environment:
*T_FDOT_Water_Environ_Data$_.pH < **5** Or T_FDOT_Water_Environ_Data$_.Chloride__ppm_ > **2000** Or T_FDOT_Water_Environ_Data$_.Sulfate__ppm_ > **1500** Or T_FDOT_Water_Environ_Data$_.Resistivity__Ohm_cm_ < **500***
Identifying concrete substructures in slightly aggressive environment:
*T_FDOT_Water_Environ_Data$_.pH > **6** And T_FDOT_Water_Environ_Data$_.Chloride__ppm_ < **500** And T_FDOT_Water_Environ_Data$_.Sulfate__ppm_ < **150** And T_FDOT_Water_Environ_Data$_.Resistivity__Ohm_cm_ > **3000***
Identifying steel bridges:
bts_bridge_jun22.STRUCTUR_2 = '3' Or bts_bridge_jun22.STRUCTUR_2 = '4'
Identifying steel substructures in extremely aggressive environment:
*T_FDOT_Water_Environ_Data$_.pH < **6** Or T_FDOT_Water_Environ_Data$_.Chloride__ppm_ > **2000** Or T_FDOT_Water_Environ_Data$_.Resistivity__Ohm_cm_ < **1000***
Identifying steel substructures in slightly aggressive environment:
*T_FDOT_Water_Environ_Data$_.pH > **7** And T_FDOT_Water_Environ_Data$_.Chloride__ppm_ < **500** And T_FDOT_Water_Environ_Data$_.Resistivity__Ohm_cm_ > **5000***

Figure 3.4. Sample queries for bridge data evaluation.

A Microsoft excel spreadsheet has been prepared to store the list of bridges under each of the various environment categories, while sample GIS displays of the bridges are shown in Figure 3.5, for the Florida Panhandle and Tampa Area locations. A partial list of bridges classified as being Superstructure Extremely Aggressive and Substructure Extremely Aggressive, are shown in Appendix Table A1.



a. The Panhandle/Tallahassee area.



b. the Tampa Bay area.

Figure 3.5. GIS display of marine and non-marine bridges.

3.2.4. Formula factors

The agency is allowed to define its own formula for computing an adjustment factor, in addition to the consideration of environmental factors and the use of protective systems. In determining the Formula (adjustment) factor, two types of environments should be considered: local and global environments.

According to Springer (2017), the local environment will include evaluation of the surroundings of the specific element, for example, evaluating bearings, beam ends, and abutments in the presence or absence of deck expansion joints. Local environment also involves consideration of marine environment, overspray (vehicles dispersing contaminated water on roadway to nearby bridge elements), splash/tidal zones, and humidity in case of weathering steel structures (Hartmann 2023). The global environments will include statewide considerations such as climates, coastal location, maintenance practices (e.g., use of deicing salt), posted speed limits, functional class, and high traffic/truck volume).

There seems to be an overlap in the issues considered for the three adjustment factors: environmental factors, formula factor, and protective systems, e.g., salinity in the water, marine environment, and effectiveness of protective systems. While the marine environment is a major criterion for the BrM environment factor, f^E, it is also a variable in determining the local environment factor when computing the Formula factor, f^F. Consideration of protective systems is also technically defined by BrM for the levels of the environmental factor, but it is major criterion for the protective systems factor, $f^{combined}$.

3.2.4.1. Local environment factors

Shown in Figure 3.6 is an illustration from Virginia DOT, of assignment of local environment factors based on the presence or lack of it for deck joints and its potential impacts on the deterioration rates of the underlying parts of the bridge. Based on the definitions stated in the earlier paragraph, the FDOT's list of bridge elements have been assessed and assigned recommended levels of the local environmental factors, considering in addition to deck joints, the marine classification of the element.

a. Bridge with deck joints b. Bridge without deck joint

Figure 3.6. Example assignment of local environment factors from Virginia DOT: 1-Benign; 2-Low; 3-Moderate; and 4-Severe. (Springer 2017).

3.2.4.2. Global environment factors

In many parts of the U.S., particularly, in northeast and upper regions, weather and climate play some role on the rate of bridge deterioration. Constant and extreme cold weather and its required maintenance efforts will influence bridge deck deterioration, and some associated elements such as the joints, and underlying superstructure. In Florida, bridges are not exposed to such an extreme range in weather conditions, but a small narration is presented as follows, regarding the weather environments of bridges in Florida. The analysis of weather distribution in a region over a long period of time defines the climate, with primary consideration of temperature and precipitation. Figure 3.7 shows the Koppen climate classifications for the state of Florida.

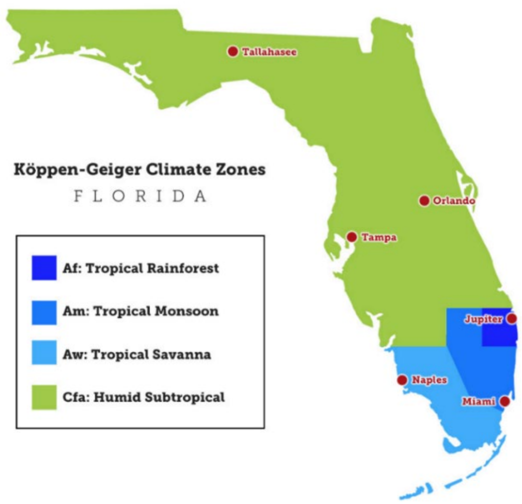


Figure 3.7. Climate zones for Florida (WeatherStem 2023).

The *humid subtropical climate* is described as having warm-to-hot summers with mild winters, with the average temperature of the coldest month below 64 ^{o}F and above 27 ^{o}F. The climate has an average rainfall, and the Florida Panhandle is typically cooler. The *tropical rainforest climate* has average monthly temperatures greater than 64 ^{o}F all year long, with lots of rainfall evenly distributed throughout the year. *The tropical monsoon climate* has an average monthly temperature greater than 64 ^{o}F all year long, with an above-average rainfall, a short dry season, and a pronounced wet season. The *tropical savanna climate* has average monthly temperatures greater than 64 ^{o}F all year long, with less than average rainfall and more than two months in the year have less than 2.4 inches of total rainfall.

While the use of deicing salts on bridges is not prevalent in Florida, the experience of above-average rainfall and humidity may influence deterioration on some types of structures. With a bridge inventory consisting of mostly concrete and steel bridges, it is not deemed critical to consider weather or climate as a factor in the establishment of environments for the bridges in most geographical parts of the state. But for steel and timber bridges located in the tropical rainforest and tropical monsoon areas identified above in Figure 3.7, it may be necessary to study further if the excessive rainfall affects these structures. By superimposing a map layer of Florida counties (Figure 3.10), the areas affected by tropical rainforest and tropical monsoon climates are approximately in the locations of Palm Beach and Broward Counties, and some parts of Hendry County.

Considering extreme cold temperatures, the freeze risk probabilities for the various counties in Florida are shown in Figure 3.8 for temperature 32 °F. These indicate the probabilities of reaching critical temperatures at least once during the winter (AgroClimate 2023). Figure 3.9 also shows the range of temperatures observed in Tallahassee (Panhandle) and Miami (South) during 2022. It is reasonable to assume that the freezing part of Florida consists of the Florida Panhandle, comprising the counties stretching from Escambia to Madison.

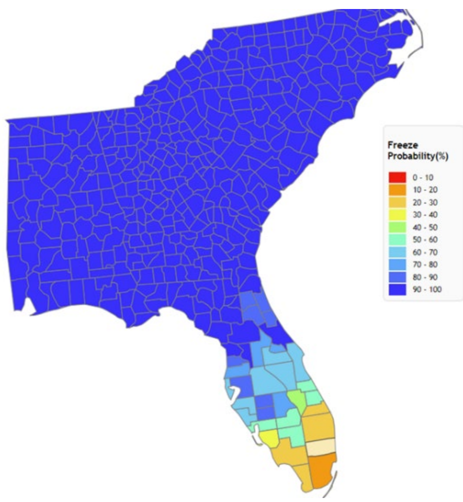
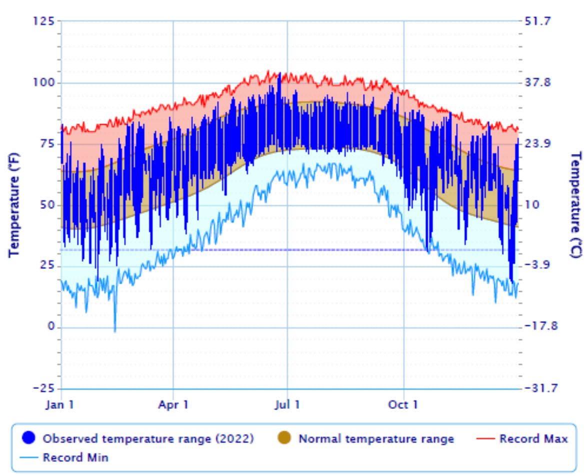
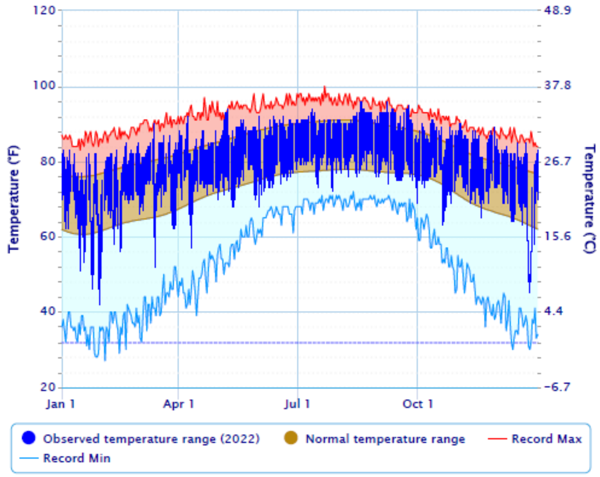


Figure 3.8. Freeze risk probabilities at 32 oF for Florida counties (AgroClimate 2023).



a. Tallahassee



b. Miami

Figure 3.9. Variation in observed temperatures in Florida in 2022 (NOAA 2023).

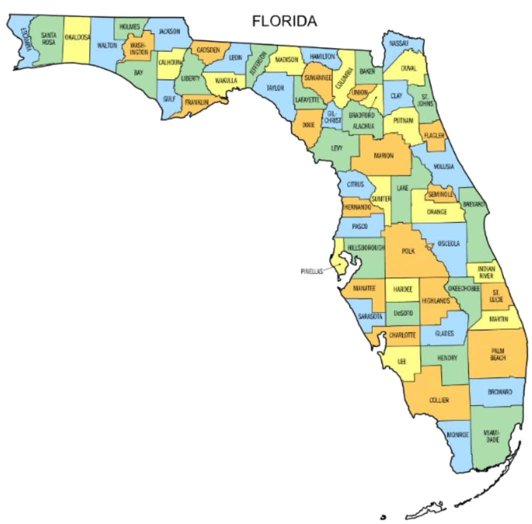


Figure 3.10. Florida county map.

The global environmental environments in Florida were evaluated and four types are recommended: Heavy traffic truck volume (Interstate/Non-interstate); Coastal location (Non-coastal/Riverine-tidal bridges); Freezing location (Non-panhandle/Panhandle bridges); and Heavy rainfall (Southeastern/Non-southeastern Florida bridges). Shown in Table 3.4 are the recommended global environmental factors using the values corresponding to each level, i.e., Benign (2.0); Low (1.5); Moderate (1.0); and Severe (0.7). As noted earlier, FDOT can modify these factor values as found necessary based on the observations of the bridge inspectors.

Table 3.4. Recommended global environmental factors for Florida bridges.

Environment	Factor	Type of bridge	Recommended environment	Recommended factor
Heavy truck traffic	$f^{intertstate}$	Non-interstate bridges	Moderate	**1.0**
		Interstate bridges	Severe	**0.7**
Coastal	$f^{coastal}$	Non-coastal bridges	Moderate	**1.0**
		Coastal bridges(Tidal or Riverine/Tidal)	Severe	**0.7**
Freezing	$f^{freezing}$	Non-panhandle bridges	Moderate	**1.0**
		Panhandle bridges	Severe	**0.7**
Heavy rainfall	$f^{rainfall}$	Southeastern Florida bridges	Moderate	**1.0**
		Non-southeastern Florida bridges	Severe	**0.7**

3.2.4.3 Computing the Formula Factor

In order to incorporate the Formula factor into the overall adjustment factor, there are requirements for weighting parameters to be developed, but there is a lack of data to perform this.

3.2.4.4. Protective systems

The factor associated with the protective systems will be computed based on the elements defined as such in BrM (Table 3.5), as well as any child protective elements that may have been created. The computation of the adjustment factor for the protective systems, $f^{combined}$, is already well established in BrM. Development of protection parameters is documented in the separate section on Markov model estimation.

Table 3.5. Florida BrM's protective elements.

Elem. No.	Elem. Long Name
510	Wearing Surfaces
515	Steel Protective Coating
520	Concrete Reinforcing Steel Protective System
521	Concrete Protective Coating
8516	Painted Steel
8517	Weathering Steel
8518	Galvanized Steel
8519	Other Steel Coatings

3.3. Conclusions

The study has described and implemented a process for establishing the bridge environmental factors for the BrM implementation. Only a few agencies have published their approaches to determining the environmental adjustment factors for BrM implementation, with Virginia DOT having the most extensive description of their ongoing approach. The adjustment factors required in BrM for the environment exposure of bridge elements consist of the environment factor, the formula factor, and the protective systems factor. Starting with and incorporating the FDOT Structures Design Guidelines approach to establishing the bridge environmental factors, this study has developed a detailed modification and implementation of the necessary steps to determine the environmental factors for the Florida bridge superstructures and substructures. The resulting factors can be assigned to the respective bridge elements. The formula factor which gives the agency its option of computing adjustment factor consists of local and global environment factors.

The study has recommended the consideration of deck joints presence and marine classifications as example criteria for assigning local environmental levels and cores. Global environmental factors have also been suggested based on the Florida bridges' exposure to freezing and extreme rainfall. Computation of the formula factor has been demonstrated, and example data are shown. It is suggested that the results provided in this environmental study be considered in re-evaluating the classification of some specific bridges, as detailed data were utilized in arriving at the results shown here. This environmental study did not address non-bridges such as sign structures and light poles, and as well as elements such as decks and movable bridge elements, due to lack of existing guidelines for these types of structures and elements.

Microsoft Excel data of the resulting classification of bridge superstructures and substructures are provided.

3.4. References

Fick, Damon, and Matthew Bell. (2022). Development of Deterioration Curves for Bridge Elements in Montana. Report No. FHWA/MT-22-003/9831-765. Research Programs, Montana Department of Transportation, Helena MT. October. DOI https://doi.org/10.21949/1518322. 56 pp.

FDOT. (2023). Structures Design Guidelines, Structures Manual, Volume 1, January 2023 Version. Florida Department of Transportation (FDOT). Accessed 6/28/2023 from https://www.fdot.gov/structures/structuresmanual/currentrelease/structuresmanual.shtm. 406 pp.

Hartmann, Joseph L. (2023). ACTION: Inspection Finding Follow-up Actions for Uncoated Weathering Steel Bridges, Federal Highway Administration, Office of Bridges and Structures. Memorandum Dated July 19, 2023. Accessed 7/31/2023 from https://www.fhwa.dot.gov/bridge/inspection/Memo_July2023_UWS.cfm.

Nasrollahi, Massoud, and Springer, Todd. (2021). Deterioration modeling for highway bridges in Virginia. Presentation, BrM Users Group Meeting 2021, September. 26 pp. Accessed Nov. 2023 from https://www.aashtowarebridge.com/bridge-management/user-group/presentations/2022-user-group-meeting/.

NJ DOT. (2015). Bridge Element Inspection Manual. Structural Evaluation & Bridge Management, New Jersey Department of Transportation. Revision 1: January 31, 2015, Originally Published May 2, 2014. 446 pp.

ODOT. (2022b). BrM Bridge Inspection Office Manual for Oklahoma Bridges. Oklahoma Department Of Transportation (ODOT), Bridge Division April 2022 Edition. (www.odot.gov). Accessed 7/28/2023 from https://www.odot.org/pontis_files/2022%20BrM%20Bridge%20Insp%20Office%20Manual.pdf. 74 pp.

ODOT. (2022a). BrM Bridge Inspection Field Manual for Oklahoma Bridges. Oklahoma Department Of Transportation (ODOT), Bridge Division April 2022 Edition. Accessed 7/28/2023 from https://www.odot.org/pontis_files/2022%20BrM%20Bridge%20Insp%20Field%20Manual.pdf. 196 pp.

Springer, Todd. (2017). BrM Implementation in VDOT – Deterioration Models – Environments for Joints. 2017 Bridge Management User Group Meeting, September 12, 2017. Accessed 7/24/2023 from https://www.aashtowarebridge.com/bridge-management/user-group/presentations/2017-user-group-meeting/.

Wells, Dixie T. (1994). Environmental classification scheme for Pontis. Report Number : VTRC 94-R20, Virginia Transportation Research Council (VTRC). June. 44 pp. Accessed July 2023 from https://rosap.ntl.bts.gov/view/dot/19359.

4. Review and enhance BrM Risk Models

In order to utilize BrM for risk-based analyses on its bridges, this research task was created to review other state DOTs experience on applying the BrM risk models and enhance the FDOT's models, including establishing necessary methodologies and data to run the model.

The Risk factor associated with a bridge is an important variable in the internal working computation in BrM. Currently, BrM maximizes Total Utility computed based on the multi-objective concept, to evaluate and forecast potential outcomes of bridge decision making. It does this by ranking projects using the change in utility relative to cost. The Total Utility is calculated based on a weighted average of scores on five variables: Condition; Life Cycle Cost; Safety; Mobility; and Risk. While the first four factors are typically obtained from already established data, the Risk factor may need to be configured by the agency to suit the predominant types of risks in their jurisdiction. For example, Alaska configured its system to account for seismic risks and impacts to the fish migrations. Louisiana tried to accommodate exposure to wave actions, while Kentucky included specific types of accidents (sideswipes, running off the road left or right, and side impacts), and Hawaii considered shoreline erosion as a type of risk.

It would therefore be valuable for FDOT to configure its Risk factor input into the BrM Utility. In 2013, FDOT completed a study on using risk models for its BMS, with Pontis being the BMS at the time (Sobanjo and Thompson 2013). The FDOT TAMP's Risk Register also considers some specific types of risks in its computation. Another pertinent research report is the short study titled "Assessing Risk for Bridge Management" that was conducted for the AASHTO Standing Committee on Highways, through the National Cooperative Highway Research Program (NCHRP) Project 20-07, Task 378 (Thompson et al. 2017). Starting with these referenced research methods and documents, important types of risks will be identified, and a methodology will be developed to make the risk data usable in BrM for the Risk factor computation.

The likelihood of extreme events can be geographically related to bridge locations, while the likelihood and consequences of transportation service disruption can be assigned based on specific bridge attributes such as deteriorated condition, vertical underclearance, available detour length, etc. These three factors (extreme event likelihood, likelihood of disruption, and consequence of disruption) with consideration of the relative weights of the structure and hazard scenarios, are used to compute the risk utility (ranging from 0 to 100), as well as the social costs associated with the risk.

4.1. Research framework

The NCHRP BMS Risk Report by Thompson et al. (2017) specifically developed guidelines, on a national scope, for risk models applications in bridge management systems, with references to the BrM software. The proposed risk assessment methodology in this study will consist primarily of three models: *occurrence likelihood, consequence, and performance (social cost/utility) models*. The consequence model can be further broken down into the "physical" or structural damage, likelihood of service disruption, mobility consequence (delay/detour), safety consequence (potential of crashes), and recovery consequence (repair or replacement costs) models.

The NCHRP BMS Risk Report defined two important concepts quoted as follows:

• <u>Hazard scenarios</u>, entail *extreme events of a specific magnitude (if applicable) causing a defined impact on transportation service*. For example, a hurricane of at least magnitude 4 that destroys a bridge.

• <u>Performance criteria</u>, represent agency objectives that may be compromised by a hazard scenario, e.g., *condition*, *cost*, *safety*, *mobility*, and *environmental sustainability*.

An example template, illustrating the hazard scenarios and performance criteria, is shown in Figure 4.1.

NCHRP 20-07 (378) Risk Analysis
Sheet A - Parameters

Hazard scenarios

ID	Class	Weight	Description
1	Eq-100	1.00	100-year earthquake, structure replacement required.
2	Fl-100a	1.00	100-year flood, structure replacement required.
3	Fl-100b	1.00	100-year flood, structure closed for 1 week for monitoring and scour mitigation.
4	Fl-500	1.00	500-year flood, structure replacement required.
5	OH-13.5	1.00	Overheight collision for bridges up to 13.5' clearance, traffic detoured for one day
6	AD-0.9	1.00	Advanced deterioration necessitates permanent load posting at rating factor 0.9 or below.
7	Fracture	1.00	A fracture causes partial failure of a structure, necessitating replacement.
8			
9			
10			

Please specify magnitude, damage severity, and service impact

Performance criteria

ID	Criterion	Weight	Description
1	Cost	1.00	Minimize recovery cost and excess life cycle cost
2	Safety	1.00	Minimize injuries and property damage
3	Mobility	1.00	Minimize excess travel time and vehicle operating cost
4	Environ	1.00	Minimize vehicle emissions and damage to environmental resources

Figure 4.1. Examples of hazard scenarios and performance criteria (Thompson et al. 2017).

Based on the current BMS practice in Florida, relative to the national-wide suggestions in the NCHRP BMS Risk report, the recommended performance criteria for FDOT BMS risks are listed and defined as follows:

Condition/cost: Minimize the reduction in condition and the recovery cost.
Safety: Minimize injuries and property damage due to crashes.
Mobility: Minimize excess travel time and vehicle operating cost.
Environment sustainability: Minimize emissions and damage to the environment.

4.1.1. Estimate of likelihood

In expressing the probability of a hazard scenario occurring in any one year, the total likelihood is defined as a product of two terms: the *likelihood of occurrence* of hazard and the *likelihood of service disruption*. The total likelihood TL_{bh} is defined as

$$TL_{bh} = LE_{bh} * LD_{bh} \qquad (1)$$

where

LE_{bh} = likelihood of occurrence of the extreme event of given magnitude that is specified by hazard scenario *h*, estimated for bridge *b*; and LD_{bh} = likelihood of a specific magnitude of service disruption, conditional on the occurrence of the extreme event specified in hazard scenario *h*, estimated for bridge *b*.

4.1.2. Consequences

Consequences of the hazard scenario, which include the agency cost of disaster recovery, and the economic values assigned to the performance measures, are estimated using economic models and defined as follows:

CQ_{bhc} = consequence, estimated in dollars per disruption event, to performance criterion *c* on bridge *b*, conditional on the occurrence of the service disruption specified in hazard scenario *h*.

In this study, it was noted that FDOT and law enforcement operating policies usually respond to warning of natural hazards typically affecting Florida bridges by closing, restricting, or actively monitoring bridges that may be threatened, so the likelihood of crashes related to bridge damage is kept low. So emphasis will be placed on three performance criteria: *condition/cost*; *mobility*; and *environmental sustainability*.

4.1.2.1. Condition/recovery cost

The NCHRP risk study made a convincing case of placing emphasis on service disruption, instead of the common focus on the functional or physical effects of hazards on bridges (Thompson et al. 2017). But with available data, the degradation in bridge function can effectively portray the impact of the hazard on the bridge. This degradation can quantitatively be assessed through a measure of reduction in the health index or condition ratings of the bridge and its elements. The degradation in condition and an eventual recovery, if done, represent the resilience of the structure.

The impact of hazard in terms of the physical damage (condition) of the bridge can be assessed using the principles of resilience. Resilience has been defined in general terms and also with respect to transportation (Murray-Tuite, 2006 and Mojtahedi et al., 2017). A reasonable start on defining resilience can be found in Bruneau et al. (2003), which is graphically demonstrated in Figure 4.2 for seismic events on an infrastructure. This definition shows a sudden reduction in quality of the infrastructure at a time t_0, to 50% of its initial level, due to an extreme event, accompanied by a recovery trend on the infrastructure, back to the initial quality level (100%) at a time t_1. The resilience is computed as a measure of how far the recovery curve falls below the initial quality level line. The resilience index, measured on a scale of 0 to 1, can simply be defined by equation 2 below.

$$Resilience = \frac{\int_{t_0}^{t_1} Q(t)}{100(t_1 - t_0)} \quad (2)$$

Where *Q(t)* = quality of the infrastructure or level of performance of the system, ranging from 0 to 100; t_0 = starting time of the incident on the infrastructure; and t_1 = the ending time of the incident. But if the initial and desired level of performance is not 100 and say it is a value Q_0, then the equation 2 can be slightly revised to replace the value 100 in the denominator with Q_0.

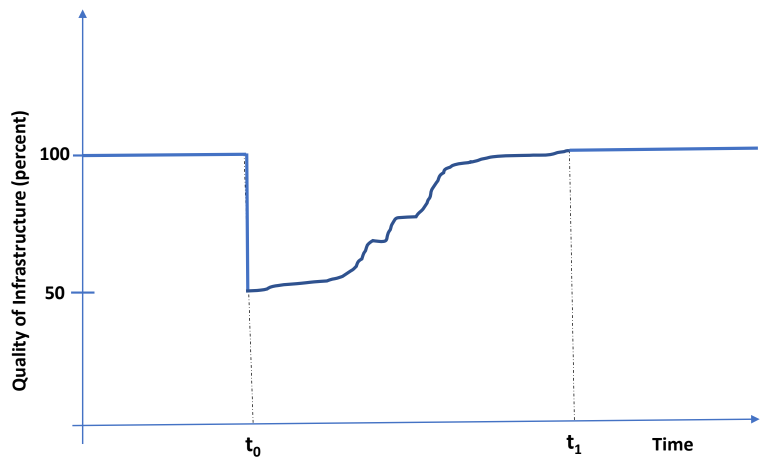


Figure 4.2. Measure of seismic resilience—conceptual definition (Bruneau et al. 2003).

Ayyub (2015), as well as Bruneau and Reinhorn (2007), described the metrics for measuring resiliency in terms of four parameters: robustness, redundancy, resourcefulness, and rapidity to recovery. Robustness is described as the strength, or the ability of elements or system to withstand a given level of stress or demand without suffering degradation or loss of function, and redundancy implies the extent to which elements or systems can be substituted to satisfy the functional requirements. Resourcefulness represents the capacity to provide monetary, physical, technological, resources, etc., necessary to recover. Rapidity means the capacity to recover functionality in a timely manner and avoid further disruption.

The recovery cost of bringing the bridges back to their functional states is also needed for the risk models.

4.1.2.2. Mobility

The most common traffic-related impact of hazards, particularly natural hazards, is the partial or total disabling of the infrastructure for service. For this study, the need to detour was taken as a consequence of the hazard scenario. Therefore, for mobility as a performance measure, the consequence cost CQ_b at each bridge *b*, is estimated from a sum of the associated vehicle operating and the time of travel costs, expressed as follows:

$$CQ_b = ADT_b * \frac{DD_b DL_b}{24} * \left(VOC\$ + \frac{TT\$*VO}{DS_b}\right) \quad (3)$$

Where,

ADT_b = forecast vehicles per day affected; DD_b = the duration of the disruption, in hours; DL_b = the detour length in miles; *VOC$* = the average vehicle operating cost per mile; DS_b = the detour speed in mph; *TT$* = travel time cost per hour; and *VO* = the average vehicle occupancy rate.

The forecast vehicles were derived based on the BrM-recommended approach using equation 4 shown below.

$$ADT_{Yi} = ADT_{Yg} * \frac{ADT_{Yf}}{ADT_{Yg}}^{\left(\frac{Yi-Yg}{Yf-Yg}\right)} \quad (4)$$

Where,

ADT_{Yi} = forecast vehicles per day for desired Year *Yi*; ADT_{Yg} = known vehicles per day for a Year Y_g (in BrM); and ADT_{Yf} = recorded vehicles per day for future Year Y_f (in BrM).

The duration of service disruption was based on observed historical data, where available, for each hazard scenario. Both the detour lengths and detour speeds are available for each bridge in the BrM database. In the case of missing or erroneous data on detour speeds, the default BrM detour speeds were adapted (depending on the functional class) as shown in Table 4.1. A vehicle occupancy of 1.0 was assumed, with the average vehicle operating cost per mile adopted as $0.247, and the travel time cost per hour taken as $36.324; these costs were derived based on the costs in NCHRP risk study (Thompson et al. 2017) and adjusted to current year using inflation factors from the consumer index (BLS 2024).

Table 4.1 BrM's default detour speeds on bridges.

Code	Description	Detour Speed (mph)
1	Rural Principal Arterial - Interstate	50
2	Rural Principal Arterial - Other	45
6	Rural Minor Arterial	40
7	Rural Major Collector	40
8	Rural Minor Collector	20
9	Rural Local	20
11	Urban Principal Arterial - Interstate	45
12	Urban Principal Arterial - Other Freeways or Expressways	40
14	Urban Other Principal Arterial	40
16	Urban Minor Arterial	25
17	Urban Collector	25
19	Urban Local	15

4.1.2.3. Environmental sustainability

One of the national goals of transportation asset management is environmental sustainability, specifically, to "enhance the performance of the transportation system while protecting and enhancing the natural environment." This ongoing FDOT BMS risk study estimated the environmental impact as the automobile emissions costs associated with the excess travel times due to the mobility (disruption) impact of the hazards. The consequence cost, CQ_b at a bridge *b*, for environmental sustainability was derived as shown in equation 5:

$$CQ_b = ADT_b * W_h * \frac{DD_b DL_b}{24} * EC\$ \qquad (5)$$

Where,

ADT_b = forecast vehicles per day affected; DD_b = the duration of the disruption, in hours; DL_b = the detour length in miles; and *EC$* = emission damage cost ($/vehicle-mile).

The emission damage cost was based on emission rates from the NCHRP BMS Risk study which were derived from FHWA data. The rates, adjusted to 2024 values using the consumer price index, are shown in Table 4.2 for the various functional classes and detour speeds.

Table 4.2 Emission damage costs in 2024$ per vehicle-mile (Adapted from Thompson et al. 2017).

	Detour speed (mph)													
	5	10	15	20	25	30	35	40	45	50	55	60	65	70
1 Rural interstate	0.0955	0.0744	0.0650	0.0605	0.0567	0.0567	0.0560	0.0563	0.0574	0.0593	0.0623	0.0667	0.0731	0.0794
2 Rural Principal Arterial	0.0736	0.0518	0.0439	0.0391	0.0367	0.0352	0.0344	0.0350	0.0351	0.0359	0.0374	0.0395	0.0425	0.0453
6 Rural Minor Arterial	0.0734	0.0517	0.0438	0.0390	0.0365	0.0351	0.0343	0.0349	0.0350	0.0358	0.0372	0.0394	0.0422	0.0452
7 Rural Major Collector	0.0670	0.0458	0.0383	0.0342	0.0320	0.0306	0.0299	0.0301	0.0303	0.0307	0.0316	0.0326	0.0342	0.0357
8 Rural Minor Collector	0.0670	0.0458	0.0383	0.0342	0.0320	0.0306	0.0299	0.0301	0.0303	0.0307	0.0316	0.0326	0.0342	0.0357
9 Rural Local	0.0670	0.0458	0.0383	0.0342	0.0320	0.0306	0.0299	0.0301	0.0303	0.0307	0.0316	0.0326	0.0342	0.0357
11 Urban Interstate	0.0593	0.0431	0.0370	0.0349	0.0337	0.0329	0.0325	0.0326	0.0331	0.0339	0.0351	0.0369	0.0395	0.0421
12 Urban Freeways	0.0483	0.0327	0.0275	0.0261	0.0253	0.0247	0.0243	0.0243	0.0246	0.0249	0.0255	0.0262	0.0272	0.0282
14 Urban Principal Arterial	0.0493	0.0339	0.0292	0.0263	0.0247	0.0237	0.0231	0.0233	0.0235	0.0238	0.0244	0.0251	0.0262	0.0274
16 Urban Minor Arterial	0.0490	0.0337	0.0291	0.0262	0.0246	0.0235	0.0230	0.0230	0.0233	0.0236	0.0242	0.0249	0.0260	0.0270
17 Urban Collector	0.0490	0.0337	0.0289	0.0261	0.0244	0.0235	0.0229	0.0230	0.0233	0.0236	0.0241	0.0249	0.0259	0.0269
19 Urban Local	0.0490	0.0337	0.0289	0.0261	0.0244	0.0235	0.0229	0.0230	0.0233	0.0236	0.0241	0.0249	0.0259	0.0269

4.1.3. Performance measures

The final results from the proposed risk methodology are two performance measures, namely, the social cost of risk, and utility.

4.1.3.1. Social cost of risk

The consequence costs computed for the individual bridge under each of the hazard scenarios is a social cost. In this study, this will specifically be the costs of recovery, mobility, and environmental sustainability, respectively, under the each of the three performance criteria. The social cost of risk, RC_b at bridge b, is computed as the weighted sum of the social costs of all hazard scenarios and all performance criteria, expressed as follows:

$$RC_b = \sum_h \sum_c RC_{bhc} \tag{6}$$

Where RC_{bhc} = statistical expected value of weighted social cost, in dollars per year, of hazard scenario h on bridge b for criterion c, i.e.,

$$RC_{bhc} = W_c * W_h * LE_{bh} * LD_{bh} * CQ_{bhc} \tag{7}$$

Where W_c = weight assigned to the performance criteria; W_h = weight assigned to the hazard scenario, with LE_{bh}, LD_{bh}, and CQ_{bhc} as defined earlier.

4.1.3.2. Utility of risk

The utility risk for each bridge is defined based on the computed vulnerability index. First, the unit risk cost URC_b is derived as the same value of the social risk cost over all the performance criteria but normalized to remove the effects of the consequences scale, as shown in equation 8 below.

$$URC_b = \sum_h \sum_c \frac{RC_{bhc}}{SW_{bc}} \tag{8}$$

Where, SW_{bc} is the normalizing factor for each performance criterion is the structure weight, stated as follows:

Cost :	Deck area (sq. ft.)
Safety:	Average daily traffic (ADT)
Mobility:	ADT × Detour length (miles) for both the roadway and the under routes
Environment:	ADT × Detour length (miles) for both on the roadway and the under routes

The unit risk cost is computed for each bridge in the inventory (or a representative set of bridges) and the maximum value is termed *MaxURC* to denote the worst end of the vulnerability scale for the agency. The vulnerability index for the bridge, V_b is calculated using equation 9:

$$V_b = \frac{URC_b}{MaxURC} \quad (9)$$

The risk utility for the bridge, U_b is computed using the vulnerability index, V_b as shown below:

$$U_b = (1 - V_b) * 100 \quad (10)$$

The risk utility serves a uniform unitless scale for comparing the status of one bridge with other bridges, and also directly implementable in AASHTOWare BrM; it is the value computed by the Risk node of the Utility Model, with values ranging from 0 to 100, where 0 is the worst possible performance and 100 is the best possible performance.

4.2. Types of Hazards

The NCHRP BMS risk study suggested the following general list of risks as affecting bridges: earthquakes, landslide, storm surge, high winds, flood, scour, wildfire, extreme temperature, permafrost instability, overloads, over-height collisions, vessel collisions, terrorism/violent extremism, advanced deterioration, and fatigue (Thompson et al. 2017). Based on the predominance of particular natural hazards in Florida, and also due to experience of the research team from the prior FDOT BMS risk study (Sobanjo and Thompson 2013), the emphasis will be on the following natural hazards: hurricane, storm surge, flooding, scour, tornado, and wildfire, while non-natural hazards include over-height collisions, and vessel collisions.

4.2.1. Hazard scenarios

The primary approach is to define hazard scenarios from a combination of the following: hazard magnitude or category (e.g., Hurricane Category I, Tornado Type EF-1, etc.); the defined physical damage on the bridge (e.g., no/slight damage, moderate damage, severe, and complete damage); and the defined mobility impact (low traffic volume detour, medium traffic volume detour, high volume detour, less than 1 day closure, 2-3 days closure, > 3 days closure, etc.). A detailed list of hazard scenarios was first developed but based on the limited hazard data available, the list had to be refined to the list shown in Table 4.3.

Table 4.3 Definition of hazard scenarios for Florida bridges.

Hazard	**Category/Type**	**Condition Damage**	**Mobility Impact: service disruption**	**Hazard scenarios**
Hurricane	Category 1,2 &3	Slight - Moderate	Low/Medium	Hurr-123
	Category 4 & 5	Severe-Complete	High/Very High	Hurr-45
Flood	Category All	Slight-Complete	Low-High	Flood
Scour	Category All	Slight-Complete	Low-High	Scour
Tornado	EF 0 to EF 5	Slight-Severe	Low-High	Tornado
Wildfire	Category All	Slight-Severe	Low/Medium	Wildfire
Over-height collisions	Vertical Underclearance >=13.5 ft.	Slight/Moderate	Medium	OverHT>=13.5
	Vertical Underclearance < 13.5 ft.	Moderate/Severe	Medium/High	OverHT<13.5
Vessel collisions	Navigable waterway: presence of protection systems	Slight-Severe	Low/Medium/ High	Vessel

4.2.2. Likelihood of service disruption

The likelihood of service disruption due to hazards has been modeled based on the deteriorated condition state of the infrastructure (Dehghani et al. 2017, Thompson et al. 2017). It is challenging to find useful quantitative data on the duration of interruptions on the roadways and bridges during hazards, but the Regional Integrated Transportation Information System (RITIS) platform provides good data on such roadway impacts, particularly, for major roadways such as Interstates and state highways (RITIS 2024).

The RITIS is a data archiving and dynamic analytics platform where pertinent transportation data are combined from various agencies and many systems, to enhance effective decision making related to traffic incident response and planning (RITIS 2024). The platform has continuously-captured and maintained data, including but not limited to the traffic volume, speed, class, and occupancy from sensors, as well as information on event, work zone, and incidents on the roadways. RITIS data is focused on major roadways, including interstates and others but not many local roadways. While closures on local roadways are important, generally, the closures on them during natural hazards are typically due to fallen trees (Ghorbanzadeh et al. 2022), and these are not directly attributable to the bridge features.

4.2.3. BrM data processing

The focus of this study was on bridges, not ancillary structures, such as sign structures. Natural hazard inspection data were extracted from the BrM database tables, specifically, from Table *Inspevnt* using the field *insptype* to filter out records with value = *M* defined as “Special - Natural Disaster Damage (flood, storm, etc.).” Similarly, for accident data on truck over-height and vessel collisions, the same BrM table and fields were utilized, but this time, the *insptype* field value was set to *L*, defined as “Special - Accident Damage (traffic).” It was assumed that any bridge inspected for these purposes must have experienced a natural hazard or an accident.

In case of the natural hazards, for records with *insptype* = *M*, hurricane was the hazard mentioned in almost all of the inspection notes reviewed (except one for an EF-2 Tornado on a sign mast in 2023). To extract the pertinent data for each hurricane, the inspection data, sorted by the inspection date for each bridge, were reviewed to identify and make a list of the bridges, which have the *inspdate* or inspection date close to the date recorded for the particular hurricane's landing in Florida. The same list of bridges was used to download the element inspection data. For the *eleminsp* table, the *elem_createdatetime* field was assumed as the inspection date. For the specific analyses on resilience, the hazard inspection records were then studied relative to time (inspection dates), to estimate any drop in the bridge health index, component condition rating (typically for the substructure and channel), or the element health index (typically for approach slab, channels, and abutment slope protection). The profile of the condition relative to inspection dates, considering both before and after the hazard, revealed the element or bridge's resilience.

Regarding the inspection data extracted from accident inspections, a text search filter of the inspection notes was done using terms such as "overheight" or "beam" combined with "collision." The results showed the needed data for truck overheight collisions with the bridges. Similarly, a text search filter of the inspection notes with the keywords {"vessel" or "barge"} with "impact" produced pertinent data for the vessel collision incidents on the bridges.

4.2.4. Formulation of risk models

The development of the various models for this study are presented in the following sections 4.3 to 4.9 of this chapter for each type of the seven hazard scenarios, with the structure and format shown below:

a. Estimate of likelihood: (a) Likelihood of occurrence; (b) Likelihood of service disruption; and (c) Total likelihood of hazard scenario
a. Consequence: (a) Condition (Physical damage) and recovery cost; (b) Safety; (c) Mobility; and (d) Environmental sustainability.

Section 4.10 of the chapter will discuss and summarize the performance measures in terms of the social cost and utility of risk, while the conclusions are presented in the final section 4.11.

4.3. Hurricane

4.3.1. Estimate of likelihood

4.3.1.1. Likelihood of occurrence

Geographic Information System (GIS) spatial analyses were done based on an overlay of the basemap layer of roadways and bridges in the Florida Inventory, on GIS layers of recent hurricane paths that were observed in Florida (nine hurricanes as listed in Table 4.4). Two approaches were taken in estimating the annual frequency of occurrence: first, by calculating the time interval between occurrence at each specific bridge; and second, by using the count of occurrences within the data range.

Table 4.4 Recent hurricanes observed in Florida.

Year	Landing Date	Hurricane/Storm	Category
2016	09/02/2016	Hermine	1
2016	10/7/2016	Mathew	2
2017	09/10/2017	Irma	4
2018	10/10/2018	Michael	5
2019	09/05/2019	Dorian	2
2020	09/12/2020	Sally/Tropical Storm	2
2022	09/28/2022	Ian	4
2022	11/10/2022	Nicole	1
2023	08/30/2023	Idalia	3

Using the data from the National Hurricane Center (NHC) (NOAA 2024), the results of the spatial analyses are presented in the following sections. The primary interest in the study is identifying those bridges that were in the path of each hurricane event. The relative intensity within each hurricane path is also represented by the wind swath, which refers to the area or “wind radii” over which speeds of a certain intensity are observed or predicted to occur due to a tropical cyclone or hurricane. The National Hurricane Center (NHC) uses wind swaths to communicate the geographical extent of various wind speed thresholds. The wind swath is a forecast of storm track and extents of winds of three categories: 34 knots, tropical storm force (39-57 mph), 50 knots, storm force winds (58-73 mph); and 64 knots, hurricane force winds (74 mph or higher) (Figure 4.3).

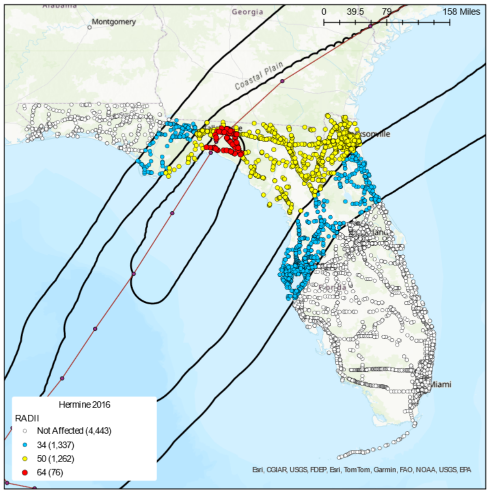
It is very challenging to make a highly accurate prediction of hurricane occurrence at a location based on historical data, as the pattern of hurricane tracks vary much over the years. For this study the 50 knots category described above was used to estimate probability of hurricane categories 1, 2, and 3, while the 64 knots paths were used to estimate the probabilities for hurricane categories 4 and 5. Many studies have adopted such approaches, but the reality is that the track of hurricanes can only be more accurately estimated once the storm is about to make a landfall, or actually make a landfall. The focus was on state-maintained bridges, with the estimates summarized as shown in Figure 4.4. Since hurricanes have typically moved along varied paths in Florida, all the bridges were assigned a minimum probability value of 0.01, even if the historical path did not indicate any experience. Also as expected, Figure 4.4 shows that the higher categories of hurricanes, being a rarer event, will have lower probabilities of occurrence, relative to those of the lower categories 1, 2, and 3 of hurricanes.

4.3.1. 2. Likelihood of service disruption

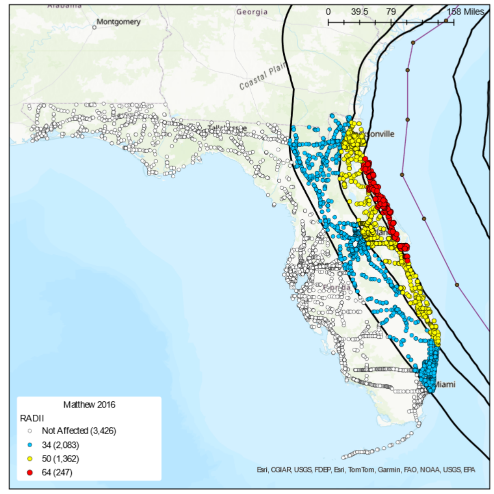
As discussed earlier, the RITIS incident data was analyzed to estimate documented durations of roadway closures during the hazard. The incident times at known bridge locations were related to the inventory of bridges to estimate the likelihood of service disruption. It is challenging to estimate this likelihood, but some assumptions were made. There were 94 bridges that could be identified as being impacted by seven of the nine recent hurricanes, as indicated later in the report in Table 4.12; two hurricanes did not have data available. This information does not explicitly indicate the severity of the impact on the traffic but mentions if and where lanes are closed during the incident duration. It can be assumed for this study that by taking total the number of bridges affected (94) relative to the bridge inventory (~7000) can provide a rough estimate of the likelihood of service disruption. By using the data for one specific hurricane that had the most indicated incidents (Irma), this estimate can be enhanced by the fact that six of the 40 incidents were located on the Interstate and 34 were on non-interstate roadways. This gives an estimate of (94/7000)*(6/40) or 0.0020 for interstate bridges and ((94/7000)*(34/40) or 0.0114 for non-interstate roadway bridges. These rough estimates will serve as the likelihoods of service disruption for the respective types of roadways.

4.3.1.3. Total likelihood of hazard scenario

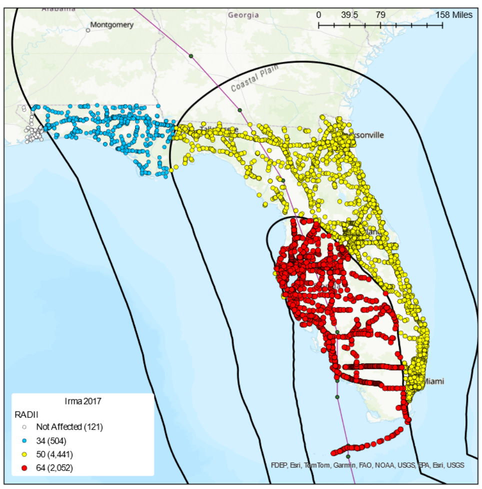
For each hazard scenario, the total likelihood is a product of the likelihood of occurrence and the likelihood of service disruption. This parameter was calculated at each bridge location and utilized later to compute the consequences.



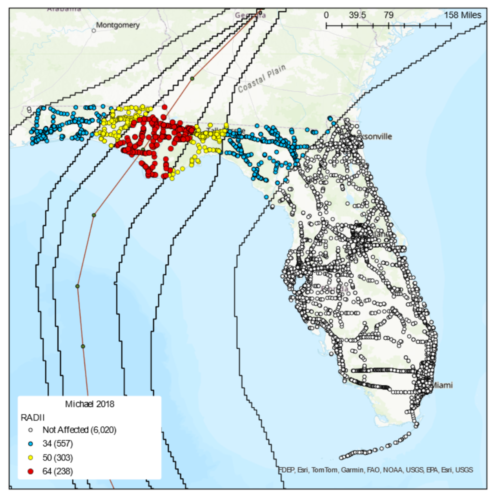
a. Hermine (2016)



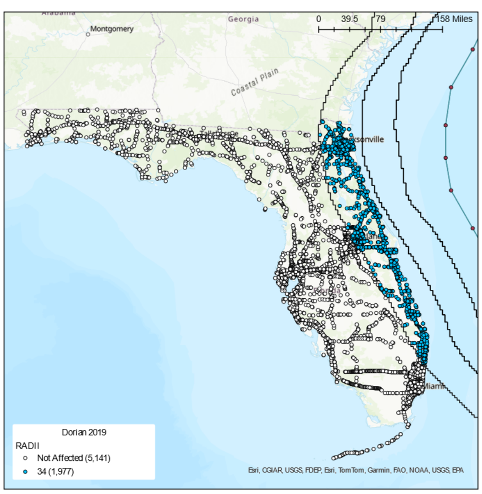
b. Matthew (2016)



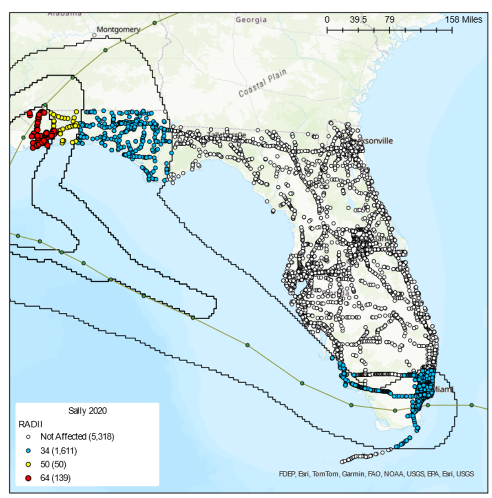
c. Irma (2017)



d. Michael (2018)

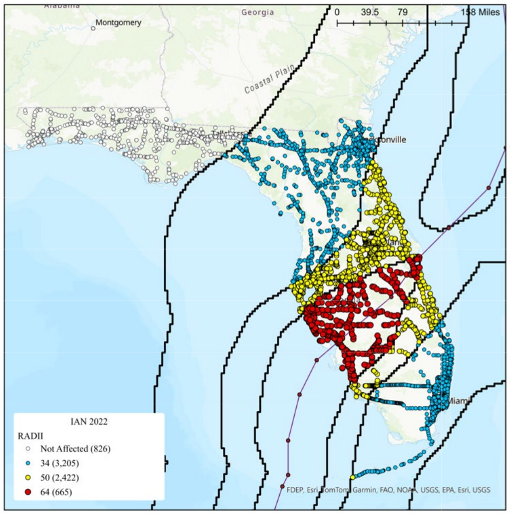


e. Dorian (2019)

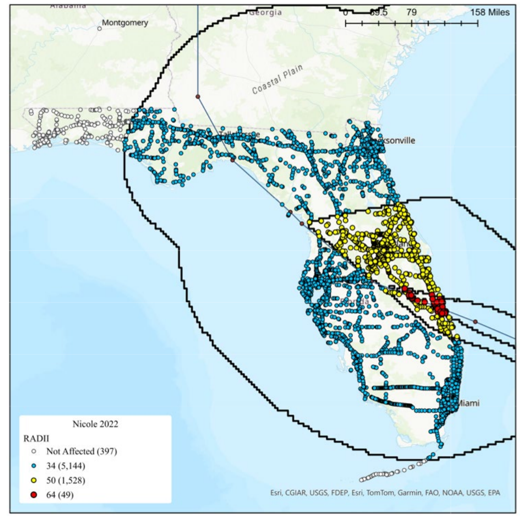


f. Sally (2020)

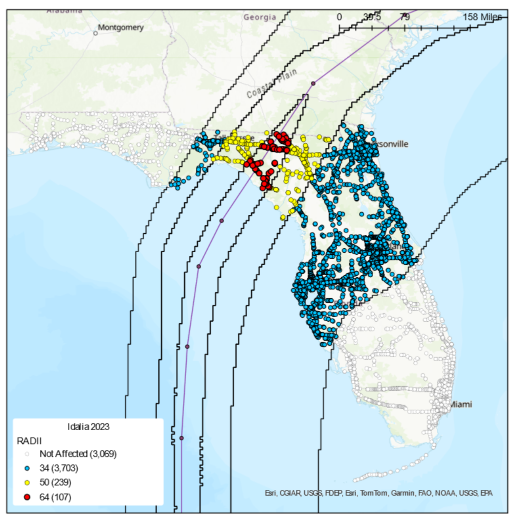
Figure 4.3. Location of Florida bridges relative to the path of hurricanes.



a. Ian (2022)



b. Nicole (2022)



c. Idalia (2022)

Figure 4.3. Location of Florida bridges relative to the path of hurricanes (Cont'd)

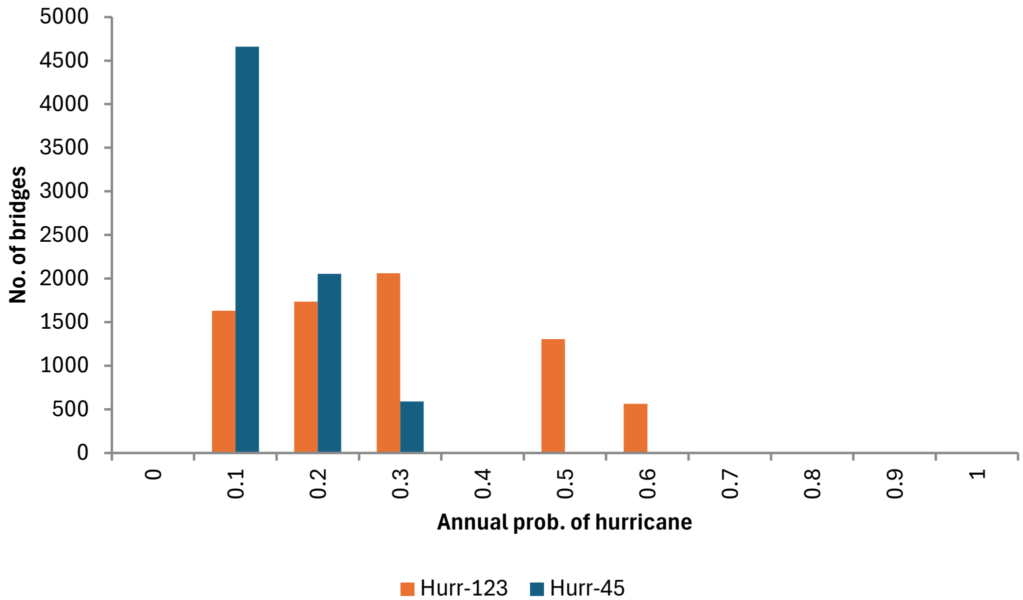


Figure 4.4. Estimated annual hurricane probabilities for Florida's state-maintained bridges.

4.3.2. Consequence

4.3.2.1. Condition

While the new proposed methodology for risk assessment focuses primarily on service disruption, it would be beneficial to also consider the condition of the bridges, in terms of physical damages. Based on the prior FDOT BMS risk study using nine hurricane events data, the following elements were considered most vulnerable (average number affected per hurricane event): channel and scour (21.8), abutment slope protection (5.3), approach slab (2.4), fender and dolphin (1.9), columns and piles (1.4), wingwall, retaining wall, and MSE walls (1.32), railing (1.2), and decks and walls (0.9) (Sobanjo and Thompson 2013). The 2013 FDOT BMS risk study also established a scheme for classifying the levels of damage to structures due to hurricanes. Most of the damages were classified as slight or moderate, except for the damage by Hurricane Ivan to the I-10 Escambia bridges which was considered a Complete damage. Hurricane Ivan was a Category 5 on the waters but landed as a Category 3 on September 2004, just west of Gulf Shores, Alabama. It should be noted that non-state-maintained bridges were not included in the 2013 risk study.

4.3.2.1.2. Resilience

Based on the bridge hazard inspection records for the related hurricane events, bridge and element condition data were analyzed to identify for each bridge inspected, the drop, if any in the Bridge Health Index (HI), channel condition rating, and substructure condition rating, as these three parameters were the metrics typically directly related to the physical damage during hurricanes. Similarly, the Element Health Index (EHI) of the following bridge elements were considered: approach slab, channel, and abutment slope protection. Two of the resilience metrics mentioned earlier in section 3 (robustness and rapidity) were noted, in addition to a new metric defined in this study as inspection response, which was calculated as the time interval between the hazard occurrence date and the inspection date of the bridge or element. Robustness is the degradation in condition, expressed as the drop in health index or condition rating, specifically, the ratio of the degraded index to the original index. Rapidity is the time it takes the bridge or element to the restored to a condition level which is at least as good as the original condition. The resilience index is computed based on the concept illustrated in equation 2 and Figure 4.2, but with a simplified geometry.

The following Figures 4.5 to 4.7 demonstrate the application of resilience on three county-maintained bridges damaged during Hurricane Irma. First, Figure 4.5 shows the degradation in condition for the two bridges; while Bridge 390023 was repaired relatively quickly, even to a better condition, Bridge 710045 was repaired to about the same condition, but it took a longer time. Figures 4.6 and 4.7 show the computation of a resilience index for Bridge 390023 and another Bridge 044012 based on the channel condition rating. Two assumptions should be noted here: the calculated index assumes the condition of the bridge or element to be same from the last inspection date to the hazard occurrence date, and the recovery time was assumed to occur at the noted inspection date when the condition was observed to be back to the original condition or better. In each case shown here, the resilience index is the ratio of the areas above the recovery line segments to the area of the rectangle representing the recovery period and the condition of the bridge or element (equation 2).

For Bridge 390023, the resilience metrics based on the HI, were estimated as Resilience Index of 97% (Area ABCD/Area AEFD), Robustness of 93% (AB/AE), Rapidity of 583 days (EF), and Inspection Response of 30 days (time from Hurricane Irma on 9/10/2017 to the hazard inspection date of 10/10/2017). For Bridge 044012, using the channel condition rating, resilience metrics were computed as Resilience Index of 84%, Robustness of 71%, Rapidity of 1233 days, and Inspection Response of 30 days.

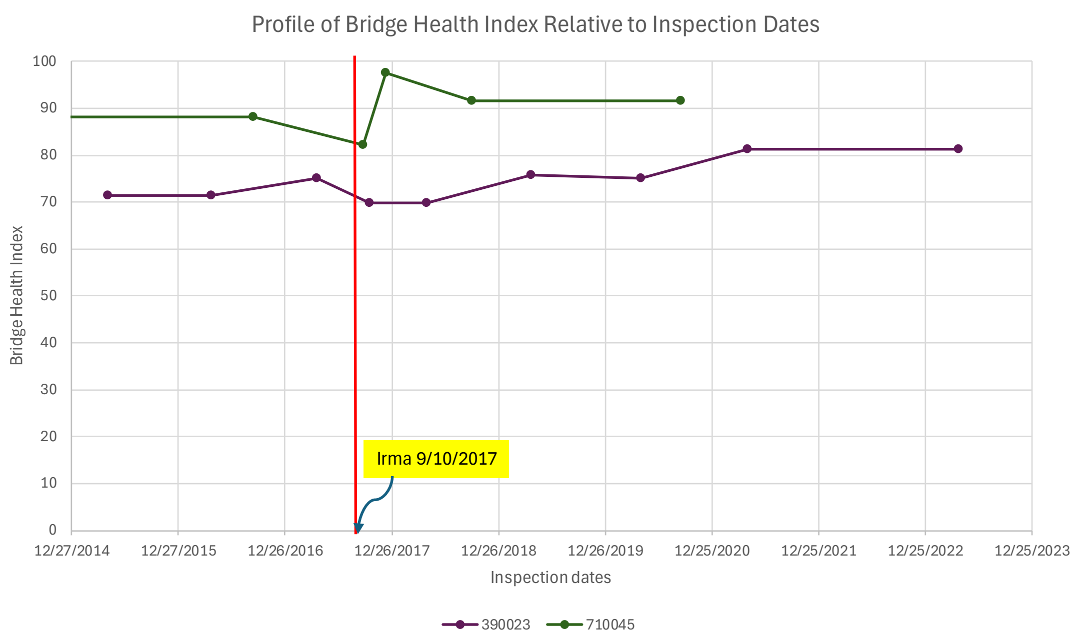


Figure 4.5. Bridge Health Index’s variation with time.

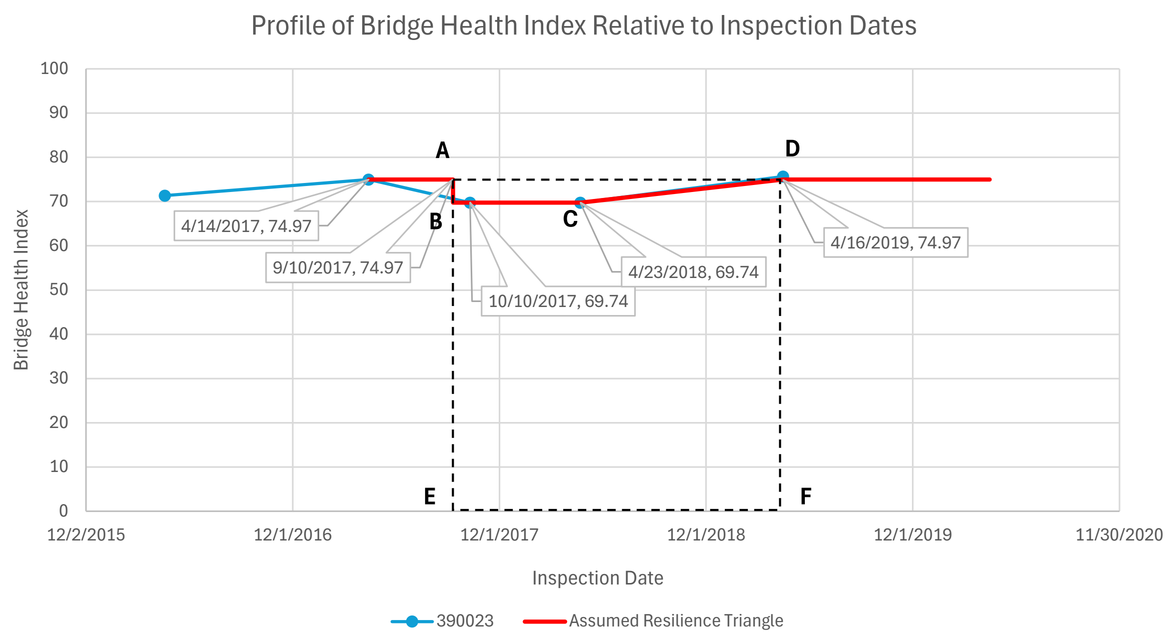


Figure 4.6. Bridge Health Index used in computing the resilience index.

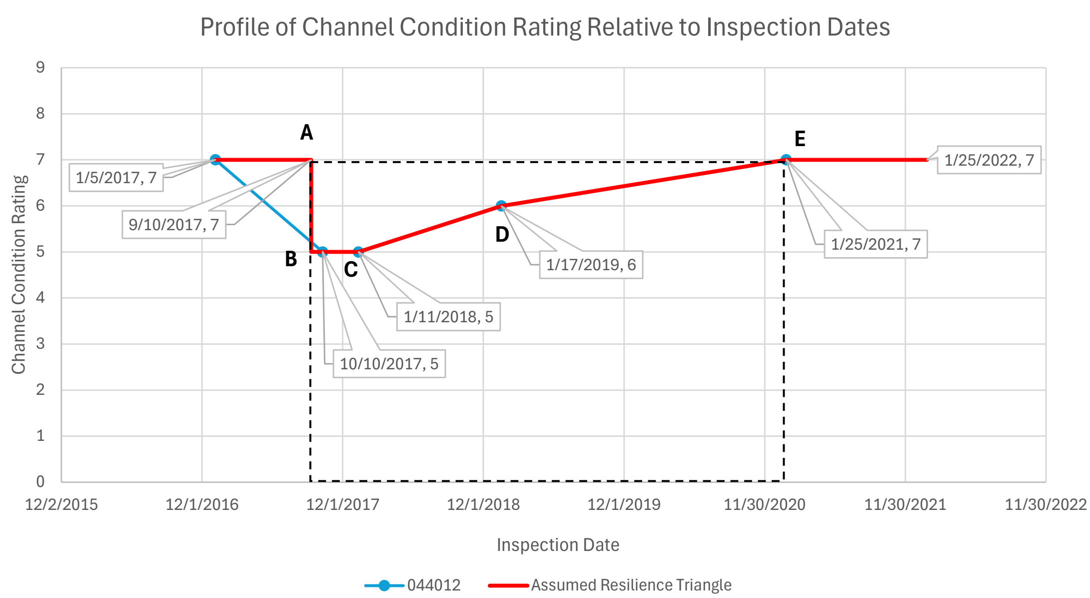


Figure 4.7. Channel Condition Rating used in computing the resilience index.

Tables 4.5 to 4.10 summarize the observations from the inspection data on how the bridges performed during the indicated hurricane hazard, in terms of the degradation in condition and resilience. An indicator of resilience (Y) in the table implies that according to the inspection data, the bridge or its indicated element was eventually restored to a condition that was at least as good as it was before the hurricane. For Hurricane Irma, Table 4.5 shows that 10 (45.5%) of the 22 county-maintained bridges (owner code = 2) inspected had BHI degradation, and of these 10 damaged bridges, three (30%) were restored to their original or better condition. During the same hurricane, using channel condition rating as a measure, 54.5

% showed degradation while 50% reflected resilience. But with substructure condition rating, only 2 or 9.1% of the bridges showed degradation with both bridges demonstrating resilience. Similar summaries can be made for the other hurricane events as shown in these tables. It can be noticed that except for Hurricanes Matthew, Ian, and Nicole, state-maintained bridges (owner code = 1) are not shown as sustaining damages. For Hurricane Mathew, the four state bridges damaged (BHI reduction) were all restored to their original condition. As noted for some hurricane events the unavailability of inspection data immediately prior to and after the hazard will make it impossible to properly assess the resilience performance. BrM data are not available prior to Hurricane Matthew, and adequate recent inspection data (latest is 2022 data) is also not available for Hurricanes Ian and Nicole. This may have affected the numbers indicated for these three hurricanes.

Table 4.11 shows for five bridges, the results of the four resilience metrics discussed earlier, which can be used to assess the bridge inventory's response to hazards, in terms of resilience. Ideally, the metrics will be based on the degradation of the BHI with time, but element and component condition measures can also be utilized. The four metrics are defined again as follows: *Resilience* -- computed based on the resilience triangle; *Robustness* -- ratio of residual condition index/rating to original value before hazard; *Rapidity* -- duration of time after hazard that condition was restored to original index/rating or better; and *InspResponse* -- time between hazard occurrence and inspection date. Overall, summarizing the results from the bridges as shown in Tables 4.5 to 4.10, will inform the agency on the bridge inventory's performance in response to the hazard, while computing metrics such as shown in Table 4.11 will provide valuable information on the individual bridge's resilience performance. The measure of resilience also evaluates the benefit of repairs and improvements that increase resilience.

4.3.2.1.3. Recovery costs

The annual recovery costs were determined based on the replacement unit costs of National Highway System (NHS) bridges indicated as $315/SF (FHWA 2024) while the major repairs were assumed to cost $150/SF. Damages to bridges during hurricane categories 4 and 5 were assumed to need replacement, while those damaged during hurricane categories 1, 2 and 3 were assumed to need major repairs. Applied to the state-maintained bridge inventory in Florida, the expected annual risk costs of recovery are summarized in Figure 4.8. About 50% of bridges under the first hazard scenario have expected risk costs greater than $500 while those under the second scenario have about 30%. While the recovery cost may be higher for the hurricane categories 4 and 5, the probabilities and likelihood of disruption are lower, so this may explain the results.

Table 4.5. Observed bridge condition data for Hurricane Irma (Cat 4 on 9/10/2017).

Bridge Owner	BRKEY (Inspected bridges)	Drop in Health Index	Resilience?	Drop in Channel Condition Rating	Resilience?	Drop in Substructure Condition Rating	Resilience?
2	40022			-1			
2	40025			-1			
2	44010			-2			
2	44012	-8.34		-2	Y		
2	44014						
2	44032	-0.05		-1	Y		
2	44033	-0.09	Y	-2	Y		
2	44039						
2	44040	-0.05		-1			
2	90007	-0.01		-1	Y		
2	94010	-0.53					
2	94044	-0.04		-1	Y		
2	390007						
2	390023	-5.23	Y	-2			
2	704144	-0.01		-4		-6	Y
2	710045	-5.94	Y	-6	Y	-5	Y
2	784010						
2	784026						
2	784040						
2	784043						
2	784051						
2	784075						
1	860001						
1	860011						
1	860060						
1	860466						
1	860467						
1	860619						
1	890138						
1	930004						
1	930005						
1	930060						
1	930064						
1	930106						
1	930154						
1	930226						
1	930349						
1	940001						
1	940045						
1	940079						
1	940094						
Count	41	10	3	12	6	2	2

Table 4.6. Observed bridge condition data for Hurricane Matthew* (Cat 2 on 10/7/2016).

Bridge Owner	BRKEY (Inspected bridges)	Drop in Health Index	Resilience?	Drop in Channel Condition Rating	Resilience?	Drop in Substructure Condition Rating	Resilience?
1	110063						
1	700030						
1	700031	-2.07	Y				
1	700117	-1.01	Y				
2	704048	-0.01	Y	-1			
1	860001						
1	860011	-1.61	Y				
1	860060						
1	860466						
1	860467						
1	890138						
1	930005	-1.01	Y				
1	930060						
1	930064						
2	930097						
1	930106						
1	930154						
1	930157						
1	930226						
1	930349						
1	940001						
1	940045						
1	940079						
1	940094						
Count	24	5	5	1	0		

*Limited data: BrM element inspection records started Dec. 2016.

Table 4.7. Observed bridge condition data for Hurricane Ian* (Cat 4 on 09/28/2022).

Bridge Owner	BRKEY (Inspected bridges)	Drop in Health Index	Resilience?	Drop in Channel Condition Rating	Resilience?	Drop in Substructure Condition Rating	Resilience?
2	120022	-3.99		-1			
2	120026	-1.87					
2	120028	-2.55	Y	-1	Y		
2	120055	-6.94					
Count	4	4	1	2	1		

*Limited data: recent BrM element inspection records not available.

Table 4.8. Observed bridge condition data for Hurricane Nicole* (Cat 1 on 11/10/2022).

Bridge Owner	BRKEY (Inspected bridges)	Drop in Health Index	Resilience?	Drop in Channel Condition Rating	Resilience?	Drop in Substructure Condition Rating	Resilience?
1	700028	-0.22					
1	700110	-0.72					
1	700114	-0.08					
1	700115	-0.02					
Count	4	4	0				

*Limited data: recent BrM element inspection records are not available.

Table 4.9. Observed bridge condition data for Hurricane Sally (Cat 2 on 09/12/2020).

Bridge Owner	BRKEY (Inspected bridges)	Drop in Health Index	Resilience?	Drop in Channel Condition Rating	Resilience?	Drop in Substructure Condition Rating	Resilience?
2	464423	-1.11				-3	
32	480123	-4.74	Y			-1	
32	480139	-0.41				-1	
2	524100	-33.96	Y				
2	524139	-0.10	Y	-4	Y		
2	524150	-29.43	Y				
2	524153						
2	524164	-0.07	Y	-2		-3	
2	524167	-26.30	Y				
2	524178	-10.19	Y	-3	Y	-4	Y
2	524182	-21.10				-5	Y
2	524194	-0.17		-1			
2	524195						
2	524196	-9.88	Y				
2	524218	-0.32	Y				
2	524224						
2	534162						
2	534182	-39.37	Y				
11	570802	-44.52	Y			-6	Y
2	584128	-0.08	Y				
2	604152	-0.06	Y	-1		-2	
2	614142	-2.78	Y			-3	Y
Count	22	18	14	5	2	9	4

Table 4.10. Observed bridge element condition data for Hurricane Sally (Cat 2 on 09/12/2020).

Bridge Owner	**BRKEY (Inspected bridges)**	**Drop in Element Health Index**	**Resilience?**	Owner	**BRKEY (Inspected bridges)**	**Drop in Element Health Index**	**Resilience?**
	Approach slab				**Timber abutment slope**		
32	480123	-40.01	Y	2	464423		
32	480139	-30.03	Y	2	524100		
2	604152	-3.09	Y	2	524139		
	Channel			2	524150		
2	464423			2	524153		
32	480123			2	524164		
32	480139			2	524167		
2	524100			2	524182		
2	524139	-33.00	Y	2	524194	-3.35	
2	524150			2	524195		
2	524153			2	524196		
2	524164	-33.00		2	524218		
2	524167			2	524224		
2	524178	-33.00	Y	2	534162		
2	524182			2	534182		
2	524194				**Other abutment slope**		
2	524195			32	480123	-76.88	Y
2	524196			32	480139	-13.00	Y
2	524218			2	524150		
2	524224			2	524182		
2	534162			2	524194		
2	534182			2	524196		
11	570802			2	534162		
2	584128			2	534182		
2	604152			2	604152		
2	614142						

Table 4.11. Resilience metrics* for sample bridges during Hurricane Irma.

BridgeID	Measure	Resilience	Robustness	Rapidity (Days)	InspResponse (Days)
044033	Bridge Health Index (BHI)	100%	100%	225	33
390023	Bridge Health Index (BHI)	97%	93%	583	30
044012	Channel Condition Rating	84%	71%	1233	30
710045	Bridge Health Index (BHI)	97%	93%	87	9
710045	Channel Condition Rating	57%	14%	87	9

** Resilience: Computed based on the resilience triangle; Robustness: Ratio of residual condition index/rating to original value before hazard; Rapidity: Duration of time after hazard that condition was restored to original index/rating or better; and InspResponse: Time between hazard occurrence and inspection date.*

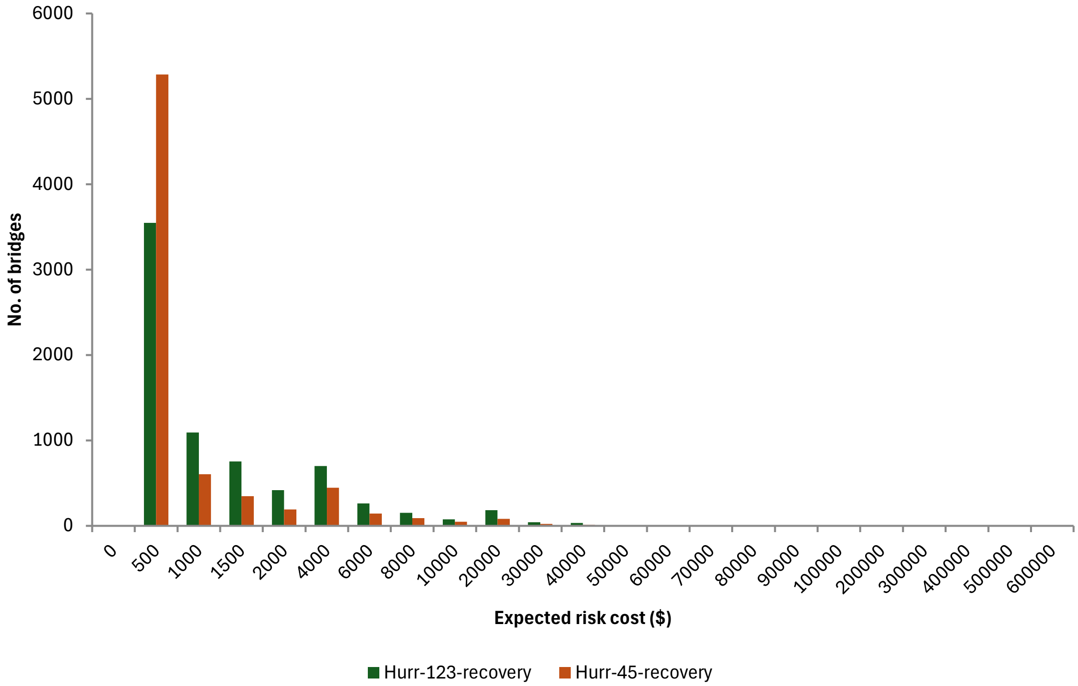


Figure 4.8. Annual recovery costs for hurricane hazard scenarios on Florida state-maintained bridges.

4.3.2.2. Safety

Hurricanes are typically not associated with safety issues of vehicular crashes on bridges since there is advance warning and operational procedures are in place to ensure safety, even if it means restricting or actively monitoring a threatened bridge. Safety-related consequences are therefore omitted in this study.

4.3.2.3. Mobility

As discussed earlier, the RITIS data was utilized to estimate incident clearance times as recorded on major roadways in Florida. This data is useful towards estimating the consequences in terms of the duration of service disruption, summarized in Table 4.12 and illustrated in Figures 4.9 and 4.10.

Pairwise correlation analyses were conducted using all the bridge duration data, relating the incident durations to pertinent bridge attributes such as the roadway's functional class, Average Daily Traffic (ADT), deck condition rating, channel condition rating, and water way adequacy. But the results of the analyses did not yield any significant coefficients. However, using only the bridge incident duration data for Hurricane Matthew (15 incidents with bridges identified), a reasonable negative correlation (-0.50) was observed between the duration and waterway adequacy, plotted as shown in Figure 4.11. It should be noted that the data size is too small to make a significant inference on this. So, waterway adequacy cannot be used as a criterion for the likelihood of roadway closure.

As shown in the Table 4.12, Figure 4.9 and Figure 4.10, the estimates from observed data on hurricane-related incident durations on the bridges on Florida major roadways are low. Based on the data summarized on Table 4. 12, the mean of incident durations on Hurricane categories 1, 2 and 3 was assumed in the consequences model as 1 day, while those on categories 4 and 5 have a duration of 5 days.

Table 4.12. Hurricane-related incident durations on Florida major roadway bridges.

Hurricane	Category	Count of Incidents	Mean Duration (Hours)	Mean Duration (Days)	Min Duration (Hours)	Max Duration (Hours)	Max Duration (Days)
Hermine	1	8	4.49	0.19	0.01	31.44	1.31
Matthew	2	25	20.38	0.85	0.02	35.60	1.48
Irma (All)	4	40	21.47	0.89	1.18	39.85	1.66
Irma: Interstate	4	6	17.66	0.74	9.03	28.7	1.20
Irma: Non-Interstate	4	34	22.15	0.92	1.18	39.85	1.66
Idalia	3	4	1.14	0.05	0.04	3.28	0.14
Ian	4	11	463.00	19.29	5.00	1975.48	82.31
Michael	5	5	25.29	1.05	6.83	45.90	1.91
Dorian	2	1	5.75	0.24	5.75	5.75	0.24
All		94	70.57	2.94	0.01	1975.48	82.31
All**		32	22.66	0.94	1.18	45.90	1.91
Cat 1,2, and 3		38	14.62	0.61	0.01	35.60	1.48
Cat 4 and 5		56	108.54	4.52	2.44	420.60	17.53

*Median for All = 21.1 hrs. (1 day);** Data with at least one lane closed.*

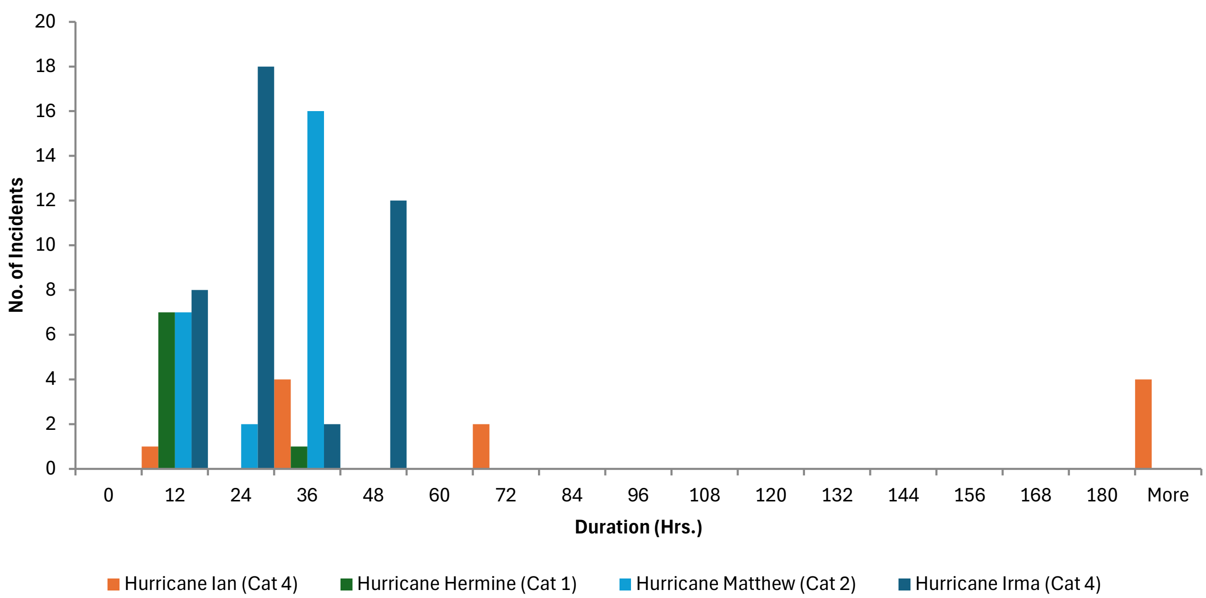


Figure 4.9. Incident durations for four hurricanes on Florida roadway bridges.

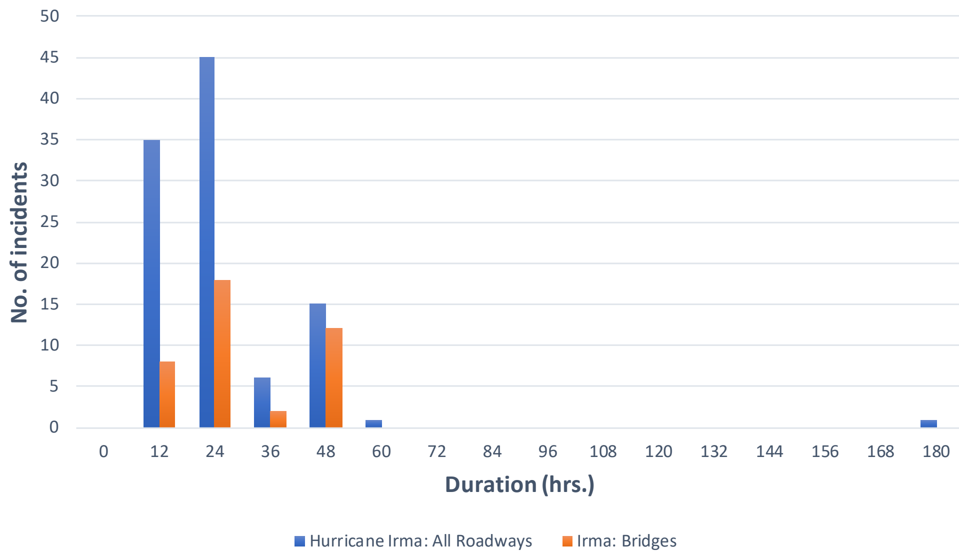


Figure 4.10. Roadway and bridge incident durations for Hurricane Irma on Florida major roadways.

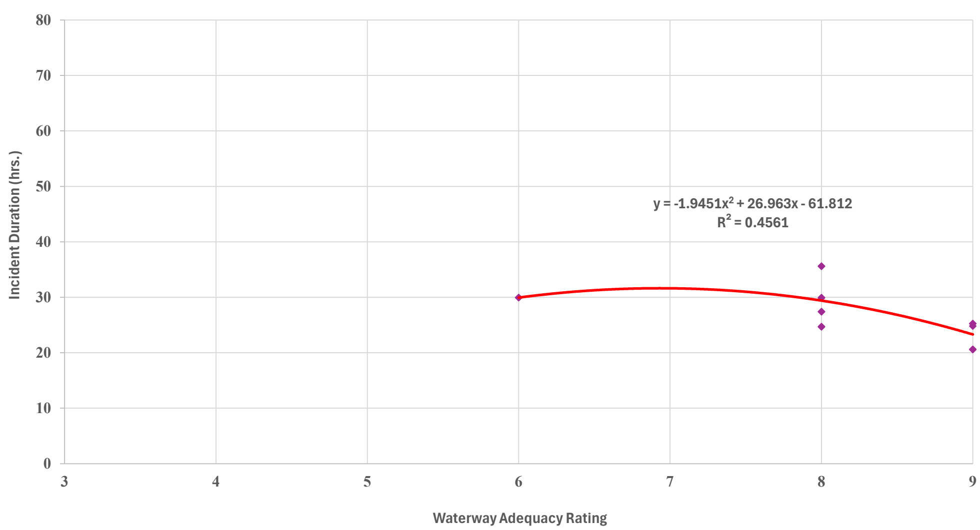


Figure 4.11. Relating Hurricane Matthew incident durations to waterway adequacy rating.

The methodology for computing the mobility costs have been presented earlier through equation 3, as well as the values for the vehicle operating cost per mile, and the unit travel time cost per hour of detour. The consequence costs were computed for each bridge, before the expected risk cost was calculated as the product of the total likelihood and the consequence cost. For the two hazard scenarios of Hurricane categories 1,2, and 3, and the Hurricane categories 4 and 5, the expected mobility risk cost for Florida state-maintained bridges are summarized in Figure 4.12. For both scenarios, most of the costs were less than $500, with about 10% having zero costs, and the hurricane 4 and 5 scenario having slightly higher costs, and two bridges with costs in excess of $6,000.

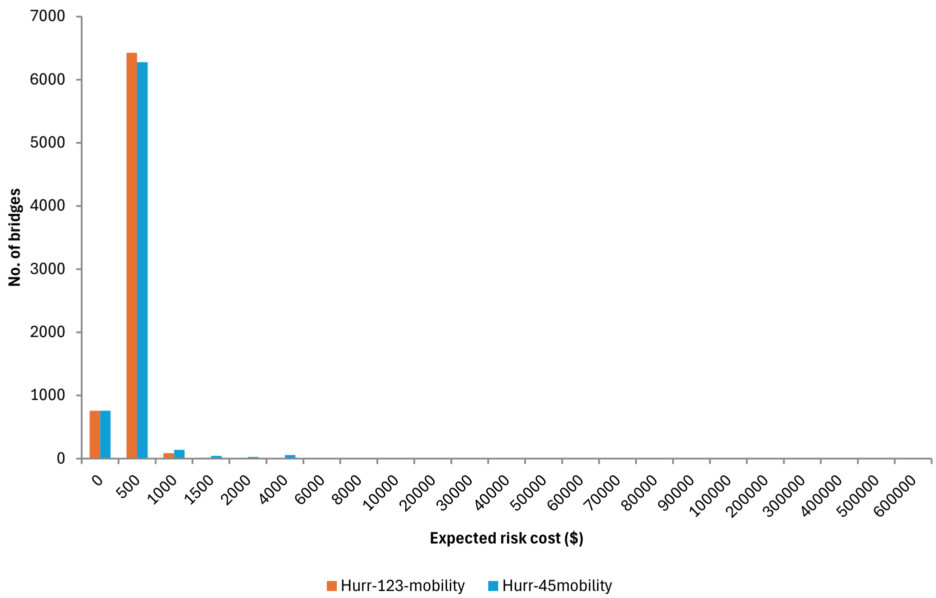


Figure 4.12. Annual mobility costs for hurricane hazard scenarios on Florida state-maintained bridges.

4.3.2.3.1. Environmental sustainability

Based on the methodology discussed earlier for computing the emissions damage costs (equation 5), the results of the calculated values of emission costs are shown in Figure 4.13 for Florida's state-maintained bridges. The values shown reflect approximately the same variations for both hazard scenarios with the stronger hurricane scenario having slightly higher costs.

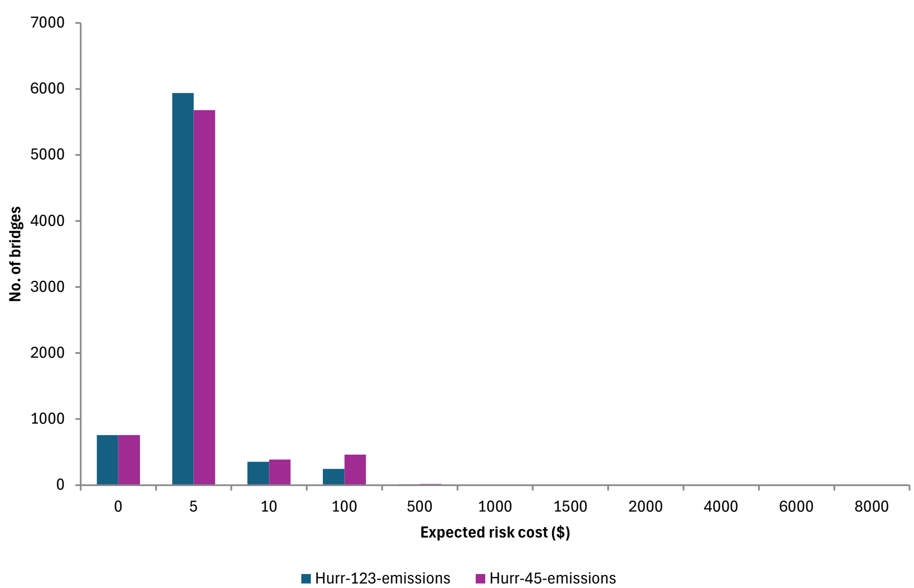


Figure 4.13. Annual environmental sustainability costs for hurricane hazard scenarios on Florida state-maintained bridges.

4.4. Flood

4.4.1. Estimate of likelihood

4.4.1.1. Likelihood of occurrence

The flood risk of individual bridges was estimated by the Geographic Information System (GIS) overlay of the FEMA's Digital Flood Insurance Rate Map (DFIRM) on the FDOT bridge layer and extracting the resulting data from the intersection analysis. The DFIRM dataset contains information about the flood hazards, showing the zones that are used by the Federal Emergency Management Agency (FEMA) to designate the Special Flood Hazard Area (SFHA) and for insurance rating purposes. The primary risk classifications used are the 1-percent-annual-chance flood event (100 year), the 0.2-percent-annual-chance flood event (500 year), and areas of minimal flood risk. According to the metadata of the DFIRM GIS layer, published at FEMA (2024), the pertinent fields of the data are defined in the following sections.

<u>FLD_ZONE:</u> This is a flood zone designation, with the following definitions:

A = The 1% annual chance (base flood) floodplains that are determined for the Flood Insurance Study (FIS) by approximate methods of analysis.

AE = The 1% annual chance floodplain. Base flood elevations derived from the hydraulic analyses are shown within this zone.

AH = Areas of 1-percent-annual-chance shallow flooding with a constant water-surface elevation (usually areas of ponding) where average depths are between 1 and 3 feet.

AO = Areas of sheet-flow shallow flooding where the potential runup < 3.0 feet above an overtopped barrier crest.

AREA NOT INCLUDED = Unknown

D = Areas where there are possible but undetermined flood hazards. In areas designated as Zone D, no analysis of flood hazards has been conducted.

OPEN WATER = Unknown

V = The 1% annual chance coastal floodplains that have additional hazards associated with storm waves. Base flood elevations are not shown within this zone.

VE = Coastal high hazard areas where wave action and/or high-velocity water can cause structural damage during the base flood.

X = Areas of 0.2% annual chance flood hazards and areas of 1% annual chance flood hazards with average depths of less than 1 foot or with drainage areas less than 1 square mile.

Levee: Areas where an accredited levee, dike, or other flood control structure has reduced the flood risk from the 1% annual chance flood.

<u>FLOODPLAIN:</u> This is the flood plain description based on FLD_ZONE field.

100-YEAR FLOODPLAIN = This is an area inundated by 100-year flooding.

500-YEAR FLOODPLAIN = This is an area inundated by 500-year flooding.

OPEN WATER = This area is an open water body.

OUTSIDE FLOODPLAIN = This is an area outside the 100 and 500-year flood plains.

UNDETERMINED = Areas with possible but undetermined flood hazards. No flood hazard analysis has been conducted. Flood insurance rates are commensurate with the uncertainty of the flood risk. Zone: D.

<u>RISK_LEVEL:</u> This is the floodplain area risk level based on FLD_ZONE field.

HIGH RISK - COASTAL AREAS = Apply to all of these zones: V, VE, V1 - 30.

HIGH RISK AREAS = Apply to all of these zones: A, AE, A1-A30, AH, AO, AR, A99.

MODERATE RISK AREAS = Apply to these zones: 0.2 PCT ANNUAL CHANCE FLOOD HAZARD

MODERATE TO LOW-RISK AREAS = Apply to these zones: B, C, and X.

OPEN WATER = Body of open water that has no defined flood hazard.

UNDETERMINED = Areas with possible but undetermined flood hazards. Zone: D.

The assigned risk levels for 12,739 bridges (state and non-state maintained bridges) on the study were based on the DFIRM layer's designated risk levels, with levels stated as follows: 1 -- Moderate To Low-Risk Areas, with annual probability of 0.001 (5341 bridges); 2 -- Moderate Risk Areas, with annual probability of 0.002 (456 bridges); 3 -- High Risk Areas, with annual probability of 0.01 (6542 bridges); 4 -- High Risk - Coastal Areas, with annual probability of 0.01 (232 bridges), and U -- Unknown flood hazards (not defined or undetermined) , with annual probability of 0.01 (168 bridges). Based on the FEMA DFIRM layer estimates, Figure 4.14 roughly shows the 2,649 state-maintained bridges in the high-risk areas, including the coastal areas. Figure 4.15 shows the variation among the bridges, with a majority (51%) of the bridges in the high-risk (risk level 1) category, and about 42% are assigned to the level 1 or low risk category.

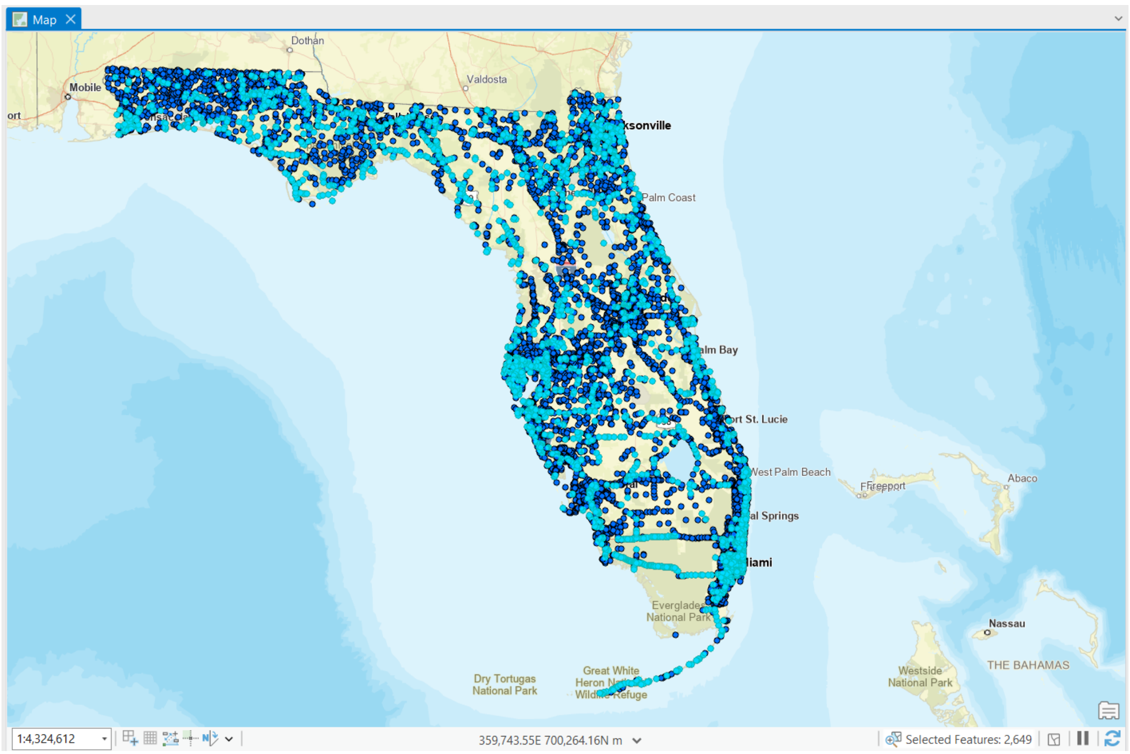


Figure 4.14. Map showing Florida state-maintained bridges in high-risk flood areas.

As discussed on the next section of this report, the NBI Item 71 Waterway Adequacy rating, shown in Table 4. 13, also provides an estimate of the annual probability of overtopping. For this study, the NBI ITEM 71 flood probability was compared to the FEMA DFIRM's estimate and the higher value chosen as the annual probability of flooding at the bridge location. Figure 4.15 summarizes the annual probability estimates for state and county-maintained bridges. For both state and county cases, most bridges have a 0.02 probability of flooding but though not clearly visible, there are a few bridges with annual probabilities of 0.1 and 0.3 for state bridges (35 and two respectively), and for county bridges (135 and 7 respectively).

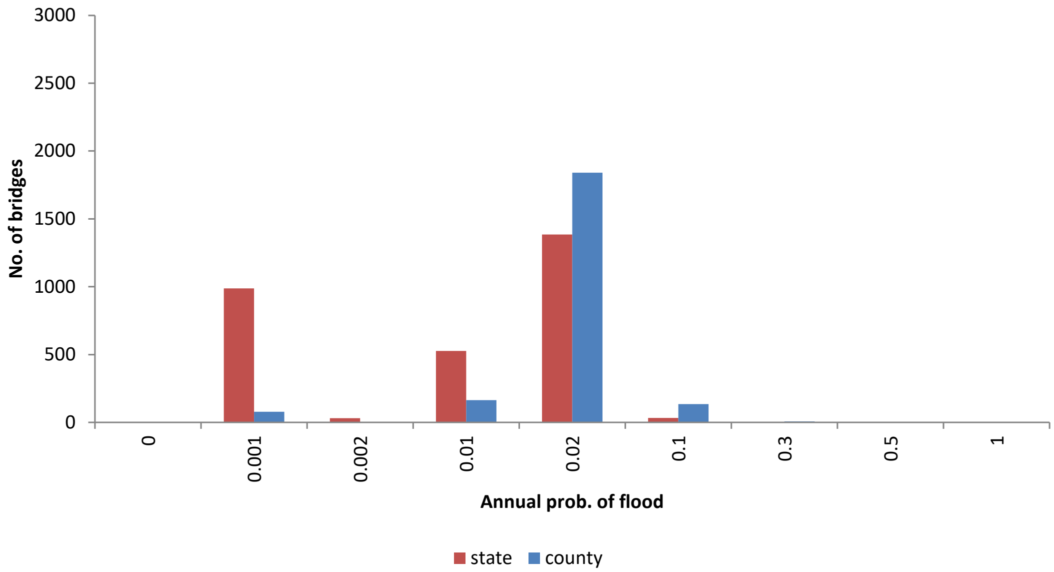


Figure 4.15. Annual flood probabilities for Florida bridges.

4.4.1.2. Likelihood of service disruption

According to the FDOT BMS Coding Guide, the NBI Item No. 71 Waterway Adequacy (Table: *Inspevnt* and Field Name: *wateradq* in BrM), adapted and shown in Table 4.13, provides a good estimate of likelihood of flooding and service disruption. Waterway adequacy reflects the chances of overtopping on the bridge, as well as considering the consequences of traffic delays due to flooding on the bridge. The overtopping frequency information is summarized as follows: Remote - greater than 100 years; Slight - 11 to 100 years; Occasional - 3 to 10 years; and Frequent - less than 3 years. The consequential traffic delays are also described as follows: Insignificant - Minor inconvenience, with highway passable in a matter of hours; Significant - Traffic delays of up to several days; and Severe - Long term delays to traffic with resulting hardship. The likelihood of service disruption will be based on the consequences of traffic delays as indicated in the water way adequacy rating.

Table 4.14 contains the same data from Table 4.13 but reorganized to assign the probability of overtopping in a clearer manner. Table 4.15 assigns the likelihood of service disruption due to flooding to the bridges based on overtopping risk levels and the severity of traffic delays.

Table 4.13. NBI Item 71 Waterway Adequacy Rating and Annual Probability of Overtopping (FDOT 2022).

Functional Classification			Description	Chance of over-topping	Annual prob-ability	Return period (yrs.)	Severity of traffic delays
Principal Arterials- Interstates, Freeways or Expressways	Other Principal and Minor Arterials and Major Collectors	Minor Collectors, Locals					
Code	Code	Code					
N	N	N	Bridge not over a waterway.	N/A	N/A	N/A	N/A
9	9	9	Bridge deck and roadway approaches above flood water elevations (high water). Chance of overtopping is remote.	Remote	0.01	> 100	None (0)
8	8	8	Bridge deck above roadway approaches. Slight chance of overtopping roadway approaches.	Slight	0.02	11 - 100	None (0)
6	6	7	Slight chance of overtopping bridge deck and roadway approaches.	Slight	0.02	11 - 100	None (0)
4	5	6	Bridge deck above roadway approaches. Occasional overtopping of roadway approaches with insignificant traffic delays.	Occasional	0.10	3 - 10	Negligible (1)
3	4	5	Bridge deck above roadway approaches. Occasional overtopping of roadway approaches with significant traffic delays.	Occasional	0.10	3 - 10	Significant (2)
2	3	4	Occasional overtopping of bridge deck and roadway approaches with significant traffic delays.	Occasional	0.10	3 - 10	Significant (2)
2	2	3	Frequent overtopping of bridge deck and roadway approaches with significant traffic delays.	Frequent	0.30	< 3	Significant (2)
2	2	2	Occasional or frequent overtopping of bridge deck and roadway approaches with severe traffic delays.	Frequent	0.30	< 3	Severe (3)
0	0	0	Bridge closed.	N/A	N/A	N/A	N/A

Table 4.14. Annual probability of overtopping (flood).

		NBI Item 71 Waterway Adequacy Rating										
NBI Item 26 Functional class	**Code**	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**N**
Rural Principal Arterial - Interstate	**1**	0.30	0.30	0.30	0.10	0.10	0.10	0.02	0.02	0.02	0.01	0.00
Rural Principal Arterial - Other	**2**	0.30	0.30	0.30	0.10	0.10	0.10	0.02	0.02	0.02	0.01	0.00
Rural Minor Arterial	**6**	0.30	0.30	0.30	0.10	0.10	0.10	0.02	0.02	0.02	0.01	0.00
Rural Major Collector	**7**	0.30	0.30	0.30	0.10	0.10	0.10	0.02	0.02	0.02	0.01	0.00
Rural Minor Collector	**8**	0.30	0.30	0.30	0.30	0.30	0.10	0.10	0.02	0.02	0.01	0.00
Rural Local	**9**	0.30	0.30	0.30	0.30	0.30	0.10	0.10	0.02	0.02	0.01	0.00
Urban Principal Arterial - Interstate	**11**	0.30	0.30	0.30	0.10	0.10	0.10	0.02	0.02	0.02	0.01	0.00
Urban Principal Arterial - Other Freeways or Expressways	**12**	0.30	0.30	0.30	0.10	0.10	0.10	0.02	0.02	0.02	0.01	0.00
Urban Other Principal Arterial	**14**	0.30	0.30	0.30	0.10	0.10	0.10	0.02	0.02	0.02	0.01	0.00
Urban Minor Arterial	**16**	0.30	0.30	0.30	0.10	0.10	0.10	0.02	0.02	0.02	0.01	0.00
Urban Collector	**17**	0.30	0.30	0.30	0.10	0.10	0.10	0.02	0.02	0.02	0.01	0.00
Urban Local	**19**	0.30	0.30	0.30	0.30	0.30	0.10	0.10	0.02	0.02	0.01	0.00

Table 4.15. Flood likelihood of service disruption: severity of traffic delays*

		NBI Item 71 Waterway Adequacy Rating										
NBI Item 26 Functional class	**Code**	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**N**
Rural Principal Arterial - Interstate	**1**	3	3	3	2	1	1	0	0	0	0	0
Rural Principal Arterial - Other	**2**	3	3	3	2	2	1	0	0	0	0	0
Rural Minor Arterial	**6**	3	3	3	2	2	1	0	0	0	0	0
Rural Major Collector	**7**	3	3	3	2	2	1	0	0	0	0	0
Rural Minor Collector	**8**	3	3	3	2	2	2	1	0	0	0	0
Rural Local	**9**	3	3	3	2	2	2	1	0	0	0	0
Urban Principal Arterial - Interstate	**11**	3	3	3	2	1	1	0	0	0	0	0
Urban Principal Arterial - Other Freeways or Expressways	**12**	3	3	3	2	1	1	0	0	0	0	0
Urban Other Principal Arterial	**14**	3	3	3	2	2	1	0	0	0	0	0
Urban Minor Arterial	**16**	3	3	3	2	2	1	0	0	0	0	0
Urban Collector	**17**	3	3	3	2	2	2	1	0	0	0	0
Urban Local	**19**	3	3	3	2	2	2	1	0	0	0	0

*Severity of traffic delays: None (0), Negligible (1), Significant (2), and Severe (3)

4.4.1.3. Total likelihood of hazard scenario

For each hazard scenario, the total likelihood is a product of the likelihood of occurrence and the likelihood of service disruption.

4.4.2. Consequence

4.4.2.1. Condition

There is limited data available on the physical damages to Florida bridges due specifically to flooding.

4.4.2.1.2. Recovery costs

The annual recovery costs for flooding damages to the bridge were determined based on an adjustment of the unit costs of major repairs of National Highway System (NHS) bridges which was originally indicated as $150/SF (FHWA 2024) for major repairs but now reduced to $100/SF for flood repairs.

4.4.2.2. Safety

Flooding may lead to safety issues of vehicular crashes but due to typical advance warning and plans to control the traffic, such crashes will be minimized. So consideration of safety as a consequence for flooding is omitted in this study.

4.4.2.3. Mobility

The RITIS data has some recorded values of incident durations on major roadways during the hazard occurrence (with focus on flooding). These values were used to estimate delays due to the closure/incident. Table 4. 16 shows the summary for the Year 2023 on Florida major roadway incidents, also indicated by FDOT District locations. In terms of the variation in the data, about 98% of the durations were a day or less. There was limited data on the incidents directly recorded for bridges; there were only five bridges, with a range of 0.05 to 3.33 hours, with a mean of 1.62 hours. These durations are generally low, so for the consequences calculations involving flooding, the duration of the impact was assumed to be 1 day.

Table 4.16. Summary of flood-related incident durations on Florida major roadways for 2023.

District	Count of incidents	Mean Duration (Hours)	Mean Duration (Days)	Min Duration (Hours)	Max Duration (Hours)	Max Duration (Days)
1	21	9.34	0.39	0.03	24.79	1.03
2	25	1.58	0.07	0.05	5.95	0.25
3	5	1.82	0.08	0.05	4.53	0.19
4	18	18.00	0.75	0.16	34.48	1.44
5	41	9.45	0.39	0.08	289.97	12.08
6	88	4.08	0.17	0.07	26.20	1.09
7	22	2.18	0.09	0.04	7.18	0.30
CFX	5	3.96	0.16	1.14	10.31	0.43
MDX	18	1.42	0.06	0.22	4.02	0.17
FTE	23	2.14	0.09	0.01	18.33	0.76
All	266	4.54	0.19	0.01	289.97	12.08
All*	83	4.57	0.19	0.07	34.48	1.44

CFX: Central Florida Expressway Authority; MDX: Miami–Dade Expressway Authority; FTE: Florida's Turnpike Enterprise; *At least one lane closed.

4.4.2.3.1. Environmental sustainability

Using the standard emission rates and equation 5 as explained earlier in the methodology, the emission damage costs were computed for disruption in service associated with flooding on Florida's state and county-maintained bridges.

Due to the very low probabilities of occurrence and likelihood of service disruption, overall, about 90% of the state-maintained bridges have zero expected annual risk cost for flooding. So, there is not much variation, and the chart of state-maintained bridges is not shown here. But Figure 4.16 shows the variation in the expected annual risk costs for mobility, emissions and recovery on Florida's county-maintained bridges, which is just slightly different, with about 93% having zero expected risk cost. What is useful from these results is the ability to evaluate the other 7% for increased priority for mitigation measures, and to quantify the potential benefit of such work.

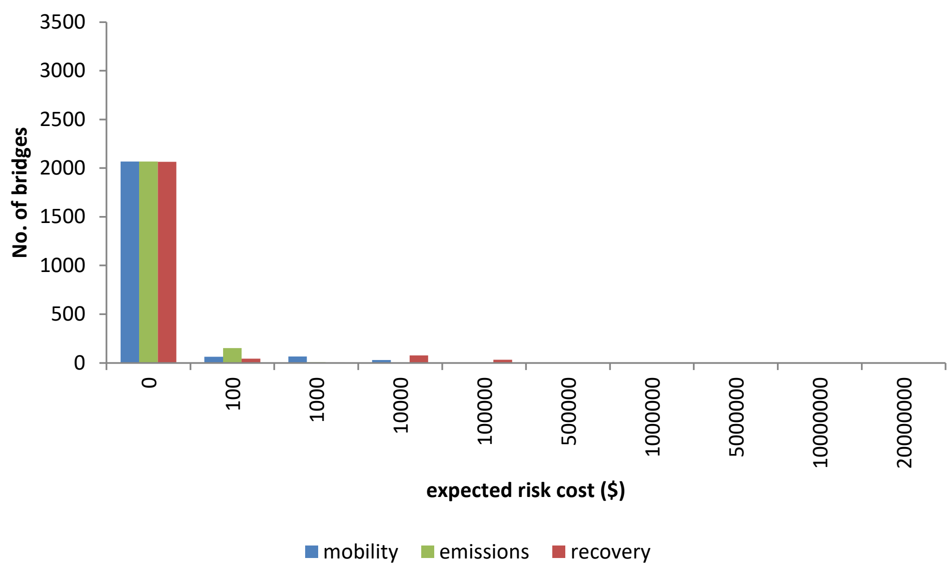


Figure 4.16. Expected annual flood risk costs for county bridges.

4.5. Scour

4.5.1. Estimate of likelihood

4.5.1.1. Likelihood of occurrence

There are many prior studies on estimating the risk of scour at bridge sites, including the pertinent studies by Stein and Sedmera (2006), Thompson et al. (2012), and Garrow and Sturm (2016), with the latter study utilizing the HYRISK model. But the approach narrated in the NCHRP risk study had considered all these prior works and recommended an approach suitable for BrM, that was adopted for this study. The NCHRP study reported that using the HYRISK model required data that were not available in BrM, and produced failure probabilities inconsistent with reported failure data. So, an estimate of the bridge susceptibility to scour was derived as indicated in Table 4.17, based on the Substructure condition (NBI 60) and Channel condition (NBI 61). This FDOT BMS risk study also considered the Scour critical (NBI 113) information as well as the probability of overtopping as an estimate of scour at the bridge (Table 4. 16 shown earlier for flood). Due to direct correlation to scour and its more realistic values, the scour critical ratings were assigned as risk levels and converted to an estimate of the probability of scour, ranging from 0 to 1.0, as shown in Table 4. 18.

Table 4.17. Scour susceptibility* based channel and substructure condition ratings (Thompson et al. 2017).

		NBI Item 60 Substructure Condition Rating										
NBI Item 61 Channel Condition Rating	**Code**	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**N**
Failed; need replacement.	**0**	0	0	0	0	0	0	0	0	0	0	0
Imminent failure; corrective action may restore service.	**1**	0	1	1	1	1	1	1	1	1	1	N
Critical; near collapse.	**2**	0	1	2	2	2	2	2	2	2	2	N
Serious; bank protection failed.	**3**	0	1	2	2	3	4	4	4	4	4	N
Poor; bank and embankment protection undermined.	**4**	0	1	2	3	4	4	5	5	6	6	N
Fair; bank protection being eroded.	**5**	0	1	2	3	4	5	5	6	7	7	N
Satisfactory; bank beginning to slump.	**6**	0	1	2	3	4	5	6	6	7	7	N
Good; bank protection in need of minor repairs.	**7**	0	1	2	3	4	6	6	7	7	8	N
Very good; banks protected or well vegetated.	**8**	0	1	2	3	4	6	7	7	8	8	N
Very good; no noticeable or noteworthy deficiencies.	**9**	0	1	2	3	4	7	7	8	8	9	N
Not applicable; not over waterway.	**N**	N	N	N	N	N	N	N	N	N	N	N

* *Scour susceptibility: 0 – Failed; 1 - Imminent failure; 2 - Critical scour; 3 - Serious scour; 4 - Advanced scour; 5 - Minor scour; 6 - Minor deterioration; 7 - Good condition; 8 - Very good condition; 9 - Excellent condition; N - Not applicable.

The estimated probabilities of scour at Florida's state-maintained and county-maintained bridges are summarized in Figure 4.17. It shows that for state bridges, about 41% have zero probability while just over 80% have 0.4 or less probability. On the other hand, about 5% of county bridges have zero probability of scour and about 51% of them have a probability of 0.4 or less.

Table 4.18. Scour Critical (NBI 113) Table (Adapted and revised from FDOT 2022).

Code	Description	Assigned risk level	Assigned prob. of scour
N	NOT APPLICABLE - Bridge not over waterway.	0	
U	UNKNOWN FOUNDATION - Bridge with "unknown" foundation that has not been evaluated for scour. Since risk cannot be determined, flag for monitoring during flood events and if appropriate, closure. This code shall not be used for interstate bridges. Use code 6 instead.	5	1
T	TIDAL, LOW RISK - Bridge over "tidal" waters that has not been evaluated for scour but considered low risk. Bridge will be monitored with regular inspection cycle and with appropriate underwater inspections. ("Unknown" foundations in "tidal" waters should be coded "U".)	1	0.2
0	SC - BRIDGE FAILED - Bridge is scour critical. Bridge has failed and is closed to traffic.	5	1
1	SC - FAIL IMMINENT - Bridge is scour critical; field review indicates that failure of piers/abutments is imminent. Bridge is closed to traffic.	5	1
2	SC - EXTENSIVE SCOUR - Bridge is scour critical; field review indicates that extensive scour has occurred at bridge foundations. Immediate action is required to provide scour countermeasures.	4	0.8
3	SC - UNSTABLE - Bridge is scour critical; bridge foundations determined to be unstable for calculated scour conditions: - Scour within limits of footing or piles. - Scour below spread-footing base or pile tips.	4	0.8
4	STABLE, NEEDS ACTION - Bridge foundations determined to be stable for calculated scour conditions; field review indicates action is required to protect exposed foundations from effects of additional erosion and corrosion.	3	0.6
5	STABLE W/IN FOOTING - Bridge foundations determined to be stable for assessed or calculated scour conditions or by installation of properly designed countermeasures; scour within limits of footing or piles. (Example B, Figure 113-1)	3	0.6
6	CALCS NOT MADE - Scour calculation/evaluation has not been made. (Use only to describe case where bridge has not yet been evaluated for scour potential.)	3	0.6
7	COUNTERMEASURES - Countermeasures have been installed to correct a previously existing problem with scour and to reduce the risk of bridge failure during a flood event. Instructions contained in a plan of action have been implemented to reduce the risk to users from a bridge failure during or immediately after a flood event.	2	0.4
8	STABLE ABOVE FOOTING - Bridge foundations determined to be stable for assessed or calculated scour conditions. Scour is determined to be above top of footing (Example A, Figure 113-1) by assessment (i.e. bridge foundations are on rock formations that have been determined to resist scour within the service life of the bridge) by calculation or by installation of properly designed countermeasures.	1	0.2
9	ON DRY LAND - Bridge foundations (including piles) on dry land well above flood water elevations.	0	0

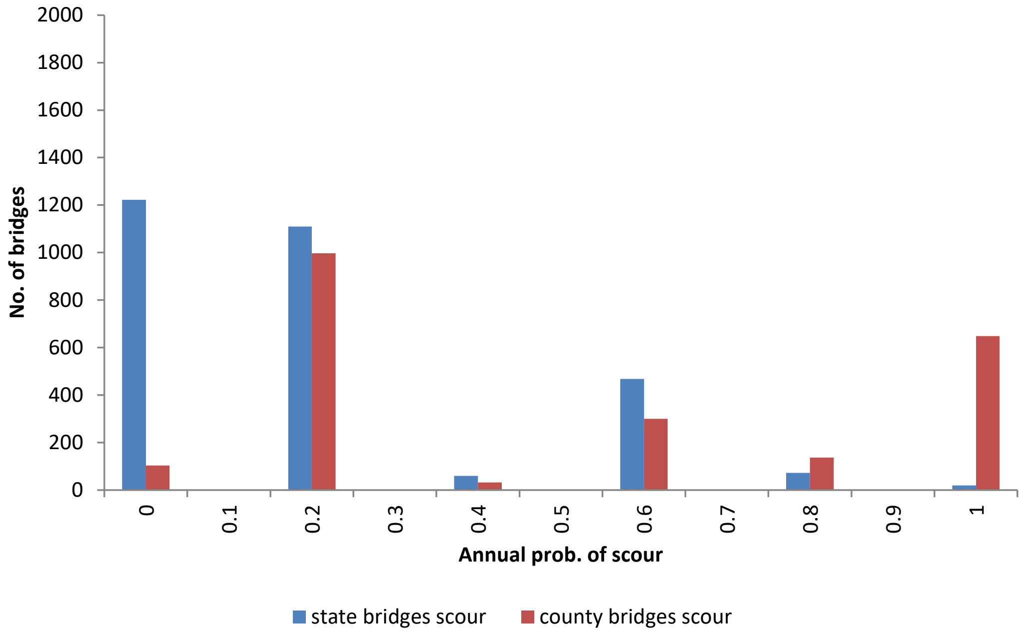


Figure 4.17. Annual probability of scour at state and county-maintained bridges in Florida.

4.5.1.2. Likelihood of service disruption

The NCHRP BMS risk study was adopted in estimating the likelihood of service disruption. The approach involves looking for the information on the overtopping frequency from Table 4. 13 and the classification of scour susceptibility from Table 4.17 shown earlier. These values are then used to obtain the annual disruption likelihood from Table 4.19.

Table 4.19. Scour likelihood of service disruption.

		Chance of overtopping (Annual probability)			
Scour susceptibility	**Code**	**0.01**	**0.02**	**0.1**	**0.5**
Failed	**0**	100.00000%	100.00000%	100.00000%	100.00000%
Imminent failure	**1**	1.00000%	1.00000%	1.00000%	1.00000%
Critical scour	**2**	0.50000%	0.60000%	0.80000%	0.90000%
Serious scour	**3**	0.11000%	0.13000%	0.16000%	0.20000%
Advanced scour	**4**	0.04000%	0.05000%	0.06000%	0.07000%
Minor scour	**5**	0.03000%	0.04000%	0.05000%	0.07000%
Minor deterioration	**6**	0.01800%	0.02500%	0.04000%	0.05000%
Good condition	**7**	0.01800%	0.02500%	0.04000%	0.05000%
Very good condition	**8**	0.00040%	0.00050%	0.00200%	0.00400%
Excellent condition	**9**	0.00025%	0.00030%	0.00040%	0.00070%

4.5.1.3. Total likelihood of hazard scenario

For each hazard scenario, the total likelihood is a product of the likelihood of occurrence and the likelihood of service disruption.

4.5.2. Consequence

4.5.2.1. Condition

The extent of physical damages and resilience were not considered for this hazard. The cost of repairs were assumed to be the same as those for major repairs on hurricane damages, i.e., $150/SF.

4.5.2.2. Safety

This hazard is not typically associated with traffic safety issues.

4.5.2.3. Mobility

The approach used here is similar to that described earlier for the floods. The duration of the service disruption was also assumed to be one day. As shown in Figure 4.18, the expected risk costs correlate well to the annual probability of scour damage for the state and county-maintained bridges.

4.5.2.4. Environmental sustainability

Using the standard emission rates, and equation 5 as explained earlier in the methodology, the emission costs were computed for disruption in service associated with flooding for Florida's state and county-maintained bridges. The results are summarized in Figure 4.18.

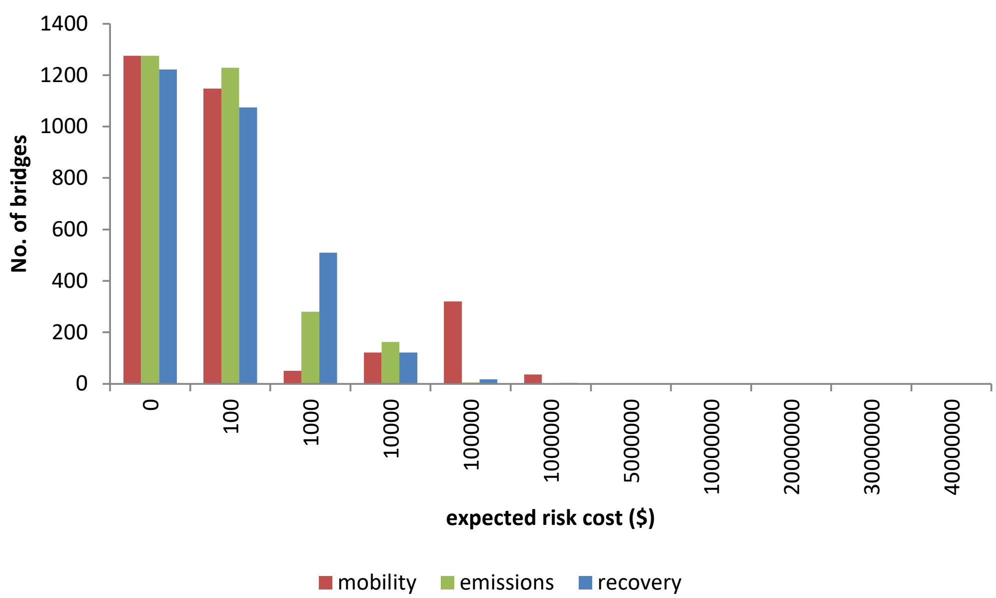


Figure 4.18. Expected annual mobility, emissions and recovery risk costs of scour on Florida bridges.

4.6. Tornado

4.6.1. Estimate of likelihood

4.6.1.1. Likelihood of occurrence

Geographic Information System (GIS) spatial analyses were done using an overlay of a GIS layer of historical tornado tracks in Florida (1951 to 2022), on the basemap layers of roadways and bridges in the Florida Inventory, to identify bridges that were located within a 1200 ft. buffer (average tornado width) of the tornado tracks. The resulting data as displayed in Figure 4.19, was analyzed to estimate the time intervals between occurrence of tornado at each bridge location and converted to the annual occurrence likelihood. For comparison, the annual frequency was also estimated based on just the count of occurrences at each bridge and the data range of the records. The variation in the results are shown in Figure 4.20 for state-maintained bridges. About 96% of the bridges expect an annual frequency of 0.1 or less, with 16 bridges identified as having probabilities above 0.10 and less than 0.40, and three bridges having probabilities greater than 0.50.

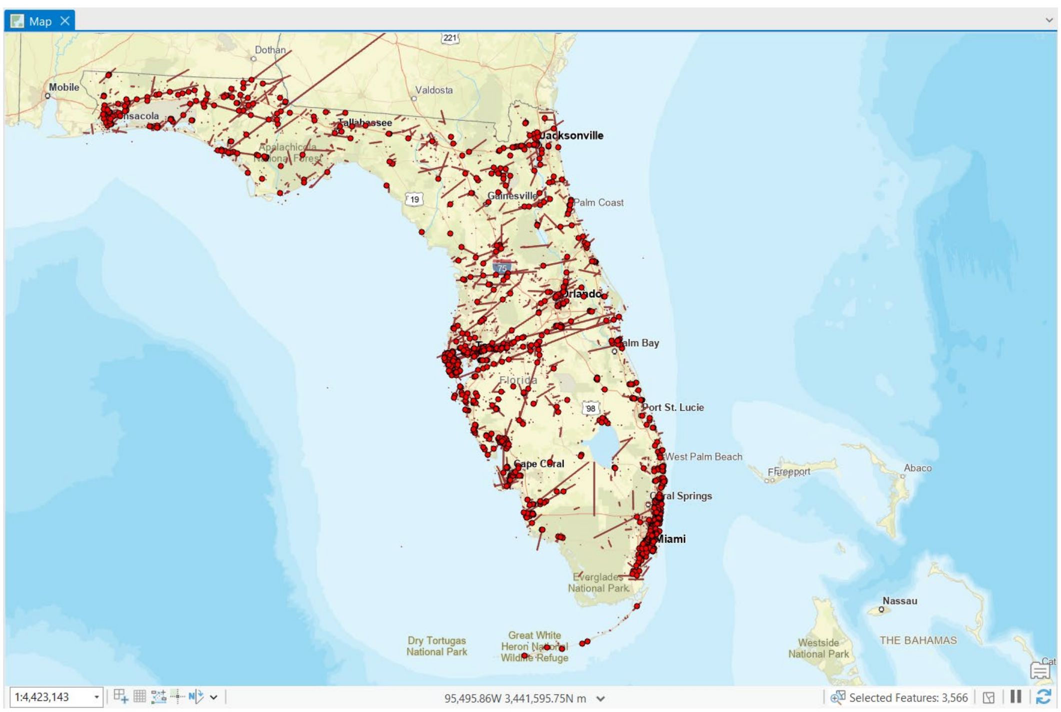


Figure 4.19. Bridges located along historical tornado tracks in Florida.

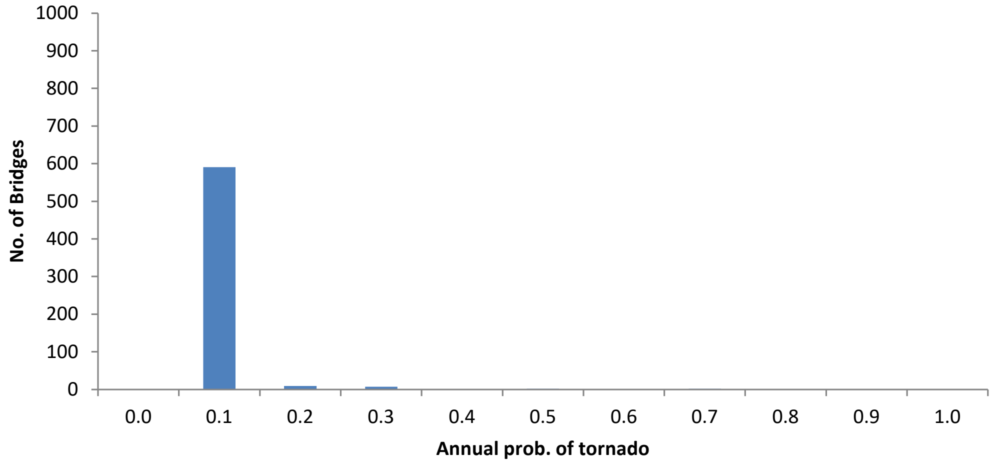


Figure 4.20. Estimated annual frequency of tornado occurrence on Florida state-maintained bridges.

4.6.1.2. Likelihood of service disruption

There is very limited incident data on roadway and bridge closures during tornado hazards. Tornadoes are more likely to affect local roadways than major roadways due to fallen trees, etc. So the likelihood of service disruption was assumed as 0.25 for roadway with functional classes 9 and 19, and 0.01 for others.

4.6.1.3. Total likelihood of hazard scenario

For each hazard scenario, the total likelihood is a product of the likelihood of occurrence and the likelihood of service disruption.

4.6.2. Consequence

4.6.2.1. Condition

There is no data available on the physical damages due to tornadoes or the associated repair costs on Florida bridges. The data and costs available are for damage to buildings, including debris removal and roof/structural repairs. The recovery cost was assumed to be $1/SF.

4.6.2.2. Safety

Tornadoes are typically not associated with safety issues of vehicular crashes since there are usually advance warning and plans to control the traffic.

4.6.2.3. Mobility

The RITIS data has no recorded values of incident times during the hazard occurrence. But roadway closures are typically due to fallen trees. The duration of service disruption during tornadoes was assumed to be the same as for flooding, i.e., 1 day.

4.6.2.4. Environmental sustainability

Using the standard emission rates, and equation 5 as explained earlier in the methodology, the emission costs were computed for disruption in service associated with tornado for Florida's state-maintained bridges.

The results for the recovery, mobility, and environmental sustainability costs are summarized in Figure 4.21, showing that for each criterion, most costs are between $0 and $10.

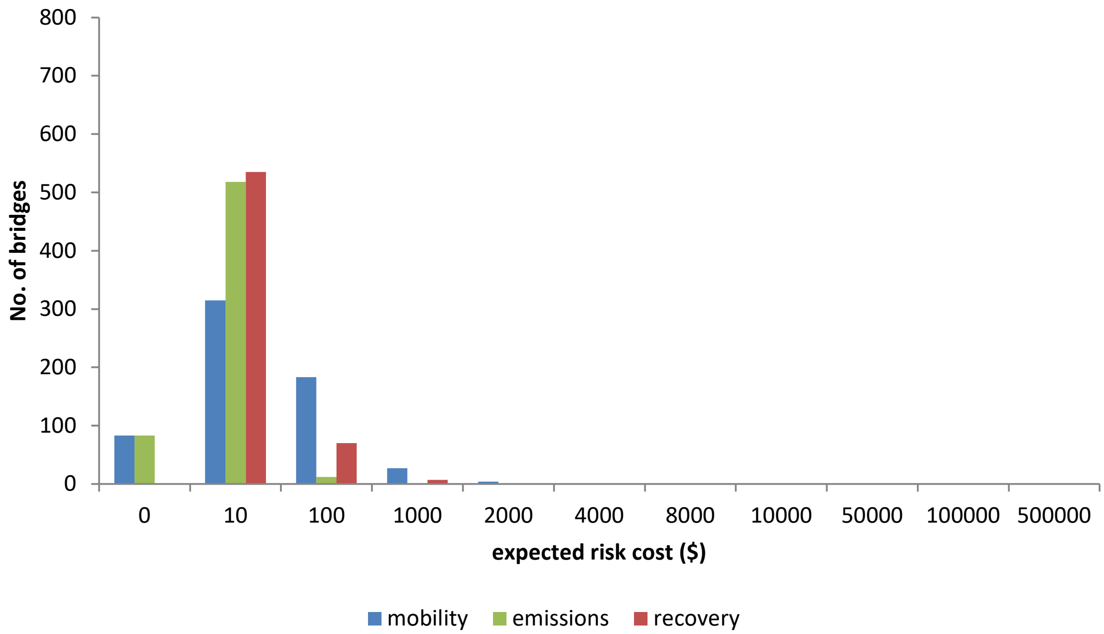


Figure 4.21. Expected annual mobility, emissions and recovery risk costs of tornadoes on Florida bridges.

4.7. Wildfire

4.7.1. Estimate of likelihood

4.7.1.1. Likelihood of occurrence

Geographic Information System (GIS) spatial analyses were done using an overlay of a GIS layer of historical wildfire events in Florida (2014 to 2024), on the basemap layers of roadways and bridges in the Florida Inventory, to identify bridges that were located within a 1-mile buffer of the wildfire events. Figure 4.22 shows the bridges located within the 1-mile vicinity of 6,196 wildfire events in the 10 year-period of 2014 to 2024. The resulting data was analyzed to estimate the time intervals between occurrence of tornado at each bridge location and converted to the annual occurrence likelihood. For comparison, the annual frequency was also estimated based on just the count of occurrences at each bridge and the data range of the records. The variation in the results are shown in Figure 4.23. About 72% of the bridges expect an annual frequency of 0.10 or less, or a return period of 10 years, while about 99% have a return period of 5 years or less, and about 11 bridges (1%) have a return period of 2 years or less.

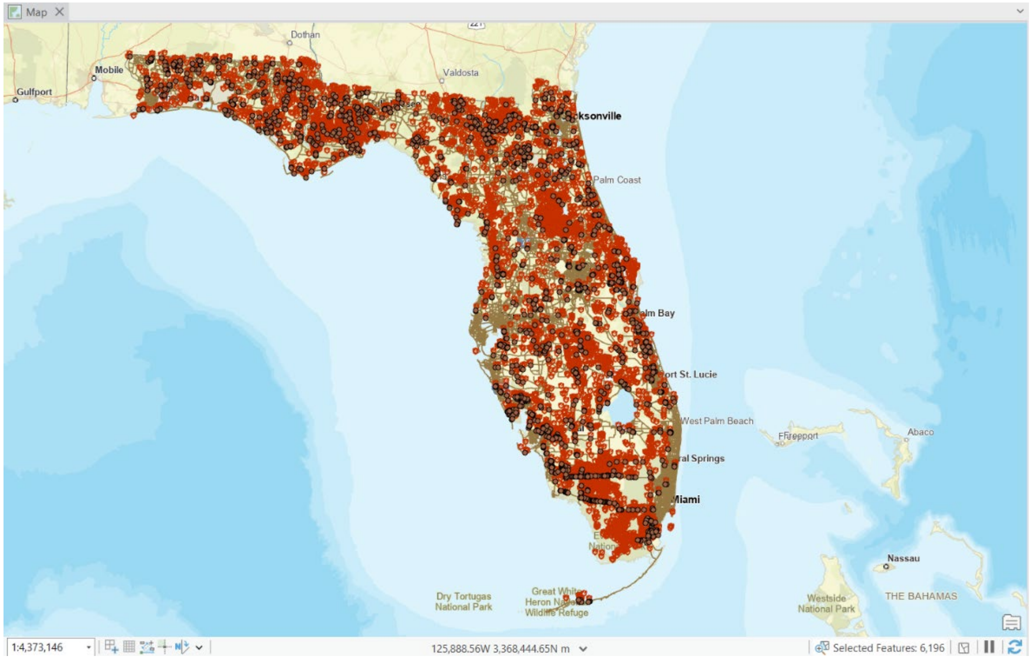


Figure 4.22. Bridges located within 1 mile of wildfire events in Florida.

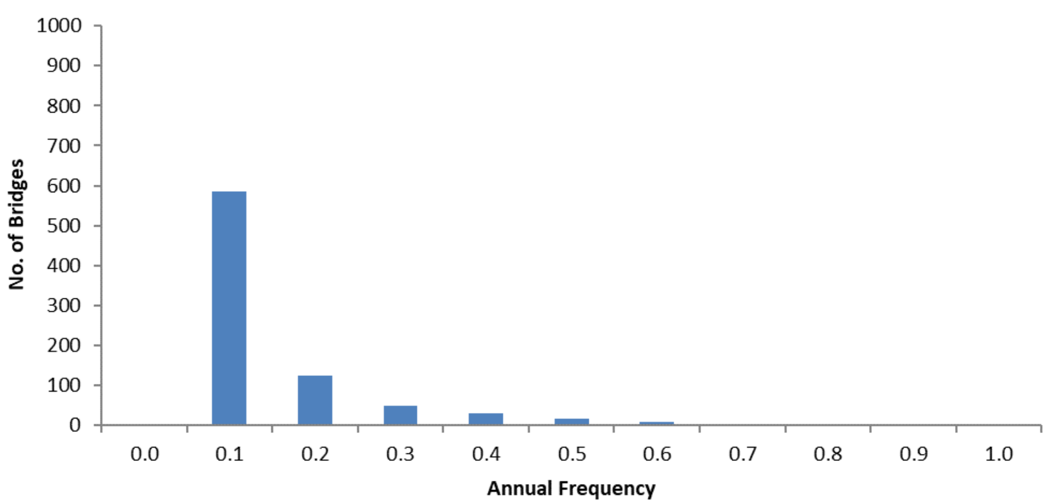


Figure 4.23. Estimated annual frequency of wildfire events near Florida state-maintained bridges.

4.7.1.2. Likelihood of service disruption

The RITIS incident data was analyzed to estimate durations of roadway closures during wildfire hazard. Typically, the roadway has to be closed due to visibility hazard during wildfires. Due to their relative importance and the volume of traffic carried, the study assumed 1.0 as the likelihood of service disruption for interstate roadways and principal arterials, and 0.5 for other roadways.

4.7.1.3. Total likelihood of hazard scenario

For each hazard scenario, the total likelihood is a product of the likelihood of occurrence and the likelihood of service disruption.

4.7.2. Consequence

4.7.2.1. Condition

There is no data available on the physical damages due to wildfires or repair costs on Florida bridges. The recovery cost was assumed to be $1/SF.

4.7.2.2. Safety

Wildfires are typically not associated with safety issues of vehicular crashes since there are usually advance warning and plans to control the traffic. Visibility problems have the potential of causing crashes but analyzing this will be complicated and outside the scope of this study.

4.7.2.3. Mobility

As discussed earlier, the RITIS data was utilized to estimated incident clearance times as recorded on major roadways in Florida. The roadway incident durations of wildfires for the Year 2023 are summarized in Table 20 and Figure 4.24. About 90% of the incidents have a day or less in duration, while there are only about 4% locations with three or more days of duration. Based on the data, FDOT District 5 bridges have relatively longer durations than other regions, so in the consequence model, the duration of disruption during wildfires is assigned 2 days for FDOT District 5 bridges, and 1 day for other bridges.

Table 4.20. Wildfire-related incident durations on Florida major roadways for 2023.

District	Count of incidents	Mean Duration (Hours)	Mean Duration (Days)	Min Duration (Hours)	Max Duration (Hours)	Max Duration (Days)
1	147	12.81	0.53	0.003	447.78	18.66
2	9	0.70	0.03	0.160	1.87	0.08
3	30	2.63	0.11	0.013	26.90	1.12
4	5	0.45	0.02	0.088	0.95	0.04
5	119	29.95	1.25	0.030	397.31	16.55
6	3	1.29	0.05	0.149	2.75	0.11
7	74	0.51	0.02	0.022	2.78	0.12
CFX	12	4.98	0.21	0.087	33.96	1.41
FTE	219	3.50	0.15	0.015	75.59	3.15
All	618	10.36	0.43	0.003	447.78	18.66
All*	108	2.04	0.08	0.058	56.39	2.35

*At least one lane closed; CFX: Central Florida Expressway Authority; FTE: Florida's Turnpike Enterprise.

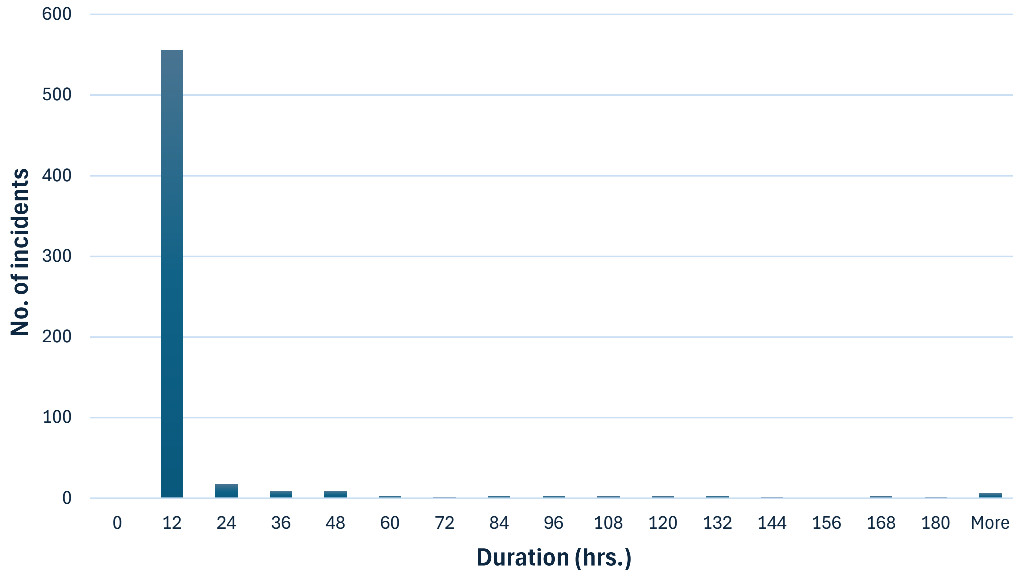


Figure 4.24. Variation in Wildfire-related incident durations on Florida major roadway bridges in 2023.

4.7.2.4. Environmental sustainability

Using the standard emission rates, and equation 5 as explained earlier in the methodology, the emission costs were computed for disruption in service associated with wildfire for Florida's state and county-maintained bridges.

The results for the recovery, mobility, and environmental sustainability costs are summarized in Figure 4.25, showing that the emission costs are relatively the lowest costs. The mobility and recovery costs are mostly between \$1000 and \$5000, and the mobility contributes most to the costs in excess of \$5000.

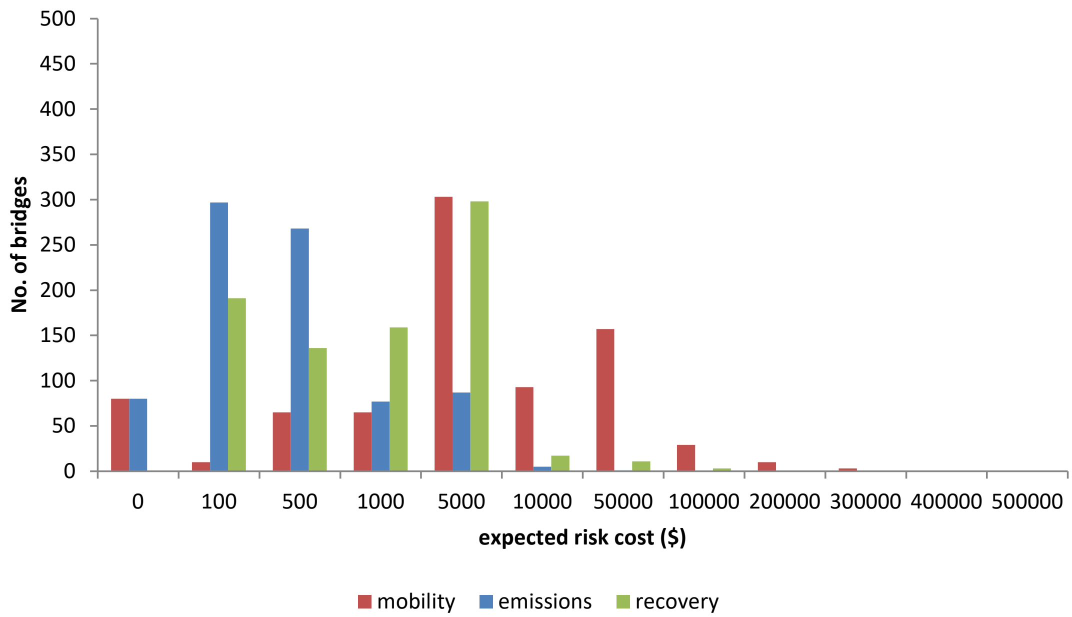


Figure 4.25. Expected annual mobility, emissions, and recovery risk costs of wildfires on Florida bridges.

4.8. Over-height collision

4.8.1. Estimate of likelihood

4.8.1.1. Likelihood of occurrence

Truck height histograms from the prior FDOT BMS study were adopted (Table 4.21 and Figures 4.26 and 4.27) and used to estimate the percentage of trucks that will need to detour due to the bridge's vertical under-clearance. The histograms were derived by collecting the actual height of trucks traversing the Florida roadways over a period of time (Sobanjo and Thompson 2004). It is assumed that the pattern of travel remained the same. These estimates can be directly correlated and estimated as the likelihood of the occurrence of overheight hits on the bridges.

Table 4.21. Truck height step function for Florida roadways (Sobanjo and Thompson 2004).

Interstate roadways		Non-Interstate roadways	
Underclearance Height (ft.)	% of Trucks Detoured	Underclearance Height (ft.)	% of Trucks Detoured
<= 10.0	100.000	<= 7.0	100.000
<= 12.0	93.700	<= 10.0	91.350
<= 13.0	79.250	<= 12.0	64.750
<= 14.0	36.200	<= 13.5	26.100
<= 16.0	0.245	<= 14.5	2.750
>16.0	0.000	> 14.5	0.000

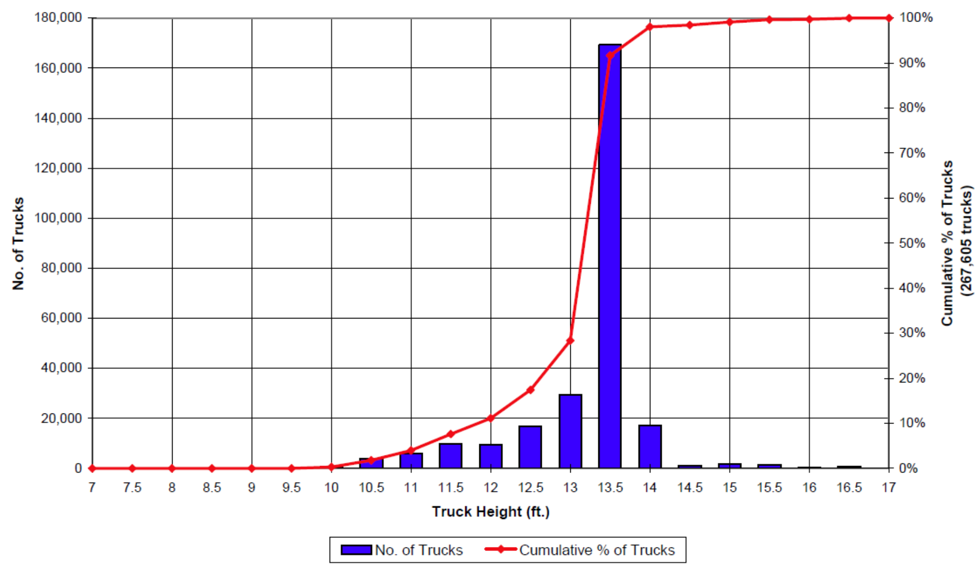


Figure 4.26. Truck height histogram for Interstate Florida roadways (Sobanjo and Thompson 2004).

Figure 4.27. Truck height histogram for Non-Interstate Florida roadways (Sobanjo and Thompson 2004).

The variation in the estimated probabilities of truck overheight hits is shown in Figure 4.28. From the estimated probabilities, based primarily on the bridge underclearance and the truck histograms as described above, just over 400 bridges or about 80% of Florida bridges over the Interstate roadways appear to be free from the likelihood of truck overheight hits, while the remaining 20 have about 0.10 probability of such hits. For the bridges over the non-Interstate roadways, there are about 92% which have zero likelihood of truck overheight hits on their under-route roadways, but there are 184 bridges with 0.10 probability, 22 with 0.30 chances, and 11 with 1.00 probability of the overheight hits.

When separated into the two scenarios of vertical underclearances of 13.5 ft., the observed probabilities of overheight hits are clearly different as shown in Figures 4.29 and 4.30. For bridges with underclearances less than 13.5 ft., there are more bridges with higher probabilities of overheight hits, compared to the inventory of bridges with their underclearances greater than or equal to 13.5 ft.

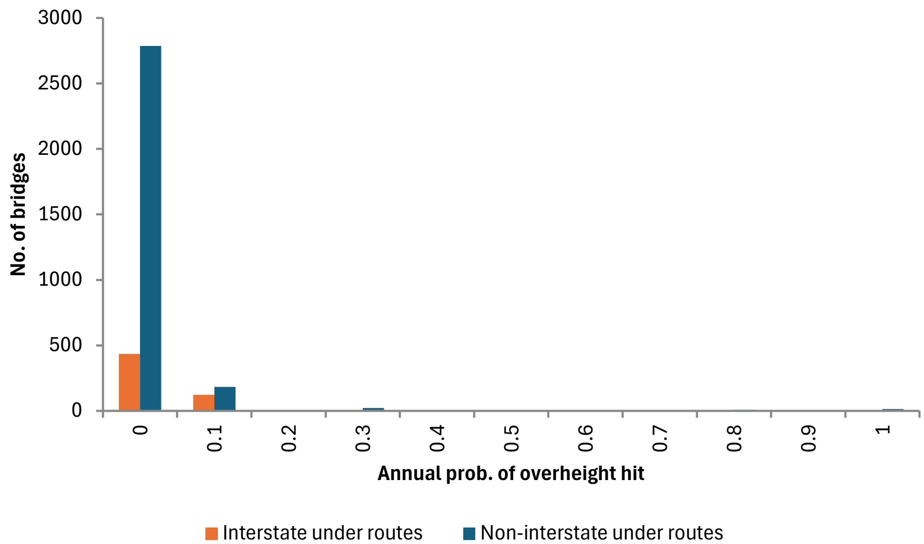


Figure 4.28. The likelihood of truck overheight hits on the under-route roadways of Florida bridges.

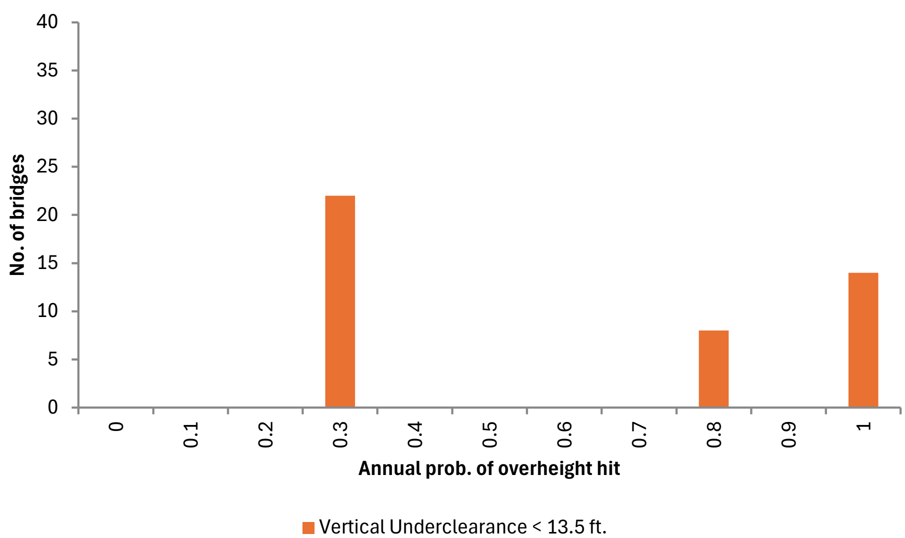


Figure 4.29. The likelihood of truck overheight hits on the under-route roadways of Florida bridges (vertical underclearance < 13.5 ft.).

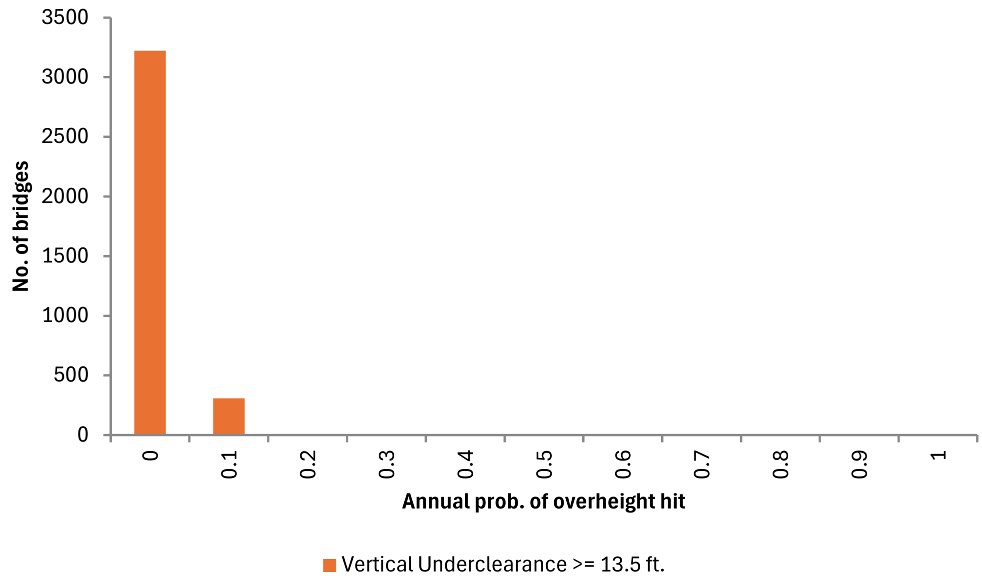


Figure 4.30. Likelihood of truck overheight hits on the under-route roadways of Florida bridges (vertical underclearance >= 13.5 ft.).

4.8.1.2. Likelihood of service disruption

The hazard of overheight hits directly affects the ongoing traffic of the under-route roadway, and the bridge superstructure of impacted element will typically have to be structurally inspected for safety. Most incidents do not disrupt the vehicular traffic service on the bridge. But occasionally severe impacts can occur that would significantly affect the under-route traffic. In the study, we assumed 0.5 likelihood for freight routes (interstates) and 0.01 for others.

4.8.1.3. Total likelihood of hazard scenario

For each hazard scenario, the total likelihood is a product of the likelihood of occurrence and the likelihood of service disruption.

4.8.2. Consequence

4.8.2.1. Condition

There are some data available on the physical damages to Florida bridges from the prior BMS risk study but the emphasis here is on the service disruption. For recovery costs, the bridge repair data from the 2013 risk study was analyzed to obtain repair costs for bridge accidents attributed to overheight hits. The costs were adjusted to 2024 equivalent values as shown in Table 4.22. Considered as minor repairs, the cost was assumed to be \$0.148/SF.

4.8.2.2. Safety

This hazard may also impact the roadway safety, in terms of crashes, but the analyses will be too complicated and outside the scope of this study.

Table 4.22. Bridge repair costs for overheight hits adjusted to 2024 dollars.

Site No.	Bridge ID	ACT No.	Unit of Measure	Activity Description	Est. Units	Total Cost ($)	Type of Bridge Element	Deck Area (SF)	Year Completed	2024 Cost	2024 Unit Cost
8886001	500052	888	MH	Repair spalls on beams with dry pack gun	7	8,530.13	Beam	15,804	1994	13,488.10	0.85
8886002	500054	888	MH	Repair spalls on beams with dry pack gun	3	4,199.71	Beam	15,804	1994	6,640.71	0.42
8886003	480061	888	MH	REPAIR BEAMS 3-1 3-2 3-3 WITH DRI PACKET	1	832.35	Beam	12,154	1996	1,234.01	0.10
8886001	100138	888	MH	Repair the damaged area caused by vehicle impact span 2 beam 1.	4	1,059.98	Beam	23,727	1996	1,571.49	0.07
8886010	290082	888	MH	Splice the broken strands in the bottom flange of Beam VI Span 3.	6	426.50	Beam	11,006	1996	632.31	0.06
8886011	290082	888	MH	Repair the spalled area in the bottom flange of Beam VI Span 3.	8	16.64	Beam	11,006	1996	24.67	0.00
8886014	720186	888	MH	Repair the spalled areas on Beam I and II in Span 2.	6	454.11	Beam	8,136	1996	673.25	0.08
8886013	720206	888	MH	Repair the spalled areas of Beam I II and V in Span 3.	80	350.00	Beam	7,390	1996	518.90	0.07
8886018	720307	888	MH	Repair the spalled areas on Beams IX and X in Span 2.	12	1,646.00	Beam	9,947	1996	2,440.30	0.25
8886028	270057	888	MH	Repair spalled areas in Beam VII/VIII and IX/Span 2.	40	286.33	Beam	7,550	1996	424.50	0.06
8886030	720103	888	MH	Repair the spalled beam Span 2.	12	145.02	Beam	7,104	1996	215.00	0.03
8886037	720309	888	MH	Repair the spalled areas on the beams, Span 2.	10	550.00	Beam	19,801	1997	794.43	0.04
8886036	720361	888	MH	Repair the spalled bottom flange Beam IV, Span 3.	8	814.64	Beam	6,099	1996	1,207.76	0.20
8886042	720242	888	MH	Patch spalled beams, Span 3.	6	292.10	Beam	27,961	1996	433.06	0.02
8886041	720315	888	MH	Patch the spalled beams, Span 3.	6	469.42	Beam	27,961	1996	695.95	0.02
8886004	100177	888	MH	Repair spalls on beams 2-5 and 2-6, midspan, and beam 1-1, south end.	16	1,117.22	Beam	5,457	1996	1,656.35	0.30
8886003	100183	888	MH	Repair the damaged area caused by vehicle impact span 2 beam 1.	4	1,405.78	Beam	5,296	1997	2,030.53	0.38

Table 4.22. Bridge repair costs for overheight hits adjusted to 2024 dollars (Cont'd).

Site No.	Bridge ID	ACT No.	Unit of Measure	Activity Description	Est. Units	Total Cost ($)	Type of Bridge Element	Deck Area (SF)	Year Completed	2024 Cost	2024 Unit Cost
8886005	100189	888	LF	Repair Spalls with exposed Reinforced strands on beams span 2	70	569.79	Beam	4,790	1996	844.75	0.18
8886047	290039	888	MH	Repair spalled area on east side of Beam 3-7 and 3-9.	100	100.91	Beam	17,663	1997	145.76	0.01
8886048	290059	888	MH	Repair spalled area on east side of Beam 3-1.	100	50.46	Beam	17,663	1997	72.89	0.00
8886052	290061	888	MH	Repair as needed spalled beams in Span 3 of Bridge Numbers 290061 and 290064.	40	786.52	Beam	10,326	1997	1,136.06	0.11
8886055	720177	888	MH	Splice severed strand, patch spalled areas and surface patch all cracks in Beams 1-1 and 1-2.	81	1,054.54	Beam	21,092	1997	1,523.19	0.07
8886056	720216	888	MH	Repair the spalled areas on Beams 3-1, 3-2 and 3-3 with exposed cable.	40	3,500.00	Beam	20,803	1997	5,055.44	0.24
8886057	780045	888	MH	Repair spalled areas on Beams 2-1, 2-2, 2-3	100	1,250.00	Beam	11,162	1997	1,805.52	0.16
8886060	260079	888	MH	Repair spall on Beams 2-8 thru 2-12.	80	1,258.45	Beam	13,526	1997	1,817.72	0.13
8886062	260079	888	MH	Repair the spalled areas on the beams with exposed cables.	40	193.49	Beam	13,526	1997	279.48	0.02
8886070	290061	888	MH	Repair the spalled area in the bottom flange of Beam 2-1 and Beams 2-3 through 2-10.	40	376.80	Beam	10,326	1997	544.25	0.05
8886071	290064	888	MH	Repair the spalled area in the bottom flange of Beams 2-8, 2-9 and 2-10.	40	156.27	Beam	10,326	1997	225.72	0.02
8886075	720122	888	MH	Repair spalled areas on south bottom flange of Beams 2-1 through 2-3.	10	423.44	Beam	9,983	1997	611.62	0.06
8886077	780067	888	MH	Repair spalled areas on beams.	40	200.47	Beam	6,824	1997	289.56	0.04
8886083	260057	888	MH	Repair the spalls in concrete Beams 2-1 through 2-5.	20	900.00	Beam	17,187	1998	1,262.91	0.07

Table 4.22. Bridge repair costs for overheight hits adjusted to 2024 dollars (Cont'd).

Site No.	Bridge ID	ACT No.	Unit of Measure	Activity Description	Est. Units	Total Cost ($)	Type of Bridge Element	Deck Area (SF)	Year Completed	2024 Cost	2024 Unit Cost
8886084	260082	888	MH	Repair the spalls in concrete Beams 2-6 through 2-8.	20	200.00	Beam	15,080	1998	280.65	0.02
8886088	270047	888	MH	Repair spalled area on Beam 2-1, 2-2 and 2-3.	40	603.69	Beam	7,549	1998	847.12	0.11
8886089	270057	888	MH	Repair spalled areas on Beams 2-6 through 2-9.	20	55.12	Beam	7,550	1998	77.35	0.01
8886093	720174	888	MH	Repair all the spalled beams in Span 2.	160	2,580.00	Beam	14,651	1998	3,620.33	0.25
8886092	720177	888	MH	Repair the spalls on Beams 2-22, 2-23 and 2-24.	40	2,900.00	Beam	21,092	1998	4,069.37	0.19
8886091	720206	888	MH	Repair spalled areas with exposed cable on Beams 2-1 and 2-5.	40	5,373.79	Beam	7,390	1999	7,333.13	0.99
8886094	720083	888	MH	Repair the spalled area on the beam with exposed cable (Beam 2-10).	40	272.44	Beam	10,724	1999	371.77	0.03
8886098	720079	888	MH	Spot paint underside of all bottom flanges and north side of web on Beam 2- 1.	20	288.06	Beam	9,790	1999	393.09	0.04
8886105	720177	888	MH	Repair spalled area 1.5 m x 0.3 m x 0.03 m with exposed steel, Beam 2-24. p=3 (888 ADR) El. 109	1	3,112.06	Beam	21,092	2000	4,127.52	0.20
8886001	790102	888	MH	Clean and patch spalls with exposed prestress strands in span 2 BEAM V SPAN 3 BEAM I.	1	553.56	Beam	7,233	2001	727.52	0.10

4.8.2.3. Mobility

In an extension of the methodology described above for estimating the likelihood of truck overheight collision on the under-routes of the bridges, the under-route detour bypass length was utilized to compute the delay and detour costs in terms of the time of travel and the Vehicle Operating Costs (VOC). The service disruption time in this case was the excess time of travel calculated from the detour length and detour speed.

4.8.2.4. Environmental sustainability

Using the standard emission rates, and equation 5 as explained earlier in the methodology, the emission costs were computed for disruption in service associated with overheight hits for Florida's state and county-maintained bridges.

The computed consequence costs are summarized in Figure 4.31 for 44 bridges with their vertical underclearances less than 13.5 ft., including 14 state-maintained bridges. Most of the bridges have their expected annual recovery costs between \$100 and \$500, while the mobility and emissions costs are mostly zeroes, with a few varied higher costs. The zero costs are due to many bridges in this category with under route detour lengths listed as zeroes.

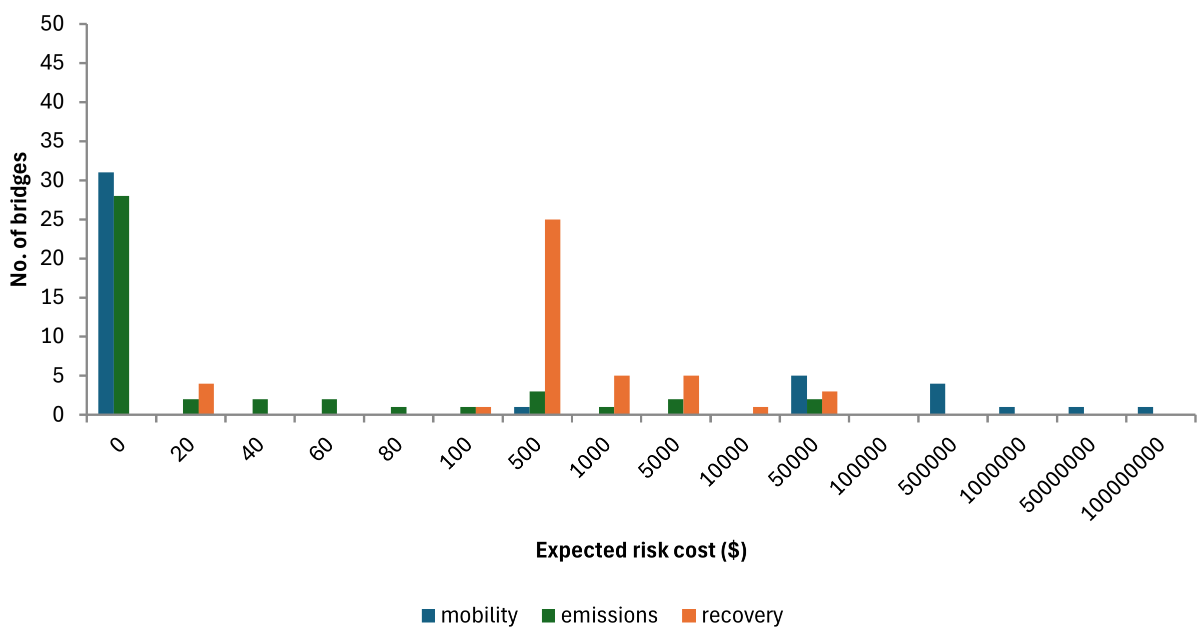


Figure 4.31. Expected annual risk cost for overheight hits by type for Florida bridges (vertical under-clearance < 13.5 ft.).

4.9. Vessel impact

4.9.1. Estimate of likelihood

4.9.1.1. Likelihood of occurrence

The hazards posed by vessel impact on bridges have existed for a long time and continue to be very important. According to the initial report by the National Transportation Safety Board (NTSB), on March 26, 2024, a 947-foot-long Singapore-flagged cargo vessel was leaving the Baltimore Harbor in Baltimore, Maryland, when it lost power and struck the pier supporting the central truss spans of the Francis Scott Key Bridge (Key Bridge). This led to the collapse of sections of the bridge into the river and the deck of the vessel, as well as resulting in the deaths of six bridge maintenance workers (NTSB 2024). In terms of the history of vessel impacts on bridges, it is reported that worldwide from 1960 to 2015, 35 major bridge collapses have been attributed to ship or barge collisions, resulting in the deaths of 342 people (AP 2024).

In this study, the NBI Item 38, Navigation Control (Table Name: Bridge, Field Name: *navcntrol*) was used to identify the bridges that would accommodate vessel traffic, with the code set to “1” which indicates navigation control on the waterway. The FDOT Structures Manual (FDOT 2024) and Fowler and Kosar (2019) describe the Department’s Vessel Collision Risk Analysis Software, which is considered a good source of pertinent information for this study. The data requirement for the FDOT’s software is very detailed and much more than what the BrM can provide, but efforts were made to develop a model that will utilize BrM data as much as possible, identifying BrM data that would serve as proxy variables needed for the FDOT’s software methodology. Another relevant study is that by Consolazio et al. (2023) which updated the estimates of vessel traffic at some bridge locations (Past Points) in Florida. The Past Point is a term for location related to vessel tracking. The specific bridge locations for the various past points in Florida, given by county, was indicated on maps provided by FDOT’s Structures Design Office (FDOT 2024b).

According to Fowler and Kosar (2019) and the AASHTO Vessel Collision Design of Highway Bridges (AASHTO 2009), the likelihood of vessel collision on a bridge is expressed as the Annual Frequency of Collapse (AFC), and defined as expressed in equation 11, with the independent variables described in Table 4.23, showing the original definitions of the variables, and the assumptions made to adopt the variables for developing the BMS risk model on vessel impacts for FDOT bridges.

$$AFC=(N)(PA)(PG)(PC)(PF) \tag{11}$$

Table 4.23. Variables for estimating the vessels' Annual Frequency of Collapse (AFC).

Variable	Original definition	Modified use for BMS risk study
N	Annual number of vessels, classified by type, size, and loading condition, that utilize the channel.	Estimate based on the FDOT's vessel traffic data on the Past Points.
PA	Probability of Aberrancy = Probability based on navigation conditions at the bridge site.	PA is discussed in more detail later in the next section of the report (see Table 4.27).
PG	Geometric Probability = Probability a vessel will hit a bridge pier or superstructure component if it is aberrant in vicinity of bridge. It is computed based on the various dimensions of the vessel, bridge span, pier, and water depth, assuming a normal distribution of the vessel accidents	The geometric probability was estimated from the channel skew, which was determined from the channel approach alignment relative to the traffic direction on the bridge. Four variables were identified. A *channel alignment rating* system has been developed in this study using the channel vessel alignment relative to 90 degrees, the result assigned a rating from 0 to 9, and then prorated between the factor values of 0 and 1. An ideal situation would be a channel that is placed parallel to the vessel's traffic direction (Rating = 9; factor = 1). Bridge attributes *MAINSPANS* which correlates to the No. of interior piers, and *NAVHC*, *NAVVC* for the Navigable Horizontal and Vertical Clearances, respectively, were normalized using the maximum values for each, and assigned as input variables. PG was computed as the maximum of the four variables.
PC	Probability of Collapse = Probability bridge will collapse if struck by aberrant vessel.	This is normally based on an elaborate structural analysis, considering collision forces and the energy involved. Assumption was made here to use the following bridge attributes as an indication of the bridge resistance to collapse: pier protection, superstructure and substructure condition ratings, rating from scour evaluation (*scrratng* -- *userbrg* table), and the scour critical information. The condition ratings are directly prorated appropriately, between 0 and 1,while the other variables were assigned ratings and probabilities using Tables 4.24 to 4.26. The maximum value from the five variables was chosen as the probability of collapse.
PF	Protection Factor = Adjustment to AF for full or partial protection of selected bridge components (typically 1.0 for FDOT projects).	The protection factor was estimated based on the presence or absence of pier protection elements, as indicated in Table 4.24.

Table 4.24. NBI Item 111 Pier or abutment protection and assigned factors.

Code	Description	Assigned Rating	Assigned Protection Factor
1	Navigation protection not required.	9.00	1.0
2	In place and functioning.	9.00	1.0
3	In place but in a deteriorated condition.	5.00	2.0
4	In place but reevaluation of design suggested.	2.00	2.0
5	None present but reevaluation suggested.	0.00	2.0
N	Not Applicable	9.00	1.0

Table 4.25. NBI Item 113 Scour Critical and assigned probability.

Code	Description	Assigned Rating	Assigned Probability
0	SC - Bridge Failed	0	1.0
1	SC - Fail Imminent	1	0.9
2	SC - Extensive Scour	2	0.8
3	SC - Unstable	3	0.7
4	Stable, Needs Action	4	0.6
5	Stable Within Footing	5	0.4
6	Calcs Not Made	6	0.3
7	Countermeasures	7	0.2
8	Stable, Above Footing	8	0.1
9	On Dry Land	9	0.0
N	Not Applicable	9	0.0
T	Tidal, Low Risk	9	0.0
U	Unknown Foundation	0	1.0

Table 4.26. FDOT Rating Scour Evaluation (userbrg Table) and assigned probability.

Code	Description	Assigned Rating	Assigned Probability
@	Unknown	0	1.0
!	Not applicable	9	0.0
A	High Risk Unknown	0	1.0
1	Low Risk - Low	6	0.3
2	Low Risk - Medium	5	0.4
3	Low Risk - High	4	0.6
4	Scour Susceptible - Low	4	0.6
5	Scour Susceptible - Medium	3	0.7
6	Scour Susceptible - High	2	0.8
7	Scour Critical	1	0.9
8	Minimal Risk	8	0.1
9	Low Risk Unknown	3	0.7

The Probability of Aberrancy (PA) is the risk of vessel collision that can be attributed to human pilot error (e.g., inattention, sleeping, etc.), adverse conditions (e.g., poor visibility, high density of vessel traffic, etc.), and vessel's mechanical failure (Fowler and Kosar 2019). It is calculated as follows using equation 12, with the variables explained in Table 4.27.

$$PA=(B_R)(R_B)(R_C)(R_{XC})(R_D) \qquad (12)$$

Table 4.27. Variables for estimating the vessels' Probability of Aberrancy (PA).

Variable	Original definition	Modified use for BMS risk study
B_R	Aberrancy Base Rate = Estimate of the base rate of vessel aberrancy under ideal conditions. $B_R = 0.6 \times 10^{-4}$ (ships) and $B_R = 1.2 \times 10^{-4}$ (barges).	Assume the value for barges, i.e., $B_R = 1.2 \times 10^{-4}$.
R_B	Bridge Correction Factor = Adjustment to PA based on the proximity of a bridge to a bend in the waterway. Based on waterway regions: R_B= 1.0 for Straight Regions; $R_B = 1 + \theta/90°$ for Transition Regions; and $R_B = 1 + \theta/45°$ for Turn/Bend Regions.	GIS maps were utilized to determine values of the turning angles θ at each of the bridge locations. The parameters for the waterway region were measured as shown in Figure 4.32 and illustrated in Figure 4.33 for a specific bridge. R_B was calculated using the equations shown here in the original definition.
R_C	Current Correction Factor = Adjustment to PA based on the velocity of the current component acting parallel to the transit path. $R_C = 1 + V_C/10$, where V_C = Current velocity component parallel to vessel transit path.	Values are not available for the proposed model, so the study assumed $R_C = 1.0$.
R_{XC}	Crosscurrent Correction Factor = Adjustment to PA based on the velocity of the current component acting perpendicular to the transit path. $R_{XC} = 1 + V_{XC}$, where V_{XC} = Current velocity component perpendicular to vessel transit path.	Values are not available for the proposed model, so the study assumed $R_{XC} = 1.0$.
R_D	Traffic Density Correction Factor = Adjustment to PA based on the density of vessel traffic in the region. R_D depends on the frequency in which vessels meet or pass each other near bridge. $R_D = 1.0$ for low (rarely), $R_D = 1.3$ for average (occasionally), and $R_D = 1.6$ for high (routinely).	A variable, *vt* was computed as the estimated daily vessel traffic divided by the maximum bridge span length. The variable was converted to R_D by prorating between 0 and 1.6, to linearly correlate with the minimum and maximum values of *vt* in the inventory.

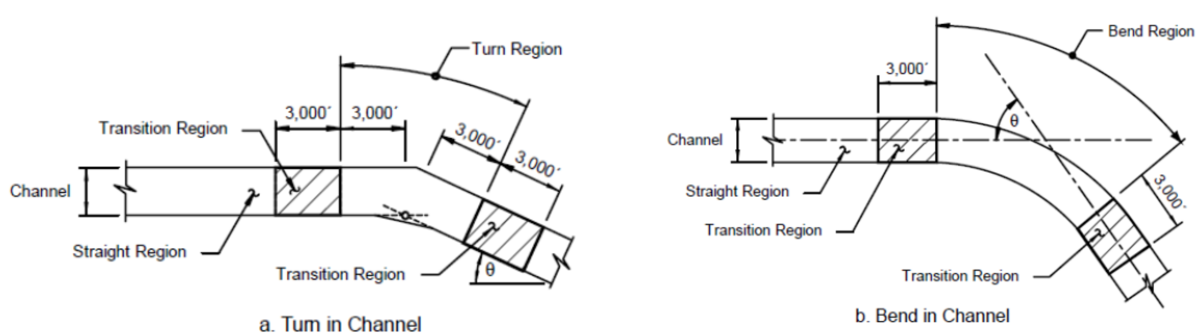


Figure 4.32. Identifying waterways regions at bridge locations (Fowler and Kosar 2019).

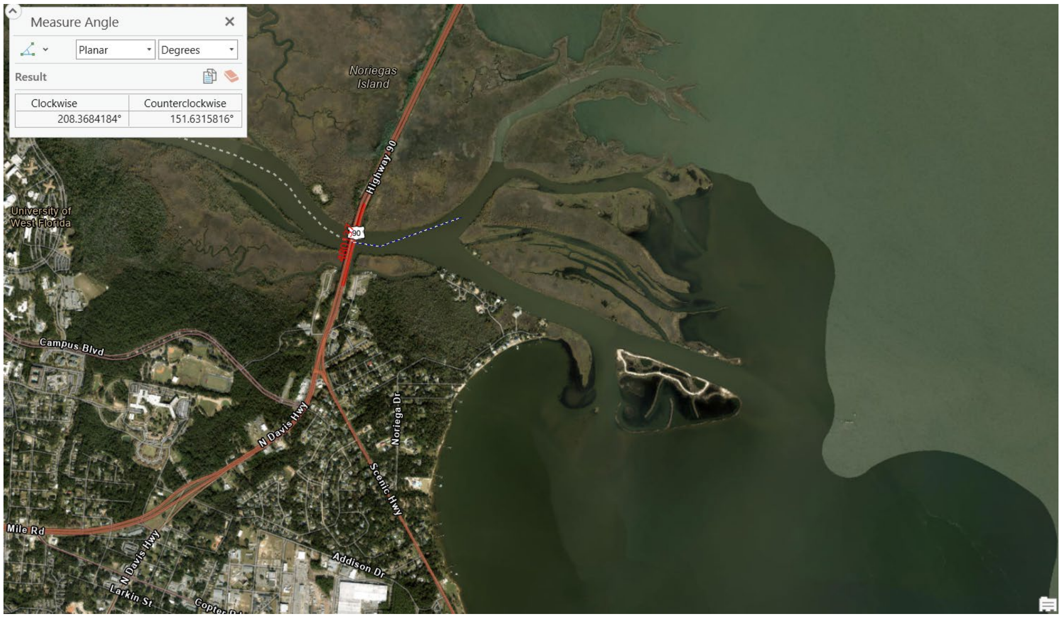


Figure 4.33. Identifying water way region and measuring channel alignment at Bridge ID 480137.

The first step in developing the vessel impact risk model was to estimate the vessel traffic, based on the results reported by Consolazio et al. (2023), who developed a model (equation 13) that estimates future vessel traffic projections at Past Points, with the coefficients as shown in Table 4.28. For a desired year (y), $t = y - y_0$, and $N(t)$ estimates the number of annual vessel trips (both upbound and downbound traffic directions).

$$N(t) = N(y - y_0) = a_0 * t^{a_1} + a_2 \qquad (13)$$

where y_0 = 2009.

Based on the 208 Past Points identified from the FDOT maps, the vessel traffic projection was done for the Year 2024 using the regression model in equation 13. The Consolazio et al. (2023)'s vessel traffic projection model has indicated in Table 4.28 that 10 of the 52 past points cannot be evaluated due to lack of data recorded by USACE or that the data was not statistically meaningful. This resulted in only 169 of the 208 bridge locations having vessel traffic data, and after projection on the GIS layers, the result showed 127 bridges, which were analyzed to estimate the risk of vessel collision, in terms of the Annual Frequency of Collision (AFC), as well as the return period of the hazard. Table 4.29 shows the forecasted values of vessel traffic, and the past points considered in the study.

As shown in Figure 4.34, three bridges are predicted to experience vessel collision at least once a year, but about 98% of the locations have an estimated annual frequency of one or less. However, within a 5-year period, 25 of the bridges (about 20%) will have at least one collision, with six bridges having at least 2 collisions, and one location having six collisions (Figure 4.35). For risk computations required in the study, the likelihood of occurrence was taken as the minimum of the annual frequency of collapse and 1, to confine with the limits of the probability estimate.

Table 4.28. Parameters of traffic projection power model curves (Consolazio et al. 2023).

Past point	a_0	a_1	a_2
1	847.821	-2.085	513.257
2	135.55	-0.019	-26.9
3	-76.754	-0.318	79.454
4	11.236	-2.169	3.983
5	-109.681	-0.304	118.741
6	-204.143	-0.399	182.894
7	872.908	0.231	626.047
8	3149.926	0.087	1154.631
9	[No data recorded by USACE]	N/A	N/A
10	[No data recorded by USACE]	N/A	N/A
11	[No data recorded by USACE]	N/A	N/A
12	[No data recorded by USACE]	N/A	N/A
13	313.524	-1.279	1124.919
14	-31.005	-0.418	32.697
15	-5.483	0.168	81.064
16	[No statistically meaningful data]	N/A	N/A
17	0	0	84.2
18	0	0	85.6
19	[No data recorded by USACE]	N/A	N/A
20	-35.567	-0.468	27.411
21	-307.39	-0.13	299.318
22	3081.644	0.182	3346.969
23	7998.852	0.03	-7820.152
24	177.008	-1.271	312.671
25	2026.778	-1.74	1763.848
26	2984.452	-1.846	2416.763
27	898.019	-2.128	698.47
28	-113.584	-0.275	126.191
29	[No data recorded by USACE]	N/A	N/A
30	287.663	-1.676	352.8
31	860.358	-2.045	579.518
32	-666.798	-1.822	696.155
33	763.232	0.252	720.182
34	-83.458	-0.679	94.898
35	-181.795	-0.356	165.221
36	580.899	0.304	809.763
37	3111.015	0.14	1853.078
38	[No statistically meaningful data]	N/A	N/A
39	208.773	-1.492	3345.386
40	2873.731	0.151	2064.967
41	120.425	-0.736	109.704
42	[No data recorded by USACE]	N/A	N/A
43	[No data recorded by USACE]	N/A	N/A
44	-89.437	-0.345	106.858
45	-106.083	-0.351	115.813
46	27.567	0.648	104.183
47	-94.745	-0.407	96.114
48	-107.025	-0.447	104.31
49	-190.576	-0.436	155.982
50	-117.088	-0.518	93.72
51	-114.787	-0.334	117.602
52	-81.262	-0.388	99.765

Table 4.29. Vessel traffic forecast estimate for past points on Florida for 2024.

No.	County	BRKEY	Past Point	Vessel Traffic
1	Bay	460012	1	516
2	Bay	460077	1	516
3	Bay	460019	2	102
4	Brevard	703001	3	47
5	Brevard	703002	3	47
6	Brevard	704049	3	47
7	Brevard	700030	4	4
8	Brevard	700031	4	4
9	Brevard	700072	4	4
10	Brevard	700110	4	4
11	Brevard	700116	4	4
12	Brevard	700201	4	4
13	Brevard	704015	4	4
14	Brevard	700061	5	71
15	Brevard	700077	5	71
16	Brevard	700137	5	71
17	Brevard	700143	5	71
18	Brevard	700174	5	71
19	Brevard	700181	5	71
20	Brevard	700184	5	71
21	Indian River	880053	5	71
22	Broward	860024	6	114
23	Broward	860043	6	114
24	Broward	860230	6	114
25	Dade	870592	6	114
26	Dade	870593	6	114
27	Dade	870606	6	114
28	Dade	870607	6	114
29	Broward	860018	7	2258
30	Broward	860034	7	2258
31	Broward	860060	7	2258
32	Broward	860144	7	2258
33	Broward	860157	7	2258
34	Broward	860466	7	2258
35	Broward	860467	7	2258
36	Broward	860941	7	2258

Table 4.29. Vessel traffic forecast estimate for past points on Florida for 2024 (Cont'd).

No.	County	BRKEY	Past Point	Vessel Traffic
37	Broward	860160	8	5141
38	Broward	860161	8	5141
39	Broward	860920	8	5141
47	Dade	870062	14	23
48	Dade	870301	14	23
49	Dade	870554	14	23
50	Dade	874262	14	23
51	Dade	874459	14	23
52	Dade	874545	14	23
53	Dade	874998	14	23
54	Dade	875101	14	23
55	Franklin	490003	15	72
56	Franklin	490031	15	72
65	Gulf	510052	17	84
66	Gulf	510951	17	84
67	Gulf	510048	18	86
75	Volusia	790940	20	17
76	Lee	120002	21	83
77	Lee	120064	21	83
78	Lee	120083	21	83
79	Lee	120084	21	83
80	Lee	120157	21	83
81	Lee	120158	21	83
82	Lee	124044	21	83
83	Manatee	130054	22	8392
84	Pinellas	150189	22	8392
85	Duval	720027	23	856
86	Duval	720076	23	856
87	Duval	720107	23	856
88	Duval	720158	23	856
89	Duval	720249	23	856
90	Duval	720343	23	856
91	Duval	720570	23	856
92	Duval	720061	24	318
93	Nassau	740055	24	318
94	Escambia	480035	25	1782
95	Escambia	480136	25	1782

Table 4.29. Vessel traffic forecast estimate for past points on Florida for 2024 (Cont'd).

No.	County	BRKEY	Past Point	Vessel Traffic
96	Escambia	480137	25	1782
97	Escambia	580058	25	1782
98	Santa Rosa	580058	25	1782
99	Escambia	580071	25	1782
101	Escambia	480118	26	2437
102	Escambia	480140	26	2437
103	Escambia	480123	27	701
104	Escambia	480139	27	701
105	Okaloosa	570034	27	701
106	Santa Rosa	580951	27	701
107	Flagler	730022	28	72
108	Flagler	734071	28	72
109	Nassau	740087	30	356
110	Nassau	740088	30	356
111	Okaloosa	570091	31	583
112	Walton	600108	31	583
113	Glades	50044	32	691
114	Hendry	70033	32	691
115	Palm Beach	930022	33	2230
116	Palm Beach	930026	33	2230
117	Palm Beach	930064	33	2230
118	Palm Beach	930094	33	2230
119	Palm Beach	930097	33	2230
120	Palm Beach	930104	33	2230
121	Palm Beach	930105	33	2230
122	Palm Beach	930154	33	2230
123	Palm Beach	930157	33	2230
124	Palm Beach	930214	33	2230
125	Palm Beach	930226	33	2230
126	Palm Beach	930318	33	2230
127	Palm Beach	930322	33	2230
128	Palm Beach	930411	33	2230
129	Palm Beach	934908	33	2230
130	Palm Beach	930004	34	82
131	Palm Beach	930007	34	82
132	Palm Beach	930042	34	82
133	Palm Beach	930106	34	82
134	Palm Beach	930269	34	82
135	Palm Beach	930339	34	82

Table 4.29. Vessel traffic forecast estimate for past points on Florida for 2024 (Cont'd).

No.	County	BRKEY	Past Point	Vessel Traffic
136	Palm Beach	930349	34	82
137	Martin	890107	35	96
138	Palm Beach	930005	35	96
139	Palm Beach	930056	35	96
140	Broward	860011	36	2133
141	Broward	860146	36	2133
142	Palm Beach	934408	36	2133
150	Hillsborough	105606	39	3349
151	Hillsborough	150189	39	3349
152	Pinellas	150028	40	6390
153	Pinellas	150030	40	6390
154	Pinellas	150044	40	6390
155	Pinellas	150049	40	6390
156	Pinellas	150050	40	6390
157	Pinellas	150068	40	6390
158	Pinellas	150112	40	6390
159	Pinellas	150135	40	6390
160	Pinellas	154355	40	6390
161	Pinellas	157800	40	6390
162	Putnam	760043	41	126
173	Duval	720044	44	72
174	Duval	720068	44	72
175	Duval	720069	44	72
176	Duval	720442	44	72
177	Duval	720518	44	72
178	Duval	720609	44	72
179	St. Johns	780099	44	72
180	St. Johns	783080	44	72
181	St. Johns	780074	45	75
182	St. Johns	780089	45	75
183	St. Johns	780090	45	75
184	St. Johns	780056	46	264
185	Indian River	880077	48	72
186	Indian River	880087	48	72
187	St. Lucie	940045	48	72
188	St. Lucie	940094	48	72
189	Martin	890002	49	97
190	Martin	890003	49	97

Table 4.29. Vessel traffic forecast estimate for past points on Florida for 2024 (Cont'd).

No.	County	BRKEY	Past Point	Vessel Traffic
191	Martin	890016	49	97
192	Martin	890038	49	97
193	Martin	890058	49	97
194	Martin	890066	49	97
195	Martin	890093	49	97
196	Martin	890103	49	97
197	Martin	890132	49	97
198	Martin	890133	49	97
199	Martin	890143	49	97
200	Martin	890060	50	65
201	Volusia	790098	51	71
202	Volusia	790132	51	71
203	Volusia	790139	51	71
204	Volusia	794004	51	71
205	Volusia	794025	51	71
206	Brevard	703004	52	71
207	Volusia	790152	52	71
208	Volusia	790172	52	71

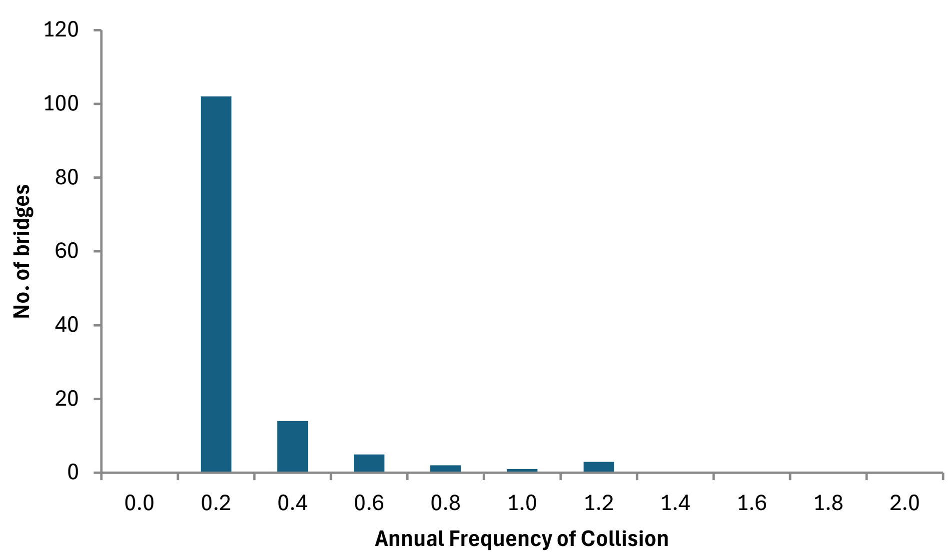


Figure 4.34. Estimated annual frequency of vessel collisions at Florida bridge locations.

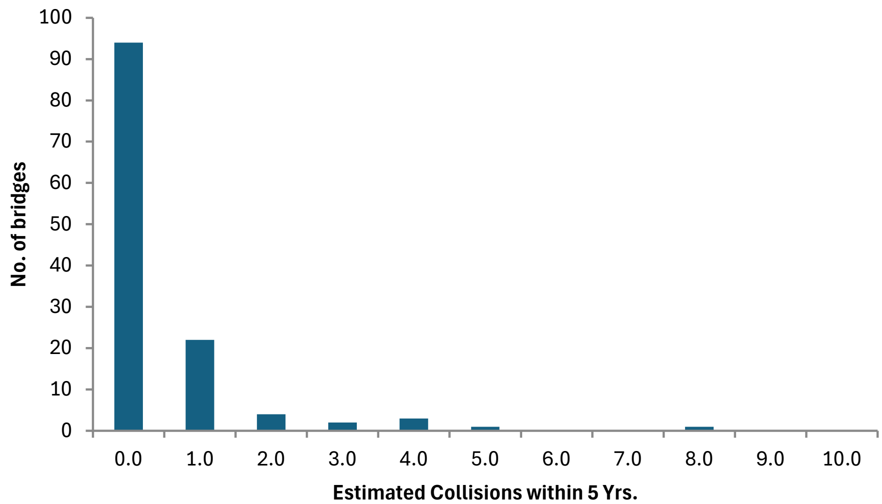


Figure 4.35. Estimated 5-year period vessel collisions at Florida bridge locations.

4.9.1.2. Likelihood of service disruption

Most vessel impact incidents may affect the vessel traffic but do not typically directly disrupt the vehicular traffic service on the bridge, though occasional severe impacts can occur. This study assumes the likelihood of service disruption value of 0.50 for freight routes (interstates) and 0.01 for other routes.

4.9.1.3. Total likelihood of hazard scenario

For each hazard scenario, the total likelihood is a product of the likelihood of occurrence and the likelihood of service disruption.

4.9.2. Consequence

4.9.2.1. Condition

In the bridge inspection records and prior BMS risk study, there is limited data available on the physical damages to Florida bridges due to vessel impacts. A review of some documented events is summarized in Tables 4.30 and 4.31, indicating the severity of damages and the repair costs. Based on the data in Table 4.31, the recovery costs for bridge damages from vessel impact was estimated as $4.18/SF.

4.9.2.2. Safety

Vessel collisions are typically not associated with safety issues of vehicular crashes, but they can affect the vehicular traffic on the severe cases. Analysis of such crashes is outside the scope of this study.

4.9.2.3. Mobility

The RITIS data has no recorded values of incident times during this type of hazard occurrence. Based on the limited data shown for past events in Table 4.31, the duration of service disruption was assumed as 1 day for all bridges, though very rare cases may have longer durations.

4.9.2.4. Environmental sustainability

Using the standard emission rates, and equation 5 as explained earlier in the methodology, the emission costs were computed for disruption in service associated with vessel impact for Florida's state and county-maintained bridges.

The consequences cost, i.e., the expected annual risk costs are shown in Figure 4.36, with the recovery costs appearing to cost most among the three categories of costs, and the emissions costing the least.

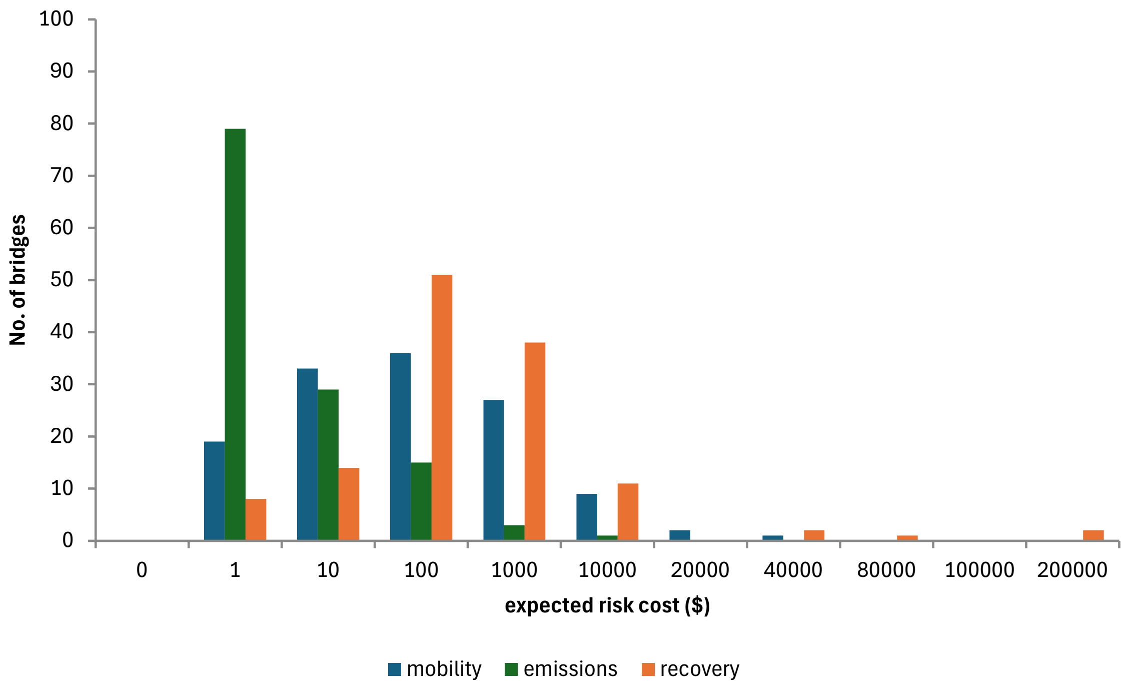


Figure 4.36. Expected annual risk costs by type due to vessel impacts on Florida bridges.

Table 4.30. Summary of damages from vessel impacts on Florida bridges.

BRKEY	Inspection Date	Bridge Owner Code	Comments	Bridge element affected				Damage Level*
				Fender	Other sub-structure	Girder/ super-structure	Other Element	
100300	7/21/2022	1	Tugboat with attached work barge. Possible damage to west fender system.	x				1
130057	3/30/2021	1	Dredging vessel. Fender impact.	x				U
150027	5/11/2001	1	Casino vessel. Fender impact. No broken piling found.	x				0
150027	4/25/2005	1	Vessel collision. Element 387 inspected. Fender Dolphin System Prestressed Concrete.	x				U
150049	4/12/2014	1	Pushed barge. Fender impacted.	x				U
150107	6/15/2006	1	Loose barge from mooring. Impact damages to underside of overhang in spans 315 and 316,bent caps, piles, and beams.		x	x		1
170064	3/29/2006	2	Pushed barge. Fender impacted.	x				U
170064	3/10/2020	2	Vessel impact, bounced of fender and damaged another fender.	x				1
460019	1/26/2022	1	Spud barge. Impact damage to main channel span.			x		1
460019	9/12/2022	1	Impact on fender.	x				U
480118	2/21/2018	1	Vessel impact.					U
480139	5/14/2015	32	Barge impact. Fender system inspected.	x				U
480289	9/18/2020	1	Heavy work barges impact.					U
490100	1/30/2019	1	Vessel impact.					U
490100	12/28/2020	1	Vessel impact.					U
490100	9/26/2022	1	Vessel impact.					U
570034	4/27/2019	1	Barge impact. Girders impacted.			x		U
570034	5/26/2022	1	Vessel impact.					U
700110	10/27/2015	1	Barge with crane. Beams inspected.			x		U
700221	10/23/2015	1	Barge with crane. Beams inspected.			x		U
720005	10/28/2002	1	Tug pushing barge with crane. Fender impacted. No damage.	x				0
720005	10/31/2005	1	Crane barge. Damaged fenders.	x				1
720005	10/31/2007	1	Vessel impact. Minor damages to fender.	x				1
720022	12/20/2005	1	Mast of vessel struck bridge. Minor damages (scrapped paint).					1
720022	4/23/2018	1	Vessel impact. Fender damaged.	x				1
720044	3/23/2004	1	Vessel impact. Fender damaged.	x				1
720044	9/28/2005	1	Vessel impact. Fender damaged.	x				1
720044	9/1/2009	1	Vessel impact. Fender damaged.	x				1

* U - Unknown/No mention of damage; 0 - No damage; 1 - Minor/unspecified damage level; 2 - Moderate damage; 3 - Severe damage.

Table 4.30. Summary of damages from vessel impacts on Florida bridges (Cont'd).

BRKEY	Inspection Date	Bridge Owner Code	Comments	Bridge element affected				Damage Level*
				Fender	Other sub-structure	Girder/ super-structure	Other Element	
720061	4/10/2001	1	Vessel mast impacted bascule span. No damage.			x		0
720061	5/17/2002	1	Barge pushed by tugboat. Impact damage to structure and fender system.	x	x	x		1
720061	12/23/2002	1	Vessel impact. Fender not damaged.	x				0
720061	4/23/2003	1	Two barges pushed by tug. Impact damage on fender.	x				1
720061	10/1/2007	1	Barge with crane. Fender damaged.	x				1
720068	3/16/2000	1	Two barges. Fender system damaged.	x				1
720069	9/6/2000	1	Barge on tugboat. Impact damage on timber fender system.	x				1
720069	1/1/2003	1	Two barges pushed by tug. Impact damage on fender.	x				1
720326	5/11/2023	1	Vessel impact. Damage to reflector sign on pile.		x			1
720571	1/4/2007	1	Barge on tugboat. Impact damage on fender system.	x				1
720571	9/10/2008	1	Barge impact. Fender system impacted but no damage.	x				0
720629	12/13/2005	1	Two tugboats and cargo vessel. Impact damage on fender.	x				1
720699	4/1/2021	1	Barge on a tugboat. Impact damage on fender system, navigational lights and signs.	x				1
760043	6/3/2003	1	Crane barge and tug. No impact damage.					0
780074	2/26/2002	1	Catamaran. Minor scraps to column. No repairs requested.		x			1
780074	7/20/2011	1	Vessel boom entangled and stuck. No damage.					0
780074	11/13/2013	1	Sailboat loose form mooring. Struck structure and hung up.					0
780074	11/17/2015	1	Vessel. Impact damage on fender.	x				1
780074	7/19/2016	1	Barge on tug. Severe impact damage on fender system.	x				3
780074	2/23/2023	1	Trawler vessel. Impact damage on fender.	x				1
780090	3/10/2011	1	Vessel. Slight impact damage on girder.			x		1
790152	11/20/2020	1	Barge and tug. Impact on fender.	x				U
790172	11/20/2020	1	Barge and tug. Impact on fender.	x				U
794025	5/26/2006	2	Barge. Impact on bascule span.			x		U
860011	11/2/2004	1	Vessel. Impact on fender.	x				U

* U - Unknown/No mention of damage; 0 - No damage; 1 - Minor/unspecified damage level; 2 - Moderate damage; 3 - Severe damage.

Table 4.30. Summary of damages from vessel impacts on Florida bridges (Cont'd).

BRKEY	Inspection Date	Bridge Owner Code	Comments	Bridge element affected				Damage Level*
				Fender	Other sub-structure	Girder/ super-structure	Other Element	
860467	11/23/2021	1	Vessel impact. Minor impact damage on 8290 - channel, 210 - pier wall, and 8562 - counterweight support.		x		x	1
870077	9/15/2022	1	Vessel. Column, pile cap, pile inspected for impact damage.		x			U
870147	8/28/2018	31	Vessel. Channel and fender inspected for impact damage.	x	x			U
870301	4/23/2014	1	Vessel . Fender and navigational lights inspected for impact damage.	x				U
870479	12/28/2015	1	Vessel. Fender inspected for impact damage.	x				U
870613	2/20/2014	1	Vessel. Fender and pier wall inspected for impact damage.	x	x			U
874161	7/25/2016	2	Vessel. Tender house (Elem 581) inspected for impact damage.				x	U
874544	7/8/2019	2	Vessel. Girder and fender inspected for impact damage.	x		x		U
874998	11/20/2020	2	Vessel. Fender inspected for impact damage.	x				U
900077	5/31/2019	1	Barge. Impact on bascule span.			x		U
900126	5/25/2023	1	Barge. Columns, bent cap, and beams inspected for impact damage.		x	x		U
930060	10/15/2004	1	Vessel. Fender and bascule pier inspected for impact damage.	x	x			U
930097	3/8/2012	26	Tug and barge. Fender system inspected for impact damage.	x				U
930269	11/23/2022	1	Vessel. Girder inspected for impact damage.			x		U
936776	8/23/2013	4	Vessel impact.					U
940045	7/27/2010	1	Vessel impact. Pier, footing, fender, and submarine cable inspected for impact damage.	x	x		x	U

* U - Unknown/No mention of damage; 0 - No damage; 1 - Minor/unspecified damage level; 2 - Moderate damage; 3 - Severe damage.

Table 4.31. Summary of vessel bridge collision (allision) damages and costs in Florida (vessel data from Le Coz and Fast 2024).

Date	Vessel Type	Reported Damage Repair Cost	Vessel Length (ft.)	Bridge	Bridge ID	Deck Area (SF)	Cost/SF	Comments
7/15/2005	Freight ship	$650,000	268.0	5th Avenue Bridge, Miami.	870990	23,287	$27.91	Damage on the north span of the bridge.
5/29/2007	N/A	$40,000	N/A	Matanzas Pass Bridge, Fort Myers Beach.	120088	103,468	$0.39	Minor damage to several girders. Closed 7 hrs for inspection.
11/13/2004	Freight barge	N/A	N/A	Sanibel Causeway Bridge, Fort Myers Beach.	124043	71,331		Impact on the fender system on Span A.
11/2/2015	Freight barge	N/A	55.0	Mather's Bridge, Melbourne.	704063	25,781		Substantial damage to the fender system; 3-4 piles and several supports and cross members needing replacement.
10/23/2015	Freight barge	$105,000	64.7	Indian River 528 Bridge, Cape Canaveral.	700247	275,209	$0.38	Crane secured to the deck of the barge. Closed 1 hr. for inspection.
9/5/2008	Freight barge	$100,000		Longboat Pass Bridge, Bradenton Beach	130057	79,636	$1.26	Damage to bridge's fender system.
7/13/2006	Freight barge	$70,853	140.0	Dick Misener Bridge, Saint Petersburg.	150214	160,681	$0.44	West bound tug and barge collided with the fender system.
9/14/2008	Freight barge	$100,000	33.4	Johns Pass Bridge, Madeira Beach.	150027	29,801	$3.36	Collided with the fender system.
11/4/2014	Freight barge	$85,000	25.5	Kennedy Boulevard Bridge, Tampa.	100100	25,123	$3.38	125 boom crane at the bow and a drill rig collided with bridge. No damage to bridge but approximately 5 gallons of diesel fuel into the Hillsborough River.
3/30/2006	Tank barge	$312,000	73.7	The Gandy Bridge, Tampa.	100300	627,092	$0.50	The inbound barge collided with the bridge. Severe damage and one lane closed to traffic.
9/26/2013	Freight ship	$3,000,000	700.4	Mathews Bridge, Jacksonville.	720076	428,517	$7.00	Vessel struck the underside support beams. The bridge remained closed to vehicular traffic for 33 days.

Table 4.31. Summary of vessel bridge collision (allision) damages and costs in Florida (Cont'd) (vessel data from Le Coz and Fast 2024).

Date	Vessel Type	Reported Damage Repair Cost	Vessel Length (ft.)	Bridge	Bridge ID	Deck Area (SF)	Cost/SF	Comments
3/24/2004	Freight barge	$450,000	N/A	Atlantic Blvd Bridge, Jacksonville Beach.	720042	21,066	$21.36	Impact and damage on the western portions of fender system.
10/19/2016	Freight ship	N/A	515.6	St Johns River, Jacksonville.				Vessel damage.
2/4/2008	Freight barge	$221,150	61.2	Atlantic Blvd Bridge, , Jacksonville Beach.	720042	21,066	$10.50	Impact and extensive damage on the fender system.
10/21/2004	Freight barge	$230,000	84.5	Sister's Creek Bridge, Jacksonville Beach.	720699	200,724	$1.15	Impact and damage on the fender system.
2/10/2005	Freight barge	$150,000	153.6	Sister's Creek Bridge, Jacksonville Beach.	720699	200,724	$0.75	Impact and damage on the fender system.
3/20/2013	Freight barge	$25,000	72.0	Brooks Bridge, Fort Walton Beach.	570034	92,392	$0.27	Boom of crane barge collided with the bridge steel girders. Concrete damage to the bridge apron and broken water line.
1/30/2008	Tank barge	$150,000	70.2	Middle Bay Bridge, Destin.	570091	824,542	$0.18	Tow drifted into the southwest bridge fender, damaging 50 ft of the cribbing.
12/3/2005	Freight barge	$100,000	60.7	Navarre Bridge, Santa Rosa Island.	580951	90,048	$1.11	Impact and damage on the fender system.
5/17/2017	Tank barge	$360,000	69.3	Pensacola Bay Bridge, Pensacola.	480290	903,728	$0.40	Westbound barge collided with the bridge dolphin, causing extensive damage to approximate 40 ft of dolphin timber and wiring.
8/7/2016	Freight barge	$85,000	66.0	Pensacola Bay Bridge, Pensacola.	480290	903,728	$0.09	Impact and damage on the fender system on the east side of the bridge.
1/2/2016	Tank barge	$410,000	62.4	Escambia River Highway 90 Bridge	480197	151,320	$2.71	Impact and damage on the bridge (northside) wooden fender system and walkway.
3/18/2017	Freight barge	$352,000	65.0	Pensacola Bay Bridge, Pensacola.	480290	903,728	$0.39	Eastbound vessel made impact and damaged on the bridge (southwest part) fender wood planks and metal wiring.

4.10. Performance Measures

Social cost of risk and utility were declared as the two performance measures under this risk model. The social costs have been defined earlier as the sum of the expected risk costs under each of the performance criteria, in this case, mobility, environmental sustainability, and condition/recovery. For each bridge, the recovery cost, mobility cost, and environmental sustainability cost have been derived and reported as consequences under each hazard scenario above. These costs are presented again but as totals for each hazard later in this section. But the focus here now is the social cost of risk and risk utility for each bridge in the inventory, considering all the hazards and the performance criteria. Under the section on the research methodology in this report, equations 6 and 7 were defined for calculating the social cost of risk, while equations 8 and 9 present the computation of the risk utility. Assuming equal weights for each of the hazard scenarios and each of the performance criteria, the social cost and utility has been computed for the FDOT's state-maintained bridge inventory, based on the research methodology presented earlier in this report, using equations 6 and 7 for the social cost of risk, and equations 8 and 9 for the risk utility.

4.10.1. Social cost

Applying the appropriate equations to the likelihood of occurrence, likelihood of service disruption, and the consequences, the social cost was estimated at each bridge. All the pertinent hazards and criteria were accounted for, and the weights for the criteria and hazards were applied to compute the social cost of risk. The results for the Florida state-maintained bridge inventory are shown in Figure 4.37, about 30% of the bridges have social costs between $1000 and $5000, with about 45% below this range, and the remaining with costs above $5000, including five bridges with costs greater than $1 million.

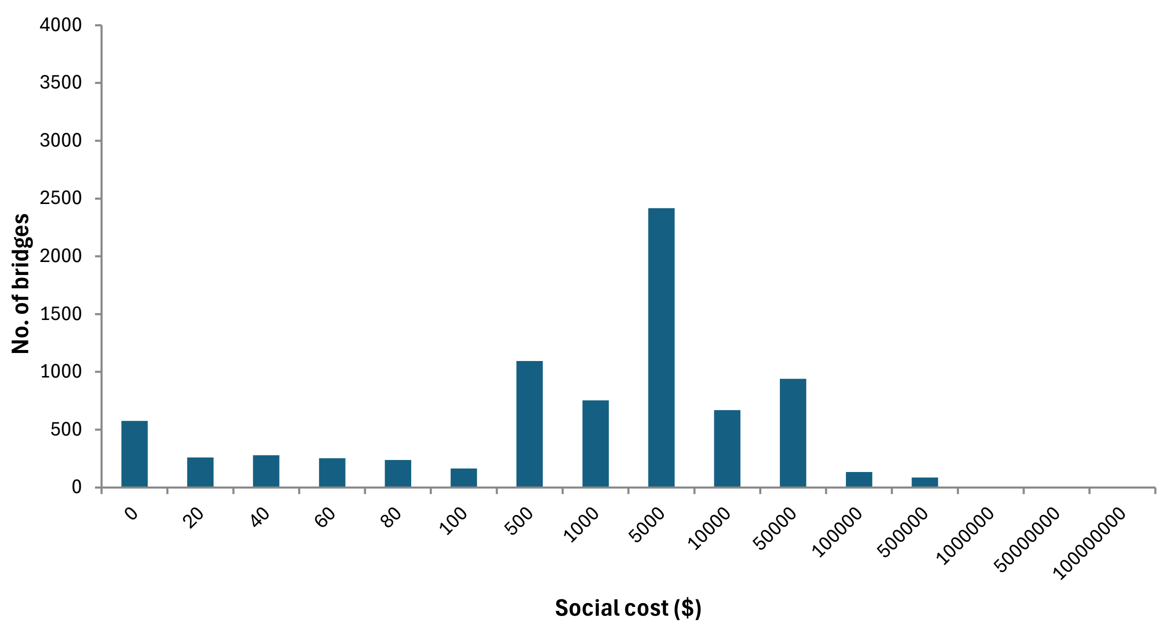


Figure 4.37. Annual social costs of risk for Florida state-maintained bridges.

The social cost of risk was also summed for each of the hazard scenarios and summarized in Figure 4.38. It shows that overheight hit for bridges with vertical underclearances under 13.5 ft. have the highest social costs of risk. But it should be noted that under this particular hazard scenario, there is a single bridge contributing about $78 million to the costs, with the next lower cost in this scenario being just under $400,000. Under the scour hazard scenario, there are two bridges costing about $29 million and $8 million, with the next lower cost being about $4 million. Without these two bridges with exceedingly high costs, the cost distribution would be significantly different, as shown in Figure 4.38.

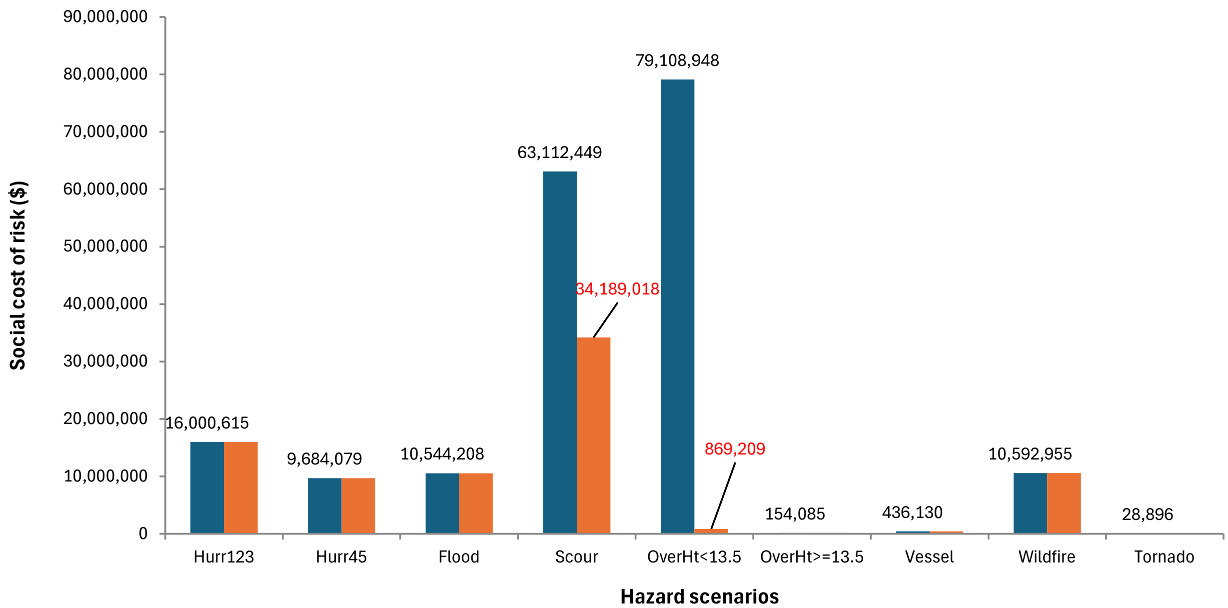


Figure 4.38. Annual social costs of risk for Florida state-maintained bridges showing hazard scenarios.

The following paragraphs discuss the variation in the social costs of risk for each hazard scenario. First, the results for hurricanes are summarized in Figure 4.39 showing that for state-maintained bridges, most bridges (about 47% of the 7303 bridges) have expected risk costs less than or equal to $500 under the scenario of Hurricane categories 1,2 and 3, while 12 bridges have such costs at $100,000 or above. For the other scenario of Hurricane categories 4 and 5, about 34% of the state bridges have an expected risk cost of $500 or less, and 29 bridges have risk costs of at least $100,000.

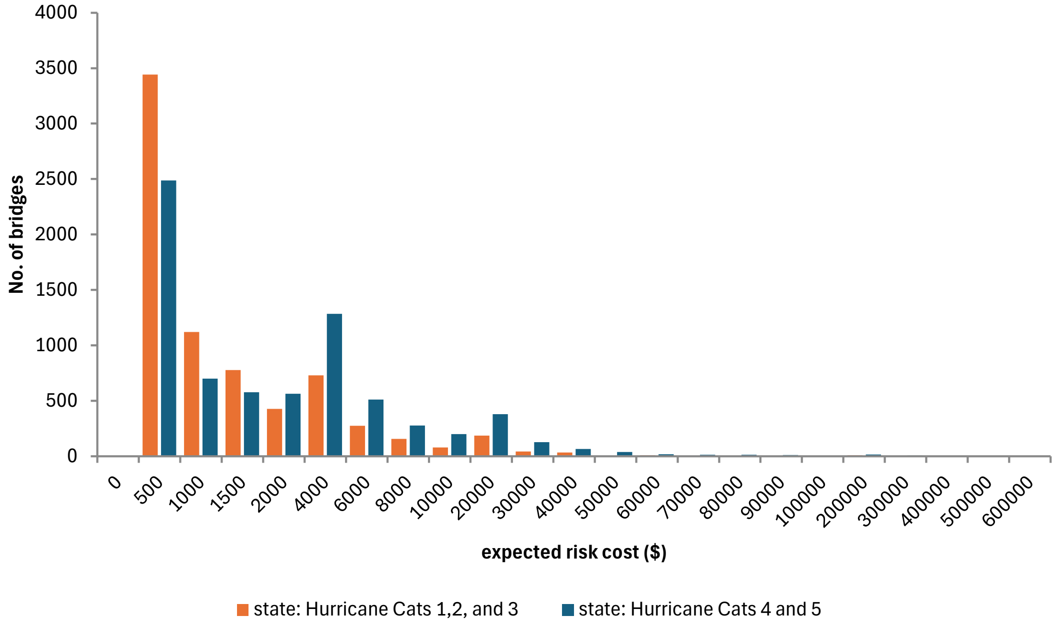


Figure 4.39. Social risk costs of state-maintained Florida bridges due to hurricanes.

Shown in Figure 4.40, it can be seen that under flooding, most bridges have zero social risk costs, with only 7% of county bridges , and 1% of state bridges having costs greater than zero.

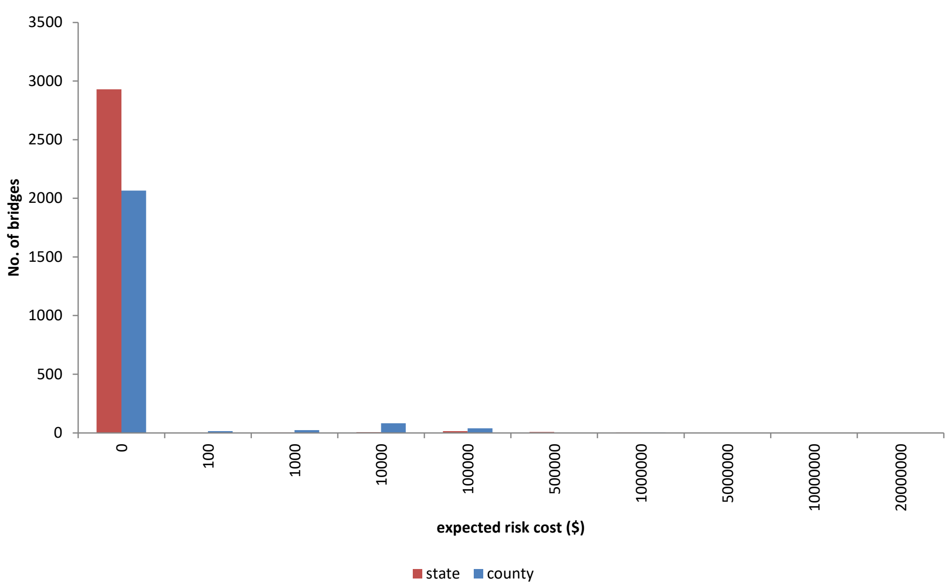


Figure 4.40. Social risk costs of state and county-maintained Florida bridges due to floods.

Shown in Figure 4.41, it can be seen that about half of the state-maintained bridges have zero social risk costs and on the overall, lower costs than the county-maintained bridges.

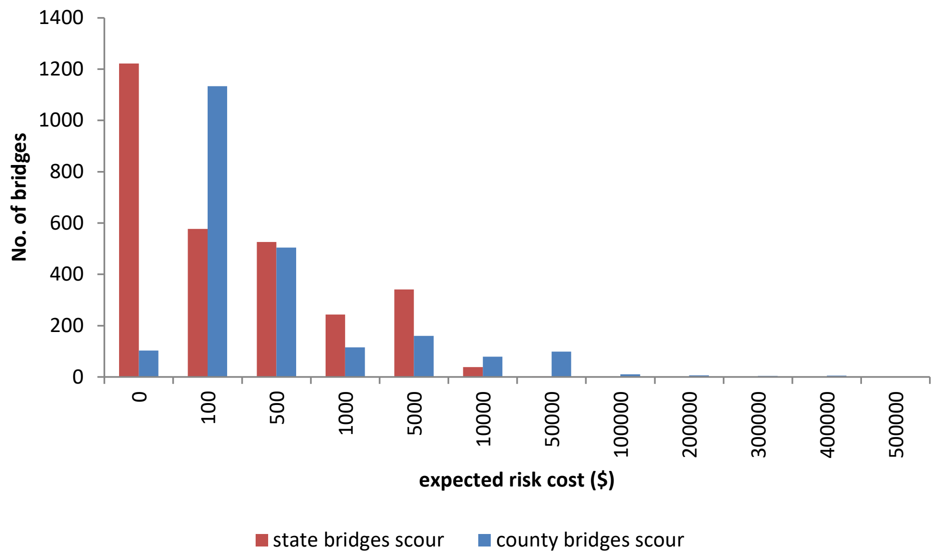


Figure 4.41. Social risk costs of state and county-maintained Florida bridges due to scour.

Shown in Figure 4.42, it can be seen that most of the state-maintained bridges have risk costs less than $2000.

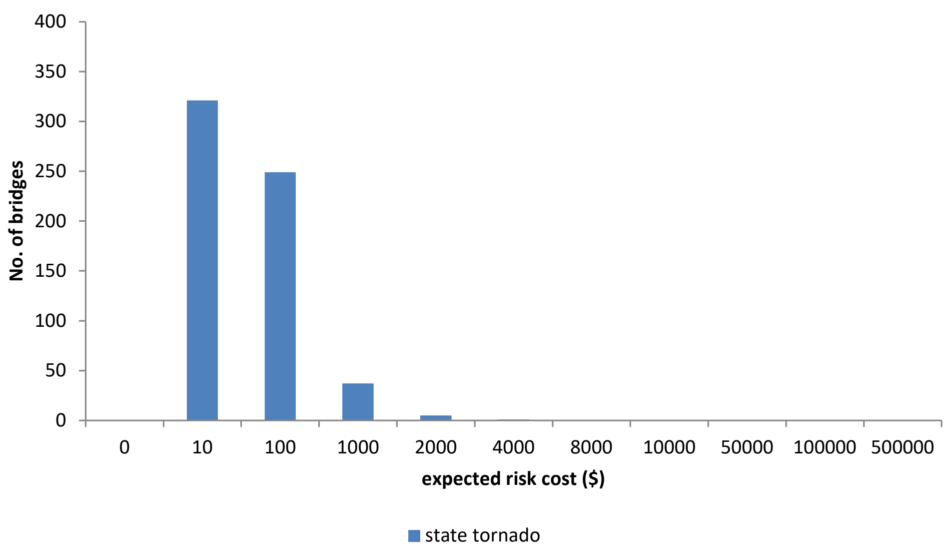


Figure 4.42. Social risk costs of state-maintained Florida bridges due to tornado.

Shown in Figure 4.43, it can be seen that more about half of the state-maintained bridges have risk costs between $1000 and $5000, with a few below that range, and about 40% above it. There are a few bridges with costs between $100000 and $300000.

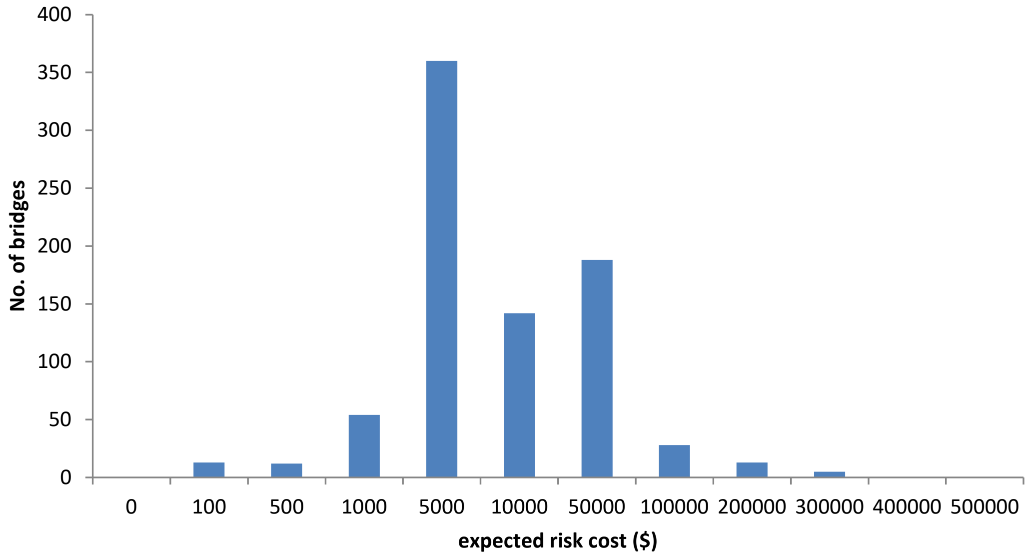


Figure 4.43. Social risk costs of state-maintained Florida bridges due to wildfire.

The social risk costs are summarized and shown below in Figure 4.44 only for bridges with vertical under clearances less than 13.5 ft. because those bridges with higher underclearances showed minimal risk costs. On bridges with the vertical underclearances of at least 13.5 ft., about 99% of them have less than $500 risk cost, and about 91% have zero costs. As shown in Figure 4.44 for the bridges with clearances less than 13.5 ft., about 16% have risk costs of more than $50,000, with some bridges having significantly higher costs, including one with a cost of $78 million.

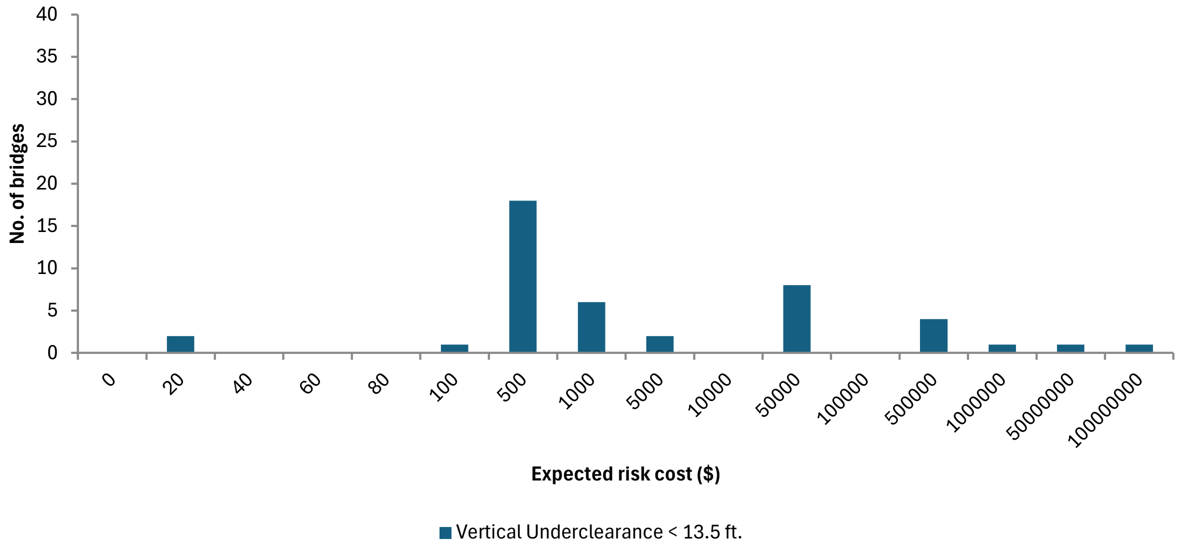


Figure 4.44. Social risk costs of state-maintained Florida bridges due to overheight hits (vertical under-clearance < 13.5 ft.).

The total social costs are shown in Figure 4.45 for bridges when exposed to the hazard of vessel impact, with about 96% of the costing less than $10,000.

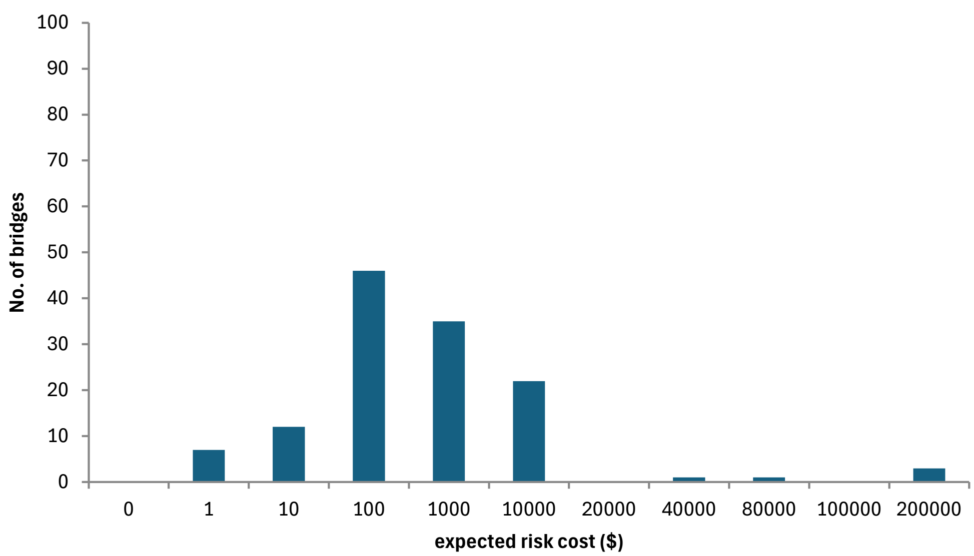


Figure 4.45. Social risk costs of state-maintained Florida bridges due to vessel impact.

4.10.2. Utility

Similarly, as described above for computing the social cost of risk, the appropriate equations were employed, first to calculate the vulnerability index for each bridge, before calculating the utility. Figure 4.46 illustrates the variation in the risk utilities for the state-maintained bridges in Florida. About 94% of the bridges have utility values between 90 and 100, while 6% have utility between 80 and 90, and only a few bridges (15) have utility values below 60.

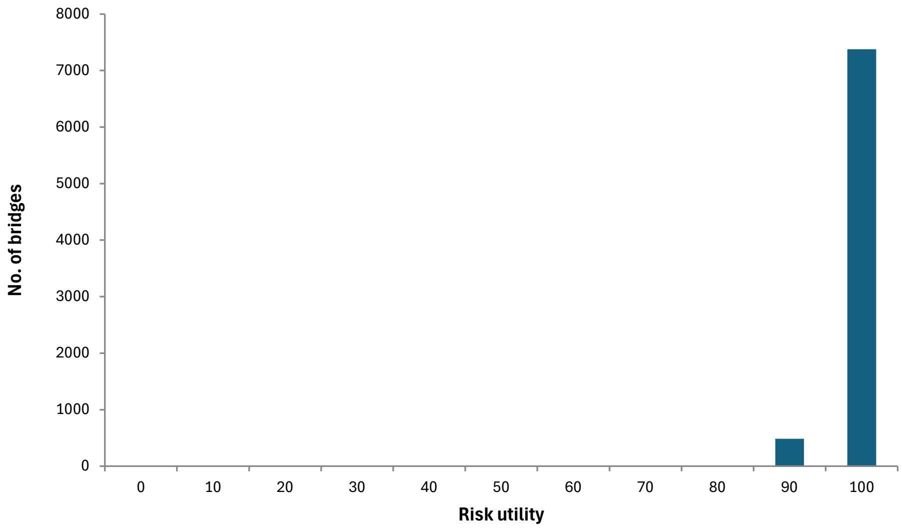


Figure 4.46. Annual risk utility for Florida state-maintained bridges.

4.10.2.1. BrM Utility weights

From Figure 4.38, the revised total social costs for each of the hazard scenarios can be used to establish the utility weights in BrM. The total social costs are summarized again in Table 4.32. It is recommended to use the wildfire hazard as the base of the wight calculation (equals 1.0) and ignore the tornado, vessel impact, and overheight hit hazards; but these three hazard scenarios will be assigned the 1.0 weight. The calculated values are shown in Table 4.32, with scour having the highest weight (3.3) followed by Hurricane categories 1, 2, and 3 with 1.6, and the other scenarios can be assigned 1.0. The final recommended weights are rounded up and shown below in the table: Scour 3.0; Hurricane categories 1,2 and 3 assigned 2.0; and other hazard scenarios 1.0.

Table 4.31. Relative utility weights for hazard scenarios in BrM.

	Hurr123	**Hurr45**	**Flood**	**Scour**	**OverHt <13.5**	**OverHt >=13.5**	**Vessel**	**Wildfire**	**Tornado**
Original social cost	16,000,615	9,684,079	10,544,208	63,112,449	79,108,948	154,085	436,130	10,592,955	28,896
Revised social cost	16,000,615	9,684,079	10,544,208	34,189,018	869,209	154,085	436,130	10,592,955	28,896
Estimated utility weight	1.51	0.91	1.00	3.23	0.08	0.01	0.04	1.00	0.00
Recomm-ended utility weight	**2.0**	**1.0**	**1.0**	**3.0**	**1.0**	**1.0**	**1.0**	**1.0**	**1.0**

4.10.2.2. Project analysis spreadsheet

A Microsoft Excel workbook has been developed to provide some of the results presented in this report for each of the hazard scenarios. In addition a project interface was designed for interactive assessment of the risk data and the computation of the risk utility. A screenshot of the project interface is shown in Figure 4.47.

FDOT BMS Risk Analysis (Template modified from NCHRP 20-07 378)

Project summary

Bridge ID	030285	Owner code	1
Alternative	Do nothing	Deck area (sq.ft)	10,055
Program year	2024	Program cost ($000)	4,687

Roadways	On structure				Under structure			
Func class	08				16			
Utilization	ADT	6,360	Trucks	10.00%	ADT	28,946	Trucks	13.00%
Roadway	Length (ft)	260	MPH	45	Length (ft)	85	MPH	70
Detour	Miles	123.7	MPH	70	Miles	51.0	MPH	60

From BMS data. If multiple roadways, use the total ADT and most significant roadway, projected to program year.
Length on-structure is bridge length. Length under-structure is bridge width..

Hazard scenarios		Consequences ($000)				Likelihood			Risk	
ID	Scenario	Cost	Safety	Mobility	Environment	Extreme	Disruption	Weight	Cost ($k)	chk
1	Hurr-123	1,508	0	602	28	28.59%	0.20%	1.00	1.22	1
2	Hurr-45	3,167	0	3,011	140	14.30%	0.20%	1.00	1.81	1
3	Flood	0	0	0	0	0.00%	0.00%	1.00	0.00	0
4	Scour	0	0	0	0	0.00%	0.00%	1.00	0.00	0
5	OverHt>=13.5	1	0	0	98	0.00%	100.00%	1.00	0.00	1
9	OverHt<13.5	0	0	0	0	0.00%	0.00%	1.00	0.00	0
6	Vessel	0	0	0	0	0.00%	0.00%	1.00	0.00	0
7	Wildfire	10	0	602	28	29.67%	50.00%	1.00	94.98	1
8	Tornado	0	0	0	0	0.00%	0.00%	1.00	0.00	0
10								1.00	0.00	

See worksheets for likelihoods and consequences

For state-maintained bridges only: Check (1) automatically indicates the applicable hazard scenarios.

Risk cost and vulnerability	Cost	Safety	Mobility	Environment
Struc weight	10,055	35,307	2,261,355	2,261,355
Criteria weight	1.00	1.00	1.00	1.00
Risk cost ($k)	3.26	0.00	90.53	4.22
Vulnerability	0.3242	0.0000	0.0400	0.0019

Risk analysis results	
Maximum unit risk cost:	100.00
Vulnerability index:	0.0037
Utility:	99.63
Social cost of risk ($000):	98.01

Figure 4.47. Project interface of the BMS risk model for Florida state-maintained bridges.

4.11. Conclusions

This research task has conducted a comprehensive investigation on considering the natural and manmade hazards that are unique to the state of Florida and incorporate the effect of risks due to these hazards into the FDOT's Bridge Management System, the AASHTOWare Bridge Management (BrM). Based on the review of nationally-recognized methodologies for BMS risk models, this study developed and applied a methodology of the risk model that involved estimating at each bridge location, the likelihood of occurrence of the hazard, the likelihood of service disruption, and costs of the associated consequences. Considering the bridge inventory, these estimates were utilized to compute the expected risk cost (social cost of risk), vulnerability index, and utility for each bridge.

The estimated likelihoods of occurrence at state-maintained bridge locations under the hazard scenarios were relatively low for most cases but a bit relatively higher for hurricanes, scour, wildfire, overheight collisions (vertical underclearance <13.5 ft.), and vessel impact. The sum of social cost of risks computed for the state-maintained bridge inventory indicated the following order among the hazard scenarios (descending): scour, hurricane categories 1, 2, and 3; wildfire; flood; hurricane categories 4 and 5; overheight collision (clearance <13.5 ft.); vessel impact; overheight collision (clearance <= 13.5 ft.); and tornado. The risk utility computed for each bridge in the state-maintained inventory indicated that most bridges (about 94%) have utility values between 90 and 100, while only a very few bridges (15) have values less than 60. In general, the bridges with higher risk costs would be considered to have higher priority for risk mitigation or would justify larger investments in mitigation. High risk costs may also make certain bridges more attractive candidates for replacement.

While the emphasis has been primarily on service disruption, a few demonstrations were presented on the physical degradation of the bridge, specifically, in defining resilience index and associated parameters, that can be used to assess the bridge inventory and agency's response to natural hazards such as the hurricane. It is recommended that future research be conducted on developing data-driven approaches to evaluating resilience of the bridge inventory after the occurrence of hazards, particularly, natural hazards. The hazard of vessel collisions is also becoming an issue of national concern. The results presented in this study can be improved with more dedicated data related to the hazard, especially, for the bridges at the vessel past points.

The BrM implementation on this research task was originally planned to be the development of utility functions in the form of SQL script to be incorporated by the FDOT IT personnel. But a simpler and more direct approach will involve creating a field for risk utility in the BrM *userbrg* table to contain the risk utility values for each bridge as computed from this study. The hazard scenarios were equally weighted in the model developed in this study, but if different weights are desired, the ratios between the total social costs of risks for each hazard scenarios suggest a relative weights that are provided in this report and can be entered in BrM when performing optimization based on the risk utility. A simple Microsoft Excel spreadsheet was also developed to contain summaries of the likelihoods and consequence costs for each hazard scenario, as well as an interactive user interface to view and compute the social cost of risks, vulnerability index and utility for each bridge in the state-maintained inventory.

4.12. References

Ayyub, Bilal M. (2015). Practical Resilience Metrics for Planning, Design, and Decision Making. *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems Part A Civil Engineering*, · May 2015

AP. (2024). A list of major US bridge collapses caused by ships and barges. The Associated Press (AP). Published: Mar. 26, 2024. Accessed July 31, 2024, from https://www.wsaz.com/2024/03/26/list-major-us-bridge-collapses-caused-by-ships-barges/.

BLS. (2024). Consumer Price Index: Trade, Transportation, and Utilities. Bureau of Labor Statistics (BLS) of the US Department of Labor. Southeast Information Office. Available at https://www.bls.gov/regions/southeast/florida.htm.

Bruneau M, and Reinhorn A. (2007). Exploring the Concept of Seismic Resilience for Acute Care Facilities. Earthquake Spectra. 2007;23(1):41-62. doi:10.1193/1.2431396

Bruneau, M., et al. (2003). A framework to quantitatively assess and enhance the seismic resilience of communities. *Earthquake Spectra*, 19(4), 733–752.

Dehghani, Mohammad Saied, Gerardo Flintsch, and Sue McNeil. (2017). Parametric Analysis of Roadway Infrastructure Vulnerability to Disruptions. Journal of Infrastructure Systems, American Society of Civil Engineers (ASCE). 23(4): 04017017. https://doi.org/10.1061/(ASCE)IS.1943-555X.0000371.

FHWA. (2023). Bridge Replacement Unit Costs 2023. Federal Highway Administration (FHWA). Available at https://www.fhwa.dot.gov/bridge/nbi/sd2023.cfm.

FDOT. (2022). Bridge management system coding guide. Florida Department of Transportation (FDOT), Office of Maintenance. Feb. 196 pp.

FDOT. (2024). 2024 Structures Manual. FDOT Structures Design Office. Topic No: 625-020-018. Florida Department of Transportation (FDOT). Accessed 5/2/2024 from https://www.fdot.gov/structures/structuresmanual/currentrelease/structuresmanual.shtm. 780 pp.

FDOT. (2024b). Vessel Past Point Maps. FDOT Structures Design Office. Florida Department of Transportation (FDOT). Accessed 5/2/2024 from https://www.fdot.gov/structures/pastpointmaps/vppm.shtm.

FEMA. (2024). Flood Hazard Zones of the Digital Flood Insurance Rate Map (DFIRM) in the State of Florida – April 2024. Metadata, NFHL Florida Data Product ID: NFHL_12_20240420, ESRI FGDB. Published 4/20/2024. Accessed May 2024 from the Florida Geographic Data Library (FGDL) at https://fgdl.org/.

Fowler, Stephen and Matthew Kosar. (2019). Basics of Vessel Collision. Presentation Slides, FDOT Transportation Symposium. Florida Department of Transportation. 60 pp.

Garrow, Laurie, and Terry Sturm. (2013). Development of a Risk-Based Scorecard to Assess Scour Vulnerability of Georgia's Bridges: Final Report. Georgia Department of Transportation Research Report RP-11-27, 2013. Available at http://www.dot.ga.gov/BuildSmart/research/Documents/11-27.pdf.

Ghorbanzadeh, Mahyar, Mohammadreza Koloushani, Eren Erman Ozguven, Arda Vanli and Reza Arghandeh (2022). City transportation network vulnerability to disasters: the case of Hurricane Hermine in Florida. Environmental Hazards, 21:3, 199-217, DOI:10.1080/17477891.2021.1933885. https://doi.org/10.1080/17477891.2021.1933885

Le Coz, Emily and Austin Fast. (2024). How many ships hit bridges, lose power every year? Data shows jarring numbers on the rise. USA TODAY, Investigations: Bridge Collapses. Published April 11, 2024. Accessed July 31, 2024 from https://www.usatoday.com/story/news/investigations/2024/04/11/baltimore-bridge-collapse-ship-blackouts-incidents/73262682007/.

Li, J., Ozbay, K. & Bartin, B. Effects of Hurricanes Irene and Sandy in New Jersey: traffic patterns and highway disruptions during evacuations. Nat Hazards 78, 2081–2107 (2015). https://doi.org/10.1007/s11069-015-1820-9.

Mojtahedi, M., Newton, S., & Von Meding, J. (2017). Predicting the resilience of transport infrastructure to a natural disaster using Cox's proportional hazards regression model. *Natural Hazards*, 85(2), 1119–1133.

Murray-Tuite, P. M. (2006). A comparison of transportation network resilience under simulated system optimum and user equilibrium conditions. Proceedings of the 38th conference on Winter simulation (pp. 1398–1405). Winter Simulation Conference. IEEE Conference Location: Monterey, CA, USA. doi: 10.1109/wsc.2006.323240. https://link.springer.com/chapter/10.1007/978-3-319-29713-2_1#citeas

NOAA. (2024). NHC Data in GIS Formats. National Oceanic and Atmospheric Administration (NOAA). National Hurricane Center and Central Pacific Hurricane Center, United States Department of Commerce. Accessed April 2024, from https://www.nhc.noaa.gov/data/tcr/.
Consolazio, Gary R., Michael T. Davidson, and Saul Licona Mendez, Jr. (2023). Update of Commercial Vessel Past Point Data for Designing Bridges across Navigable Florida Waterway. Final Report, Contract No. BDV31-977-134, Florida Department of Transportation. Feb. 242 pp.

NTSB. (2024). Contact of Containership Dali with Francis Scott Key Bridge and Subsequent Bridge Collapse. The National Transportation Safety Board (NTSB). Investigative Update. Release Date 24 June 2024. Accessed August 9, 2024, from https://www.ntsb.gov/investigations/Pages/DCA24MM031.aspx.

NTSB. (2024). Contact of Containership Dali with Francis Scott Key Bridge and Subsequent Bridge Collapse. The National Transportation Safety Board (NTSB). Marine Investigation Preliminary Report. Published May 16, 2024. 24 pp. Accessed August 9, 2024, from https://www.ntsb.gov/investigations/Pages/DCA24MM031.aspx.

NWS (2005). Floods: The awesome power. National Oceanic and Atmospheric Administration NOAA's National Weather Service (NWS). U.S. Department of Commerce. March. 16 pp.

RITIS. (2024). RITIS Introduction. Regional Integrated Transportation Information System (RITIS), The Center for Advanced Transportation Technology (CATT) Laboratory, The University of Maryland, Maryland. Accessed March 15, 2024, from https://ritis.org/intro.

Sobanjo, J., and Thompson, P. (2013). Development of risk models for Florida's bridge management system, Final Report, Research Contract #BDK83 977-11, Florida Department of Transportation, Tallahassee, Florida, 298p.

Sobanjo, J., and Thompson, P. (2004). Project planning models for Florida's Bridge Management System. Final Report, Contract No. BC 352-9. Florida Department of Transportation, (FDOT), State maintenance Office. Feb. 178 pp.

Stein, Stuart, and Karsten Sedmera. (2006). Risk-Based Management Guidelines for Scour at Bridges with Unknown Foundations. National Cooperative Highway Research Program Web-Only Document 107. Transportation Research Board of the National Academies, 2006. Available at http://onlinepubs.trb.org/onlinepubs/nchrp/nchrp_w107.pdf.

Thompson, Paul D., Hal Rogers, and Dustin Thomas. (2012). "Risk-Based Bridge Planning in Minnesota." Proceedings of the Sixth International Conference on Bridge Maintenance, Safety, and Management, Stresa, Italy, 2012. Available at http://www.crcnetbase.com/doi/abs/10.1201/b12352-78.

Thompson, Paul D., Patricia Bye, Jeff Western, and Meghann Valeo. (2017). Risk assessment for bridge management systems. Proc., 11th International Bridge and Structure Management Conference, Mesa, Arizona.

Western, Jeffrey, Patricia Bye, Meghann Valeo, Paul D. Thompson, and Ernest “Ron” Frazier. (2016). Assessing risk for bridge management systems. NCHRP 20-07/Task 378 Final Report. Prepared for AASHTO Standing Committee on Highways. Unofficial publication of the National Cooperative Highway Research Program, Transportation Research Board, National Research Council, or The National Academies. 121 pp.

5. Development of an improved NBI Translator

The primary motivation for developing an NBI Translator currently is to provide agencies with a tool for expressing forecasts of future condition of their bridges, in the form of either NBI 0-9 ratings or FHWA good-fair-poor ratings. While the number of agencies that use a translator with current inspection data may be declining, all agencies need the tool for the forecasts. The need for an NBI Translator tool in bridge management systems has also been expressed for several years, starting with the first BMSNBI Translator tool developed for the FHWA (Hearn et al. 1997). Efforts to improve the BMSNBI has included application of neural networks by Wazeer et al. (2007), use of trained regression models by Sobanjo et al. (2011), and more recently, proposed machine learning approaches by Bektas et al. (2013) and Hanif et al. (2019).

The widespread changes in condition state definitions in the new inspection manual have biased the NBI Translator's calculation of condition ratings, so they no longer closely match the NBI ratings produced by inspectors. In order to meet the needs of upcoming federal requirements, there is also a need for the forecasting of the probability of Good and Poor overall condition ratings for each bridge, which can be aggregated over the inventory to evaluate asset management performance targets. Recalibration of the Translator model will need to rely on field-collected element data, preferably dual inspections where the inspector has determined the element conditions and the NBI rating. It may be necessary to take defects into account, although the reliability of these data is still unknown.

It was observed that in the early studies, the Pontis-based approaches utilized smart flags to modify the element condition, and the recent approaches did not consider the element defects information in the algorithms presented for the translator models. This study approached the task with four objectives: make the translator simple to understand and use by the bridge engineers and managers; incorporate various pertinent bridge attributes from the inventory and condition data into the models, including the defect data; consider the FHWA's reporting of performance measures in terms of three condition ratings, i.e., 3-Good (NBI Ratings 7, 8 and 9); 2-Fair (NBI Ratings 5 and 6); and 1-Poor (NBI Ratings 0, 1,2, 3, and 4), in addition to the regular rating scale of 0 to 9; and also explore new innovative methodologies available in formulating the translator model.

Established by the Federal Highway Administration (FHWA), the National Bridge Inventory (NBI) rating system describes the health and deterioration of bridges and culverts across the United States. The system monitors the condition of bridge components from their initial construction through various stages of wear and tear. Bridge inspectors assess the deterioration of the bridge components, including culverts mostly through visual inspections, but occasionally also using non-destructive testing (NDT), or destructive testing methods. The NBI ratings relate to the key components of a bridge system, such as the deck, superstructure, substructure, culverts, and channels. According to the FHWA, the NBI component ratings range from 0 to 9, with 0 indicating a failed component and 9 indicating an excellent condition (FHWA 1995, 2022). As shown in Table 5.1, the FHWA also specifies the performance measures on bridges in terms of three generalized ratings: Good, Fair, and Poor, corresponding respectively to NBI ratings 7, 8, or 9, NBI ratings 5 and 6, and NBI ratings 0 to 4 (FHWA 2017).

While the NBI component ratings are crucial for various bridge management stakeholders in making decisions to ensure the safe operation of existing bridges and allocating maintenance resources, they are especially important for the federal allocation of financial resources for bridge maintenance. Aside from the NBI component rating system, the transportation agencies in the United States also utilize various element-based condition assessment and inventory methods, including the AASHTOWare BrM system. The BrM provides significantly more detailed information about the condition of bridge elements, which make up the major components. In BrM, the bridge element condition is reported in terms of four states, ranging from condition state 1 to 4, corresponding to good, fair, poor, and severe, respectively. In addition to reporting the condition state data for each primary element, there are also four-state condition data for specific defects, as well as for secondary and protection elements associated with the primary element. Both the NBI condition rating and BrM element-based system consider defect identification in their respective rating methodologies, but the element-based system provides more details, including the rating of the specific defects present.

Table 5.1. FHWA definition of condition ratings (FHWA 1995, 2017).

NBI Code	NBI Generalized* Code	NBI Code Description	NBI Generalized Code Description
9	3	EXCELLENT CONDI TI ON	GOOD
8	3	VERY GOOD CONDITION - no problems noted.	GOOD
7	3	GOOD CONDITION - some minor problems.	GOOD
6	2	SATISFACTORY CONDITION - structural elements show some minor deterioration.	FAIR
5	2	FAIR CONDITION - all primary structural elements are sound but may have minor section loss, cracking, spalling or scour.	FAIR
4	1	POOR CONDITION - advanced section loss, deterioration, spalling or scour.	POOR
3	1	SERIOUS CONDITION - loss of section, deterioration, spalling or scour have seriously affected primary structural components. Local failures are possible. Fatigue cracks in steel or shear cracks in concrete may be present.	POOR
2	1	CRITICAL CONDITION - advanced deterioration of primary structural elements. Fatigue cracks in steel or shear cracks in concrete may be present or scour may have removed substructure support. Unless closely monitored it may be necessary to close the bridge until corrective action is taken.	POOR
1	1	"IMMINENT" FAILURE CONDITION - major deterioration or section loss present in critical structural components or obvious vertical or horizontal movement affecting structure stability. Bridge is closed to traffic, but corrective action may put back in light service.	POOR
0	1	FAILED CONDITION - out of service - beyond corrective action.	POOR

* The FHWA performance measure classes of Good (3), Fair (2), and Poor (1).

Developing an NBI translator can reduce the cost of field data collection and ensure compliance with FHWA NBI rating requirements for funding allocation. Therefore, there is need for an effective and accurate NBI translator that various agencies can utilize. While some agencies, like the Florida Department of Transportation (FDOT), collect bridge condition data using both element and NBI condition ratings, other agencies collect their data only at the element level. This discrepancy has created a need for a classification model that can convert element-level data into NBI ratings.

The NBI translator developed by Hearn et al. (1997) applied smart flags to adjust the predicted NBI ratings and improve accuracy. This modification indicates that the tabular NBI translator algorithm was not inherently defect data driven. Al-Wazeer et al. (2007) tried to improve the NBI translator by developing a neural network classifier. It was concluded that the proposed neural network classifier model outperformed Hearn's (1997) NBI translator model, provided the data used to train the model was sampled from the same state as the data used for prediction. However, Al-Wazeer et al. (2007)'s model was based on the old Pontis element condition data, with only the primary element condition data and no defect or secondary elements considered.

Bektaş and Smadi (2008) performed a statistical comparison of the actual NBI component ratings with the predictions made by the BMSNBI translator in Pontis and found that the predictions did not accurately represent the actual NBI ratings. Bektas et al. (2013) used decision tree techniques to map NBI condition ratings from bridge element condition data. Their algorithm was compared with the BMSNBI Translator developed by Hearn (1997). However, the technique developed by Bektas et al. (2013) had limited predictive variables, using only about four predictive variables. A typical decision tree model has 4 predictive variables i.e. condition state 1 to 4, and most times only two of the predictive variables in a model were significant. It was noted that the authors also considered secondary (or other primary) elements for the superstructure and substructure models. However, the results of these models were not discussed in the paper. The authors stated that other deck- elements, bridge railings, and deck joints, are not to be considered in the overall NBI deck evaluation (FHWA 1995) and were thus not included in the analyses. In all, 20 decision trees models were developed which included models for deck, superstructure and substructure components.

Sobanjo and Thompson (2011) integrated the fundamentals and processes of bridge inspection at both the element level and NBI standards to design an NBI translator; they proposed an empirical relationship between the element health condition index and the expected condition state. These computed condition states are then used to predict NBI rating conditions using a linear regression model. Weight factors were also proposed to achieve a more realistic prediction of NBI ratings through linear regression and optimization techniques.

Fiorillo and Nassif (2019) documented the results of five machine learning classifier models using bridge condition data from the New Jersey Department of Transportation (DOT) and Northeastern states of the US. The models showed poor classification results for bridges in New Jersey. However, surprisingly high accuracy results of 97.3% for superstructure and 99.7% for substructure were achieved using the nearest neighbor classifier for bridge data in the Northeastern states. The other four classifiers produced poor results.

Thompson (2021) developed a non-linear maximum likelihood model of the probabilities of the federal good, fair, and poor categories, suitable for satisfying federal requirements for transportation performance management at the network level. This model did not attempt to forecast the 0-9 scale. By reducing model requirements, the model produced very accurate results from element condition state data while being easy to calibrate in a spreadsheet model. The procedure was included as part of the open source StruPlan model for long-range renewal planning for transportation structures.

The conclusion of the literature review is that all previous work on NBI translators used very few predictive variables in their statistical or machine learning models. This limitation led to poor prediction accuracy because it is challenging to map from a low 4-dimensional space to a higher 10-dimensional space. Incorporating other element and defect data from the bridge element database can provide additional predictive variables, enhancing the accuracy of statistical or machine learning models for more precise prediction results.

5.1. Data preparation

Based on the FDOT's BrM database, the 242 elements defined in the Element Definition Table (*ELEM_DEF*), were assigned to components or subgroups of elements, created and listed as follows: deck; deck support (secondary); superstructure; superstructure support (secondary); substructure; culvert; channel; sign structures, defects; and protection. While the typical components (deck, superstructure, etc.) are known, this study defined the secondary or support type of elements based on their contribution to the function of their respective NBI components. For instance, stringers and floor beams typically augment the main girders, so they will be assigned as support or secondary members to the superstructure (girder). Sign structures were excluded from consideration in this study, and substructures were considered individually, without support or secondary elements.

Using the FDOT's 2020 bridge data, the element inspection records (*ELEM_DEF* table) were matched to the corresponding NBI 2020 inspection records (*INSP_EVNT* table) to obtain the NBI condition ratings for each component. Use of the elements' data for the assignment to the appropriate bridge component is roughly illustrated in Figure 5.1. Each element inspection record was assigned the appropriate major component (deck, superstructure, substructure, culvert or channel) or its representation of a support element, protection element, or defect. The detailed list of the elements assignment to bridge components is shown in the Appendix B's Table B1. For instance, the strip seal expansion joint was considered as secondary element to decks, where present, while stringers, floor beams, and bearings were assigned as support elements to superstructures. Considering the set of element inspection data for a specific bridge, the *ELEM_PARENT_KEY* was used to assign parent components to each defect and protection element indicated. For example on Bridge ID 010029, *ELEM_KEY* 1090 is first identified as a defect (Exposed Rebar) and then linked using the *ELEM_PARENT_KEY*, to the primary element # 109 (Prestressed Concrete Open Girder/Beam) which is identified as a Superstructure. Similarly, on the same bridge, the record for *ELEM_KEY* 8516 is identified as a protection (Painted Steel) and assigned to the superstructure element #109. The final inspection data contained the variables defined in Tables 5.2 to 5.6, respectively, for the deck, superstructure, substructure, culvert, and channel.

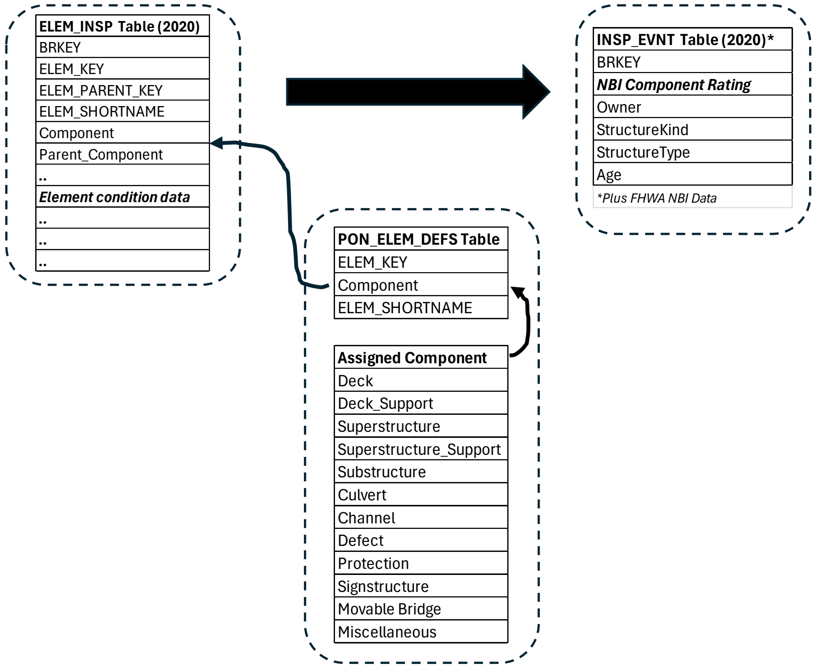


Figure 5.1. Overall framework of BrM data and bridge component assignment in the NBI Translator Model.

Table 5.2. Definition of variables evaluated for deck condition data.

Variable	Description
NoOfDeckElem	No. of deck elements
NoOfDeckSupportElem	No. of deck support (secondary) elements
NoOfDeckProtectionElem	No. of deck protection elements
NoOfDeckDefects	No. of deck defects
DeckHI	Deck Health Index (primary element)
DeckSuppHI	Deck Health Index (support elements)
DeckProtHI	Deck Health Index (protection elements)
DeckDefHI	Deck Health Index (defects)
PercentDeckSt1	Percent of deck (primary element) in condition state 1
PercentDeckSt2	Percent of deck (primary element) in condition state 2
PercentDeckSt3	Percent of deck (primary element) in condition state 3
PercentDeckSt4	Percent of deck (primary element) in condition state 4
PercentDeckSuppSt1	Percent of deck (support elements) in condition state 1
PercentDeckSuppSt2	Percent of deck (support elements) in condition state 2
PercentDeckSuppSt3	Percent of deck (support elements) in condition state 3
PercentDeckSuppSt4	Percent of deck (support elements) in condition state 4
PercentDeckProtSt1	Percent of deck (protection elements) in condition state 1
PercentDeckProtSt2	Percent of deck (protection elements) in condition state 2
PercentDeckProtSt3	Percent of deck (protection elements) in condition state 3
PercentDeckProtSt4	Percent of deck (protection elements) in condition state 4
PercentDeckDefSt1	Percent of deck (defects) in condition state 1
PercentDeckDefSt2	Percent of deck (defects) in condition state 2
PercentDeckDefSt3	Percent of deck (defects) in condition state 3
PercentDeckDefSt4	Percent of deck (defects) in condition state 4
PercentDeckNonSt1	Percent of deck (primary element) not in condition state 1
PercentDeckSuppNonSt1	Percent of deck (support elements) not in condition state 1
PercentDeckProtNonSt1	Percent of deck (protection elements) not in condition state 1
PercentDeckDefNonSt1	Percent of deck (defects) not in condition state 1
Owner	Agency responsible for bridge
StructureKind	Material type of bridge superstructure
StructureType	Design type of bridge
Age	Age of the bridge at inspection
DeckNBI[#]	The inspected Deck NBI condition rating

[#] *Dependent variable*

Table 5.3. Definition of variables evaluated for superstructure condition data.

Variable	Description
NoOfSupstrElem	No. of superstructure elements
NoOfSupstrSupport	No. of superstructure support (secondary) elements
NoOfSuspstrProtection	No. of superstructure protection elements
NoOfSupstrDefects	No. of superstructure defects
SupstrHI	Superstructure Health Index (primary element)
SupstrSuppHI	Superstructure Health Index (support elements)
SupstrProtHI	Superstructure Health Index (protection elements)
SupstrDefHI	Superstructure Health Index (defects)
PercentSupstrSt1	Percent of superstructure (primary element) in condition state 1
PercentSupstrSt2	Percent of superstructure (primary element) in condition state 2
PercentSupstrSt3	Percent of superstructure (primary element) in condition state 3
PercentSupstrSt4	Percent of superstructure (primary element) in condition state 4
PercentSupstrSuppSt1	Percent of superstructure (support elements) in condition state 1
PercentSupstrSuppSt2	Percent of superstructure (support elements) in condition state 2
PercentSupstrSuppSt3	Percent of superstructure (support elements) in condition state 3
PercentSupstrSuppSt4	Percent of superstructure (support elements) in condition state 4
PercentSupstrProtSt1	Percent of superstructure (protection elements) in condition state 1
PercentSupstrProtSt2	Percent of superstructure (protection elements) in condition state 2
PercentSupstrProtSt3	Percent of superstructure (protection elements) in condition state 3
PercentSupstrProtSt4	Percent of superstructure (protection elements) in condition state 4
PercentSupstrDefSt1	Percent of superstructure (defects) in condition state 1
PercentSupstrDefSt2	Percent of superstructure (defects) in condition state 2
PercentSupstrDefSt3	Percent of superstructure (defects) in condition state 3
PercentSupstrDefSt4	Percent of superstructure (defects) in condition state 4
PercentSupstrNonSt1	Percent of superstructure (primary element) not in condition state 1
PercentSupstrSuppNonSt1	Percent of superstructure (support elements) not in condition state 1
PercentSupstrProtNonSt1	Percent of superstructure (protection elements) NOT in condition state 1
PercentSupstrDefNonSt1	Percent of superstructure (defects) not in condition state 1
Owner	Agency responsible for bridge
StructureKind	Material type of bridge superstructure
StructureType	Design type of bridge
Age	Age of the bridge at inspection
SupstrNBI[#]	The inspected Superstructure NBI condition rating

[#] *Dependent variable*

Table 5.4. Definition of variables evaluated for substructure condition data.

Variable	Description
NoOfSubElem	No. of substructure elements
NoOfSubProtection	No. of substructure protection elements
NoOfSubDefects	No. of substructure defects
SubHI	Substructure Health Index (primary element)
SubProtHI	Substructure Health Index (protection elements)
SubDefHI	Substructure Health Index (defects)
PercentSubSt1	Percent of substructure (primary element) in condition state 1
PercentSubSt2	Percent of substructure (primary element) in condition state 2
PercentSubSt3	Percent of substructure (primary element) in condition state 3
PercentSubSt4	Percent of substructure (primary element) in condition state 4
PercentSubProtSt1	Percent of substructure (protection elements) in condition state 1
PercentSubProtSt2	Percent of substructure (protection elements) in condition state 2
PercentSubProtSt3	Percent of substructure (protection elements) in condition state 3
PercentSubProtSt4	Percent of substructure (protection elements) in condition state 4
PercentSubDefSt1	Percent of substructure (defects) in condition state 1
PercentSubDefSt2	Percent of substructure (defects) in condition state 2
PercentSubDefSt3	Percent of substructure (defects) in condition state 3
PercentSubDefSt4	Percent of substructure (defects) in condition state 4
PercentSubNonSt1	Percent of substructure (primary element) not in condition state 1
PercentSubProtNonSt1	Percent of substructure (protection elements) not in condition state 1
PercentSubDefNonSt1	Percent of substructure (defects) not in condition state 1
Owner	Agency responsible for bridge
StructureKind	Material type of bridge superstructure
StructureType	Design type of bridge
Age	Age of the bridge at inspection
SubNBI[#]	The inspected Substructure NBI condition rating

[#] *Dependent variable*

Table 5.5. Definition of variables evaluated for culvert condition data.

Variable	Description
NoOfCulvElem	No. of culvert elements
NoOfCulvProtection	No. of culvert protection elements
NoOfCulvDefects	No. of culvert defects
CulvHI	Culvert Health Index (primary element)
CulvProtHI	Culvert Health Index (protection elements)
CulvDefHI	Culvert Health Index (defects)
PercentCulvSt1	Percent of culvert (primary element) in condition state 1
PercentCulvSt2	Percent of culvert (primary element) in condition state 2
PercentCulvSt3	Percent of culvert (primary element) in condition state 3
PercentCulvSt4	Percent of culvert (primary element) in condition state 4
PercentCulvProtSt1	Percent of culvert (protection elements) in condition state 1
PercentCulvProtSt2	Percent of culvert (protection elements) in condition state 2
PercentCulvProtSt3	Percent of culvert (protection elements) in condition state 3
PercentCulvProtSt4	Percent of culvert (protection elements) in condition state 4
PercentCulvDefSt1	Percent of culvert (defects) in condition state 1
PercentCulvDefSt2	Percent of culvert (defects) in condition state 2
PercentCulvDefSt3	Percent of culvert (defects) in condition state 3
PercentCulvDefSt4	Percent of culvert (defects) in condition state 4
PercentCulvNonSt1	Percent of culvert (primary element) not in condition state 1
PercentCulvProtNonSt1	Percent of culvert (protection elements) not in condition state 1
PercentCulvDefNonSt1	Percent of culvert (defects) not in condition state 1
Owner	Agency responsible for bridge
StructureKind	Material type of bridge superstructure
StructureType	Design type of bridge
Age	Age of the bridge at inspection
CulvNBI[#]	The inspected Culvert NBI condition rating

[#] *Dependent variable*

Table 5.6. Definition of variables evaluated for channel condition data.

Variable	Description
NoOfChanElem	No. of channel elements
NoOfChanDefects	No. of channel defects
ChanHI	Channel Health Index (primary element)
ChanDefHI	Channel Health Index (defects)
PercentChanSt1	Percent of channel (primary element) in condition state 1
PercentChanSt2	Percent of channel (primary element) in condition state 2
PercentChanSt3	Percent of channel (primary element) in condition state 3
PercentChanSt4	Percent of channel (primary element) in condition state 4
PercentChanDefSt1	Percent of channel (protection elements) in condition state 1
PercentChanDefSt2	Percent of channel (protection elements) in condition state 2
PercentChanDefSt3	Percent of channel (protection elements) in condition state 3
PercentChanDefSt4	Percent of channel (protection elements) in condition state 4
PercentChanNonSt1	Percent of channel (primary element) not in condition state 1
PercentChanDefNonSt1	Percent of channel (defects) not in condition state 1
Owner	Agency responsible for bridge
StructureKind	Material type of bridge superstructure
StructureType	Design type of bridge
Age	Age of the bridge at inspection
ChanNBI[#]	The inspected Channel NBI condition rating

[#] *Dependent variable*

5.2. Research methodology

As discussed earlier, one of the task objectives is to have an easy-to-use model for the Translator. Correlation analyses and multiple linear regression models are not complicated, relating the NBI ratings of the bridge component (deck, superstructure, substructure, culvert, and channel) to the corresponding bridge element data such as the condition of the primary element, the secondary elements, the protection elements, the defects, the estimated heath indexes, as well as other attributes such as age, type of bridge design, bridge material type, and maintenance responsibility. Multinomial logistic regression models, considered more powerful than the linear regression models, are also applicable, using the same dependent and explanatory variables considered for the linear regression models. An extensive effort was also made using the modern innovative approach of machine learning to formulate the translator models, using the input condition data just described to label and train the models. All models were developed relating the element condition data and other bridge attributes to the NBI ratings, and the prediction errors noted for each type of bridge component.

5.2.1. Multiple Linear Regression

With the associated NBI condition rating as the dependent variable, and other bridge attributes as the independent variables, development of the translator models were explored first through Pearson statistical correlation. This identified the important variables that could explain the variation in the NBI rating, as well as any inter-correlation between the independent variables. The latter information helps to avoid duplicating the similar but redundant impact of variables on the overall contribution to the model. For instance, the Deck's Health Index (*DeckHI*) was found to be typically highly correlated to the percentage primary element condition state 1 (PercentDeckSt1), so the variable with the higher correlation coefficient (i.e., *DeckHI*) was selected among the two variables into the regression model. The best set of independent variables was then utilized to develop a Multiple Linear Regression model for each type of bridge component.

The linear regression concept can simply be defined as relating a dependent variable to one explanatory variable, whereas the multiple linear regression model utilizes more than one explanatory variable. The principle in both concepts is the same, in which the dependent variable *y* is expressed mathematically as a function of the *n* explanatory variables x_1, x_2, x_3,…. x_n. and for multiple linear regression, the equation is written as

$$y_i = \alpha_1 x_{1i} + \alpha_2 x_{2i} + \alpha_3 x_{3i} + \cdots \alpha_n x_{ni} + \varepsilon_i \quad (1)$$

Where y_i = observation *i* of the dependent variable *y*; x_{mi} = independent variable x_m associated with observation *i*; α_m = the coefficient for the independent variable x_m; and ε_i = error term for the model. The model is developed by estimating the coefficients, based on using the method of ordinary least squares to minimize the error term.

Multiple Linear Regression model's goodness of fit is reported as the coefficient of correlation (R), and the coefficient of determination (R^2). These coefficients range from 0, where there is no fit, to 1, in which the explanatory variables perfectly account for the variability and gives an ideal fit.

5.2.2. Multinomial Logistic Regression

Logistic regression is an approach to express how an event may or not occur based on some explanatory variables. In a similar way to the linear regression models, logistic regression can also utilize a linear combination of explanatory variables. While the variables in the linear regression are assumed to follow the normal distribution, those in the logistic regression models follow the Bernoulli distribution. The multinomial logistic regression model is defined as when the dependent variable is extended from binary (occur or not occur) to a set of optional values, and there is also more than one explanatory variable.

Each of the possible values of the dependent variable is expressed in an exponential function relating to the linear combination of the independent variables (Equation 2). The unknown coefficients are estimated based on the method of maximum likelihood. Membership probabilities are then computed for each observation (Equation 3), and the model selects the state with the highest probability as the prediction.

$$S_i = \beta_0 x_i + \beta_1 x_{1i} + \beta_2 x_{2i} + \ldots + \beta_n x_{ni} \quad (2)$$

$$\Pr(y = i|x) = \frac{\exp\left(\beta_0 x_i + \beta_1 x_{1i} + \beta_2 x_{2i} + \ldots + \beta_n x_{ni}\right)}{\sum_{k=i}^{i} \exp\left(\beta_0 x_j + \beta_1 x_{1j} + \beta_2 x_{2j} + \ldots + \beta_n x_{nj}\right)} \quad (3)$$

From the results to be presented later in this report, the computation of the various coefficients and membership probabilities for the Deck NBI translator using the multinomial logistic regression is demonstrated through the following equations:

$$S_1 = e^{(-2.435737+2.402414*\mathbf{NoOfDeckDefects}+1.367506*\mathbf{DeckHI}-1.436090*\mathbf{PercentDeckSt1}+0.215022*\mathbf{Age})}$$

$$S_2 = e^{(-2.507459+2.386925*\mathbf{NoOfDeckDefects}+1.406220*\mathbf{DeckHI}-1.461093*\mathbf{PercentDeckSt1}+0.187186*\mathbf{Age})}$$

$$S_3 = e^{(-12.026500+2.665328*\mathbf{NoOfDeckDefects}+1.495361*\mathbf{DeckHI}-1.483974*\mathbf{PercentDeckSt1}+0.229287*\mathbf{Age})}$$

$S_4 = e^{(-4.708682+2.321792*\mathbf{NoOfDeckDefects}+1.389477*\mathbf{DeckHI}-1.417630*\mathbf{PercentDeckSt1}+0.260668*\mathbf{Age})}$

$S_5 = e^{(-3.390757+2.425679*\mathbf{NoOfDeckDefects}+1.390369*\mathbf{DeckHI}-1.412856*\mathbf{PercentDeckSt1}+0.252957*\mathbf{Age})}$

$S_6 = e^{(-3.469492+2.269725*\mathbf{NoOfDeckDefects}+1.419919*\mathbf{DeckHI}-1.435790*\mathbf{PercentDeckSt1}+0.259298*\mathbf{Age})}$

$S_7 = e^{(-1.934867+2.229060*\mathbf{NoOfDeckDefects}+1.431273*\mathbf{DeckHI}-1.449525*\mathbf{PercentDeckSt1}+0.250848*\mathbf{Age})}$

$S_8 = e^{(-3.064101+1.736166*\mathbf{NoOfDeckDefects}+1.468438*\mathbf{DeckHI}-1.441579*\mathbf{PercentDeckSt1}+0.235107*\mathbf{Age})}$

$S_9 = e^{(-0.250177+0.805281*\mathbf{NoOfDeckDefects}+1.355653*\mathbf{DeckHI}-1.343485*\mathbf{PercentDeckSt1}+0.162321*\mathbf{Age})}$

$S_{10}=1+\sum_{j=1...9} S_j$

$Pr(i) = S_i/S_{10}$, i=1...9

$Pr(DeckNBI=9) = 1 - \sum_{i=1...9} Pr(i)$

The estimated probabilities Pr(i) for each destination rating are evaluated at each translation, and the rating with the highest value is selected.

5.2.3. Machine Learning

Various machine learning classification algorithms were explored in this study, but the emphasis here will be on those that were used, listed as follows: Decision Trees, Discriminant Analysis, Logistic Regression, Naive Bayes, Support Vector Machines, Nearest Neighbor, Ensemble, and Neural Network. Classifiers are developed to model dependent variables that are discrete, i.e., different classes. For dependent continuous variables, the regression algorithms such as the linear and logistic models described earlier, are more appropriate. The description of these machine learning algorithms are widely available in the literature, and the next section of the report briefly describes each of the classifiers.

5.2.3.1. Decision Trees

A decision tree is a machine learning model used for classification and regression tasks. It operates by breaking down a dataset into smaller subsets through a series of binary decisions based on feature values. Each internal node represents a "decision" (based on a feature), and each leaf node represents an outcome or classification. The tree starts at the root, where a condition on one of the input variables (features) is tested. Based on the result of this test, the data is split into branches, leading to further nodes, until it reaches a leaf node where a prediction is made. The tree can handle both categorical and numerical data, making it versatile for various types of prediction problems. Key advantages of decision trees include the following: simplicity and interpretability, as decision trees are easy to understand and visualize; non-linearity, as they can model complex relationships by capturing interactions between features; and versatility, because they can handle both regression (predicting continuous values) and classification (predicting categories).

However, decision trees have some drawbacks, including their tendency to overfit data, especially when the tree becomes too deep and overly specific to the training data. Techniques like pruning, random forests, or gradient boosting are often used to improve their performance and prevent overfitting. In summary, decision trees are intuitive, powerful tools for predictive modeling, especially useful when interpretability and flexibility are important.

5.2.3.2. Support Vector Machine (SVM)

A Support Vector Machine (SVM) is a supervised learning algorithm used for both classification and regression tasks. It is especially effective in classification problems such as image recognition, speech recognition, medical diagnosis, and natural language processing. The main objective of an SVM is to find the best hyperplane that separates data points of different classes with the widest possible margin. This "margin" refers to the distance between the closest points (support vectors) from each class to the separating hyperplane. The SVM aims to maximize this margin to ensure that the data points are classified with minimal error.

For linearly separable data, an SVM can draw a clear hyperplane between classes. For non-linearly separable data, it uses techniques like the kernel trick to project data into higher dimensions, allowing the algorithm to find a separating hyperplane in this transformed space (Figure 5.2). The SVM also incorporates a concept of "soft margins" to allow for some misclassifications in complex datasets. In summary, SVMs are powerful tools for binary classification and can be extended to handle multiclass problems by reducing them to a series of binary classifications. They work well in high-dimensional spaces, making them useful for a variety of practical problems.

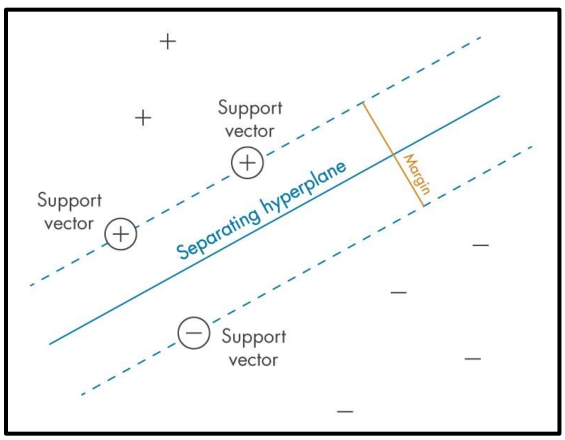


Figure 5.2. Demonstration of the SVM algorithm: defining the “margin” between classes.

5.2.3.3. Kernel Approximation Classifiers

Kernel Approximation Classifiers are used in machine learning to perform nonlinear classification tasks more efficiently, particularly with large datasets. These classifiers approximate the behavior of more complex kernel-based models, like Support Vector Machines (SVM), but with faster training and prediction times. The main idea is to map the input data into a higher-dimensional space, making it easier to apply linear classifiers to solve nonlinear problems. The Gaussian kernel is commonly used in kernel approximation, where data is transformed from a low-dimensional space to a high-dimensional one. Once transformed, linear models, such as logistic regression or linear SVM, are applied to classify the data.

Key benefits of kernel approximation classifiers include the following: faster training and prediction compared to traditional SVM with Gaussian kernels, especially for large datasets; flexibility in choosing different kernel types and scales for improving model performance; and efficiency in memory usage and processing power when dealing with high-dimensional data. This approach balances the need for speed with maintaining the predictive power of kernel-based models.

5.2.3.4. Ensemble Classifiers

Ensemble classifiers or Bootstrap Aggregation (Bagging) is a form of ensemble learning where multiple weak learners, such as decision trees, are trained on different bootstrap samples of the data. A bootstrap sample is created by randomly selecting data points with replacement, meaning some data points may appear multiple times while others may not appear at all. The number of samples in each replica equals the size of the original dataset. Each tree in the ensemble is grown on its bootstrap sample, and for each decision split, a random subset of predictors is chosen. By default, the number of predictors selected at random for classification is the square root of the total predictors, and for regression, it is one-third.

The final prediction of the ensemble model is obtained by averaging the predictions of all the individual trees. This method enhances model stability and reduces overfitting. Key features include the following: random predictor selection, which boosts accuracy by reducing the correlation between trees; and deep trees, which are usually optimal with larger leaves for better prediction power. In summary, bagging improves the robustness of weak models by reducing variance and improving predictive power through aggregation.

5.2.3.5. Neural Network Classifiers

Neural Network classifiers are a type of machine learning model inspired by the human brain's neural connections. They are especially effective for tasks involving pattern recognition, such as identifying objects in images, recognizing speech, or processing text. Neural networks are highly capable of modeling complex, nonlinear relationships between inputs and outputs, making them suitable for tasks that require understanding high-dimensional data.

Key Points of Neural Network Classifiers include the structure, weights and learning, deep learning, and feedforward networks. The structure of a neural network consists of layers, including an input layer, one or more hidden layers, and an output layer. Each layer contains neurons (nodes) that are interconnected, passing information forward through the network. The hidden layers allow the network to model complex features. Each connection between neurons has a weight that is adjusted during training. The network learns by minimizing errors between predicted and actual outcomes, adjusting these weights to improve accuracy. Deep neural networks, with multiple hidden layers, are particularly powerful for handling large datasets and complex patterns. They form the backbone of many modern AI systems in fields like computer vision, natural language processing, and robotics. The simplest form of neural networks, known as feedforward networks, involve data moving in one direction—from input to output—without looping back.

5.2.3.6. Logistic Regression Classifiers

Logistic Regression classifiers utilize an extension of the traditional binary logistic regression to handle *discrete* classification tasks where there are more than two classes. This is done by applying one of two primary techniques: One-vs-Rest (OvR) or Softmax (Multinomial Logistic Regression). The One-vs-Rest (OvR) approach involves training a separate binary logistic regression model for each class, treating that class as "positive" and all other classes as "negative." During prediction, each model outputs a probability, and the class with the highest probability is chosen as the predicted label. OvR is simple but can become computationally expensive with many classes. In the Multinomial Logistic Regression (Softmax) approach, a single model is trained that directly outputs probabilities for all classes using the Softmax function. This method generalizes logistic regression to multiclass problems, ensuring that the sum of the predicted probabilities across all classes equals 1. The class with the highest probability is selected as the final prediction. This method is computationally more efficient for large multiclass datasets.

The key features can be summarized in terms of Linear Decision Boundaries, Probabilistic Output, and Regularization. Logistic regression assumes that the classes can be separated by linear boundaries, which may limit its use in complex datasets unless combined with feature engineering. Logistic regression outputs probabilities for each class, allowing for more informative predictions. To avoid overfitting in multiclass classification, logistic regression models can be regularized using techniques like L1 or L2 regularization. In summary, Logistic Regression Classifiers are a fundamental tool for multiclass classification problems, offering a balance between simplicity, interpretability, and performance. For more complex tasks, they may be extended or combined with other techniques like feature engineering or kernel methods to improve performance.

5.3. Results

The outputs from the three methodologies (multiple linear regression, multinomial logistic regression, and machine learning) are presented here in detail, including the accuracies and prediction errors for each approach.

5.3.1. Multiple Linear Regression

Pearson correlation coefficients were estimated for relationships between the explanatory and the dependent variables, with the results shown in Appendix B in Figures B2 to B11. These matrices show how for each bridge component, the explanatory variables that were initially selected for the linear regression model, based on the correlation coefficients (yellow highlight) and some of them eliminated due to high inter-correlation coefficient values between them and other variables. For example, the Deck primary element's Health Index (*DeckHI*) was observed to have a high correlation coefficient of 0.90 with the Percent of deck (primary element) in condition state 1 (*PercentDeckSt1*) and the Superstructure primary element's Health Index (*SupstrHI*) also had a high coefficient of 0.89 with the percent of superstructure primary element in condition state 1 (*PercentSupstrSt1*). While the individual correlation coefficients are close for each component to the NBI condition ratings, the *DeckHI* and *SupstrHI* were chosen for the regression model as their computation encompass many more variables. The selected model and the regression coefficients for each component are shown in Tables 5.7 and 5.8, for the NBI condition ratings (0 to 9) and the Generalized NBI ratings (Good, Fair and Poor), respectively. For the deck, the selected explanatory variables included No. of Defects, Health Index (Primary elements), Percent in Defect Condition State 3, and Age, while for superstructure the explanatory variables included No. of Defects, Health Index (Primary elements), Health Index (Secondary elements), and Age. The selected variables for the other bridge components are shown in Tables 5.7 and 5.8.

Multiple linear regression models are useful for incorporating explanatory variables and they are also easy to understand. The predicted output from the models is originally in the form of a continuous variable but it should be noted that the actual NBI ratings are discrete. So each output from these regression models was rounded to a whole number to match the NBI ratings format. As shown in Tables 5.7 and 5.8, the primary element health index was selected and modeled as an explanatory variable for all the five bridge components, as well as Age in all except for the channel. Other selected variables include the number of defects associated with the primary element. While the goodness of fit reported for the NBI condition ratings are very good using the correlation R, ranging from 0.57 (Deck) to 0.67 (Substructure), the coefficients of determination (R^2) are not very high, ranging from 0.32 (Deck) to 0.44 (Substructure). For the Generalized NBI ratings, R varied from 0.54 (Deck) to 0.61 (Culvert), and R^2 ranged from 0.29 (Deck) to 0.37 (Culvert). Given the extent of uncertainty and subjectivity inherent in the bridge inspection process, particularly, when converting from the element inspection to the component ratings, these R^2 values can be considered reasonable. The low values mean that there are other factors that can be used to explain the variability of the NBI ratings.

Table 5.7. Multiple Linear Regression models for NBI Translators.

Deck	Multiple R	0.57
	R Square	0.32
		Coefficients
	Intercept	6.312
	No. of Defects	-0.195
	Health Index (Primary elements)	0.014
	Percent in Defect Condition State 3	-0.004
	Age	-0.011
Superstructure	Multiple R	0.66
	R Square	0.43
		Coefficients
	Intercept	5.554
	No. of Defects	-0.246
	Health Index (Primary elements)	0.013
	Health Index (Secondary elements)	0.010
	Age	-0.015
Substructure	Multiple R	0.67
	R Square	0.44
		Coefficients
	Intercept	5.997
	No. of Defects	-0.091
	Health Index (Primary elements)	0.019
	Percent in Condition State 3	-0.012
	Age	-0.012
Culvert	Multiple R	0.61
	R Square	0.37
		Coefficients
	Intercept	5.371
	Health Index (Primary elements)	0.021
	Age	-0.011
Channel	Multiple R	0.64
	R Square	0.41
		Coefficients
	Intercept	5.142
	No. of Defects	-0.250
	Health Index (Primary elements)	0.026

Table 5.8. Multiple Linear Regression models for Generalized NBI Translators*.

Deck	Multiple R	0.54
	R Square	0.29
		Coefficients
	Intercept	2.193
	No. of Defects	-0.102
	Health Index (Primary elements)	0.009
	Percent in Defect Condition State 3	-0.002
	Age	-0.003
Superstructure	Multiple R	0.60
	R Square	0.36
		Coefficients
	Intercept	1.928
	No. of Defects	-0.104
	Health Index (Primary elements)	0.007
	Health Index (Secondary elements)	0.005
	Age	-0.005
Substructure	Multiple R	0.60
	R Square	0.36
		Coefficients
	Intercept	1.839
	No. of Defects	-0.046
	Health Index (Primary elements)	0.013
	Age	-0.012
Culvert	Multiple R	0.61
	R Square	0.37
		Coefficients
	Intercept	5.371
	Health Index (Primary elements)	0.021
	Age	-0.011
Channel	Multiple R	0.56
	R Square	0.31
		Coefficients
	Intercept	1.579
	No. of Defects	0.111
	Health Index (Primary elements)	0.014

*Rating: 3- Good; 2-Fair; and 1-Poor.

The prediction errors from the regression models are displayed in various forms in Tables 5.9 to 5.12, and shown for the NBI Deck translation, in Figures 5.3 to 5.5. Except for the culverts at NBI rating 6, the mean prediction error was observed to the lowest at the NBI rating 7 in all the bridge components (Table 5.9). The mean errors at ratings 5, 6, 7, and 8 were low, with rating 6 showing the next desirable accuracy after rating 7. For the Generalized NBI rating, as shown in Table 5.10, the best accuracy was observed for the "Good" rating, in all components, except for culverts, which had the best accuracy at the "Fair" rating. The mean prediction error for the "Good" rating were very low with 0.0 for the channel, 0.1 for deck, superstructure and substructure, and 0.4 for culvert. As shown in Table 5.11 for the NBI rating, the Translator's results for the five bridge components showed the zero-error prediction ranging from about 50% for culverts, to 65% for substructure. For the Generalized NBI ratings, the zero-error prediction ranged from 69% for the culvert to 84% for substructure (Table 5.12). Overall, allowing a tolerance of plus-or-minus 1 in the prediction, NBI rating predictions will range from about 92% for culvert to 95% for substructure (Table 5.11), while those for the Generalized NBI rating will be about 99% for all the components (Table 5.12). Figures 5.5, 5.10, 5.13, 5.16 and 5.19 also indicate a high proportion of the bridges being predicted well within the plus-or-minus 1 accuracy for the NBI ratings.

It can be observed in Figures 5.3 and 5.4 that the best accuracy for Deck NBI condition ratings was at the rating of 7, with other ratings also having reasonable accuracy, except for ratings 0 to 4. This can be attributed to the ratings of 5 to 9 being the most predominant in the data, so the model can adequately predict those ratings. A brief investigation was done of just considering two separate data sets of the ratings where the predictions were relatively less accurate, i.e., one for the actual ratings 0 to 4, and the other for the actual ratings 8 and 9. The premise here is that the age and primary element health index may influence the predicted NBI ratings on these two groups of condition ratings. The premise was supported by what is shown in Figure 5.7 for the bridge decks with NBI ratings 8 and 9, but not for the other group with ratings 0 to 4, as shown in Figure 5.6. Thus bridge decks with age less than 14 years can be assumed to have an NBI condition rating of at least 8, and deck elements with primary element health index above 98 can also be assumed to have a rating of at least 8. Another revision involved making any bridge with age of five years or less have the condition rating of 9. The effects of these age-based revisions are reflected in Figure 5.8 for the bridge deck. There are improvements in accuracy at the ratings 8 and 9, with the mean predicted NBI ratings increasing from 7.4 to 7.9, and 7.8 to 8.7, respectively. But there is a cost; while the prediction accuracy at rating 9 increased from 0% to 72.1%, the accuracy at ratings 7 and 8 were reduced from 76% to 69.8%, and 45.4% to 31.2%, respectively, and the overall the accuracy for the inventory decreased from 61.2% to 56.5% (Tables 5.13 and 5.14).

The prediction results for the other bridge components are shown in Figures 5.9 to 5.20, with observations very similar to those described here for the deck. The classification table for the Generalized NBI ratings are also summarized in Table 5.15. Appendix B shows more detailed results on the multiple linear regression models for the NBI Translator for all bridge components, for both the NBI 0 to 9 ratings and Generalized ratings of Good, Fair, and Poor.

Table 5.9. Summary of prediction error by count of bridges at NBI Ratings.

			Prediction Error								
	NBI Rating	Mean Prediction Error	0	1	2	3	4	5	6	7	8
Deck (6007 bridges)	0	6.1	0	0	0	0	0	1	5	2	
	1	5.5	0	0	0	0	0	7	3	1	
	2	4.0	0	0	0	0	2	0	0	0	
	3	3.2	0	0	3	18	10	0	0	0	
	4	2.2	0	9	113	37	0	0	0	0	
	5	1.2	29	193	109	0	0	0	0	0	
	6	0.4	632	417	2	0	0	0	0	0	
	7	0.2	2609	807	18	0	0	0	0	0	
	8	0.6	406	465	23	0	0	0	0	0	
	9	1.2	0	72	8	6	0	0	0	0	
Superstructure (4174 bridges)	0	5.5	0	0	0	0	1	4	2	0	1
	1	4.2	0	0	0	0	7	2	0	0	0
	2	3.1	0	0	0	10	1	0	0	0	0
	3	3.0	0	0	2	20	2	0	0	0	0
	4	1.8	3	26	71	7	0	0	0	0	0
	5	1.0	55	141	58	0	0	0	0	0	0
	6	0.5	269	252	12	0	0	0	0	0	0
	7	0.3	1636	599	31	3	0	0	0	0	0
	8	0.4	541	316	12	5	0	0	0	0	0
	9	1.4	0	64	10	11	0	0	0	0	0
Substructure (6026 bridges)	0	6.1	0	0	0	0	0	1	4	2	
	1	4.2	0	0	0	0	8	2	0	0	
	2	3.8	0	0	0	1	5	0	0	0	
	3	2.8	0	0	11	26	3	0	0	0	
	4	1.7	3	50	72	13	0	0	0	0	
	5	0.9	59	178	33	0	0	0	0	0	
	6	0.5	479	384	8	0	0	0	0	0	
	7	0.2	2657	737	28	5	0	0	0	0	
	8	0.4	686	441	17	0	0	0	0	0	
	9	1.3	0	92	7	14	0	0	0	0	
Culvert (1246 bridges)	0	5.0	0	0	0	0	0	2			
	1	0.0	0	0	0	0	0	0			
	2	0.0	0	0	0	0	0	0			
	3	2.2	0	0	24	6	0	0			
	4	1.6	1	31	33	4	0	0			
	5	0.8	29	69	9	0	0	0			
	6	0.3	323	152	0	0	0	0			
	7	0.5	273	199	18	1	0	0			
	8	1.1	0	66	1	2	0	0			
	9	2.0	0	0	3	0	0	0			
Channel (5127 bridges)	0	6.0	0	0	0	0	0	0	2		
	1	4.0	0	0	0	0	3	0	0		
	2	3.3	0	0	0	7	0	1	0		
	3	2.1	0	0	21	2	0	0	0		
	4	2.0	0	10	104	6	2	0	0		
	5	1.3	5	253	107	3	0	0	0		
	6	0.8	320	740	71	0	0	0	0		
	7	0.3	1800	659	14	0	0	0	0		
	8	0.4	492	195	4	23	0	0	0		
	9	1.1	0	265	9	2	7	0	0		

Table 5.10. Summary of prediction error by count of bridges at Generalized NBI Ratings*.

	Generalized NBI Rating*	Mean Prediction Error	Prediction Error 0	1	2
Deck (6007 bridges)	1	1.4	0	124	87
	2	0.5	746	636	0
	3	0.1	4000	414	0
Superstructure (4174 bridges)	1	1.1	2	137	20
	2	0.5	369	418	0
	3	0.1	2964	264	0
Substructure (6026 bridges)	1	1.2	0	170	31
	2	0.5	623	518	0
	3	0.1	4343	339	2
Culvert (1246 bridges)	1	1.0	4	93	4
	2	0.1	499	83	0
	3	0.4	360	202	1
Channel (5127 bridges)	1	1.1	0	149	9
	2	0.6	588	911	0
	3	0.0	3351	119	0

*Rating: 3- Good; 2-Fair; and 1-Poor.

Table 5.11. Summary of prediction error in NBI ratings by count and percentage of bridges.

	Deck		Superstructure		Substructure		Culvert		Channel	
Prediction error	Count	Percent	Count	Percent	Count	Percent	Count	Percent	Count	Percent
0	3676	61.2%	2504	60.0%	3884	64.5%	626	50.2%	2617	51.0%
1	1963	32.7%	1398	33.5%	1882	31.2%	517	41.5%	2122	41.4%
2	276	4.6%	196	4.7%	176	2.9%	88	7.1%	330	6.4%
3	61	1.0%	56	1.3%	59	1.0%	13	1.0%	43	0.8%
4	12	0.2%	11	0.3%	16	0.3%	0	0.0%	12	0.2%
5	8	0.1%	6	0.1%	3	0.0%	2	0.2%	1	0.0%
6	8	0.1%	2	0.0%	4	0.1%			2	0.0%
7	3	0.0%	0	0.0%	2	0.0%				
8			1	0.0%						
Totals:	6007		4174		6026		1246		5127	

Table 5.12. Summary of prediction error in Generalized NBI ratings* by count and percentage of bridges.

	Deck		Superstructure		Substructure		Culvert		Channel	
Prediction error	Count	Percent	Count	Percent	Count	Percent	Count	Percent	Count	Percent
0	4746	79.0%	3335	79.9%	4966	82.4%	863	69.3%	3939	76.8%
1	1174	19.5%	819	19.6%	1027	17.0%	378	30.3%	1179	23.0%
2	87	1.4%	20	0.5%	33	0.5%	5	0.4%	9	0.2%
Totals:	6007		4174		6026		1246		5127	

*Rating: 3- Good; 2-Fair; and 1-Poor.

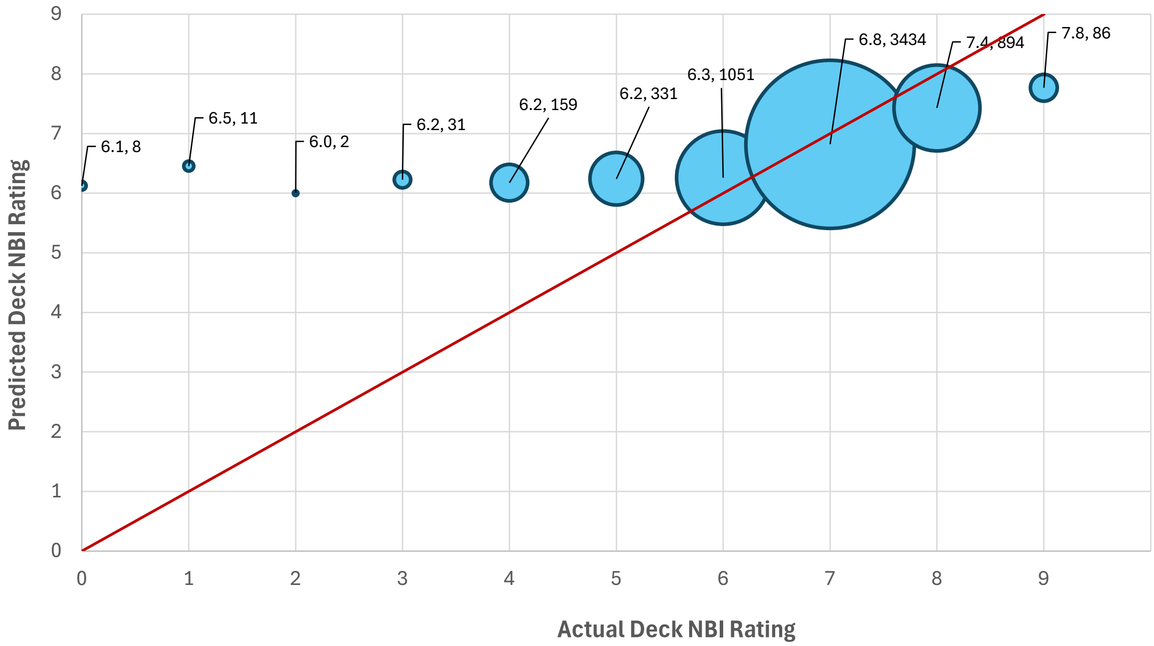


Figure 5.3. Predicted Deck NBI Ratings relative to the actual Ratings (showing no. of bridges).

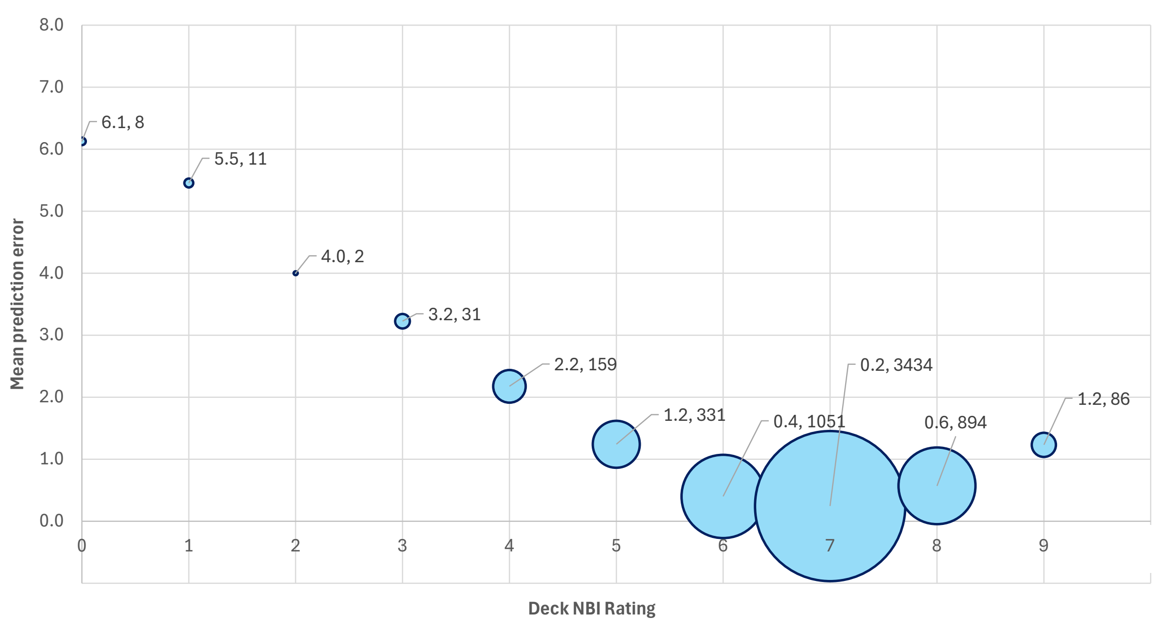


Figure 5.4. Mean prediction errors at each Deck NBI Rating (showing no. of bridges).

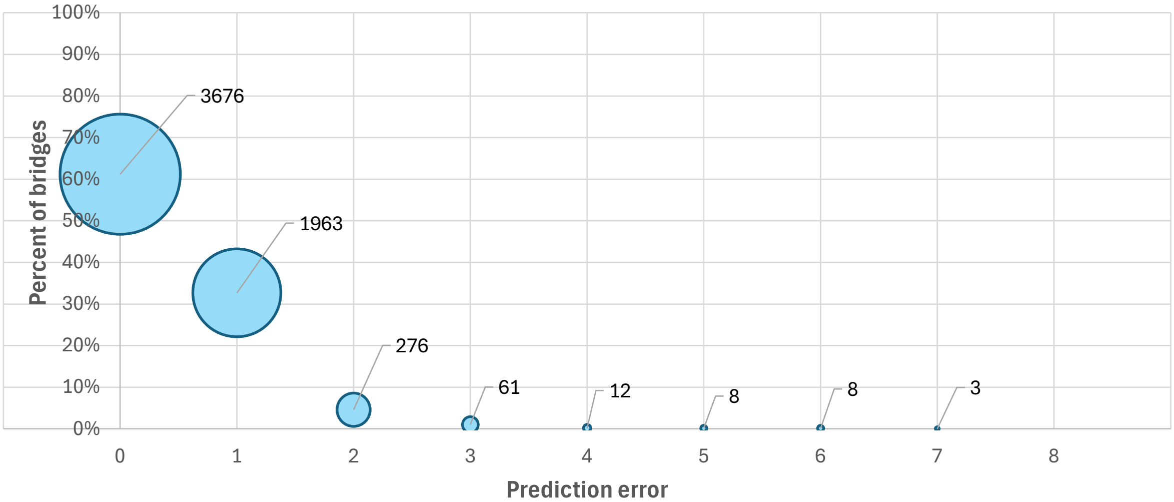
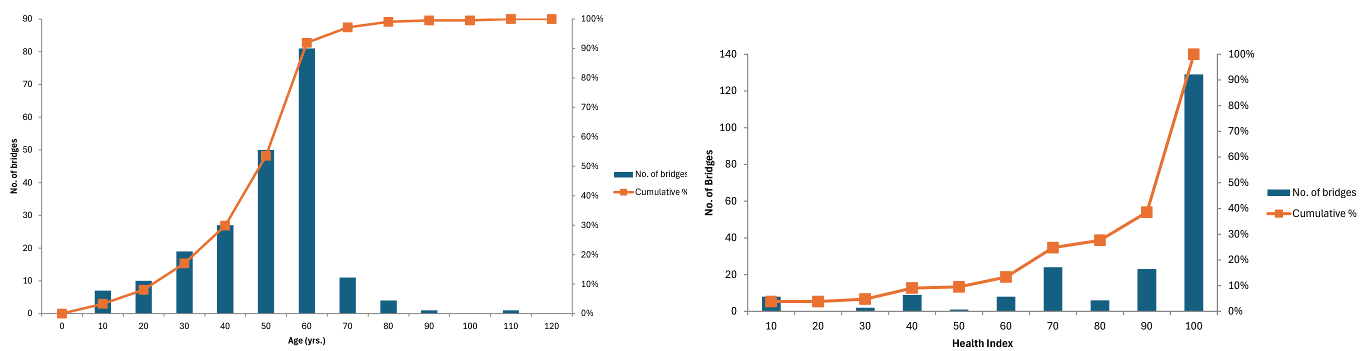


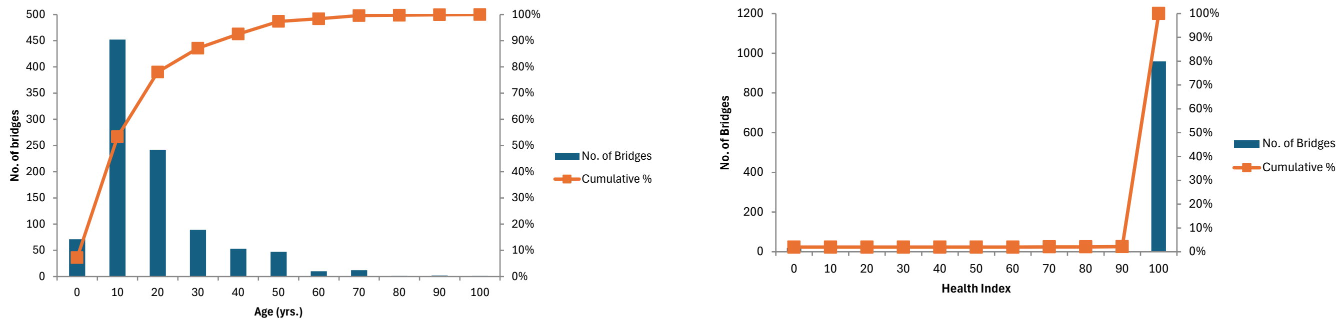
Figure 5.5. Variation in prediction errors for Deck NBI Ratings (showing no. of bridges).



a. Age (Mean = 45.6 yrs.)

b. Health Index (Mean = 82.5)

Figure 5.6. Attributes of bridges with actual Deck NBI Ratings 0 to 4.



a. Age (Mean = 13.9 yrs.)

b. Health Index (Mean = 97.9)

Figure 5.7. Attributes of bridges with actual Deck NBI Ratings 8 and 9.

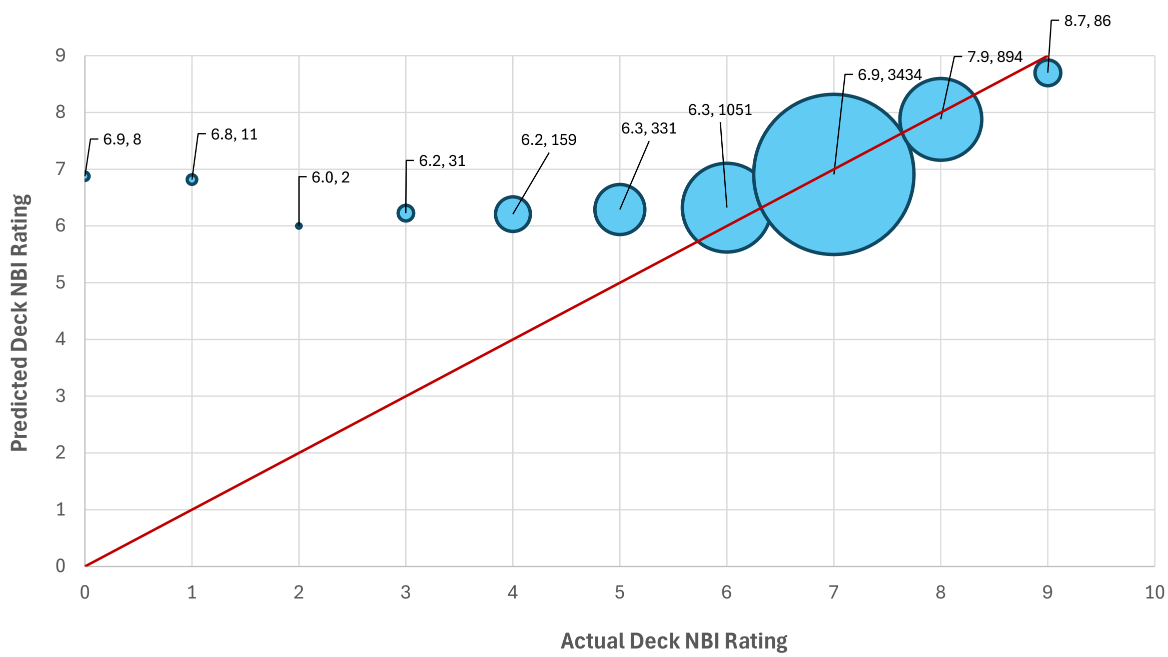


Figure 5.8. . Age-based predicted Deck NBI Ratings relative to the actual Ratings (showing no. of bridges).

Table 5.13. Classification table on NBI ratings for bridge deck (Linear regression).

PREDICTED

	0	1	2	3	4	5	6	7	8	9	*Accuracy*	*Total Count*	*Zero Error*	*+/- 1 Error*	*+/- 1 Accuracy*
0	0	0	0	0	0	1	5	2	0	0	0.0%	8	0	0	0.0%
1	0	0	0	0	0	0	7	3	1	0	0.0%	11	0	0	0.0%
2	0	0	0	0	0	0	2	0	0	0	0.0%	2	0	0	0.0%
3	0	0	0	0	0	3	18	10	0	0	0.0%	31	0	0	0.0%
4	0	0	0	0	0	9	113	37	0	0	0.0%	159	0	9	5.7%
5	0	0	0	0	0	29	193	109	0	0	8.8%	331	29	222	67.1%
6	0	0	0	0	1	72	632	345	1	0	60.1%	1051	632	1049	99.8%
7	0	0	0	0	0	18	695	2609	112	0	76.0%	3434	2609	3416	99.5%
8	0	0	0	0	0	0	23	465	406	0	45.4%	894	406	871	97.4%
9	0	0	0	0	0	0	6	8	72	0	0.0%	86	0	72	83.7%
	0	0	0	0	1	132	1694	3588	592	0	**61.2%**	6007	3676	5639	93.9%

Table 5.14. Classification table on age-based predicted NBI ratings for bridge deck (Linear regression).

PREDICTED

	0	1	2	3	4	5	6	7	8	9	*Accuracy*	*Total Count*	*Zero Error*	*+/- 1 Error*	*+/- 1 Accuracy*
0	0	0	0	0	0	1	3	1	2	1	0.0%	8	0	0	0.0%
1	0	0	0	0	0	0	7	1	1	2	0.0%	11	0	0	0.0%
2	0	0	0	0	0	0	2	0	0	0	0.0%	2	0	0	0.0%
3	0	0	0	0	0	3	18	10	0	0	0.0%	31	0	0	0.0%
4	0	0	0	0	0	9	111	37	1	1	0.0%	159	0	9	5.7%
5	0	0	0	0	0	29	189	105	4	4	8.8%	331	29	218	65.9%
6	0	0	0	0	1	72	625	306	34	13	59.5%	1051	625	1003	95.4%
7	0	0	0	0	0	18	688	2398	254	76	69.8%	3434	2398	3340	97.3%
8	0	0	0	0	0	0	14	341	279	260	31.2%	894	279	880	98.4%
9	0	0	0	0	0	0	0	2	22	62	72.1%	86	62	84	97.7%
	0	0	0	0	1	132	1657	3201	597	419	**56.5%**	6007	3393	5534	92.1%

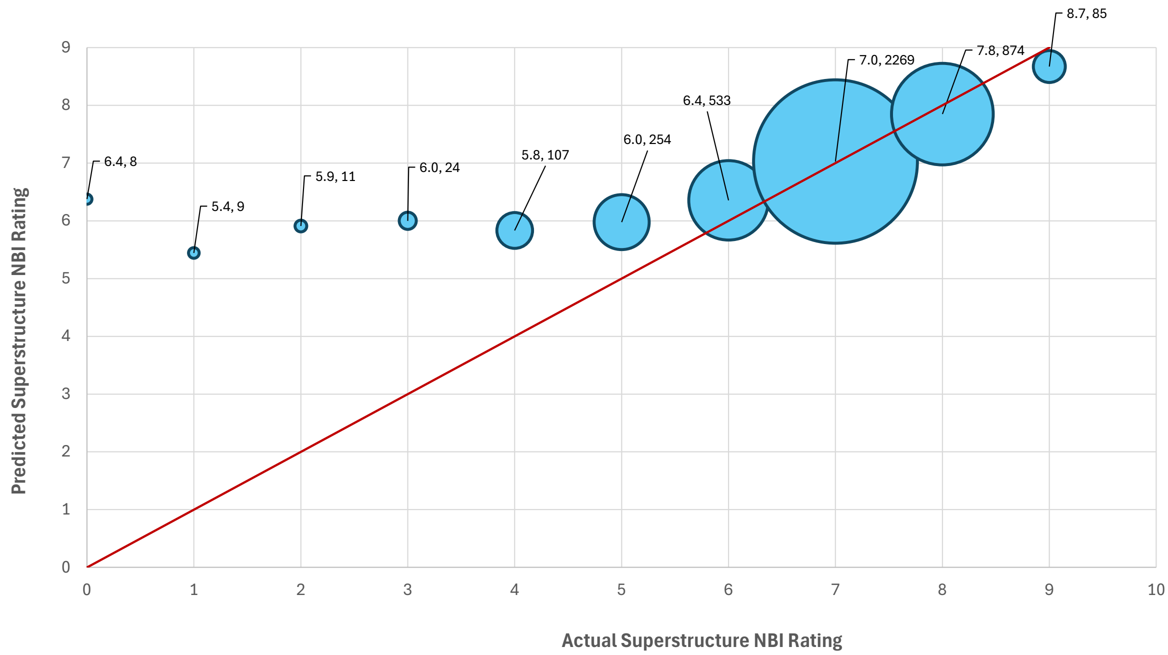


Figure 5.9. Mean predicted Superstructure NBI Ratings relative to the actual Ratings (showing no. of bridges).

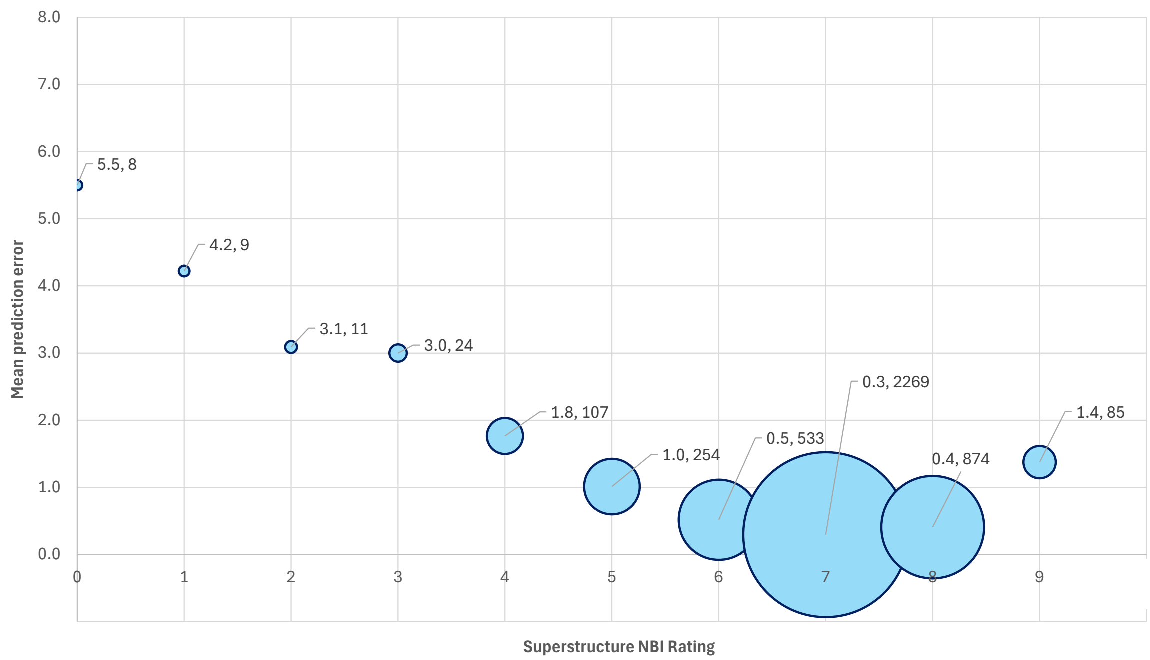


Figure 5.10. Mean prediction errors at each Superstructure NBI Rating (showing no. of bridges).

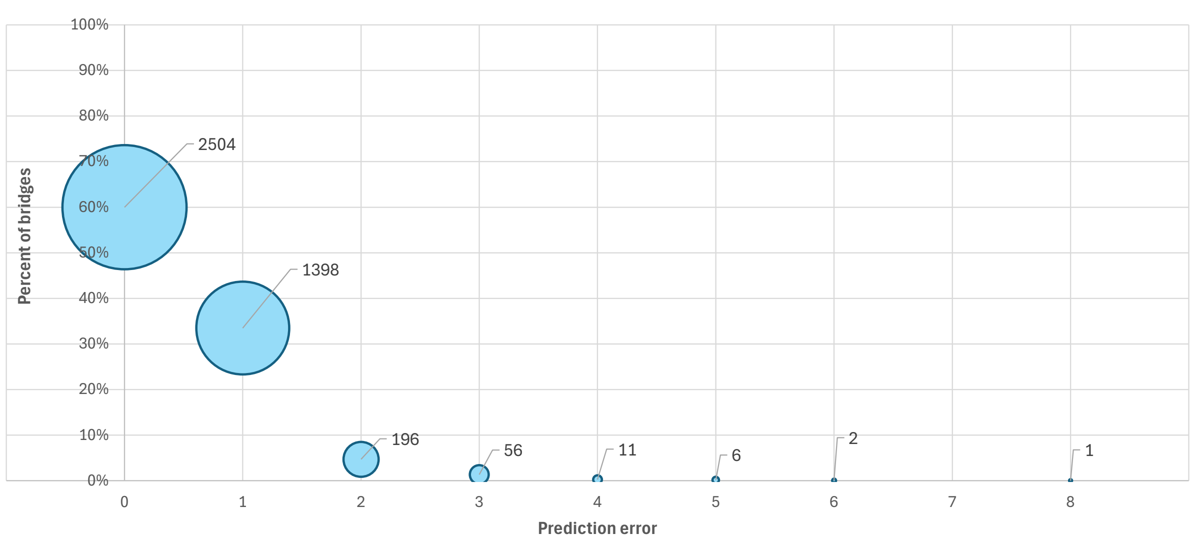


Figure 5.11. Variation in prediction errors for Superstructure NBI Ratings (showing no. of bridges).

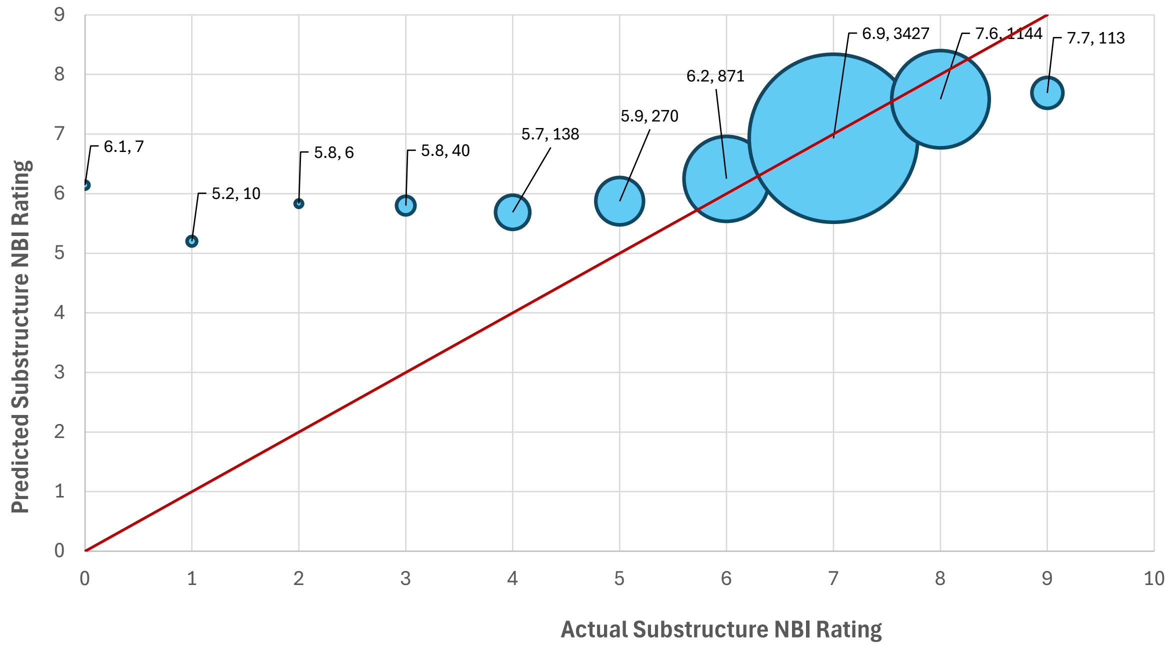


Figure 5.12. Mean predicted Substructure NBI Ratings relative to the actual Ratings (showing no. of bridges).

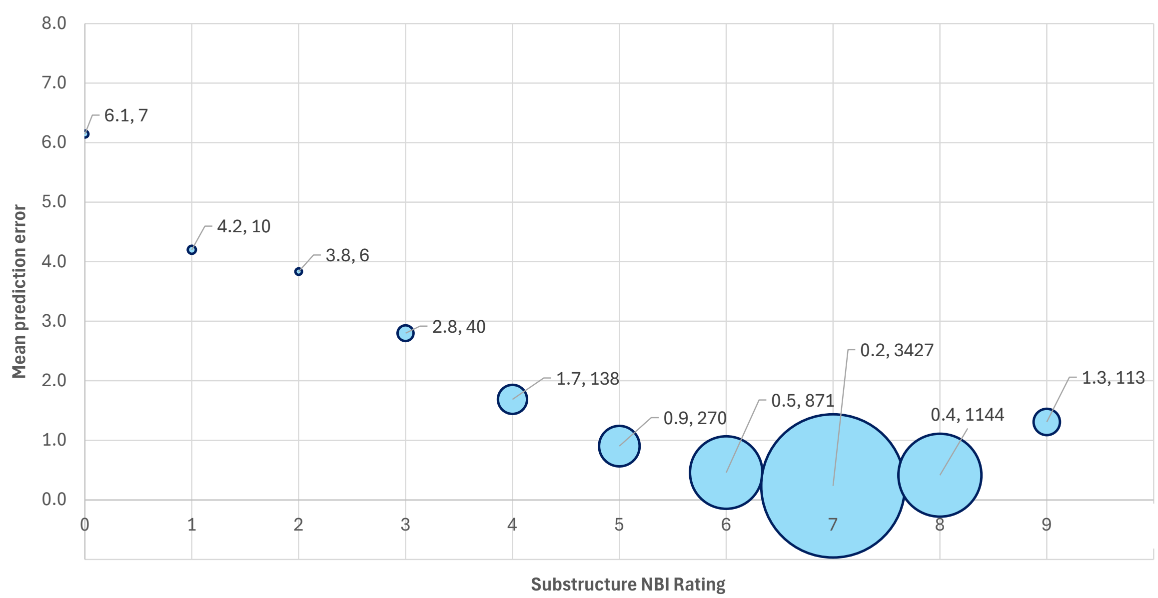


Figure 5.13. Variation in mean prediction errors at each Substructure NBI Rating (showing no. of bridges).

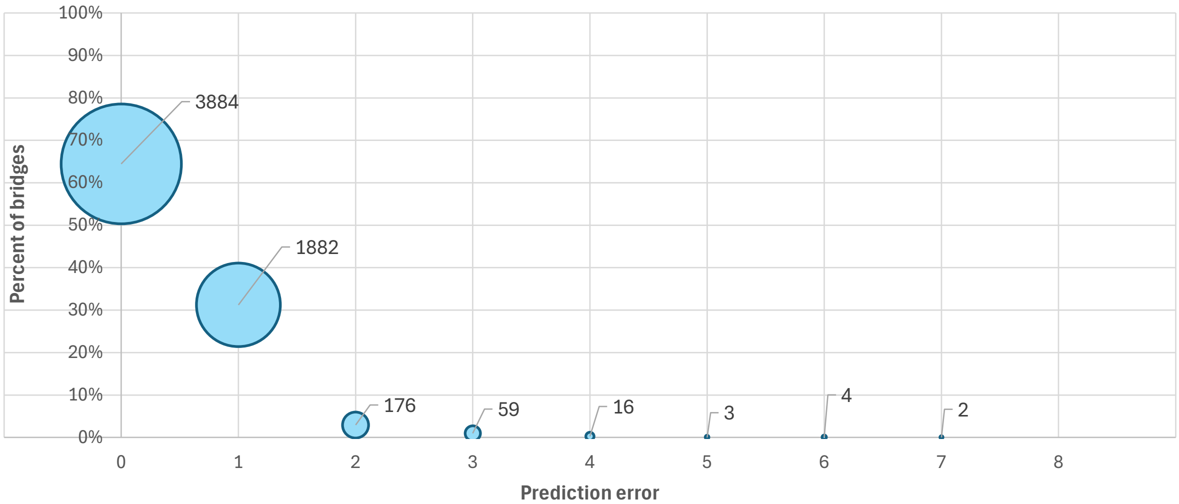


Figure 5.14. Variation in prediction errors for Substructure NBI Ratings (showing no. of bridges).

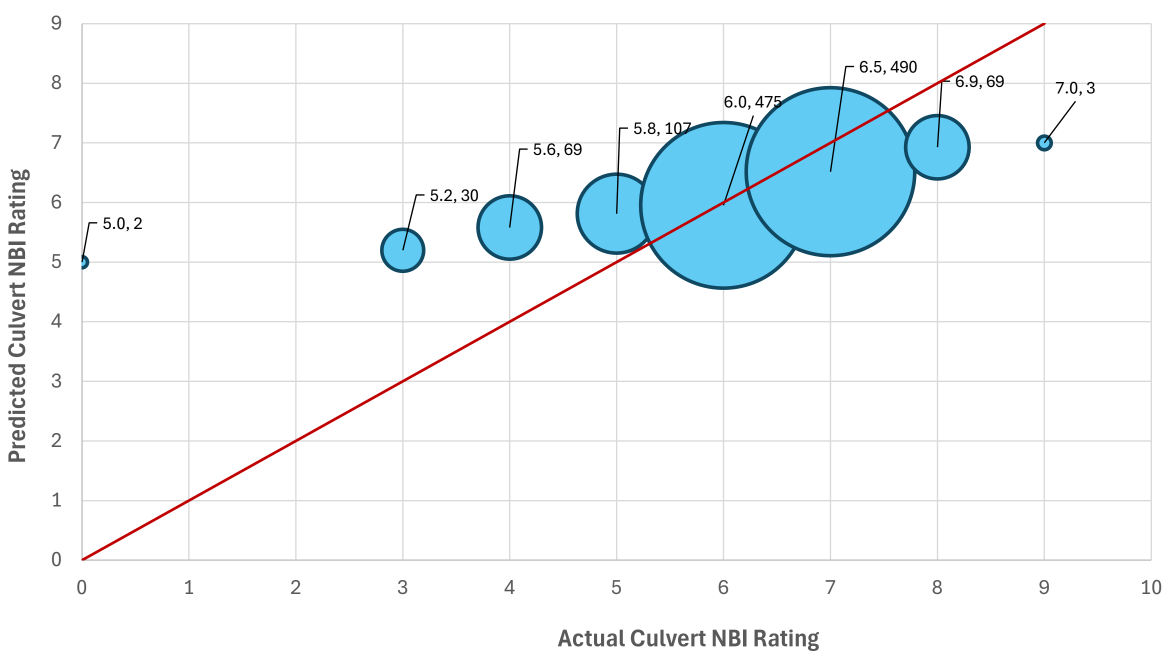


Figure 5.15. Mean predicted Culvert NBI Ratings relative to the actual Ratings (showing no. of bridges).

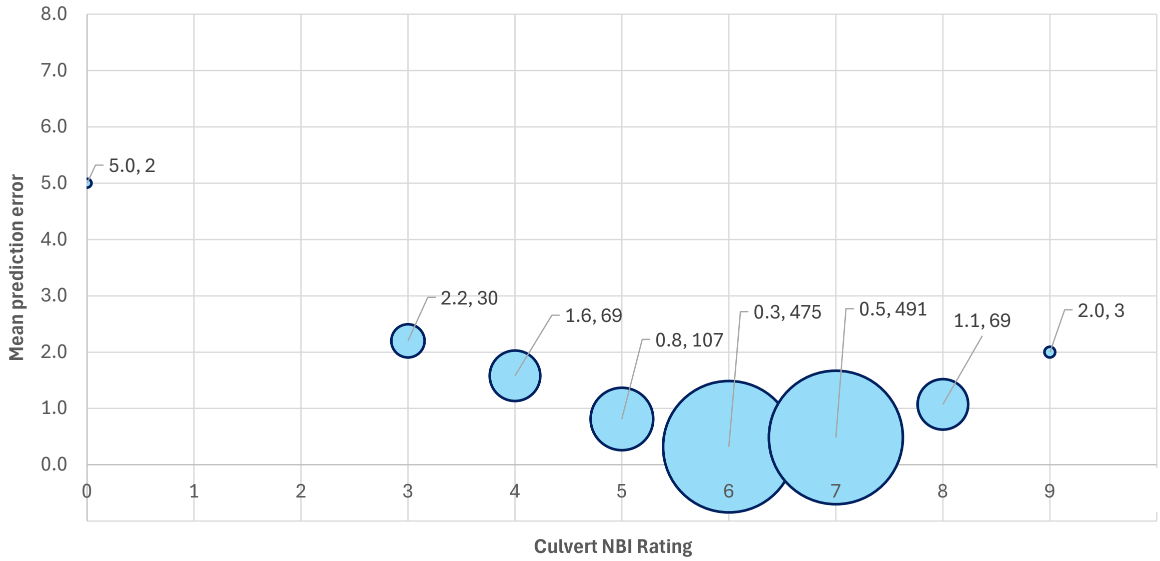


Figure 5.16. Variation in mean prediction errors at each Culvert NBI Rating (showing no. of bridges).

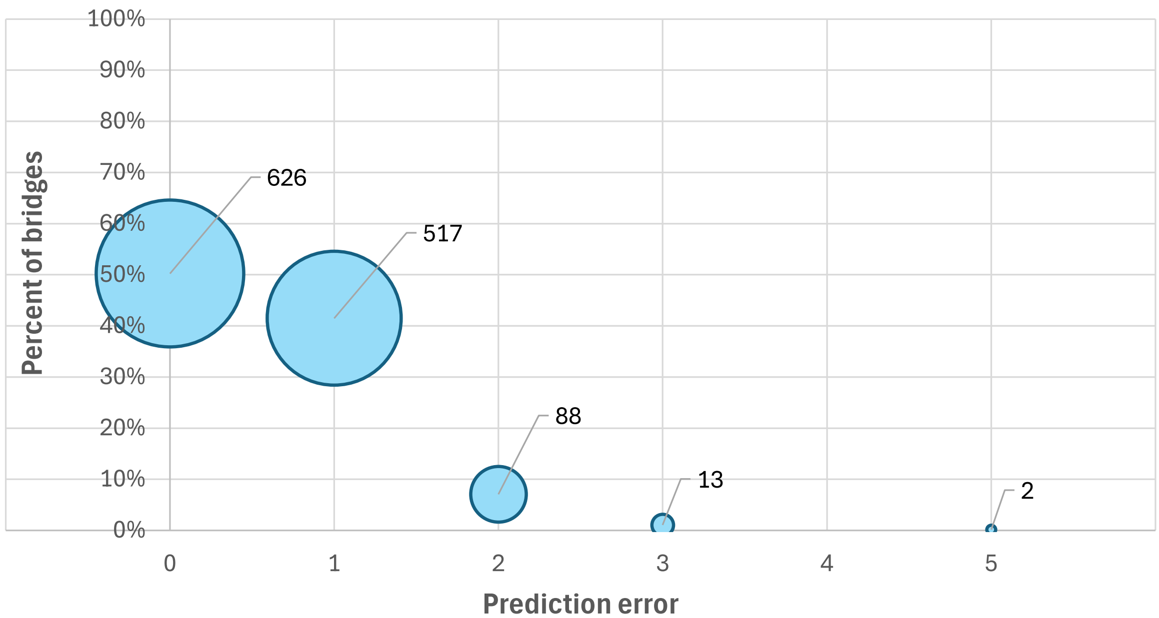


Figure 5.17. Variation in prediction errors for Culvert NBI Ratings (showing no. of bridges).

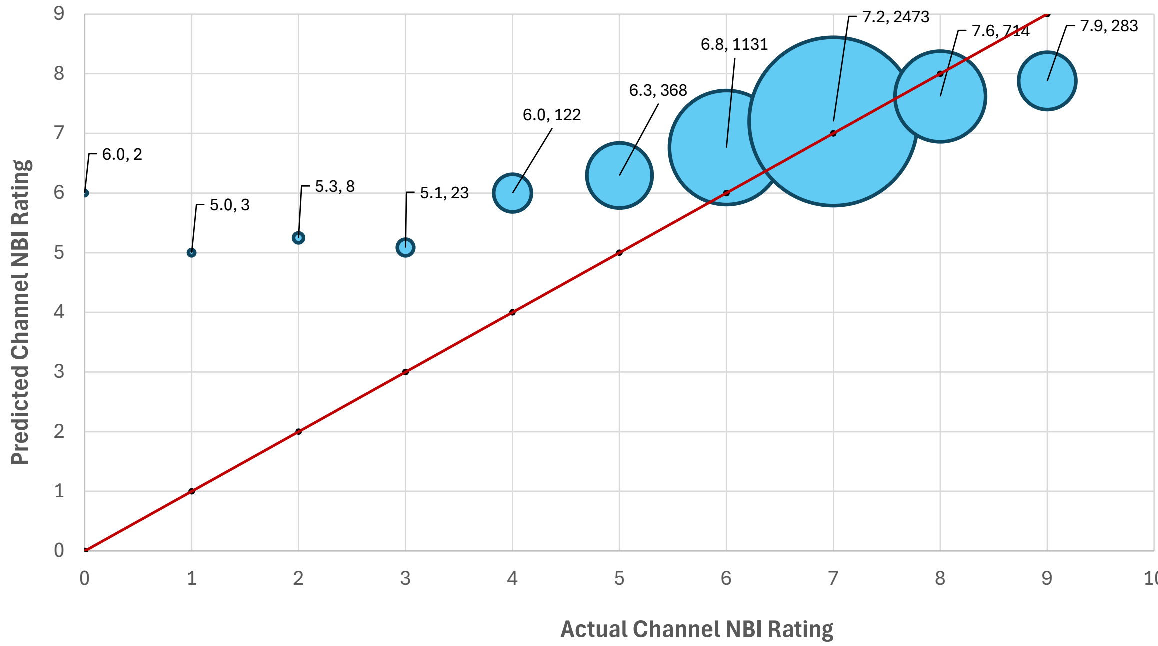


Figure 5.18. Mean predicted Channel NBI Ratings relative to the actual Ratings (showing no. of bridges).

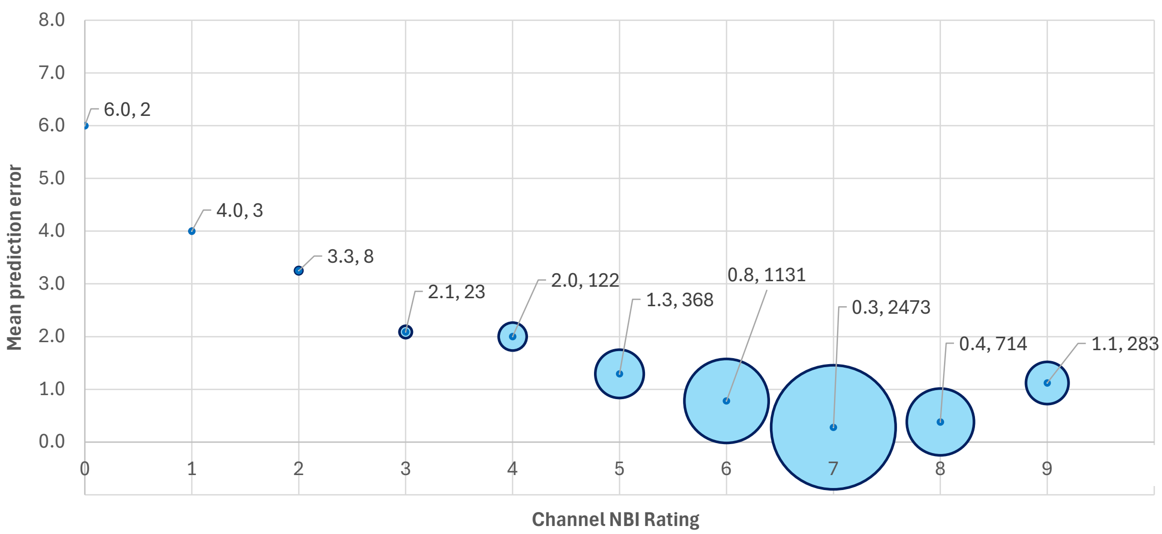


Figure 5.19. Variation in mean prediction errors at each Channel NBI Rating (showing no. of bridges).

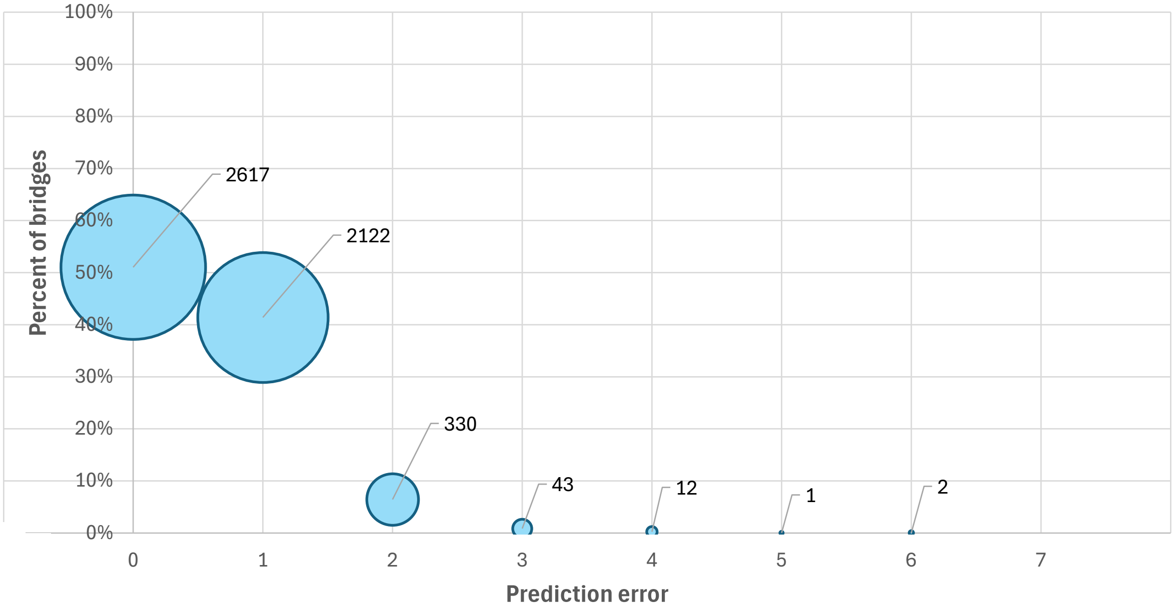


Figure 5.20. Variation in prediction errors for Channel NBI Ratings (showing no. of bridges).

Table 5.15. Classification table on Generalized NBI ratings for bridge deck (Linear regression).

a. Deck

Actual \ Predicted	1	2	3	Total	% correct
1	0	124	87	211	0.0%
2	1	746	635	1382	54.0%
3	0	414	4000	4414	90.6%
Total	1	1284	4722	6007	**79.0%**

b. Superstructure

Actual \ Predicted	1	2	3	Total	% correct
1	2	137	20	159	1.3%
2	10	369	408	787	46.9%
3	0	264	2964	3228	91.8%
Total	12	770	3392	4174	**79.9%**

c. Substructure

Actual \ Predicted	1	2	3	Total	% correct
1	0	170	31	201	0.0%
2	1	623	517	1141	54.6%
3	2	339	4343	4684	92.7%
Total	3	1132	4891	6026	**82.4%**

d. Culvert

Actual \ Predicted	1	2	3	Total	% correct
1	4	93	4	101	4.0%
2	1	499	82	582	85.7%
3	1	202	360	563	63.9%
Total	6	794	446	1246	**69.3%**

e. Channel

Actual \ Predicted	1	2	3	Total	% correct
1	0	149	9	158	0.0%
2	0	588	911	1499	39.2%
3	0	119	3351	3470	96.6%
Total	0	856	4271	5127	**76.8%**

5.3.2. Multinomial Logistic Regression

The results of the Translator models for the bridge components, based on the Multinomial Logistic Regression approach are shown first as the regression equations for the deck in Table 5.16. As explained previously under the methodology section of this report, Table 5.16 shows the coefficients obtained for the logistic regression equations, for each of the 10 probable NBI ratings (0 to 9), and each of the Generalized rating (1,2, or 3). The probabilities are computed at each instance of the translation, and the rating with the highest probability is chosen as the predicted translated rating (*DeckNBI* or *DeckNBIGen*).

Table 5.16. Multinomial logistic regression equations for Deck NBI Translator.

<u>Deck NBI Ratings:</u>
$S_1 = e^{(-2.435737+2.402414*\mathbf{NoOfDeckDefects}+1.367506*\mathbf{DeckHI}-1.436090*\mathbf{PercentDeckSt1}+0.215022*\mathbf{Age})}$
$S_2 = e^{(-2.507459+2.386925*\mathbf{NoOfDeckDefects}+1.406220*\mathbf{DeckHI}-1.461093*\mathbf{PercentDeckSt1}+0.187186*\mathbf{Age})}$
$S_3 = e^{(-12.026500+2.665328*\mathbf{NoOfDeckDefects}+1.495361*\mathbf{DeckHI}-1.483974*\mathbf{PercentDeckSt1}+0.229287*\mathbf{Age})}$
$S_4 = e^{(-4.708682+2.321792*\mathbf{NoOfDeckDefects}+1.389477*\mathbf{DeckHI}-1.417630*\mathbf{PercentDeckSt1}+0.260668*\mathbf{Age})}$
$S_5 = e^{(-3.390757+2.425679*\mathbf{NoOfDeckDefects}+1.390369*\mathbf{DeckHI}-1.412856*\mathbf{PercentDeckSt1}+0.252957*\mathbf{Age})}$
$S_6 = e^{(-3.469492+2.269725*\mathbf{NoOfDeckDefects}+1.419919*\mathbf{DeckHI}-1.435790*\mathbf{PercentDeckSt1}+0.259298*\mathbf{Age})}$
$S_7 = e^{(-1.934867+2.229060*\mathbf{NoOfDeckDefects}+1.431273*\mathbf{DeckHI}-1.449525*\mathbf{PercentDeckSt1}+0.250848*\mathbf{Age})}$
$S_8 = e^{(-3.064101+1.736166*\mathbf{NoOfDeckDefects}+1.468438*\mathbf{DeckHI}-1.441579*\mathbf{PercentDeckSt1}+0.235107*\mathbf{Age})}$
$S_9 = e^{(-0.250177+0.805281*\mathbf{NoOfDeckDefects}+1.355653*\mathbf{DeckHI}-1.343485*\mathbf{PercentDeckSt1}+0.162321*\mathbf{Age})}$
$S_{10}=1+\sum_{j=1...9} S_j$
$Pr(i) = S_i/S_{10}$, i=1...9
$Pr(DeckNBI=9) = 1 - \sum_{i=1...9} Pr(i)$
<u>Generalized Deck NBI Ratings:</u>
S(1) = Exp(-1.895754+0.670070***NoOfDeckDefects**-0.041224***DeckHI**+0.021300***PercentDeckDefSt3**+0.015031***Age**)
S(2) = Exp(0.740959+0.554844***NoOfDeckDefects**-0.045738***DeckHI**+0.010962***PercentDeckDefSt3**+0.022938***Age**)
S(3)=1+Sum[j=1...2] S(j)
Pr(i) = S(i)/S(3), i=1...2
Pr(DeckNBIGen=3) = 1 - Sum[i=1...2] Pr(i)

The results are shown in the form of classification in Tables 5.17 to 5.21, indicating the accuracy in prediction at each rating as well as the overall accuracy. Table 5.22 shows for the five bridge components, the results of the Translator predictions for the Generalized NBI ratings of Good, Fair, and Poor. Appendix C presents more detailed results for the Multiple Logistic Regression models.

The overall prediction accuracy varied from the lowest of 53.2% for the channel, to the highest value of 65.6% for the deck and substructure. Except for the culvert, the best prediction for the bridge components was at the NBI rating of 7, with channels having an accuracy 96% at the rating 7. Results for NBI ratings 0 to 4 ranged from 0% to low values, except for the channel, but the count of the bridges at these ratings are also very low. The prediction accuracies at rating 9 were very poor for all bridge components, with the superstructure having the highest value at 17.6%. These are similar to the results from the multiple linear regression. For the generalized NBI ratings, the overall accuracy varies from 71.7% for the culvert, to 81.7% for the substructure (Table 5.22). The predictions were best at the “Good” rating (3), with the culvert having an accuracy of 71.6% while the channel had 96.8%.

Table 5.17. Classification table on predicted NBI ratings for bridge deck (Logistic regression).

PREDICTED

	0	1	2	3	4	5	6	7	8	9	*Accuracy*	*Total Count*	*Zero Error*	*+/- 1 Error*	*+/- 1 Accuracy*
0	0	0	0	0	0	0	6	2	0	0	0.0%	8	0	0	0.0%
1	0	0	0	0	0	0	7	3	1	0	0.0%	11	0	0	0.0%
2	0	0	0	0	0	0	1	1	0	0	0.0%	2	0	0	0.0%
3	0	0	0	0	0	0	11	20	0	0	0.0%	31	0	0	0.0%
4	0	0	0	0	0	0	36	123	0	0	0.0%	159	0	0	0.0%
5	0	0	0	0	0	0	106	225	0	0	0.0%	331	0	106	32.0%
6	0	0	0	0	2	0	439	604	6	0	41.8%	1051	439	1043	99.2%
7	0	0	0	0	1	0	233	3001	199	0	87.4%	3434	3001	3433	100.0%
8	0	0	0	0	0	0	2	393	497	2	55.6%	894	497	892	99.8%
9	0	0	0	0	0	0	0	4	78	4	4.7%	86	4	82	95.3%
	0	0	0	0	3	0	841	4376	781	6	**65.6%**	6007	3941	5556	92.5%

Table 5.18. Classification table on predicted NBI ratings for bridge superstructure (Logistic regression).

PREDICTED

	0	1	2	3	4	5	6	7	8	9	*Accuracy*	*Total Count*	*Zero Error*	*+/- 1 Error*	*+/- 1 Accuracy*
0	0	0	0	0	5	0	1	1	1	0	0.0%	8	0	0	0.0%
1	0	0	0	0	6	0	2	1	0	0	0.0%	9	0	0	0.0%
2	0	0	0	0	1	1	8	1	0	0	0.0%	11	0	0	0.0%
3	0	0	0	0	0	3	11	10	0	0	0.0%	24	0	0	0.0%
4	0	0	0	0	2	13	47	45	0	0	1.9%	107	2	15	14.0%
5	0	0	0	0	3	47	59	144	1	0	18.5%	254	47	109	42.9%
6	0	0	0	0	10	26	98	394	5	0	18.4%	533	98	518	97.2%
7	0	0	0	0	11	16	74	1926	241	1	84.9%	2269	1926	2241	98.8%
8	0	0	0	0	4	0	0	326	539	5	61.7%	874	539	870	99.5%
9	0	0	0	0	0	0	0	10	60	15	17.6%	85	15	75	88.2%
	0	0	0	0	42	106	300	2858	847	21	**62.9%**	4174	2627	3828	91.7%

Table 5.19. Classification table on predicted NBI ratings for bridge substructure (Logistic regression).

ACTUAL \ PREDICTED	0	1	2	3	4	5	6	7	8	9	*Accuracy*	*Total Count*	*Zero Error*	*+/- 1 Error*	*+/- 1 Accuracy*
0	0	0	0	0	0	0	4	2	0	1	0.0%	7	0	0	0.0%
1	0	0	0	0	0	0	8	2	0	0	0.0%	10	0	0	0.0%
2	0	0	0	0	0	0	6	0	0	0	0.0%	6	0	0	0.0%
3	0	0	0	0	0	1	28	11	0	0	0.0%	40	0	0	0.0%
4	0	0	0	0	3	4	90	41	0	0	2.2%	138	3	7	5.1%
5	0	0	0	0	0	12	141	117	0	0	4.4%	270	12	153	56.7%
6	0	0	0	0	3	7	269	590	2	0	30.9%	871	269	866	99.4%
7	0	0	0	0	2	5	169	2991	259	1	87.3%	3427	2991	3419	99.8%
8	0	0	0	0	0	0	9	466	666	3	58.2%	1144	666	1135	99.2%
9	0	0	0	0	0	0	1	9	91	12	10.6%	113	12	103	91.2%
	0	0	0	0	8	29	725	4229	1018	17	**65.6%**	6026	3953	5683	94.3%

Table 5.20. Classification table on predicted NBI ratings for bridge culvert (Logistic regression).

ACTUAL \ PREDICTED	0	1	2	3	4	5	6	7	8	9	*Accuracy*	*Total Count*	*Zero Error*	*+/- 1 Error*	*+/- 1 Accuracy*
0	0	0	0	0	0	0	2	0	0	0	0.0%	2	0	0	0.0%
1	0	0	0	0	0	0	0	0	0	0	0.0%	0	0	0	0.0%
2	0	0	0	0	0	0	0	0	0	0	0.0%	0	0	0	0.0%
3	16	0	0	0	0	0	12	2	0	0	0.0%	30	0	0	0.0%
4	7	0	0	0	0	0	53	9	0	0	0.0%	69	0	0	0.0%
5	2	0	0	0	0	0	94	11	0	0	0.0%	107	0	94	87.9%
6	5	0	0	0	0	0	370	100	0	0	77.9%	475	370	470	98.9%
7	6	0	0	0	0	0	139	346	0	0	70.5%	491	346	485	98.8%
8	2	0	0	0	0	0	0	59	8	0	11.6%	69	8	67	97.1%
9	0	0	0	0	0	0	0	1	2	0	0.0%	3	0	2	66.7%
	38	0	0	0	0	0	670	528	10	0	**58.1%**	1246	724	1118	89.7%

Table 5.21. Classification table on predicted NBI ratings for bridge channel (Logistic regression).

PREDICTED

ACTUAL	0	1	2	3	4	5	6	7	8	9	*Accuracy*	*Total Count*	*Zero Error*	*+/- 1 Error*	*+/- 1 Accuracy*
0	0	0	0	0	0	0	2	0	0	0	0.0%	2	0	0	0.0%
1	0	0	0	2	0	0	1	0	0	0	0.0%	3	0	0	0.0%
2	0	0	0	7	0	0	0	1	0	0	0.0%	8	0	7	0.0%
3	0	0	0	21	0	0	2	0	0	0	91.3%	23	21	21	91.3%
4	0	0	0	8	0	0	104	8	2	0	0.0%	122	0	8	6.6%
5	0	0	0	2	0	0	254	109	3	0	0.0%	368	0	254	69.0%
6	0	0	0	5	0	0	325	790	11	0	28.7%	1131	325	1115	98.6%
7	0	0	0	1	0	0	76	2373	23	0	96.0%	2473	2373	2472	100.0%
8	0	0	0	0	0	0	27	676	11	0	1.5%	714	11	687	96.2%
9	0	0	0	0	0	0	8	273	2	0	0.0%	283	0	2	0.7%
	0	0	0	46	0	0	799	4230	52	0	**53.2%**	5127	2730	4566	89.1%

Table 5.22. Classification Table on Generalized NBI Rating models (Logistic regression).

a. Deck

Actual \ Predicted	1	2	3	Total	% correct
1	0	96	115	211	0.00%
2	0	605	777	1382	43.78%
3	0	299	4115	4414	93.23%
Total	0	1000	5007	6007	**78.57%**

b. Superstructure

Actual \ Predicted	1	2	3	Total	% correct
1	13	102	44	159	8.18%
2	13	309	465	787	39.26%
3	28	145	3055	3228	94.64%
Total	54	556	3564	4174	**80.91%**

c. Substructure

Actual \ Predicted	1	2	3	Total	% correct
1	2	150	49	201	1.00%
2	3	486	652	1141	42.59%
3	11	236	4437	4684	94.73%
Total	16	872	5138	6026	**81.73%**

d. Culvert

Actual \ Predicted	1	2	3	Total	% correct
1	20	70	11	101	19.80%
2	7	470	105	582	80.76%
3	8	152	403	563	71.58%
Total	35	692	519	1246	**71.67%**

e. Channel

Actual \ Predicted	1	2	3	Total	% correct
1	38	109	11	158	24.05%
2	7	579	913	1499	38.63%
3	1	111	3358	3470	96.77%
Total	46	799	4282	5127	**77.53%**

5.3.3. Machine Learning (ML) Models

Results for the Translators developed based on the machine learning approach are presented in this section. For each bridge component, the development of the Translator is discussed, including the various model scenarios in terms of the combination of the explanatory variables, and the results are presented in terms of the prediction accuracy and identification of the most important variable for explaining the predicted NBI rating.

5.3.3.1. Development of the Bridge Deck NBI ML Translator

The complete dataset from merging the decks' NBI rating inspection data with the element inspection data was categorized into six main types of records for the deck component datasets: Primary element records; Records of defects in primary elements; Secondary element records, which include joints, approach slabs, and railing decks; Records of defects in secondary elements; Various other counting variables; and Age of the deck. Counting variables were added to the deck dataset, reflecting the number of inspection records for each bridge, the number of inspections for primary deck elements, the number of inspections for secondary deck elements, the number of defect records for primary deck elements, and the number of defect records for secondary deck elements associated with a primary deck element record. The primary defects, secondary defects, and secondary element records were aggregated using an averaging operation, with the results linked back to the primary element records. Element health index variables were computed for the primary element condition, defects, as well as for secondary and protection elements.

To investigate the influence of the various predictor variables, eight different scenarios were developed to create Trial Translator models, with each model comprising a unique combination of bridge attributes. For instance, the Trial Model 1 for the NBI Deck Translator predicts the 10 NBI condition ratings (0 to 9), considering 10 predictors, which include the primary element data only. Trial Model 2 is similar to Trial Model 1 in terms of the predictors, but it models the three generalized NBI ratings of Good, Fair and Poor. In a similar pattern, other trial models are developed by including more bridge attributes. Trial Models 3 and 4 add the defect data to those of Trial Model 1 and 2, respectively. These and other Trial Translator Models for the Deck NBI rating are summarized in terms of the predictor and response variables in Table 5.23. For each of the trial translator models, the top four suitable machine learning (ML) algorithms were ranked and the best selected based on the accuracy of the results. Also shown are the most important predictor variable and the computing times for training the ML models. Table 5.24 further describes the details of the predictor variables and their inclusion on the different trial models.

<u>Deck Model 1: Primary element data (NBI Rating 0 to 9).</u>

The 10 predictor variables used include the following: Inspection count per bridge; Age; Element key; Element Type Key; Element Material key; Primary element percent in condition state 1; Primary element percent in condition state 2; Primary element percent in condition state 3; Primary element percent in condition state 4; and the primary element health index.

The Ensemble classification produced the most accurate results compared with other classifier models. Figures 5.21 and 5.22 show the confusion matrix, reflecting accuracy of the prediction, in terms of the predicted ratings compared to the actual ratings. The numbers in the diagonals indicate the exact prediction of the ratings. In Figure 5.25, the True Positive Rate (TPR) represents the proportion of correctly classified observations within each true class. The False Negative Rate (FNR) indicates the proportion of incorrectly classified observations within each true class. The best performance on the model was on bridge decks with actual ratings of 7, in which 2480 or 87% were precisely predicted to be rating 7. With a tolerance of ±1, the overall performance can be deemed acceptable, with ratings 6, 7, and 8 having correct predictions up to about 90% accuracy, and the majority of the classes exceeding 70%.

Table 5.23. Summary of Machine Learning (ML) model results for Deck NBI Translator.

Trial Translator Models	ML Models	Accuracy (Validation) (%)	Most important predictor	Training time (sec.)
Model 1: Primary element data -- 5022 observations, 10 predictors, 10 response classes (NBI rating 0 to 9).	Ensemble	69.3	Primary element % in condition state 4	813.6
	Tree	65.9		
	Kernel	65.7		
	SVM	62.1		
Model 2: Primary element data -- 5022 observations, 10 predictors, 3 response classes (NBI Generalized ratings Good, Fair, and Poor).	Ensemble	78.9	Primary element health index	148.3
	Tree	75.6		
	Kernel	74.1		
	SVM	71.2		
Model 3: Primary element defect data -- 5022 observations, 10 predictors, 10 response classes (NBI rating 0 to 9).	Ensemble	65.6	Primary element % in defect condition state 4	1520.4
	Tree	62.7		
	Kernel	61.4		
	Linear SVM	58.9		
Model 4: Primary element defect data -- 5022 observations, 10 predictors, 3 response classes (NBI Generalized ratings Good, Fair, and Poor).	Ensemble	75.9	Primary element % in defect condition state 4	539.3
	Tree	72.3		
	Kernel	70.2		
	Linear SVM	65.8		
Model 5: Primary element condition and defect data -- 5022 observations, 15 predictors, 10 response classes (NBI rating 0 to 9).	Ensemble	68.9	Primary element % in defect condition state 4	1585.5
	Tree	65.6		
	Neural Network	63.2		
	Efficient Linear SVM	62.4		
Model 6: Primary element condition and defect data -- 5022 observations, 15 predictors, 3 response classes (NBI Generalized ratings Good, Fair, and Poor).	Ensemble	80.2	Primary element health index	908.1
	Tree	76.7		
	Neural Network	76.4		
	Kernel	74.9		
Model 7: All element condition and defect data -- 4546 observations, 25 predictors, 10 response classes (NBI rating 0 to 9).	Ensemble	71.8	Primary element % in defect condition state 4	256.2
	Kernel	67.1		
	SVM	67.0		
	Neural Network	66.4		
Model 8: All element condition and defect data -- 4546 observations, 25 predictors, 3 response classes (NBI Generalized ratings Good, Fair, and Poor).	Ensemble	81.2	Primary element health index	621.5
	Tree	76.6		
	Neural Network	76.4		
	SVM	75.9		

Table 5.24. Summary of variables in the Trial Models for Deck NBI Translator using the machine learning approach.

Variable	**Description**	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**
ChkBrInsp	No. of inspections	*	*	*	*	*	*	*	*
ElemKey	Element key	*	*	*	*	*	*	*	*
ElemType	Element type	*	*	*	*	*	*	*	*
ElemMatl	Element material	*	*	*	*	*	*	*	*
Age	Age of bridge at inspection	*	*	*	*	*	*	*	*
ElemPctState1	Percent in primary element condition state 1	*	*			*	*	*	*
ElemPctState2	Percent in primary element condition state 2	*	*			*	*	*	*
ElemPctState3	Percent in primary element condition state 3	*	*			*	*	*	*
ElemPctState4	Percent in primary element condition state 4	*	*			*	*	*	*
ElemPctStateHI	Health index of primary element	*	*			*	*	*	*
ElemDefPctState1	Percent in primary element defect condition state 1			*	*	*	*	*	*
ElemDefPctState2	Percent in primary element defect condition state 2			*	*	*	*	*	*
ElemDefPctState3	Percent in primary element defect condition state 3			*	*	*	*	*	*
ElemDefPctState4	Percent in primary element defect condition state 4			*	*	*	*	*	*
ElemDefPctStateHI	Health index of primary element defect			*	*	*	*	*	*
SecondElemPctState1	Percent in secondary element condition state 1							*	*
SecondElemPctState2	Percent in secondary element condition state 2							*	*
SecondElemPctState3	Percent in secondary element condition state 3							*	*
SecondElemPctState4	Percent in secondary element condition state 4							*	*
SecondElemPctStateHI	Health index of secondary element defect							*	*
SecondElemDefPctState1	Percent in secondary element defect condition state 1							*	*
SecondElemDefPctState2	Percent in secondary element defect condition state 2							*	*
SecondElemDefPctState3	Percent in secondary element defect condition state 3							*	*
SecondElemDefPctState4	Percent in secondary element defect condition state 4							*	*
SecondElemDefPctStateHI	Health index of secondary element defect							*	*
DkRating#	NBI condition rating	*		*		*		*	
GenDkRating#	Generalized NBI condition rating (Good, Fair, Poor)		*		*		*		*

 # Dependent variables.

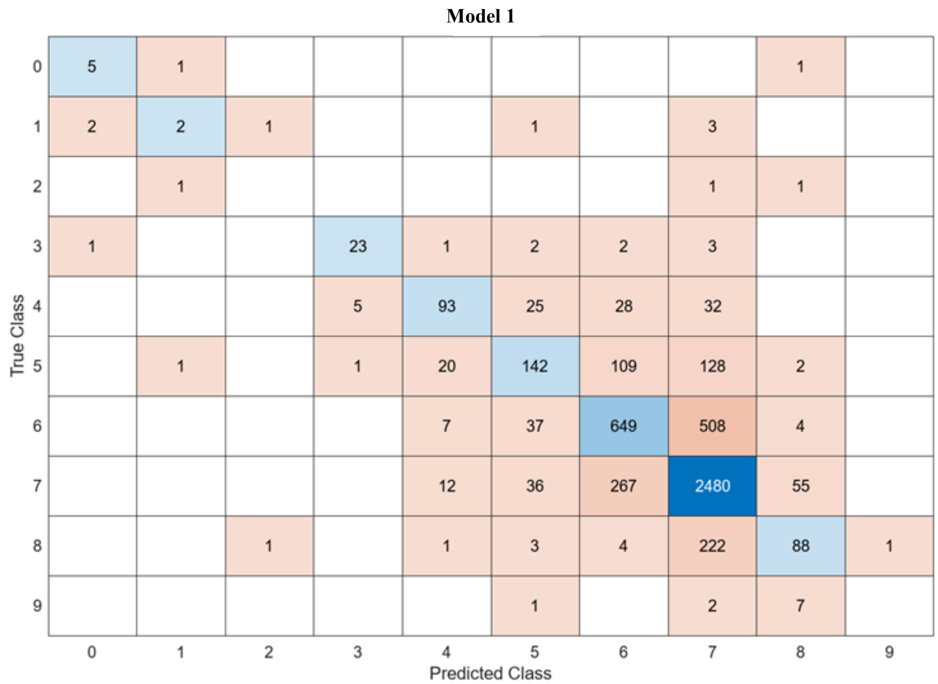


Figure 5.21. Deck Model 1: Ensemble, Bagging Trees Classifier (69.3 %) Performance, Number of Observations.

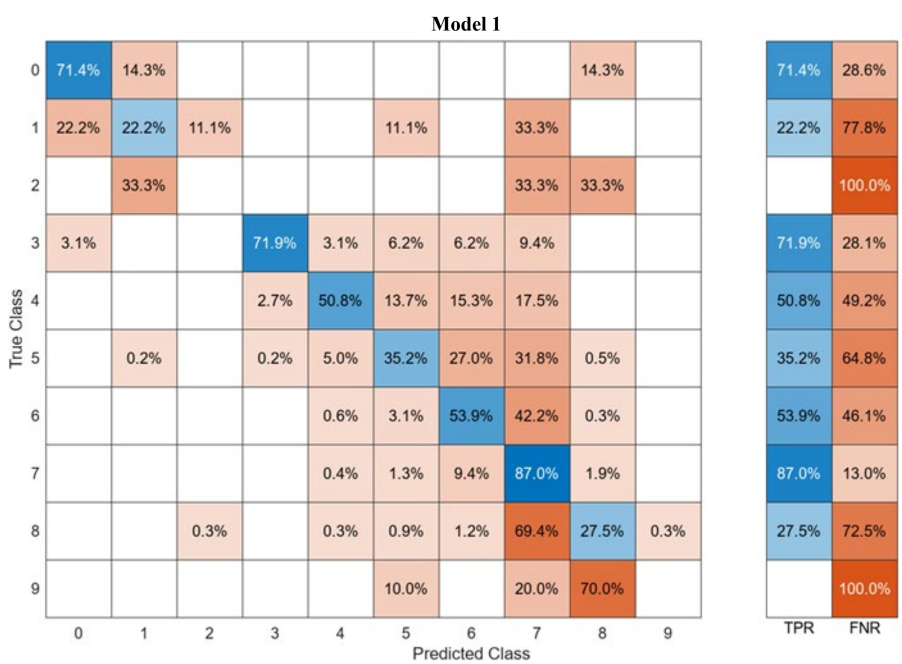


Figure 5.22. Deck Model 1: Ensemble, Bagging Trees Classifier (69.3%) Performance, True Positive Rates (TPR), False Negative Rates (FNR).

The contribution of each of the explanatory variable (feature) to the model is reflected in the importance factor. The ANOVA feature selection method computes an F-statistic for each feature. The F-statistic is a measure of the ratio of variance explained by the feature compared to the variance that is unexplained (error). A higher F-statistic indicates that the feature contributes more to the prediction of the target variable. As shown in Figure 5.23, the most important factor, i.e., that explains most of the variability, compared to other factors, is the percentage of the primary element in condition state 4.

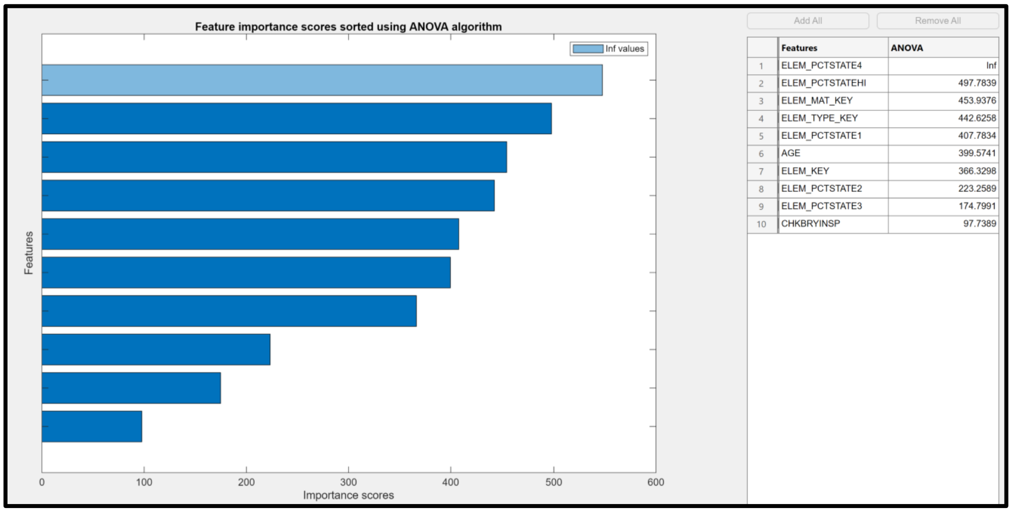


Figure 5.23. ANOVA feature ranking result for Deck Model1.

<u>Deck Model 2: Primary element data (NBI Generalized Ratings Good, Fair, and Poor).</u>
Using the generalized NBI ratings, as explained earlier with designations Good (NBI ratings 9 and 8), Fair (NBI Ratings 5, 6 and 7), and Poor (NBI ratings 0 to 4), the machine learning models were run again with the same set of explanatory variables. The results are summarized as shown earlier in Table 5.23. It can be seen that by aggregating the NBI ratings inro fewer designated classes, the accuracy improved to almost 80%, with the Ensemble model again being the best model among those evaluated. The confusion matrices are shown in Figures 5.24 and 5.25.

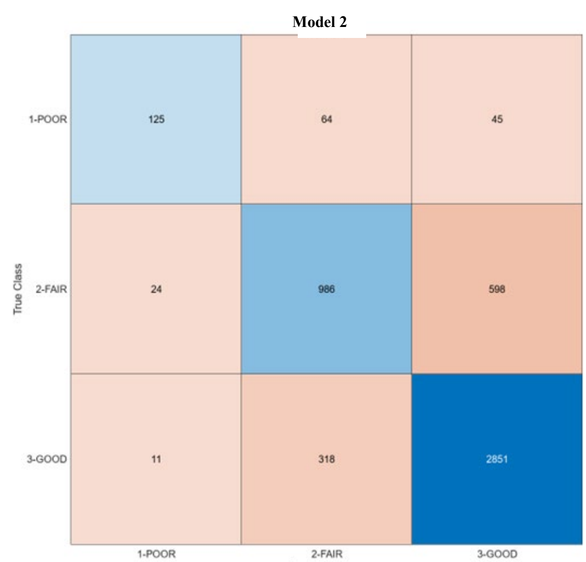


Figure 5.24. Deck Model 2: Ensemble, Bagging Trees Classifier (78.9 %) Performance, Number of Observations

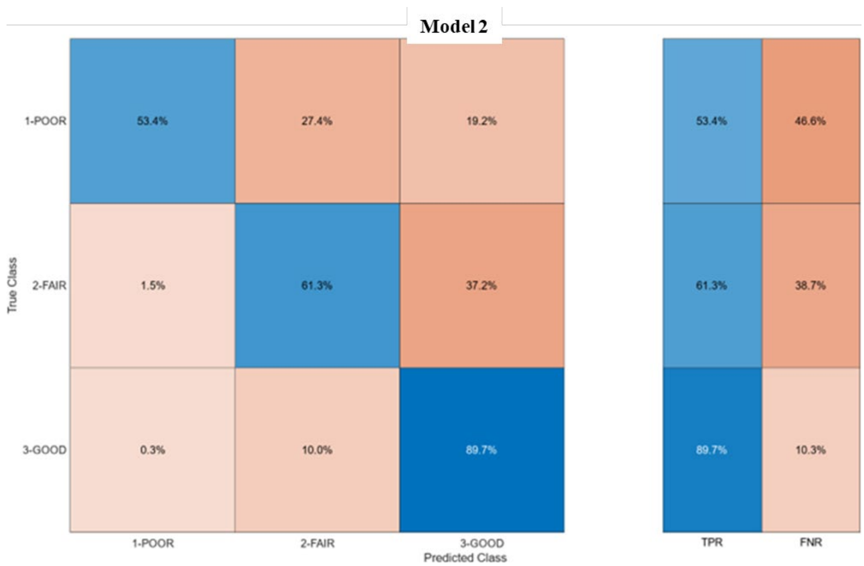


Figure 5.25. Deck Model 2: Ensemble, Bagging Trees Classifier (78.9%) Performance, True Positive Rates (TPR), False Negative Rates (FNR)

In Figure 5.25, the True Positive Rate (TPR) represents the proportion of correctly classified observations within each true class. The False Negative Rate (FNR) indicates the proportion of incorrectly classified observations within each true class. The plot displays summaries per true class in the last two columns on the right. This model performed best for NBI predictions of the Good rating, i.e. accuracy of almost 90%.

The most important of the explanatory variables was identified using the ANOVA feature selection method as the primary element health index (Figure 5.26).

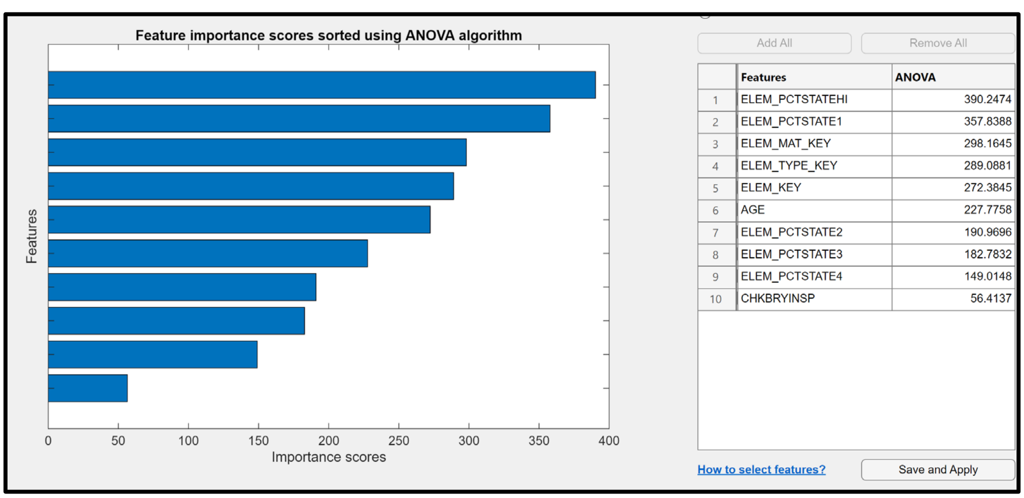


Figure 5.26. ANOVA feature ranking result for Deck Model 2.

Deck Model 3: Primary element defect data (NBI rating 0 to 9).

The 10 predictor variables used include the following: Inspection count per bridge; Age; Element key; Element Type Key; Element Material key; Primary element defect percent in condition state 1; Primary element defect percent in condition state 2; Primary element defect percent in condition state 3; Primary element defect percent in condition state 4; and the primary element defect health index.

The Ensemble classification produced the most accurate results compared with other classifier models. The results are summarized using the confusion matrix in Figures 5.27 and 5.28. Bridge decks at NBI rating 7 have the most accurate predictions, for 2337 or 82% of the bridge decks at rating 7. Though it was for a very small number of bridges, the translator results for deck ratings 0 and 3 was also very good at accuracy levels above 85% for both ratings. This model performed well for NBI predictions 0, 3, and 7. However, it could not predict 2 and 9. If positive prediction is considered as being within ±1 of the actual class, the majority of the prediction classes exceed 70%, which is a fair result.

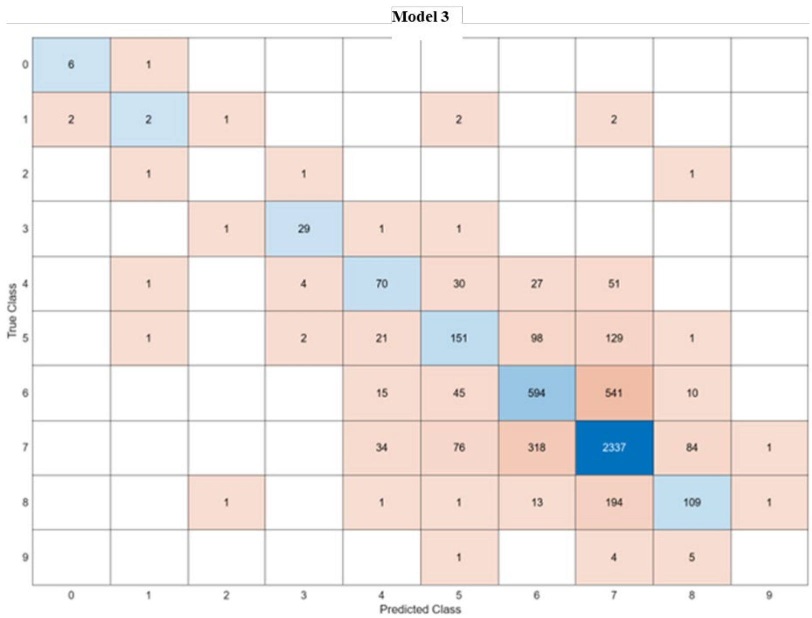


Figure 5.27. Deck Model 3: Ensemble, Bagging Trees Classifier (65.7%) Performance, Number of Observations

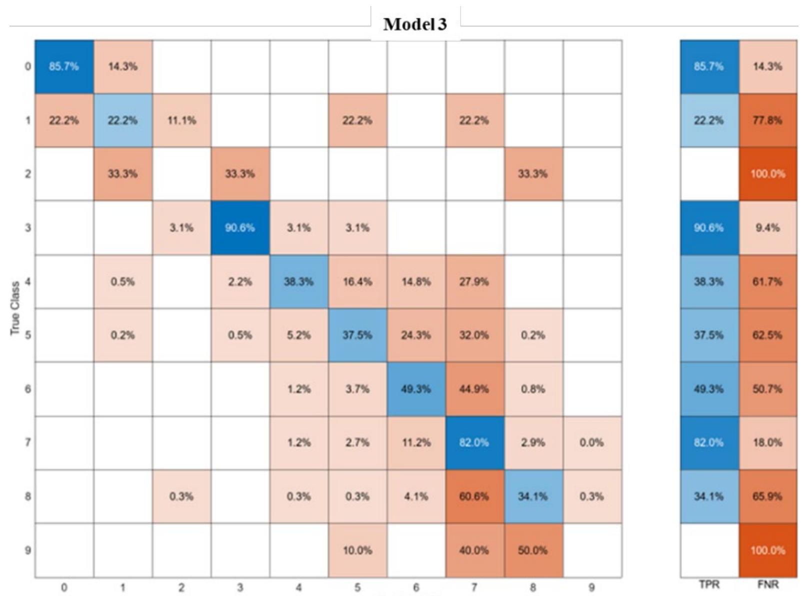
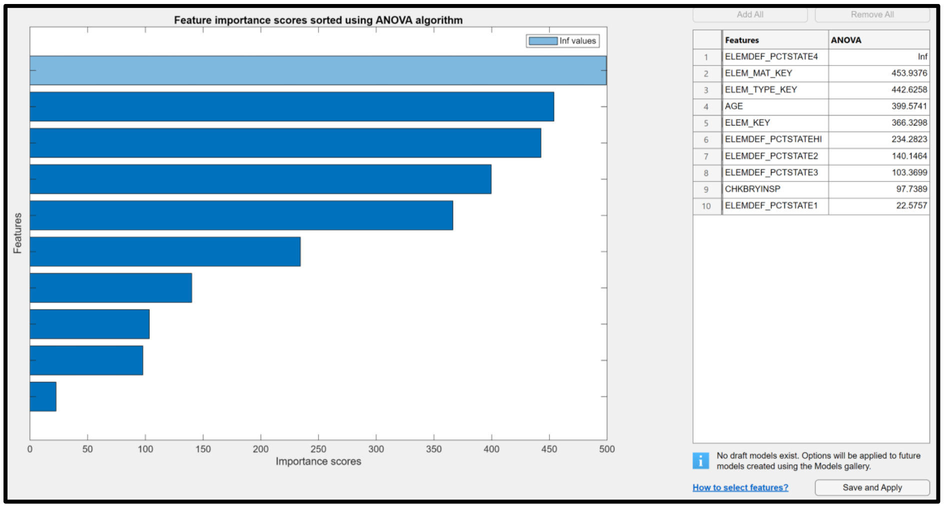


Figure 5.28. Deck Model 3: Ensemble, Bagging Trees Classifier (65.7%) Performance, True Positive Rates (TPR), False Negative Rates (FNR)

The most important of the 10 explanatory variables, with the highest importance factor, was identified as the primary element percentage in condition state 4 (Figure 5.29).



	Features	ANOVA
1	ELEMDEF_PCTSTATE4	Inf
2	ELEM_MAT_KEY	453.9376
3	ELEM_TYPE_KEY	442.6258
4	AGE	399.5741
5	ELEM_KEY	366.3298
6	ELEMDEF_PCTSTATEHI	234.2823
7	ELEMDEF_PCTSTATE2	140.1464
8	ELEMDEF_PCTSTATE3	103.3699
9	CHKBRYINSP	97.7389
10	ELEMDEF_PCTSTATE1	22.5757

Figure 5.29. ANOVA feature ranking result for Deck Model 3.

<u>Model 4: Primary element defect data (NBI generalized ratings Good, Fair, and Poor)</u>
The 10 predictor variables used include the following: Inspection count per bridge; Age; Element key; Element Type Key; Element Material key; Primary element defect percent in condition state 1; Primary element defect percent in condition state 2; Primary element defect percent in condition state 3; Primary element defect percent in condition state 4; and the primary element defect health index.

The Ensemble classification gives the most accurate results compared with other classifier models. The confusion matrices in Figures 5.30 and 5.31 show that the most accurate prediction was for the “Good” rating, indicated as 85.8%, i.e., correctly for 2728 of 3180 bridge decks which actually had ratings of 7. Of the 1608 bridge decks inspected to be in “Fair” rating, the model predicted 978 of them (60.8%) accurately, while 107 (45.7%) of the 234 decks at the “Poor” rating were accurately predicted.

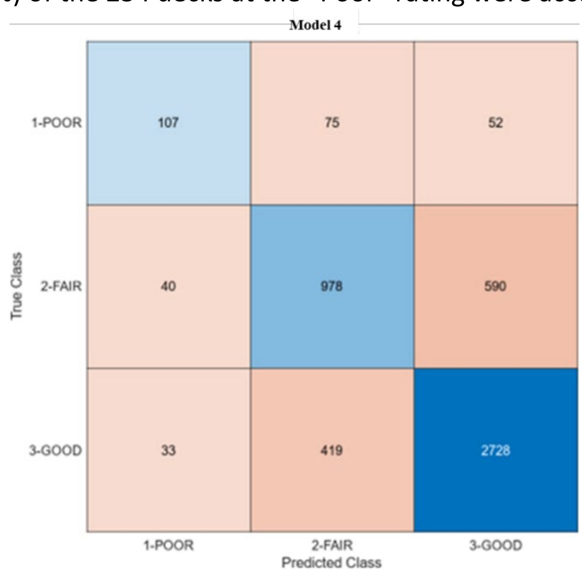


Figure 5.30. Deck Model 4: Ensemble, Bagging Trees Classifier (75.9%) Performance, Number of Observations

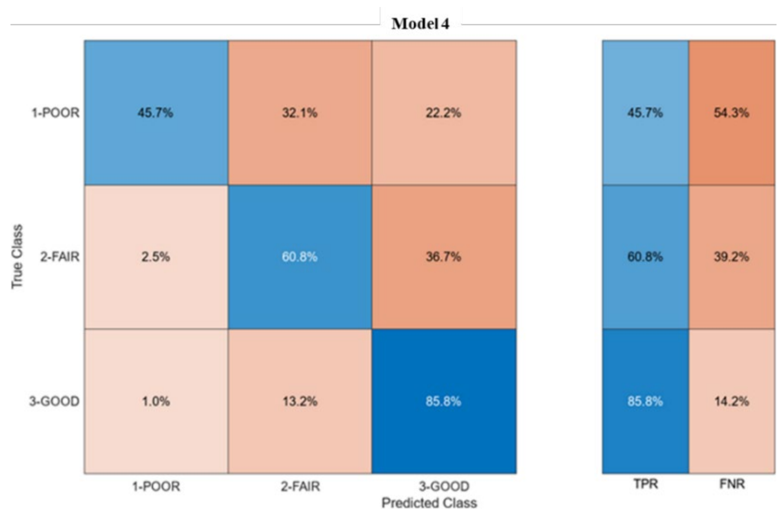


Figure 5.31. Deck Model 4: Ensemble, Bagging Trees Classifier (75.9%) Performance, True Positive Rates (TPR), False Negative Rates (FNR)

As shown in Figure 5.32, the most significant variable was identified as the primary element percentage in condition state 4.

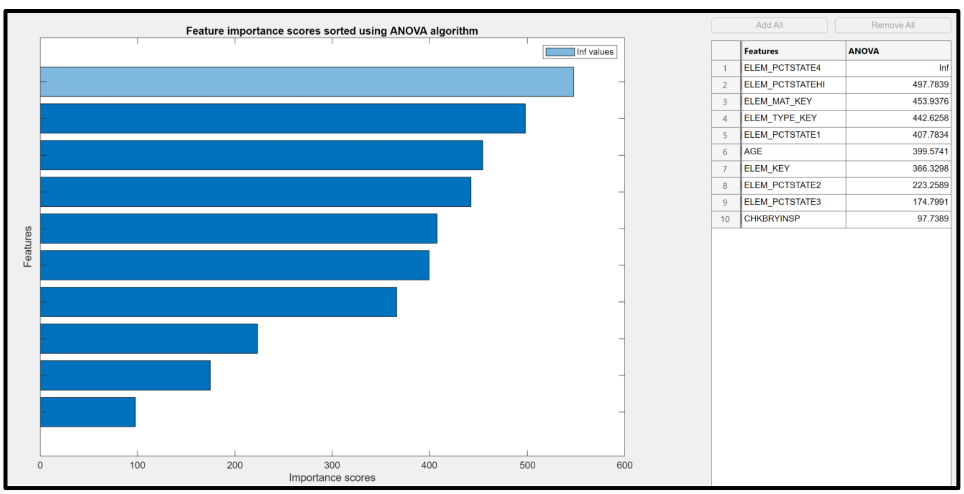


Figure 5.32. ANOVA feature ranking result for Deck Model 4.

Model 5: Primary element condition and defect data (NBI rating 0 to 9).

In this model, the explanatory variables were expanded to include both the primary element condition data and the defect data. The 15 predictor variables used include the following: Inspection count per bridge; Age; Element key; Element Type Key; Element Material key; Primary element percent in condition state 1; Primary element percent in condition state 2; Primary element percent in condition state 3; Primary element percent in condition state 4; the primary element health index; Primary element defect percent in condition state 1; Primary element defect percent in condition state 2; Primary element defect percent in condition state 3; Primary element defect percent in condition state 4; and the primary element defect health index.

The Ensemble classification gives the most accurate results compared with other classifier models. Figures 5.33 and 5.34 show the confusion matrices, indicating that the best predictions were for NBI rating 7 with 91.6 accuracy (2610 bridge decks) and also for 100% of the 0 rating decks, though with a very small number of 7 bridge decks.

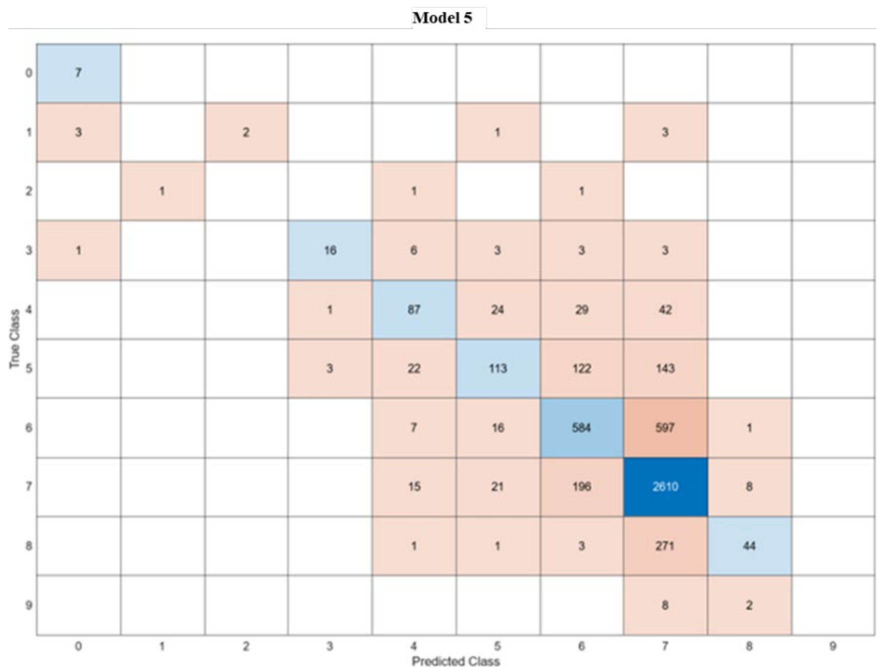


Figure 5.33. Deck Model 5: Ensemble, Bagging Trees Classifier (68.9%) Performance, Number of Observations

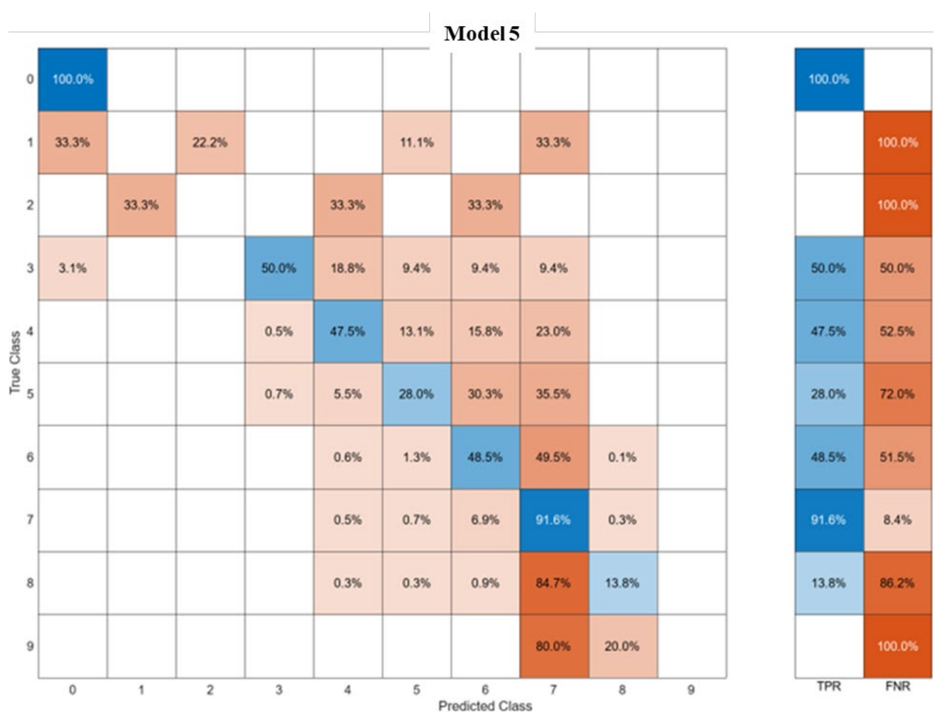


Figure 5.34. Deck Model 5: Ensemble, Bagging Trees Classifier (68.9%) Performance, True Positive Rates (TPR), False Negative Rates (FNR)

In this model, the explanatory variable with the highest importance factor is the primary element defect percentage in condition state 4 (Figure 5.35).

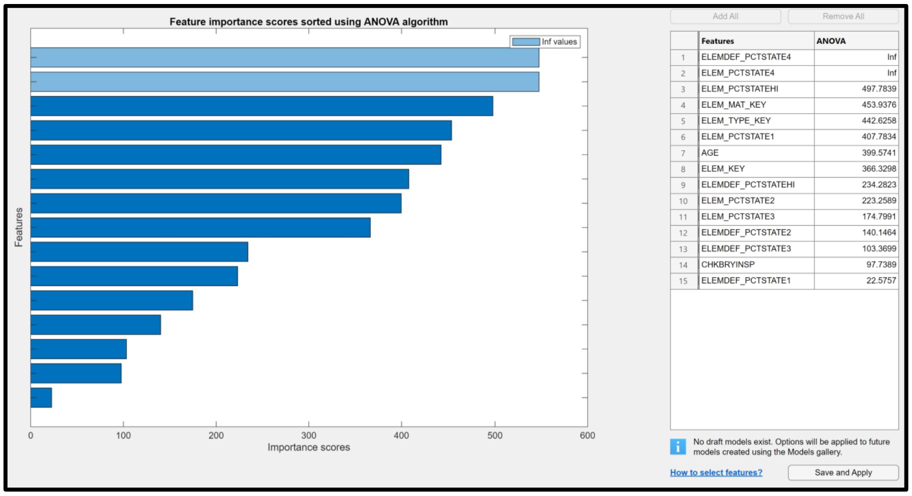


Figure 5.35. ANOVA feature ranking result for Deck Model 5.

<u>Model 6: Primary element condition and defect data (Generalized NBI ratings Good, Fair, and Poor).</u>
The 15 predictor variables used include the following: Inspection count per bridge; Age; Element key; Element Type Key; Element Material key; Primary element percent in condition state 1; Primary element percent in condition state 2; Primary element percent in condition state 3; Primary element percent in condition state 4; the primary element health index; Primary element defect percent in condition state 1; Primary element defect percent in condition state 2; Primary element defect percent in condition state 3; Primary element defect percent in condition state 4; and the primary element defect health index.

The classification ensemble produced the most accurate results compared with other classifier models. The confusion matrices (Figures 5.36 and 5.37) show that the predictions were most accurate for the "Good" bridge decks at 89.1%, and 66.1%, and 55.1%, respectively for the "Fair" and "Poor" bridge decks.

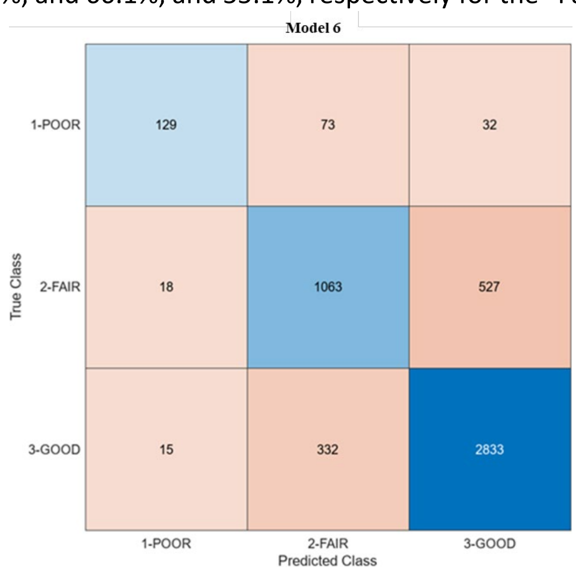


Figure 5.36. Deck Model 6: Ensemble, Bagging Trees Classifier (80.1%) Performance, Number of Observations

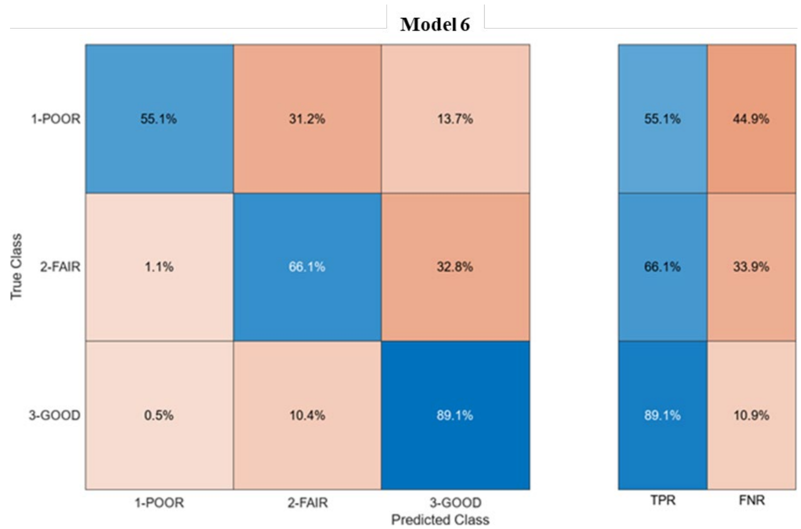


Figure 5.37**.** Deck Model 6: Ensemble, Bagging Trees Classifier (80.1%) Performance, True Positive Rates (TPR), False Negative Rates (FNR)

The model computed the highest importance factor for the primary element heath index, implying that it contributed most to the predictions in the model (Figure 5.38).

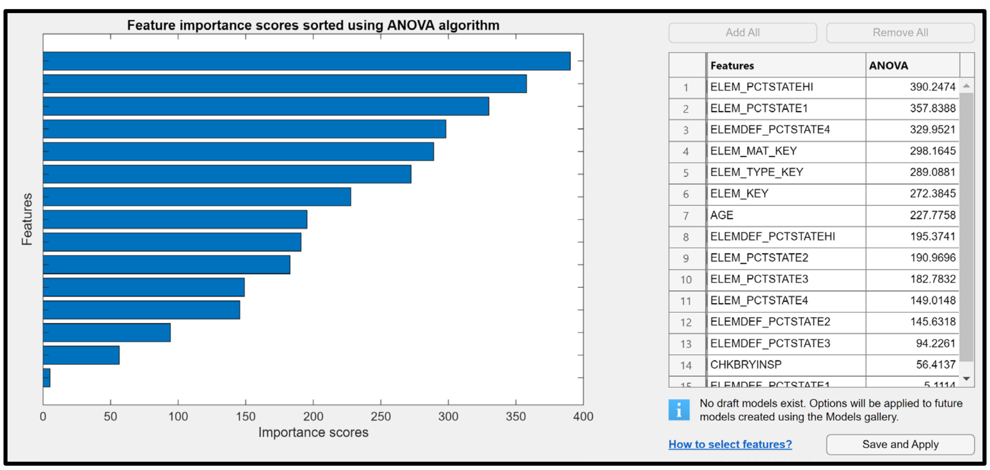


Figure 5.38. ANOVA feature ranking result for Deck Model 6.

<u>Model 7: All element condition and defect data (NBI rating 0 to 9).</u>

The 25 predictor variables used include the following: Inspection count per bridge; Age; Element key; Element Type Key; Element Material key; Primary element percent in condition state 1; Primary element percent in condition state 2; Primary element percent in condition state 3; Primary element percent in condition state 4; the primary element health index; Primary element defect percent in condition state 1; Primary element defect percent in condition state 2; Primary element defect percent in condition state 3; Primary element defect percent in condition state 4; Primary element defect health index; Secondary element percent in condition state 1; Secondary element percent in condition state 2; Secondary element percent in condition state 3; Secondary element percent in condition state 4; Secondary element health index; Secondary element defect percent in condition state 1; Secondary element defect percent in condition state 2; Secondary element defect percent in condition state 3; Secondary element defect percent in condition state 4; and the Secondary element defect health index.

The classification ensemble gives the best accuracy results compared with other classifier models (Figures 5.39 and 5.40). The best prediction was at the NBI deck rating of 7, with 87.8% accuracy. In Figure 5.40, the True Positive Rate (TPR) represents the proportion of correctly classified observations within each true class. The False Negative Rate (FNR) indicates the proportion of incorrectly classified observations within each true class. The plot displays summaries per true class in the last two columns on the right. This model performed well for NBI predictions 0, 3, and 7. However, it could not predict 2 and 9. If positive prediction is considered as being within ±1 of the actual class, the majority of the prediction classes exceed 70%, which is a fair result. The model could not predict 2 and 9. This model result accuracy characteristics are similar to the best model accuracy result when only primary element variables are considered.

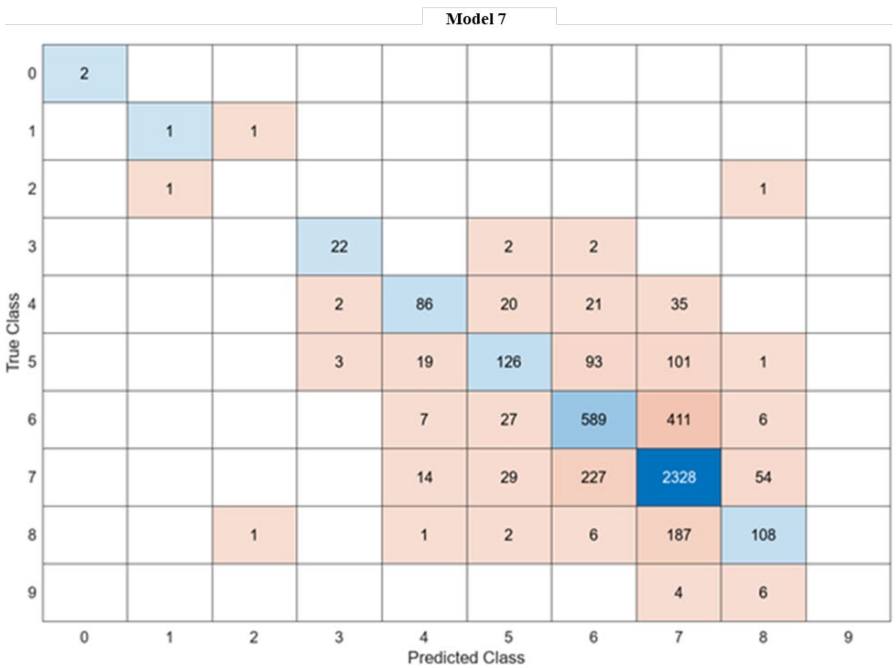


Figure 5.39. Deck Model 7: Ensemble, Bagging Trees Classifier (71.8 %) Performance, Number of Observations

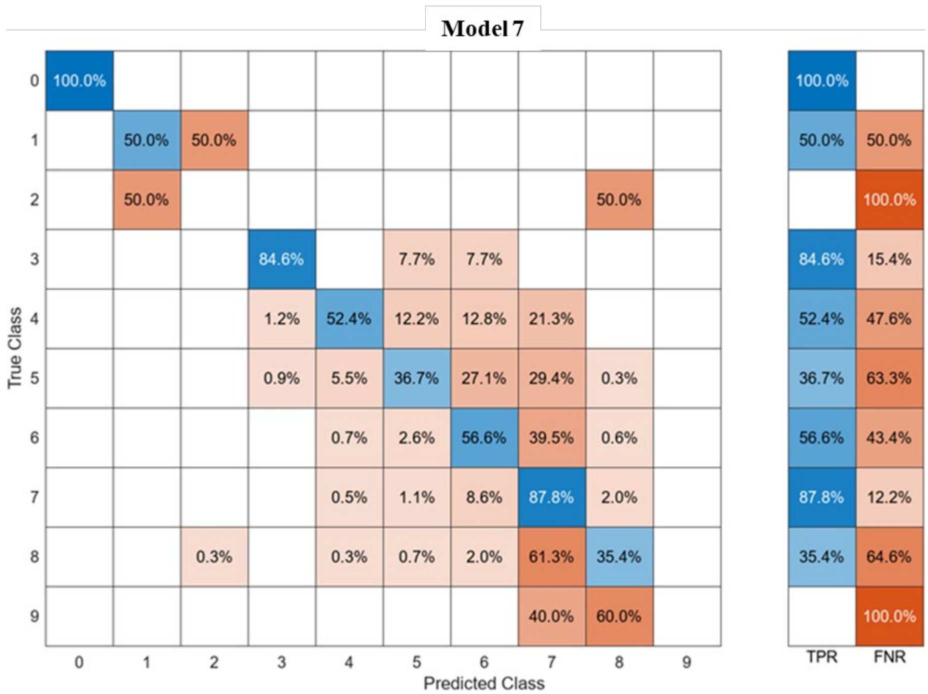


Figure 5.40. Deck Model 7: Ensemble, Bagging Trees Classifier (71.8 %) Performance, True Positive Rates (TPR), False Negative Rates (FNR)

In this model, the explanatory variable with the highest importance factor is the primary element defect percentage in condition state 4 (Figure 5.41).

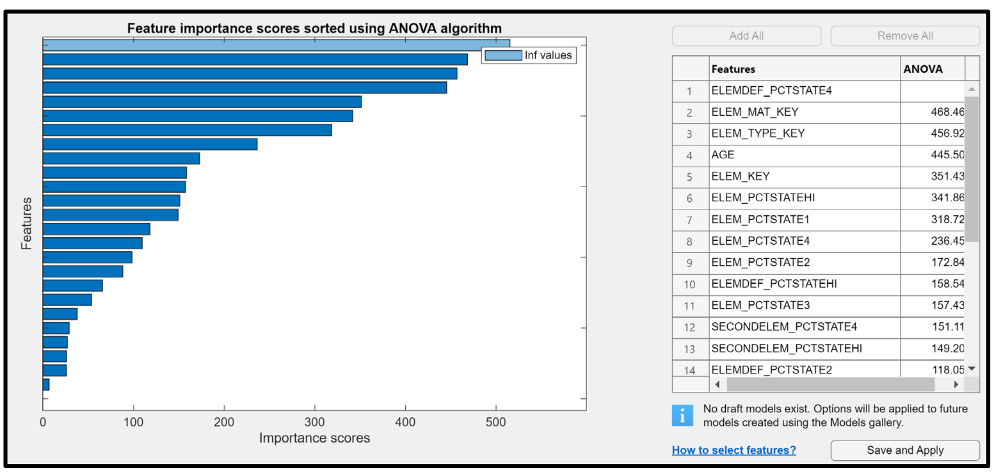


Figure 5.41. ANOVA feature ranking result for Deck Model 7.

<u>Model 8: All element condition and defect data (Generalized NBI ratings Good, Fair, and Poor).</u>

The 25 predictor variables used include the following: Inspection count per bridge; Age; Element key; Element Type Key; Element Material key; Primary element percent in condition state 1; Primary element percent in condition state 2; Primary element percent in condition state 3; Primary element percent in condition state 4; the primary element health index; Primary element defect percent in condition state 1; Primary element defect percent in condition state 2; Primary element defect percent in condition state 3; Primary element defect percent in condition state 4; Primary element defect health index; Secondary element percent in condition state 1; Secondary element percent in condition state 2; Secondary element percent in condition state 3; Secondary element percent in condition state 4; Secondary element health index; Secondary element defect percent in condition state 1; Secondary element defect percent in condition state 2; Secondary element defect percent in condition state 3; Secondary element defect percent in condition state 4; and the Secondary element defect health index.

The classification ensemble gives the best accuracy results compared with other classifier models (Figures 5.42 and 5.43). The most accurate prediction was observed to be at the “Good” rating, with an. accuracy of more than 90%.

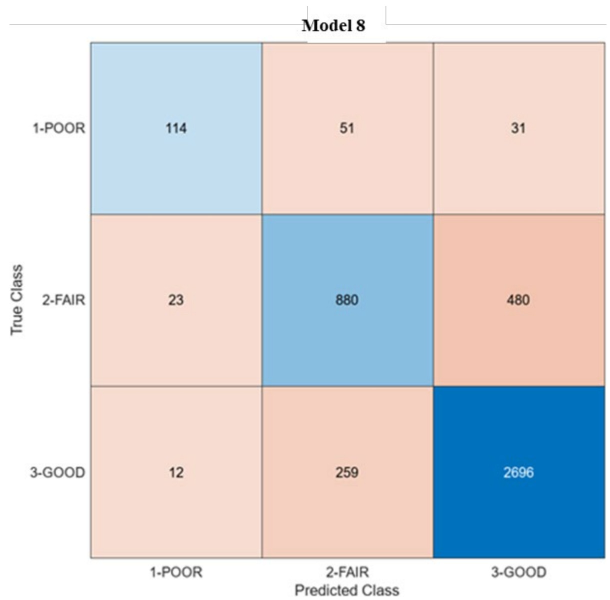


Figure 5.42. Deck Model 8: Ensemble, Bagging Trees Classifier (81.9 %) Performance, Number of Observations

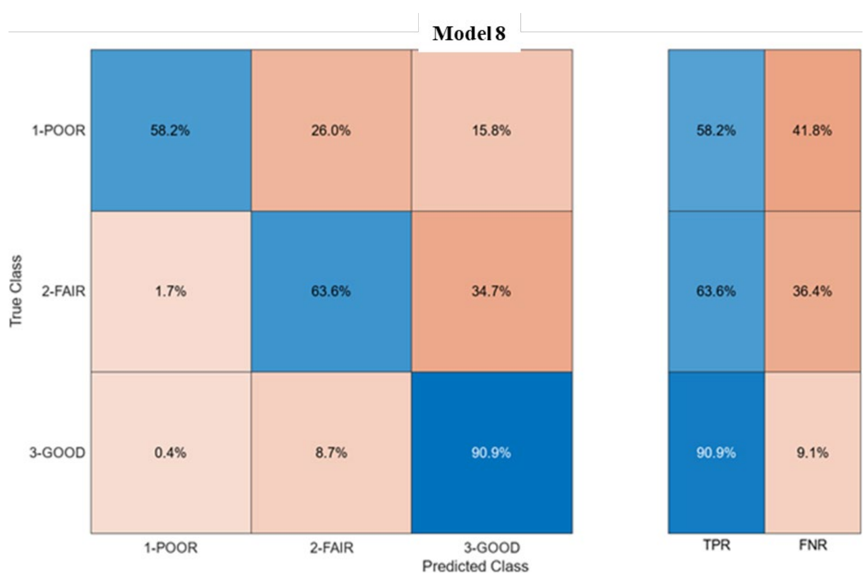


Figure 5.43. Deck Model 8: Ensemble, Bagging Trees Classifier (81.9 %) Performance, True Positive Rates (TPR), False Negative Rates (FNR)

Element material key and Element Type key were the top two variables in terms of the importance factor, while the primary element health index was the third. For practical purposes, the primary element health index will be considered the most important variable for this model (Figure 5.44).

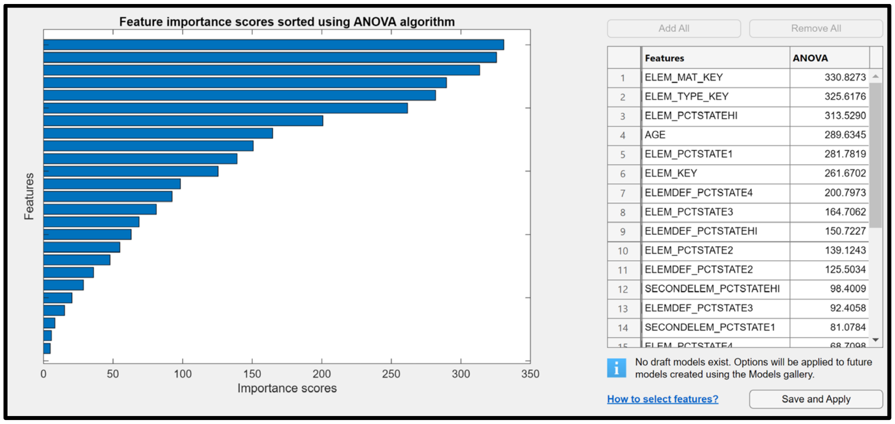


Figure 5.44. ANOVA feature ranking result for Deck Model 8.

5.3.3.2. Development of Superstructure NBI ML Translator Models

Using the complete merged, four categories were established: Primary element records; Primary defect records; Bearing element records; Bearing defect records; Protection records; and Protection defect records. Each category was appended to the primary element records by averaging. Each category offers four independent predictor variables to map the element condition to the NBI condition rating, specifically condition states 1, 2, 3, and 4. Therefore, a total of 24 independent predictor variables can be preprocessed from the element condition data for the superstructure components. The primary defect, bearing and protection element and bearing defect and protection defect records were aggregated by performing an averaging operation and linking the output to the primary element records.

The Trial Translator Models for the Superstructure NBI rating are summarized in terms of the predictor and response variables in Table 5.25. For each of the trial translator models, the best four suitable machine learning (ML) algorithms were selected based on the accuracy of the results. Also shown are the most important predictor variable and the computing times for training the ML models. Table 5.26 further describes the details of the predictor variables and their inclusion on the different trial models.

Table 5.25. Summary of machine learning (ML) model results for Superstructure NBI Translator.

Trial Translator Models	ML Models	Accuracy (Validation) (%)	Most important predictor	Training time (sec.)
Model 1: Primary element data -- 3850 observations, 10 predictors, 10 response classes (NBI rating 0 to 9).	Ensemble	72.6	Primary element % in defect condition state 4	636.6
	SVM	69.1		
	Tree	66.8		
	Neural Network	65.4		
Model 2: Primary element defect data: 3850 observations, 10 predictors, 10 response classes (NBI rating 0 to 9).	Ensemble	74.0	Primary element % in defect condition state 4	1330.0
	Neural Network	69.5		
	SVM	69.4		
	Kernel	68.7		
Model 3: Primary element condition and defect data: 3850 observations, 15 predictors, 10 response classes (NBI rating 0 to 9).	Ensemble	71.5	Primary element % in defect condition state 4	16.5
	Neural Network	67.3		
	SVM	67.2		
	Tree	65.6		
Model 4: All element condition and defect data: 984 observations, 40 predictors, 7 response classes (NBI rating 3 to 9).	Ensemble	89.2	Age	530.9
	Neural Network	86.1		
	Tree	77.4		
	SVM	66.1		
Model 5: All element condition and defect data: 984 observations, 40 predictors, 3 response classes (NBI Generalized ratings Good, Fair, and Poor).	Ensemble	94.7	Primary element % in defect condition state 4	164.9
	Neural Network	91.8		
	Tree	87.2		
	SVM	87.1		

<u>Superstructure Model 1: Primary element data (NBI rating 0 to 9).</u>

The 10 predictor variables used include the following: Inspection count per bridge; Age; Element key; Element Type Key; Element Material key; Primary element percent in condition state 1; Primary element percent in condition state 2; Primary element percent in condition state 3; Primary element percent in condition state 4; and the primary element health index.

The classification ensemble produced the most accurate results. To evaluate the classifier's performance for each class, refer to Figures 5.45 and 5.46. This model performed well for NBI predictions 0 and 7. However, if we consider a positive prediction as being within ±1 of the actual class, the majority of the prediction classes exceed 90%, which is a good result.

Table 5.26. Summary of variables in the Trial Models for Superstructure NBI Translator using the machine learning approach.

Variable	Description	Model 1	Model 2	Model 3	Model 4	Model 5
ChkBrInsp	No. of inspections	*	*	*	*	*
ElemKey	Element key	*	*	*	*	*
ElemType	Element type	*	*	*	*	*
ElemMatl	Element material	*	*	*	*	*
NoOfBearingInsp	No. of bearing inspections				*	*
NoOfBearingDefInsp	No. of bearing defect inspections				*	*
NoOfProtectionInsp	No. of protection element inspections				*	*
NoOfProtectionDefInsp	No. of protection element defect inspections				*	*
Age	Age of bridge at inspection	*	*	*	*	*
ElemPctState1	Percent in primary element condition state 1	*		*	*	*
ElemPctState2	Percent in primary element condition state 2	*		*	*	*
ElemPctState3	Percent in primary element condition state 3	*		*	*	*
ElemPctState4	Percent in primary element condition state 4	*		*	*	*
ElemPctStateHI	Health index of primary element	*		*	*	*
ElemDefPctState1	Percent in primary element defect condition state 1		*	*	*	*
ElemDefPctState2	Percent in primary element defect condition state 2		*	*	*	*
ElemDefPctState3	Percent in primary element defect condition state 3		*	*	*	*
ElemDefPctState4	Percent in primary element defect condition state 4		*	*	*	*
ElemDefPctStateHI	Health index of primary element defect		*	*	*	*
BearingElemPctState1	Percent in Bearing element condition state 1				*	*
BearingElemPctState2	Percent in Bearing element condition state 2				*	*
BearingElemPctState3	Percent in Bearing element condition state 3				*	*
BearingElemPctState4	Percent in Bearing element condition state 4				*	*
BearingElemPctStateHI	Health index of Bearing element				*	*
BearingElemDefPctState1	Percent in Bearing element defect condition state 1				*	*
BearingElemDefPctState2	Percent in Bearing element defect condition state 2				*	*
BearingElemDefPctState3	Percent in Bearing element defect condition state 3				*	*
BearingElemDefPctState4	Percent in Bearing element defect condition state 4				*	*
BearingElemDefPctStateHI	Health index of Bearing element defect				*	*
ProtElemPctState1	Percent in Protection element condition state 1				*	*
ProtElemPctState2	Percent in Protection element condition state 2				*	*
ProtElemPctState3	Percent in Protection element condition state 3				*	*
ProtElemPctState4	Percent in Protection element condition state 4				*	*
ProtElemPctStateHI	Health index of Protection element				*	*
ProtElemDefPctState1	Percent in Protection element defect condition state				*	*
ProtElemDefPctState2	Percent in Protection element defect condition state				*	*
ProtElemDefPctState3	Percent in Protection element defect condition state				*	*
ProtElemDefPctState4	Percent in Protection element defect condition state				*	*
ProtElemDefPctStateHI	Health index of Protection element defect				*	*
SupRating#	NBI condition rating	*	*	*	*	
GenSupRating#	Generalized NBI condition rating (Good, Fair, Poor)					*

Dependent variables.

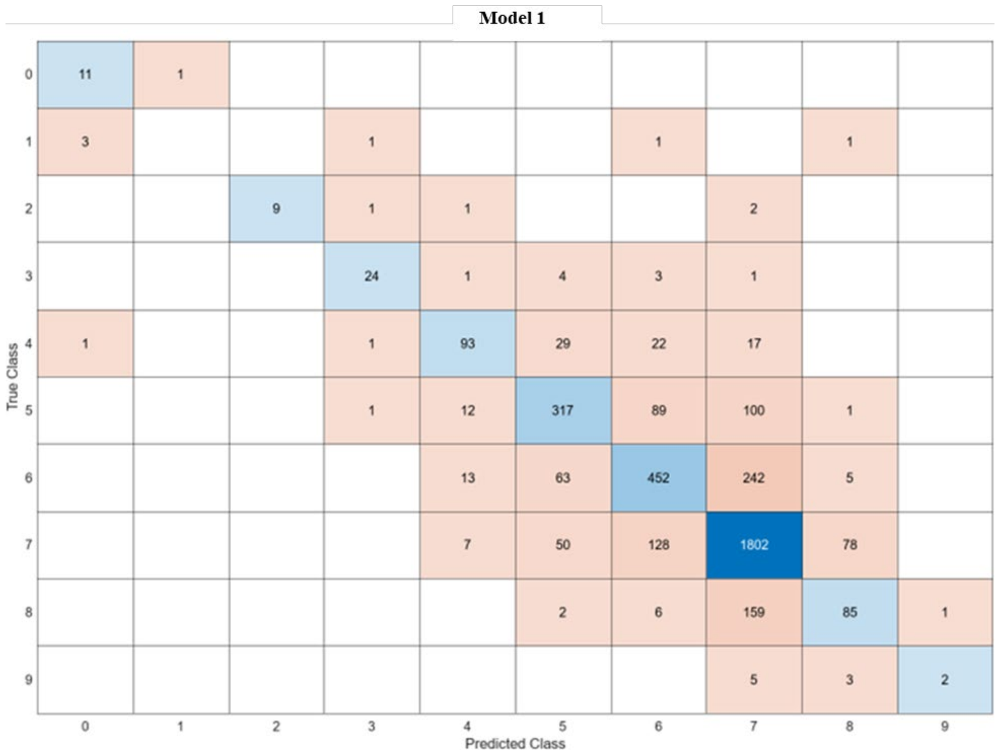


Figure 5.45. Superstructure Model 1: Ensemble Classifier (72.6%) Performance, Number of Observations

Figure 5.46. Superstructure Model 1: Ensemble, Bagging Trees Classifier (72.6 %) Performance, True Positive Rates (TPR), False Negative Rates (FNR)

The most important factor was identified as the primary element defect percentage in state 4 (Figure 5.47).

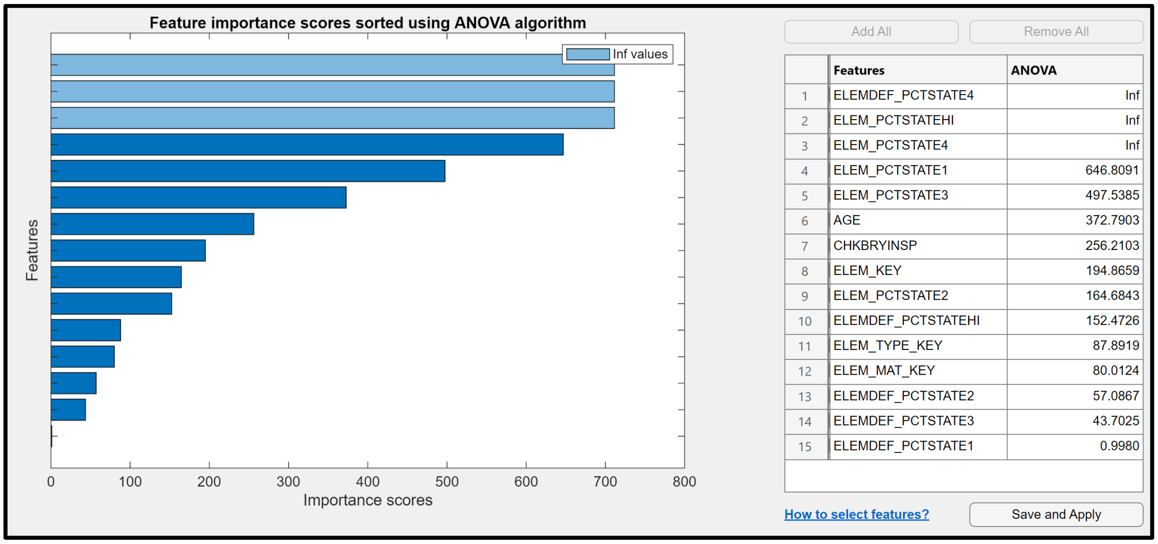


Figure 5.47. ANOVA feature ranking result for Superstructure Model 1.

Superstructure Model 2: Primary element defect data (NBI rating 0 to 9).

The 10 predictor variables used include the following: Inspection count per bridge; Age; Element key; Element Type Key; Element Material key; Primary element defect percent in condition state 1; Primary element defect percent in condition state 2; Primary element defect percent in condition state 3; Primary element defect percent in condition state 4; and Primary element defect health index.

The classification ensemble produced the most accurate results compared with other classifier models. This model performed well for NBI prediction of rating 7 (Figures 5.48 and 5.49). However, if we consider a positive prediction as being within ±1 of the actual class, the majority of the prediction classes exceed 90%, which is a good result.

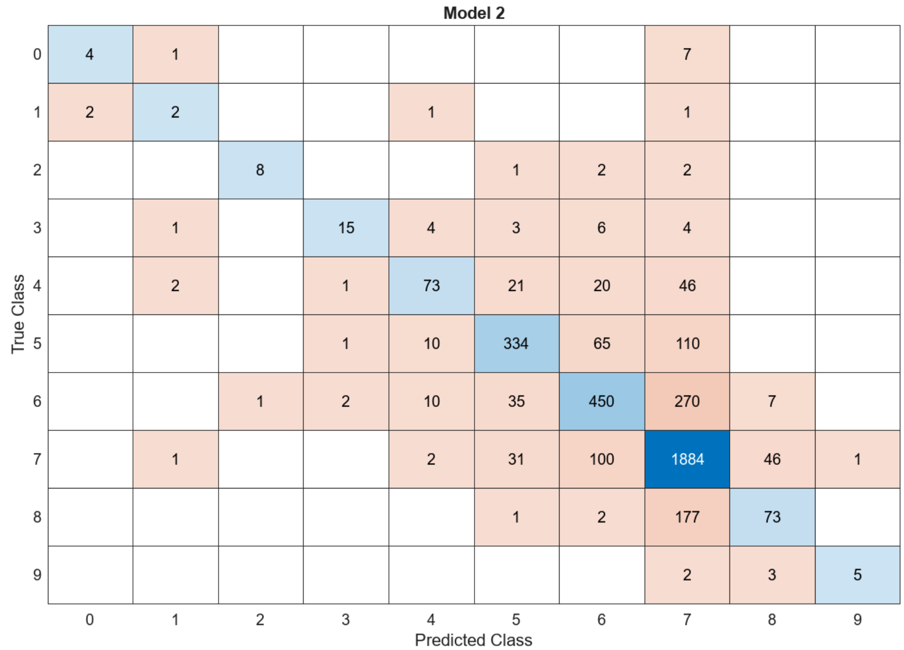


Figure 5.48. Superstructure Model 2: Ensemble Classifier (74%) Performance, Number of Observations

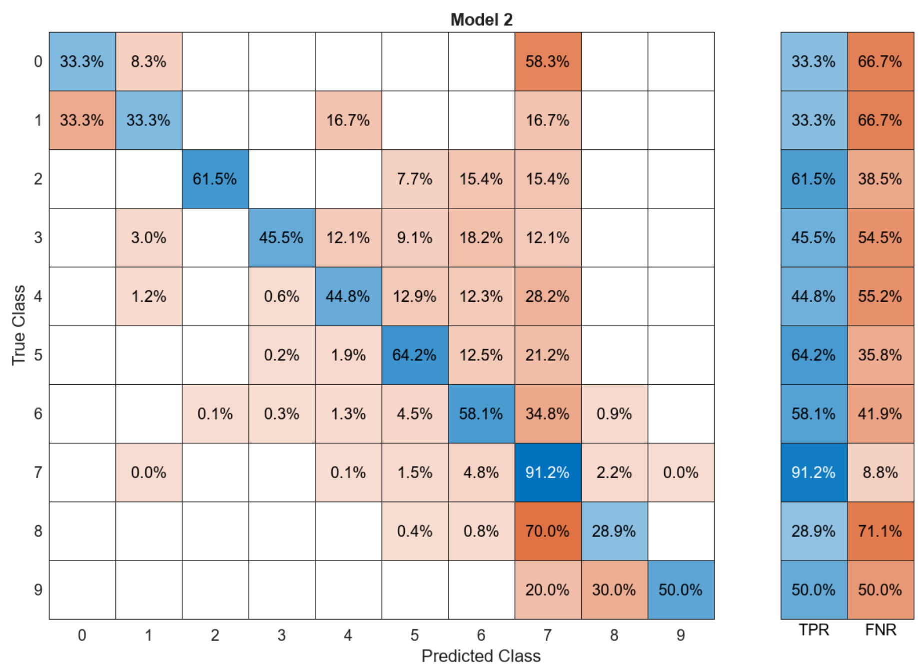


Figure 5.49. Superstructure Model 2: Ensemble Classifier (74%) Performance, True Positive Rates (TPR), False Negative Rates (FNR)

The most important factor was identified as the primary element percentage in defect state 4 (Figure 5.55).

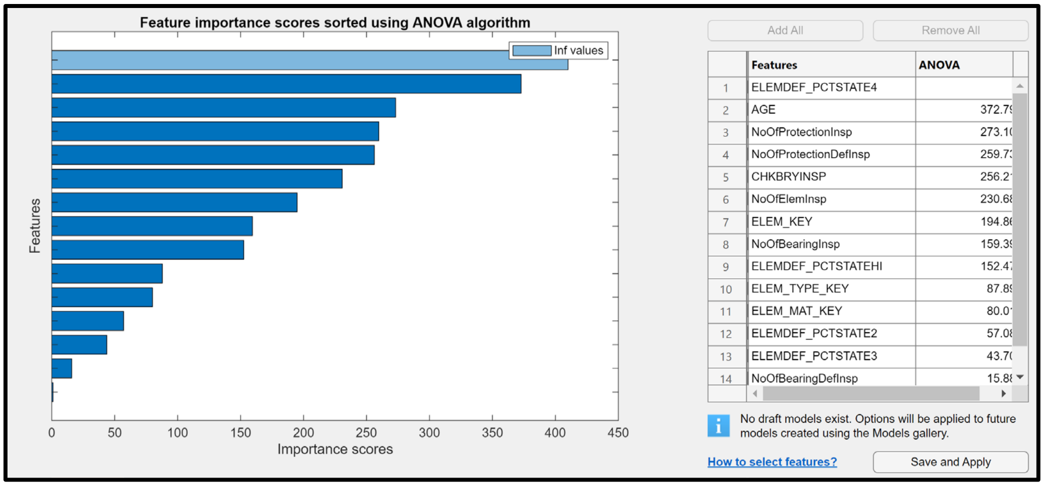


Figure 5.50. ANOVA feature ranking result for Superstructure Model 2.

<u>Superstructure Model 3: Primary element condition and defect data (NBI rating 0 to 9).</u>
The 15 predictor variables used include the following: Inspection count per bridge; Age; Element key; Element Type Key; Element Material key; Primary element percent in condition state 1; Primary element percent in condition state 2; Primary element percent in condition state 3; Primary element percent in condition state 4; the primary element health index; Primary element defect percent in condition state 1; Primary element defect percent in condition state 2; Primary element defect percent in condition state 3; Primary element defect percent in condition state 4; and Primary element defect health index.

The classification ensemble produced the most accurate results compared with other classifier models. This model performed well for NBI prediction 7 as shown in the confusion matrices in Figures 5.51 and 5.52. However, if we consider a positive prediction as being within ±1 of the actual class, the majority of the prediction classes exceed 90%, which is a good result.

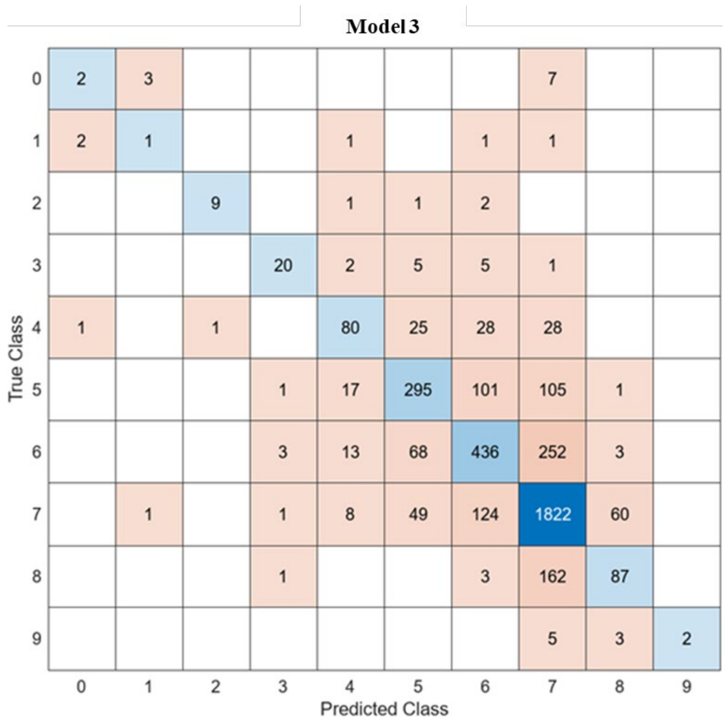


Figure 5.51. Superstructure Model 3: Ensemble Classifier (71.5%) Performance, Number of Observations

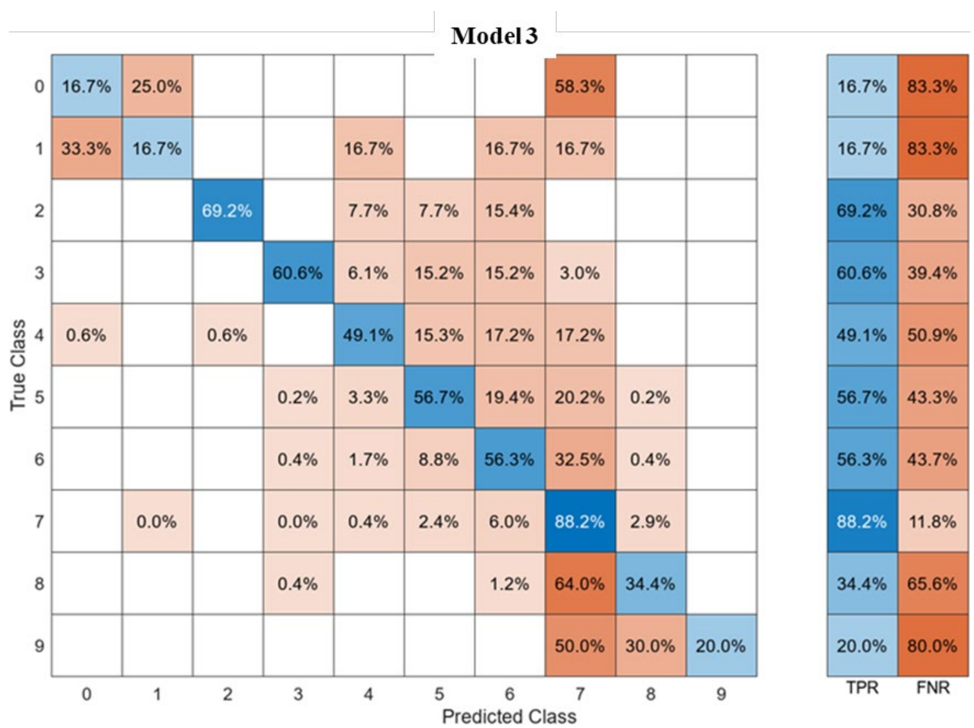


Figure 5.52. Superstructure Model 3: Ensemble Classifier (71.5%) Performance, True Positive Rates (TPR), False Negative Rates (FNR)

The most important factor was identified as the primary element percentage in defect state 4 (Figure 5.53).

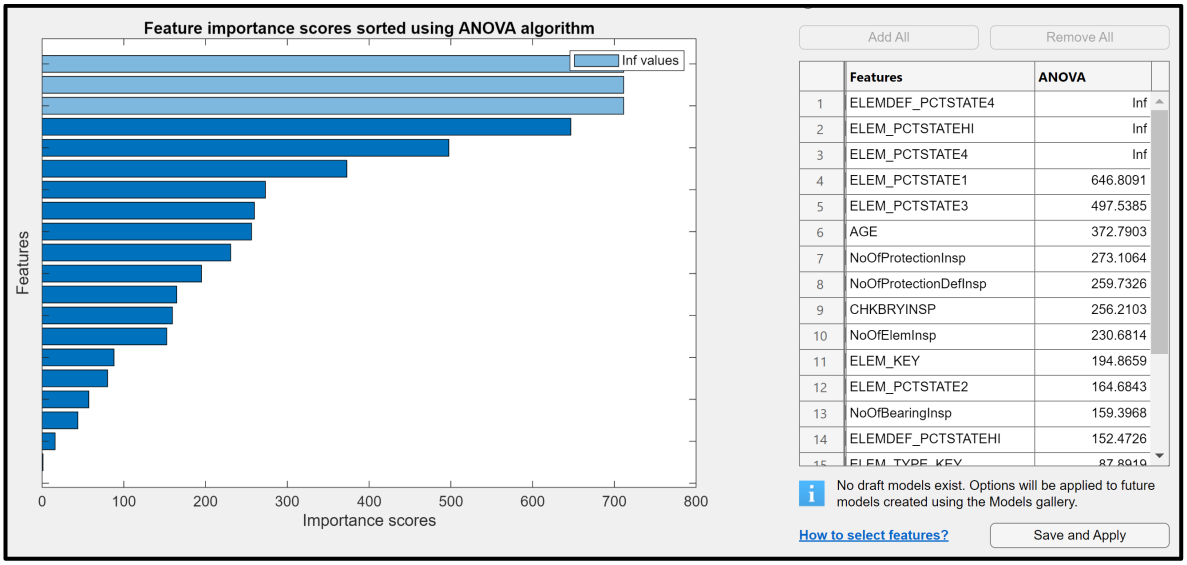


Figure 5.53. ANOVA feature ranking result for Superstructure Model 2.

<u>Superstructure Model 4: All element condition and defect data (NBI rating 3 to 9).</u>

The 40 predictor variables used include the following: Inspection count per bridge; Age; Element key; Element Type Key; Element Material key; Number of superstructure elements inspected; Number of bearing elements inspected; Number of bearing element defects inspected; Number of protection elements inspected; Number of bearing element defects inspected; Primary element percent in condition state 1; Primary element percent in condition state 2; Primary element percent in condition state 3; Primary element percent in condition state 4; the primary element health index; Primary element defect percent in condition state 1; Primary element defect percent in condition state 2; Primary element defect percent in condition state 3; Primary element defect percent in condition state 4; Primary element defect health index; Bearing element percent state 1, Bearing element percent state 2, Bearing element percent state 3; Bearing element percent state 4; Bearing element health index; Bearing element defect percent state 1; Bearing element defect percent state 2; Bearing element defect percent state 3; Bearing element defect percent state 4; Bearing element defect health index; Protection element percent in condition state 1; Protection element percent in condition state 2; Protection element percent in condition state 3; Protection element percent in condition state 4; Protection element health index; Protection element defect percent in condition state 1; Protection element defect percent in condition state 2; Protection element defect percent in condition state 3; Protection element defect percent in condition state 4; and Protection element defect health index.

The classification ensemble produced the most accurate results compared with other classifier models. This model performed well for NBI prediction 3, 5, 6, 7, and 9 (Figures 5.54 and 5.55). However, if we consider a positive prediction as being within ±1 of the actual class, the majority of the prediction classes exceed 95%, which is a good result.

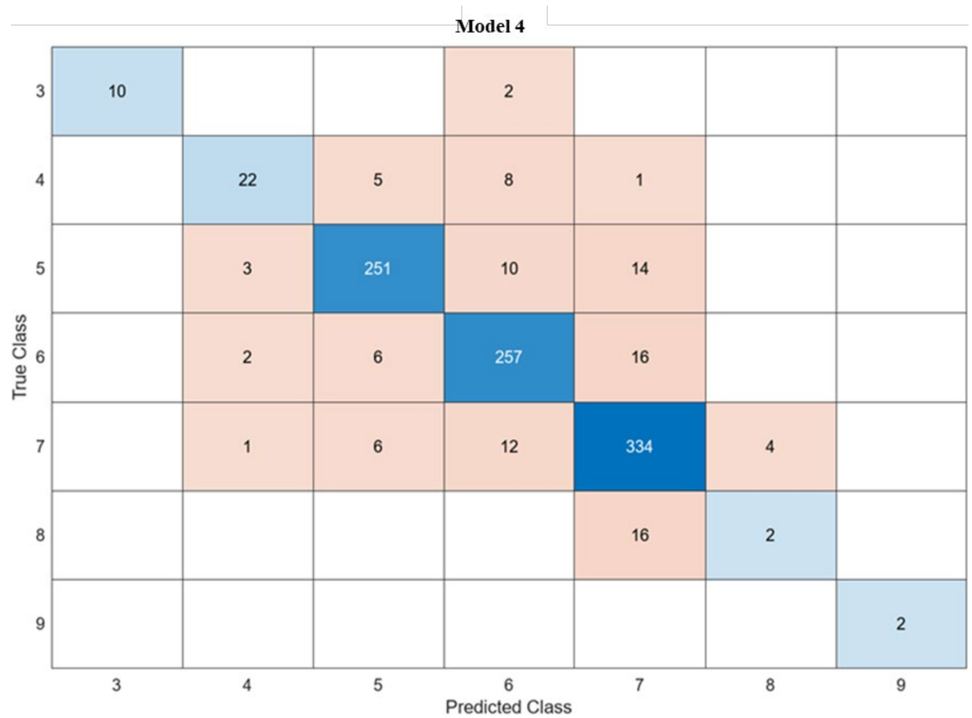


Figure 5.54. Superstructure Model 4: Ensemble Classifier (89.2%) Performance, Number of Observations

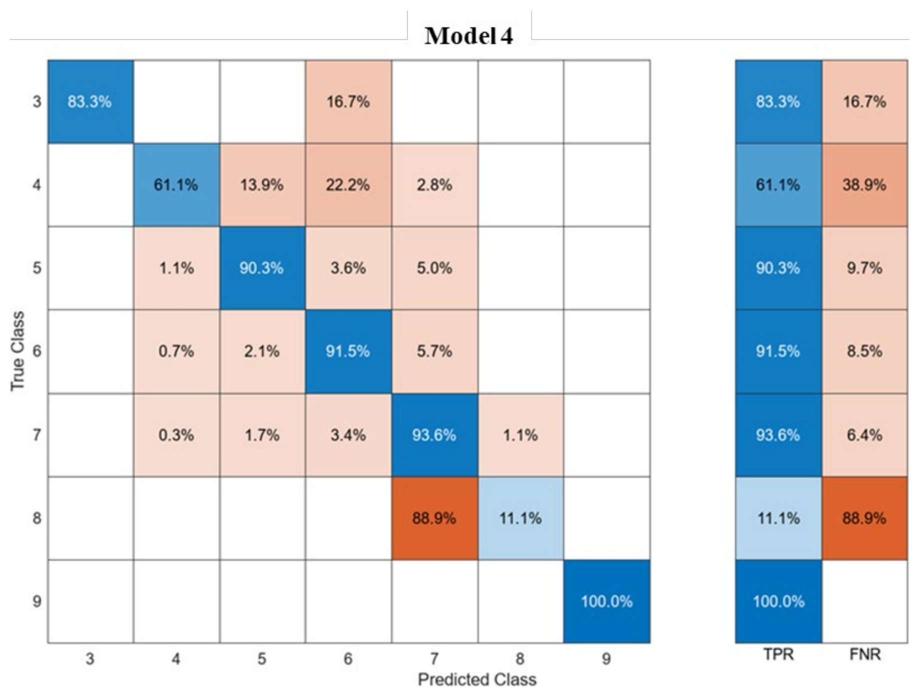


Figure 5.55. Superstructure Model 4: Ensemble Classifier (89.2%) Performance, True Positive Rates (TPR), False Negative Rates (FNR)

The most important of the explanatory variables, with the highest importance factor, was identified as the Age (Figure 5.56).

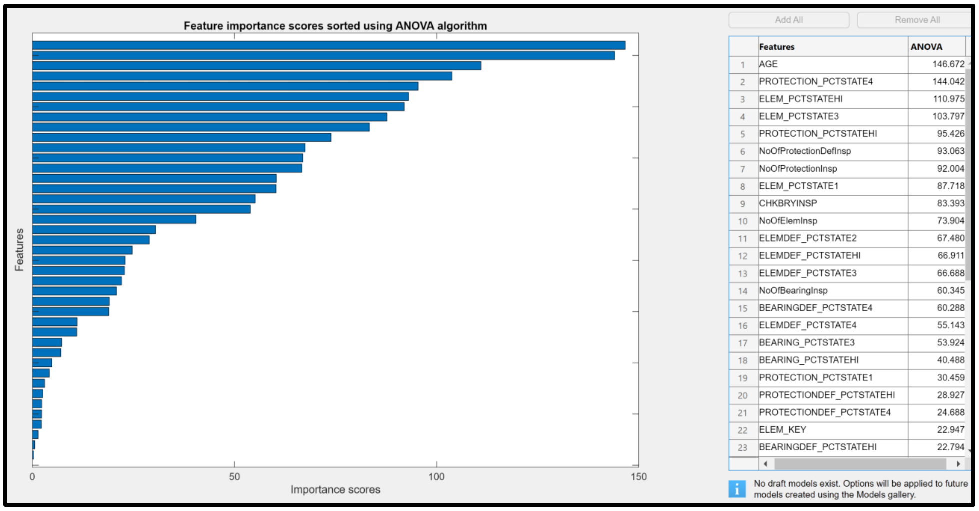


Figure 5.56. ANOVA feature ranking result for Superstructure Model 4.

<u>Superstructure Model 5: All element condition and defect data (NBI Generalized ratings Good, Fair, and Poor).</u>

The 40 predictor variables used include the following: Inspection count per bridge; Age; Element key; Element Type Key; Element Material key; Number of superstructure elements inspected; Number of bearing elements inspected; Number of bearing element defects inspected; Number of protection elements inspected; Number of bearing element defects inspected; Primary element percent in condition state 1; Primary element percent in condition state 2; Primary element percent in condition state 3; Primary element percent in condition state 4; the primary element health index; Primary element defect percent in condition state 1; Primary element defect percent in condition state 2; Primary element defect percent in condition state 3; Primary element defect percent in condition state 4; Primary element defect health index; Bearing element percent state 1, Bearing element percent state 2, Bearing element percent state 3; Bearing element percent state 4; Bearing element health index; Bearing element defect percent state 1; Bearing element defect percent state 2; Bearing element defect percent state 3; Bearing element defect percent state 4; Bearing element defect health index; Protection element percent in condition state 1; Protection element percent in condition state 2; Protection element percent in condition state 3; Protection element percent in condition state 4; Protection element health index; Protection element defect percent in condition state 1; Protection element defect percent in condition state 2; Protection element defect percent in condition state 3; Protection element defect percent in condition state 4; and Protection element defect health index.

The classification ensemble produced the most accurate results compared with other classifier models. This model performed well for NBI predictions GOOD and FAIR (Figures 5.57 and 5.58). However, if we consider a positive prediction as being within ±1 of the actual class, the majority of the prediction classes exceed 98%, which is a good result.

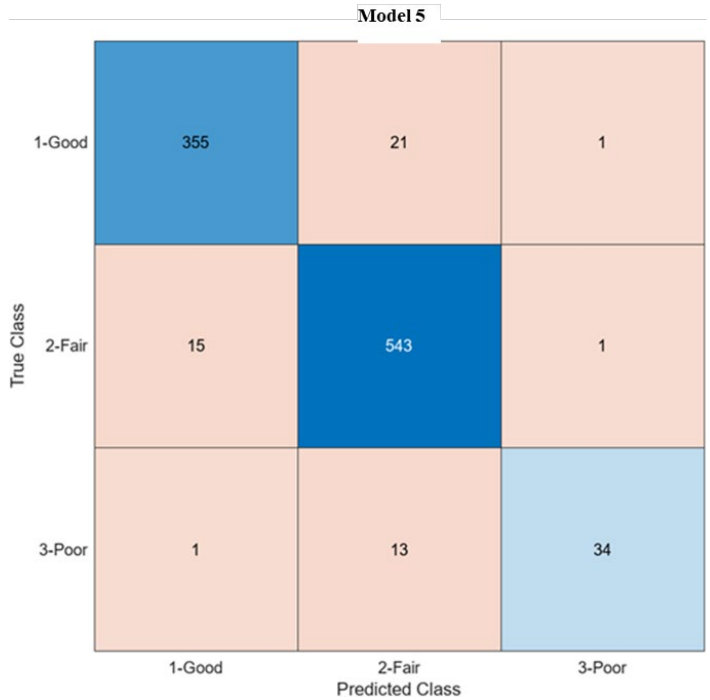


Figure 5.57. Superstructure Model 5: Ensemble, Bagging Trees Classifier (94.7 %) Performance, Number of Observations

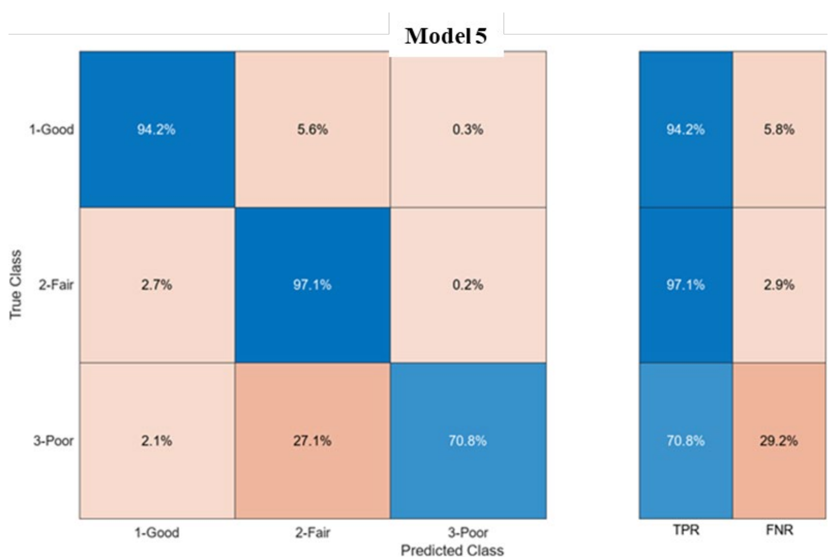


Figure 5.58. Superstructure Model 5: Ensemble, Bagging Trees Classifier (94.7 %) Performance, True Positive Rates (TPR), False Negative Rates (FNR)

The most important of the explanatory variables, with the highest importance factor, was identified as the primary element percentage in defect state 4 (Figure 5.59).

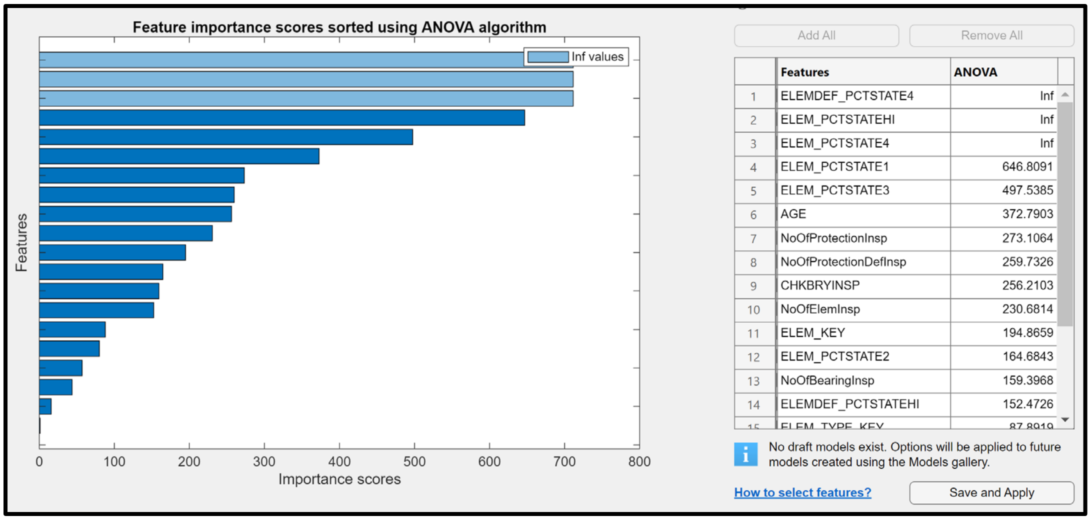


Figure 5.59. ANOVA feature ranking result for Superstructure Model 5.

5.3.3.3. Development of Substructure NBI ML Translator Models

Using the fully merged data from above, the element dataset will be divided into 5 categories: Primary element records; Protection element records; Protection defect records; Defect element records; and Protection coating records.

Each category was appended to the primary element records by averaging, with each category offering independent predictor variables to map the element condition to the NBI condition rating, specifically condition states 1, 2, 3, and 4. Therefore, a total of 20 independent predictor variables can be preprocessed from the element condition data for the substructure components. The primary and protection element defect records, protection coating and protection element records were aggregated by performing an averaging operation and linking the output to the primary element records.

The Trial Translator Models for the Superstructure NBI rating are summarized in terms of the predictor and response variables in Table 5.27. For each of the trial translator models, the best four suitable machine learning (ML) algorithms were selected based on the accuracy of the results. Also shown are the most important predictor variable and the computing times for training the ML models. Table 5.28 further describes the details of the predictor variables and their inclusion on the different trial models.

<u>Substructure Model 1: Primary element data (NBI rating 0 to 9).</u>

The 10 predictor variables used include the following: Inspection count per bridge; Age; Element key; Element Type Key; Element Material key; Primary element percent in condition state 1; Primary element percent in condition state 2; Primary element percent in condition state 3; Primary element percent in condition state 4; and Primary element health index.

The classification ensemble produced the most accurate results compared with other classifier models. This model performed well for NBI predictions 3 and 7 (Figure 5.60 and 61). However, if we consider a positive prediction as being within ±1 of the actual class, the majority of the prediction classes exceed 80%, which is a good result.

Table 5.27. Summary of machine learning (ML) model results for Substructure NBI Translator.

Trial Translator Models	ML Models	Accuracy (Validation) (%)	Most important predictor	Training time (sec.)
Model 1: Primary element data -- 14002 observations, 10 predictors, 10 response classes (NBI rating 0 to 9).	Ensemble	69.9	Primary element health index	566.1
	Tree	65.1		
	Neural Network	64.6		
	Linear SVM	62.4		
Model 2: Primary element data -- 14002 observations, 10 predictors, 3 response classes (NBI Generalized ratings Good, Fair, and Poor).	Ensemble	91.9	Primary element health index	1161.3
	Tree	85.3		
	Neural Network	78.9		
	Kernel	77.2		
Model 3: Primary element defect data -- 14002 observations, 10 predictors, 10 response classes (NBI rating 0 to 9).	Ensemble	86.1	Primary element % in defect condition state 4.	2799.2
	Tree	77.1		
	Neural Network	66.4		
	Kernel	65.5		
Model 4: Primary element defect data -- 14002 observations, 10 predictors, 3 response classes (NBI Generalized ratings Good, Fair, and Poor).	Ensemble	92.5	Primary element % in defect condition state 4.	2292.3
	Tree	86.3		
	Neural Network	77.4		
	Kernel	76.1		
Model 5: Primary element condition and defect data -- 14002 observations, 15 predictors, 10 response classes (NBI rating 0 to 9).	Ensemble	80.2	Primary element % in defect condition state 4.	504.4
	Tree	72.3		
	Neural Network	66.3		
	Kernel	65.4		
Model 6: All element condition and defect data -- 804 observations, 30 predictors, 8 response classes (NBI rating 1 to 8).	Ensemble	96.1	Primary element % in defect condition state 4.	179.6
	Tree	95.3		
	Kernel	80.1		
	SVM	65.7		
Model 7: All element condition and defect data -- 804 observations, 30 predictors, 3 response classes (NBI Generalized ratings Good, Fair, and Poor).	Ensemble	98.0	Age	379.7
	Tree	96.1		
	Neural Network	94.3		
	Kernel	84.1		

Table 5.28. Summary of variables in the Trial Models for Substructure NBI Translator using the machine learning approach.

Variable	**Description**	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
ChkBrInsp	No. of inspections	*	*	*	*	*	*	*
ElemKey	Element key	*	*	*	*	*	*	*
ElemType	Element type	*	*	*	*	*	*	*
ElemMatl	Element material	*	*	*	*	*	*	*
Age	Age of bridge at inspection	*	*	*	*	*	*	*
ElemPctState1	Percent in primary element condition state 1	*	*			*	*	*
ElemPctState2	Percent in primary element condition state 2	*	*			*	*	*
ElemPctState3	Percent in primary element condition state 3	*	*			*	*	*
ElemPctState4	Percent in primary element condition state 4	*	*			*	*	*
ElemPctStateHI	Health index of primary element	*	*			*	*	*
ElemDefPctState1	Percent in primary element defect condition state 1			*	*	*	*	*
ElemDefPctState2	Percent in primary element defect condition state 2			*	*	*	*	*
ElemDefPctState3	Percent in primary element defect condition state 3			*	*	*	*	*
ElemDefPctState4	Percent in primary element defect condition state 4			*	*	*	*	*
ElemDefPctStateHI	Health index of primary element defect			*	*	*	*	*
SubRating#	NBI condition rating	*		*		*	*	
GenSubRating#	Generalized NBI condition rating (Good, Fair, Poor)		*		*			*

 # Dependent variables.

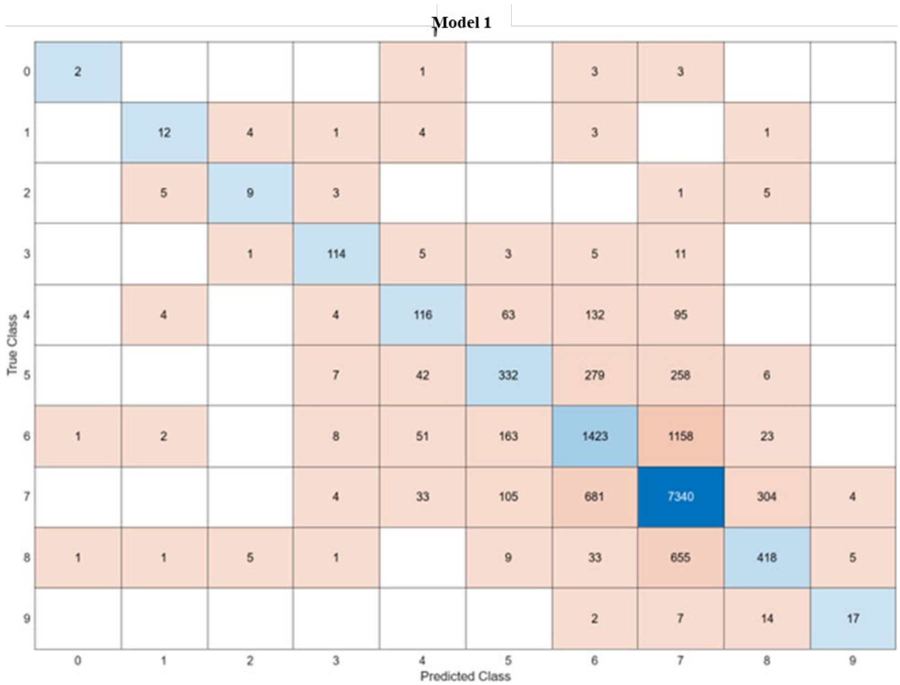


Figure 5.60. Substructure Model 1: Ensemble Classifier (69.9 %) Performance, Number of Observations

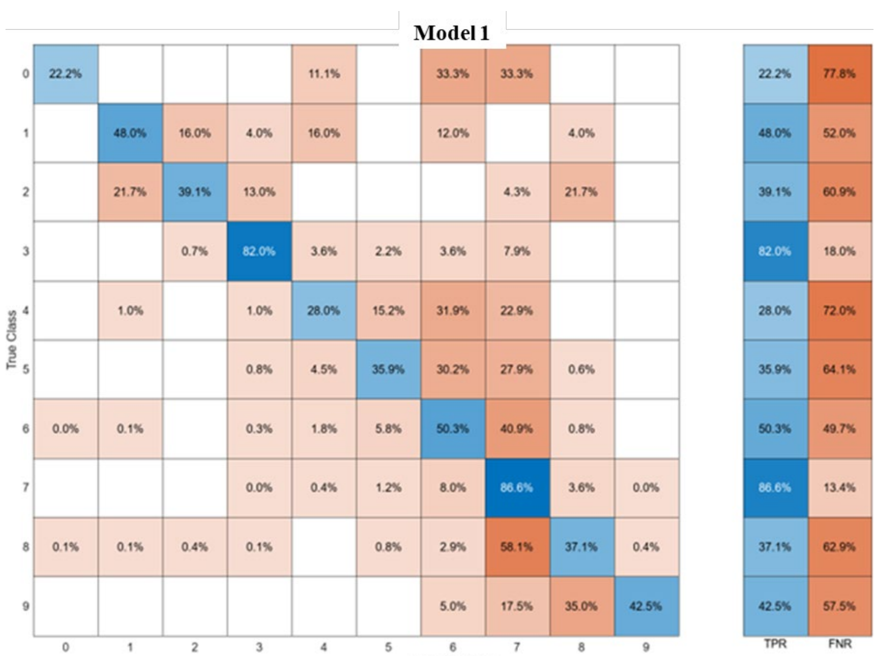


Figure 5.61. Substructure Model 1: Ensemble Classifier (69.9%) Performance, True Positive Rates (TPR), False Negative Rates (FNR)

The most important of the explanatory variables, with the highest importance factor, was identified as the primary element health index (Figure 5.62).

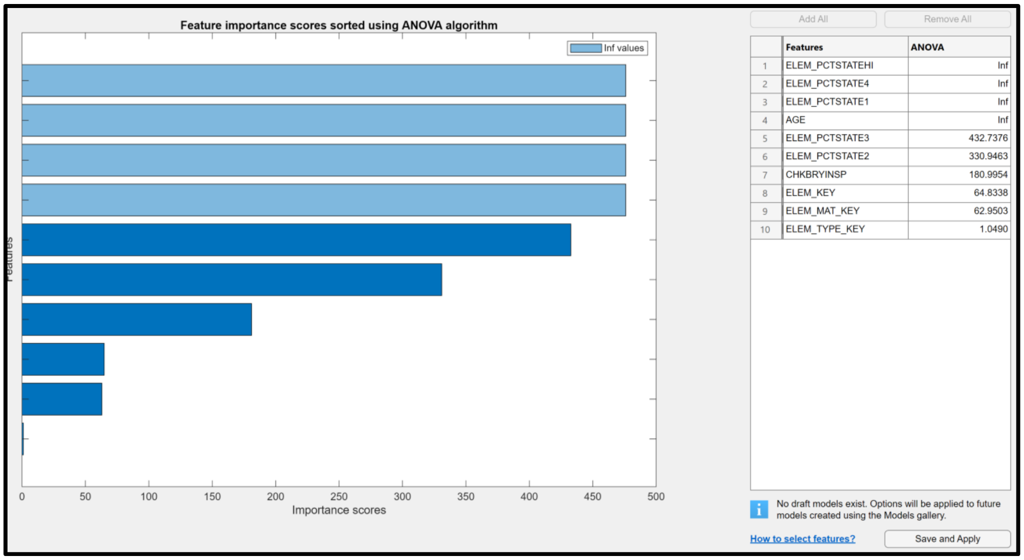


Figure 5.62. ANOVA feature ranking result for Substructure Model 1.

<u>Substructure Model 2: Primary element data (NBI Generalized ratings Good, Fair, and Poor).</u>
The 10 predictor variables used include the following: Inspection count per bridge; Age; Element key; Element Type Key; Element Material key; Primary element percent in condition state 1; Primary element percent in condition state 2; Primary element percent in condition state 3; Primary element percent in condition state 4; and primary element health index.

The classification ensemble produced the most accurate results compared with other classifier models. This model performed well for predictions of the Good rating (Figures 5.63 and 5.64).

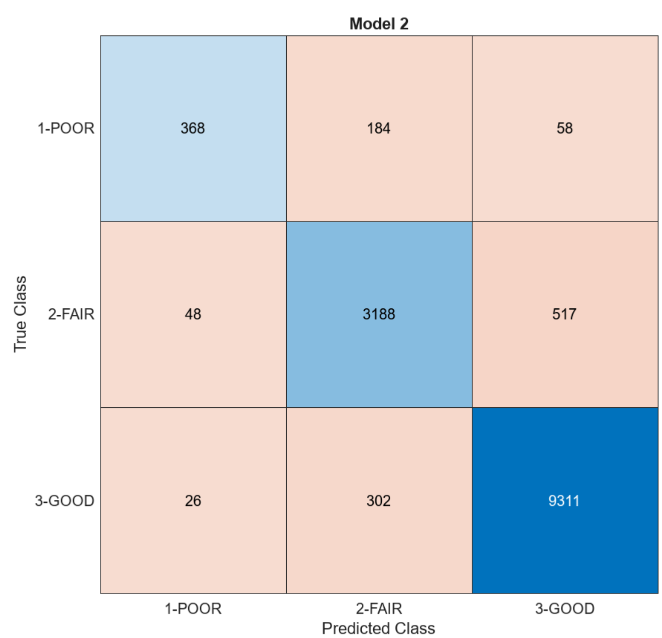


Figure 5.63. Substructure Model 2: Ensemble Classifier (91.9 %) Performance, Number of Observations

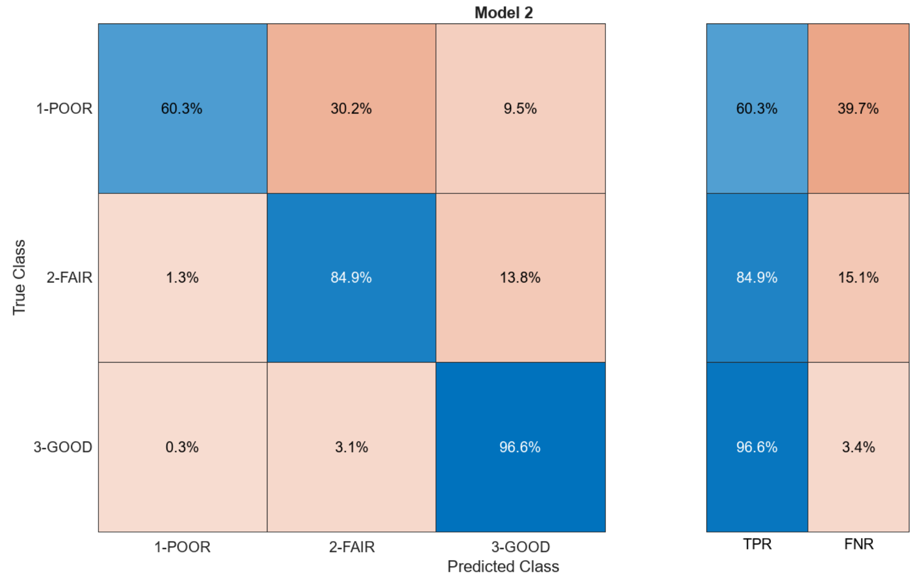


Figure 5.64. Substructure Model 2: Ensemble Classifier (91.9%) Performance, True Positive Rates (TPR), False Negative Rates (FNR)

The most important of the explanatory variables, with the highest importance factor, was identified as the primary element health index (Figure 5.65).

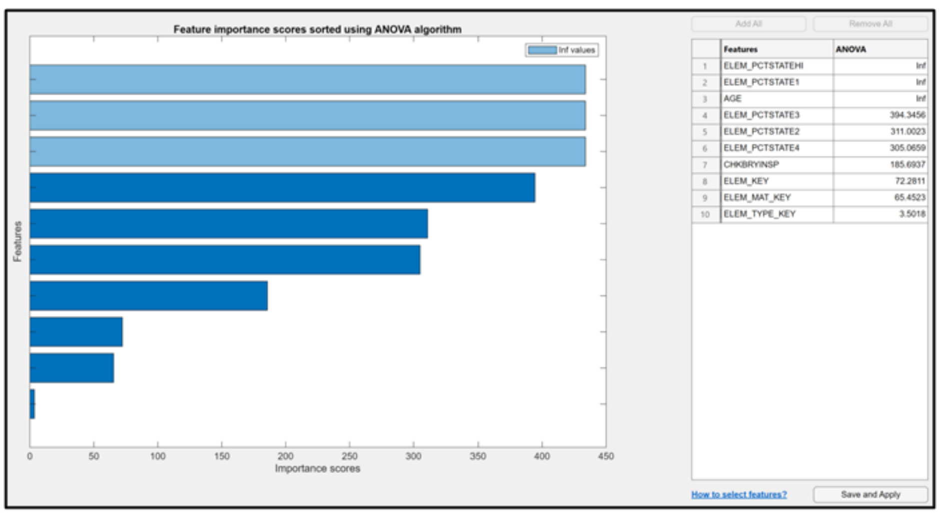


Figure 5.65. ANOVA feature ranking result for Substructure Model 2.

<u>Substructure Model 3: Primary element defect (NBI rating 0 to 9).</u>

The 10 predictor variables used include the following: Inspection count per bridge; Age; Element key; Element Type Key; Element Material key; Primary element percent in condition state 1; Primary element percent in condition state 2; Primary element percent in condition state 3; Primary element percent in condition state 4; and primary element health index.

The classification ensemble produced the most accurate results compared with other classifier models.

This model performed well for NBI predictions 0, 3 and 7. However, if we consider a positive prediction as being within ±1 of the actual class, the majority of the prediction classes exceed 85%, which is a good result (Figures 5.66 and 5.67).

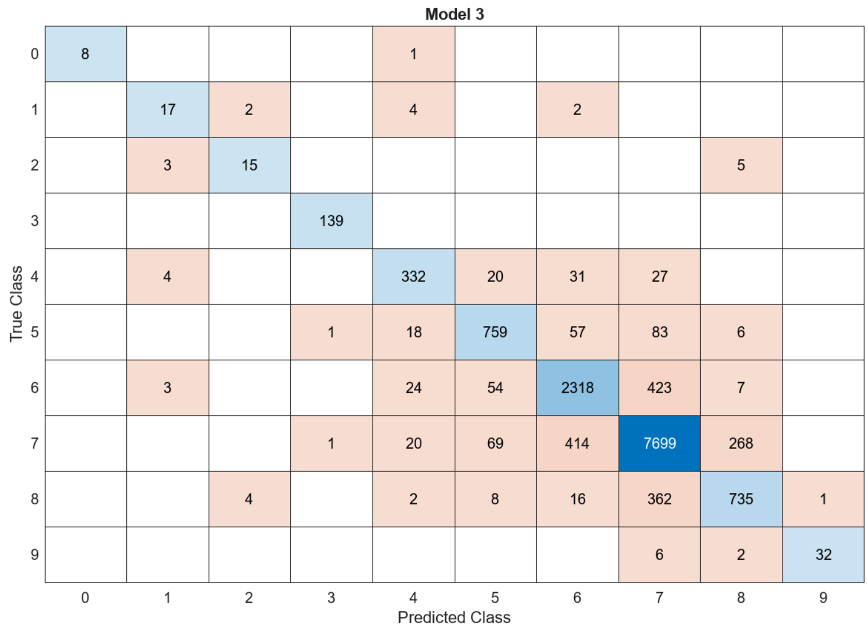


Figure 5.66. Substructure Model 3: Ensemble Classifier (86.1 %) Performance, Number of Observations

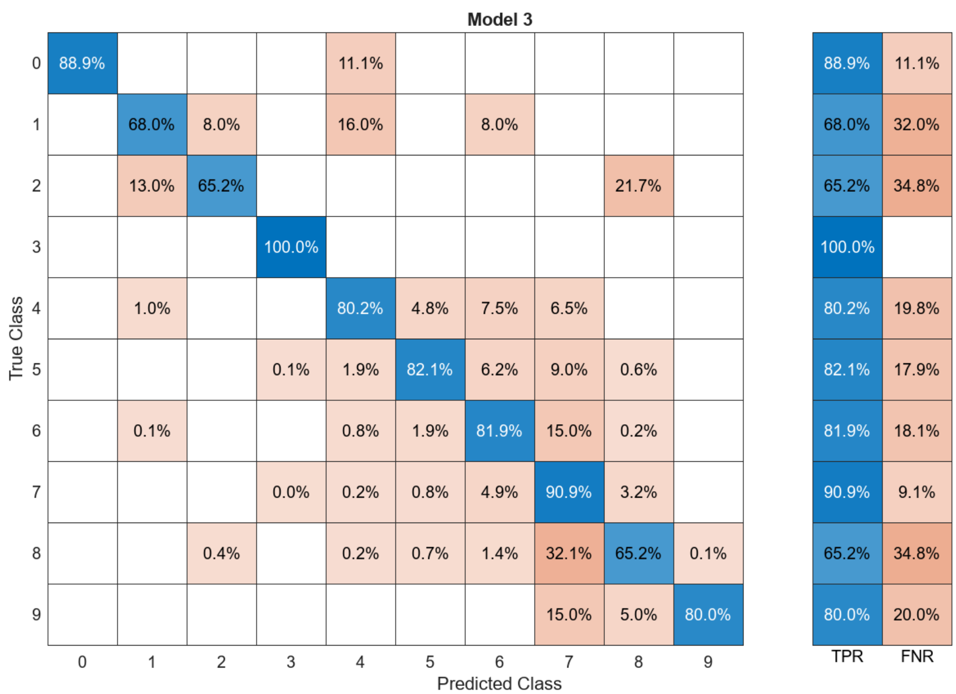


Figure 5.67. Substructure Model 3: Ensemble Classifier (86.1 %) Performance, True Positive Rates (TPR), False Negative Rates (FNR)

The most important of the explanatory variables, with the highest importance factor, was identified as the primary element percentage in defects state 4 (Figure 5.68).

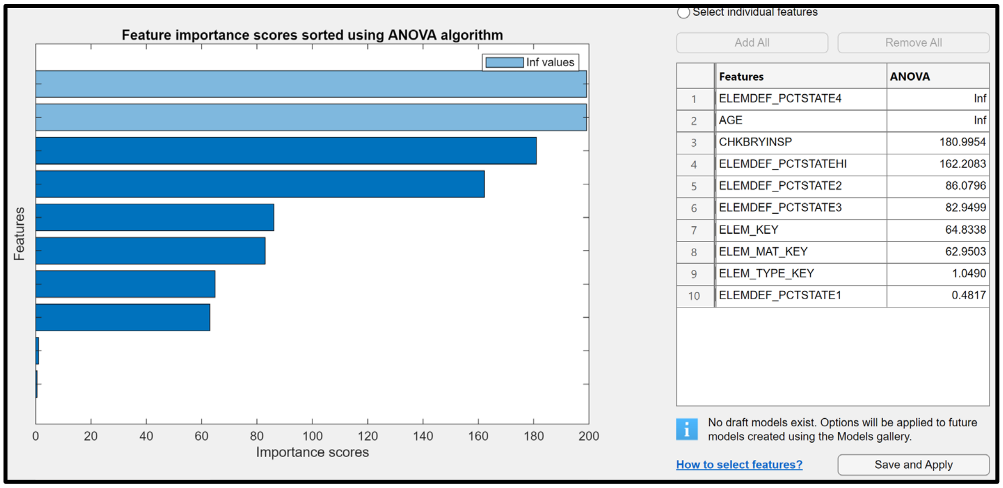


Figure 5.68. ANOVA feature ranking result for Substructure Model 3.

<u>Substructure Model 4: Primary element defect data (NBI Generalized ratings Good, Fair, and Poor).</u>
The 10 predictor variables used include the following: Inspection count per bridge; Age; Element key; Element Type Key; Element Material key; Primary element percent in condition state 1; Primary element percent in condition state 2; Primary element percent in condition state 3; Primary element percent in condition state 4; and primary element health index.

The classification ensemble produced the most accurate results compared with other classifier models. This model performed well for predictions for the rating of Good (Figures 5.69 and 5.70).

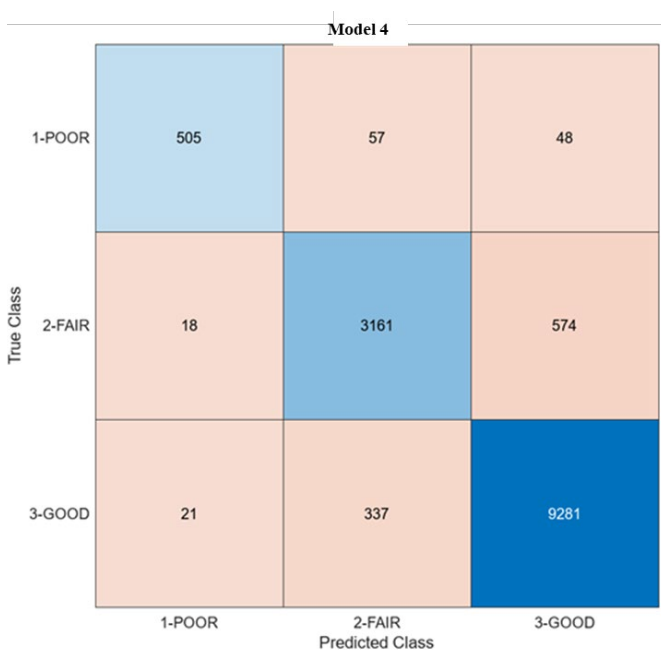


Figure 5.69. Substructure Model 4: Ensemble Classifier (92.5 %) Performance, Number of Observations

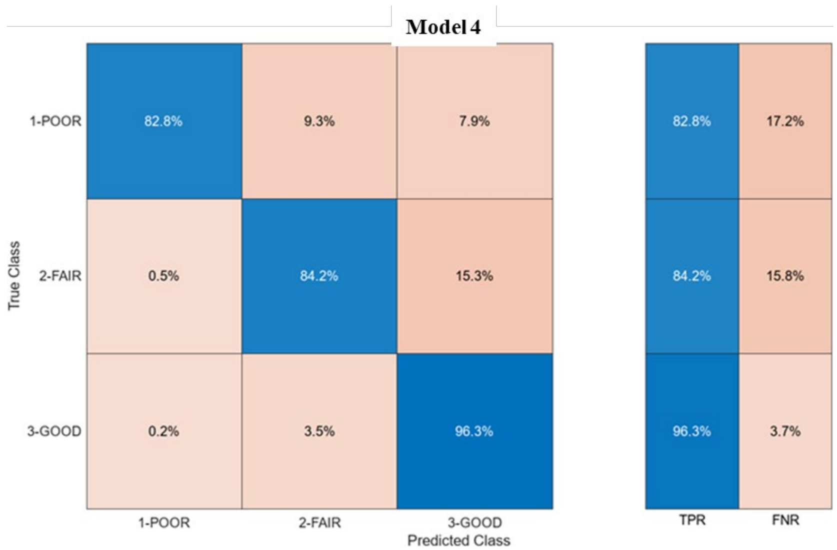


Figure 5.70. Substructure Model 4: Ensemble Classifier (92.5 %) Performance, True Positive Rates (TPR), False Negative Rates (FNR)

The most important of the explanatory variables, with the highest importance factor, was identified as the primary element percentage in defects state 4 (Figure 5.71).

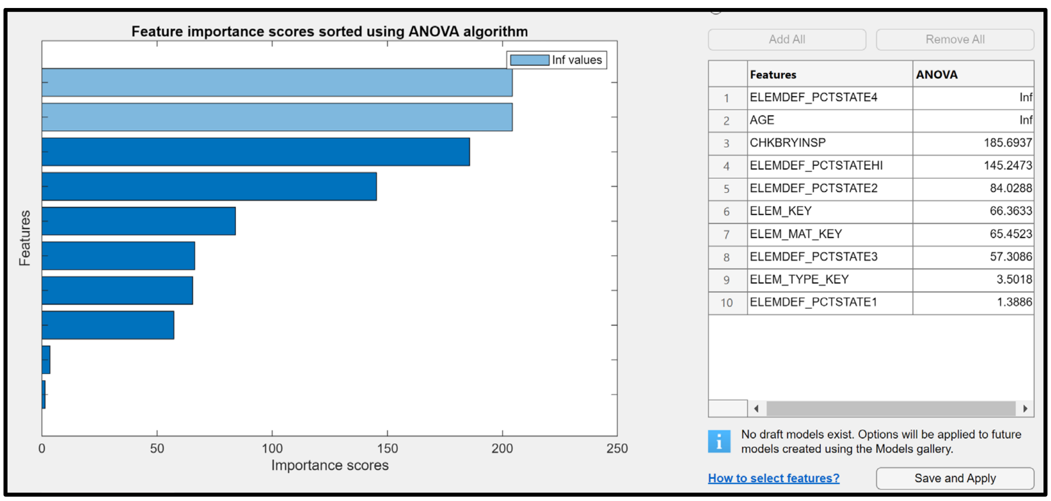


Figure 5.71. ANOVA feature ranking result for Substructure Model 4.

<u>Substructure Model 5: Primary element condition and defect data (NBI rating 0 to 9).</u>

The 15 predictor variables used include the following: Inspection count per bridge; Age; Element key; Element Type Key; Element Material key; Primary element percent in condition state 1; Primary element percent in condition state 2; Primary element percent in condition state 3; Primary element percent in condition state 4; Primary element health index; Primary element percent in defect condition state 1; Primary element percent in defect condition state 2; Primary element percent in defect condition state 3; Primary element percent in defect condition state 4; and Primary element defect health index.

The classification ensemble produced the most accurate results compared with other classifier models. This model performed well for NBI predictions 0, 3 and 7 (Figures 5.72 and 5.73). However, if we consider a positive prediction as being within ±1 of the actual class, the majority of the prediction classes exceed 90%, which is a good result.

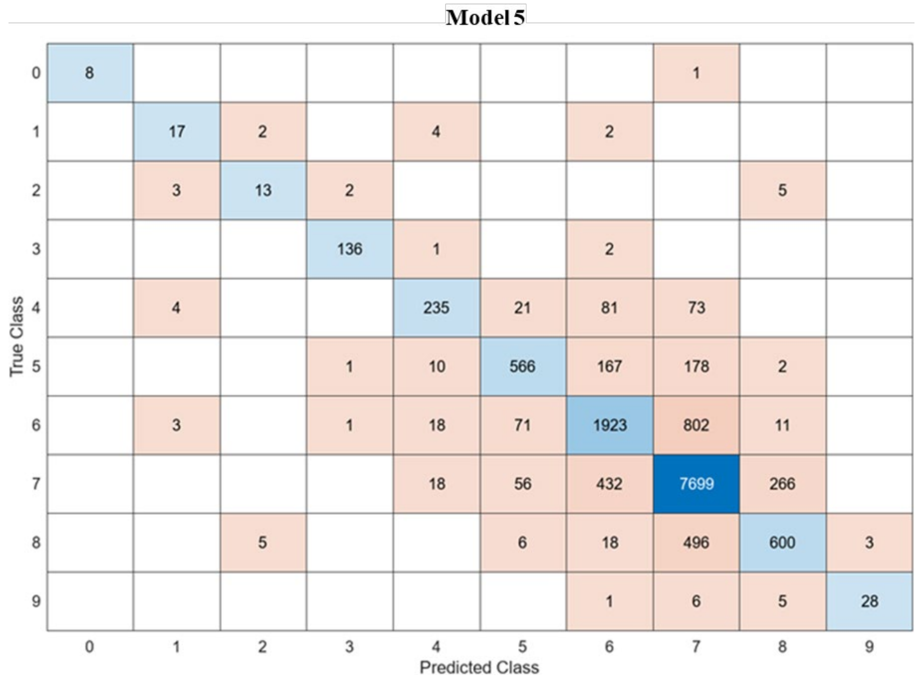


Figure 5.72. Substructure Model 5: Ensemble Classifier (80.2%) Performance, Number of Observations

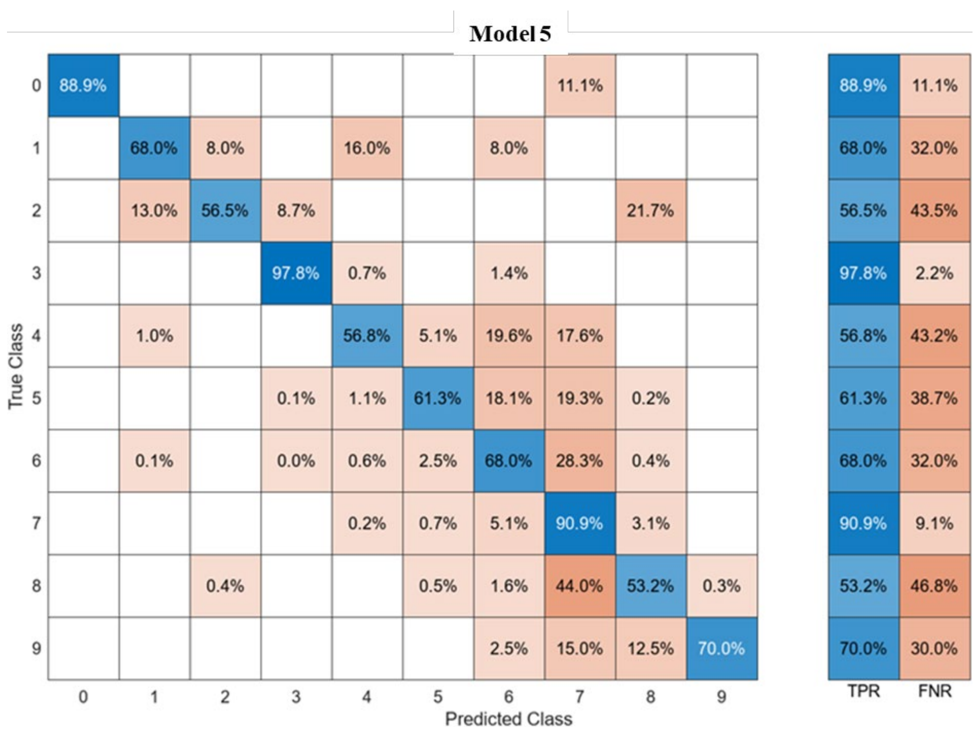


Figure 5.73. Substructure Model 5: Ensemble Classifier (80.2%) Performance, True Positive Rates (TPR), False Negative Rates (FNR)

The most important of the explanatory variables, with the highest importance factor, was identified as the primary element percentage in defects state 4 (Figure 5.74).

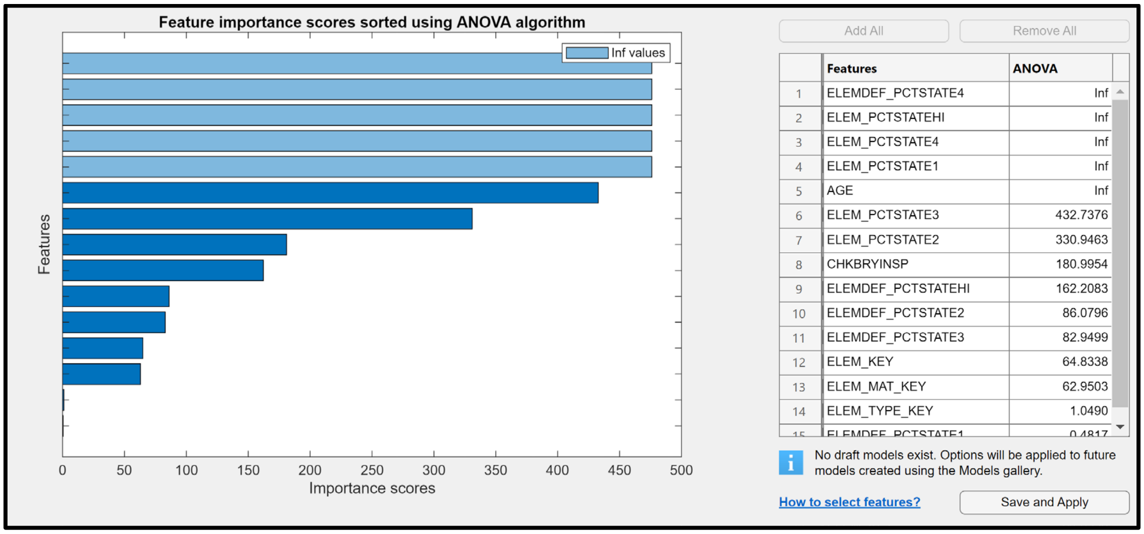


Figure 5.74. ANOVA feature ranking result for Substructure Model 5.

<u>Substructure Model 6: All element condition and defect data (NBI rating 1 to 8).</u>
The 30 predictor variables used include the following: Inspection count per bridge; Age; Element key; Element Type Key; Element Material key; Primary element percent in condition state 1; Primary element percent in condition state 2; Primary element percent in condition state 3; Primary element percent in condition state 4; Primary element health index; Primary element percent in defect condition state 1; Primary element percent in defect condition state 2; Primary element percent in defect condition state 3; Primary element percent in defect condition state 4; Primary element defect health index; Protection element percent in condition state 1; Protection element percent in condition state 2; Protection element percent in condition state 3; Protection element percent in condition state 4; Protection element health index; Protection coating element percent in condition state 1; Protection coating element percent in condition state 2; Protection coating element percent in condition state 3; Protection coating element percent in condition state 4; Protection coating element health index.

The classification ensemble produced the most accurate results compared with other classifier models. This model performed well for all NBI predictions from 3 to 8 (Figures 5.75 and 5.76). However, the ratings 0 and 9 were not considered in this model because of missing data.

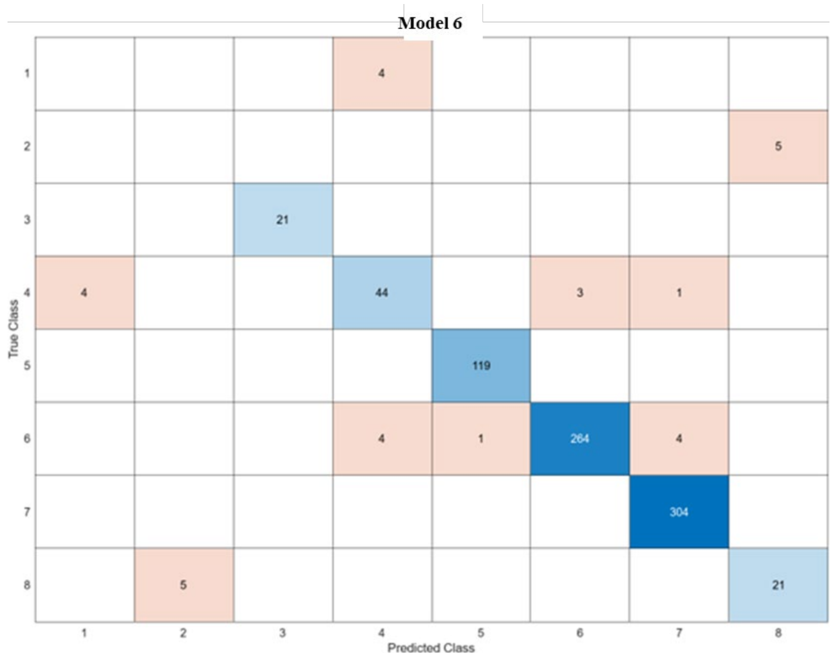


Figure 5.75. Substructure Model 6: Ensemble Classifier (96.1%) Performance, Number of Observations

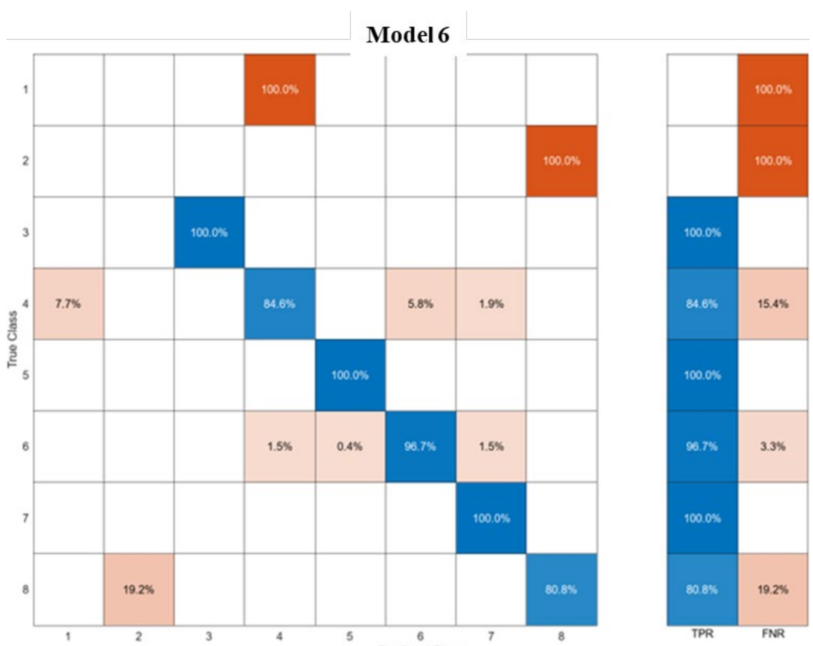


Figure 5.76. Substructure Model 6: Ensemble Classifier (96.1%) Performance, True Positive Rates (TPR), False Negative Rates (FNR)

The most important of the explanatory variables, with the highest importance factor, was identified as the primary element percentage in defects state 4 (Figure 5.77).

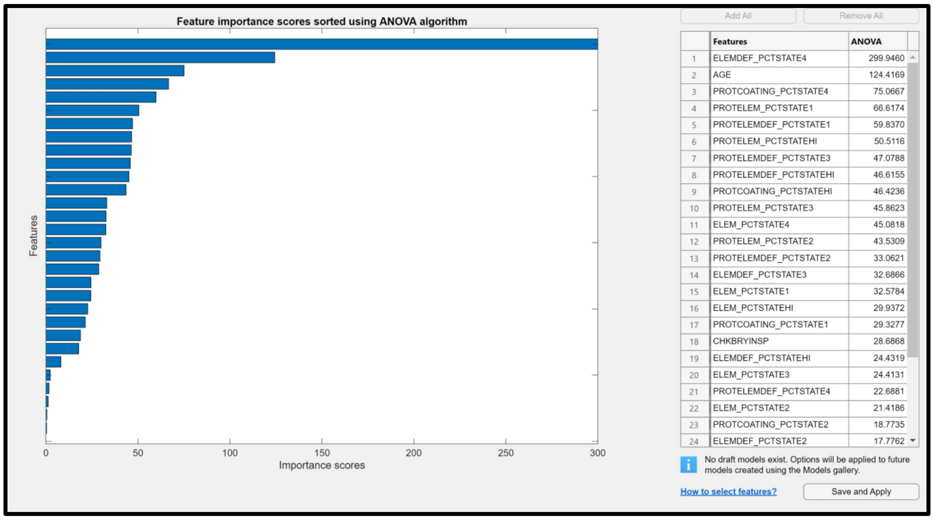


Figure 5.77. ANOVA feature ranking result for Substructure Model 6.

<u>Substructure Model 7: All element condition and defect data (NBI Generalized ratings Good, Fair, and Poor).</u>

The 30 predictor variables used include the following: Inspection count per bridge; Age; Element key; Element Type Key; Element Material key; Primary element percent in condition state 1; Primary element percent in condition state 2; Primary element percent in condition state 3; Primary element percent in condition state 4; Primary element health index; Primary element percent in defect condition state 1; Primary element percent in defect condition state 2; Primary element percent in defect condition state 3; Primary element percent in defect condition state 4; Primary element defect health index; Protection element percent in condition state 1; Protection element percent in condition state 2; Protection element percent in condition state 3; Protection element percent in condition state 4; Protection element health index; Protection coating element percent in condition state 1; Protection coating element percent in condition state 2; Protection coating element percent in condition state 3; Protection coating element percent in condition state 4; Protection coating element health index.

The classification ensemble produced the most accurate results compared with other classifier models. This model performed best for all NBI predictions for ratings GOOD, FAIR and POOR, i.e., accuracy of more than 90% (Figures 5.78 and 5.79).

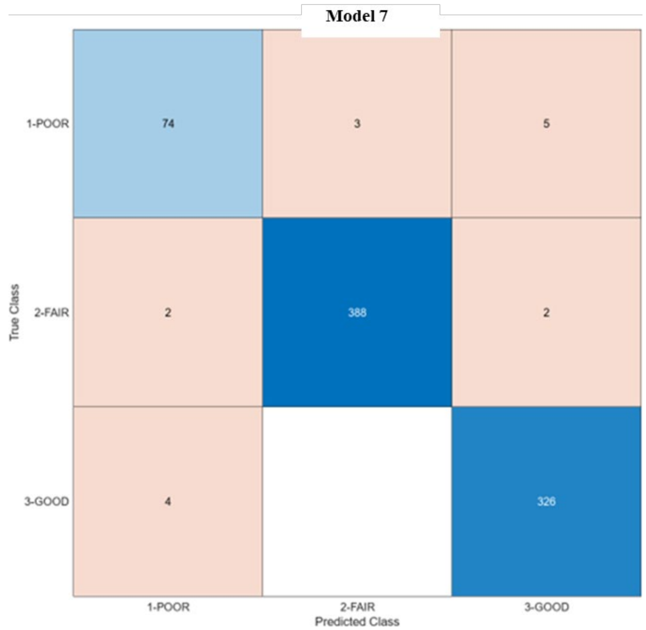


Figure 5.78. Substructure Model 7: Ensemble Classifier (98%) Performance, Number of Observations

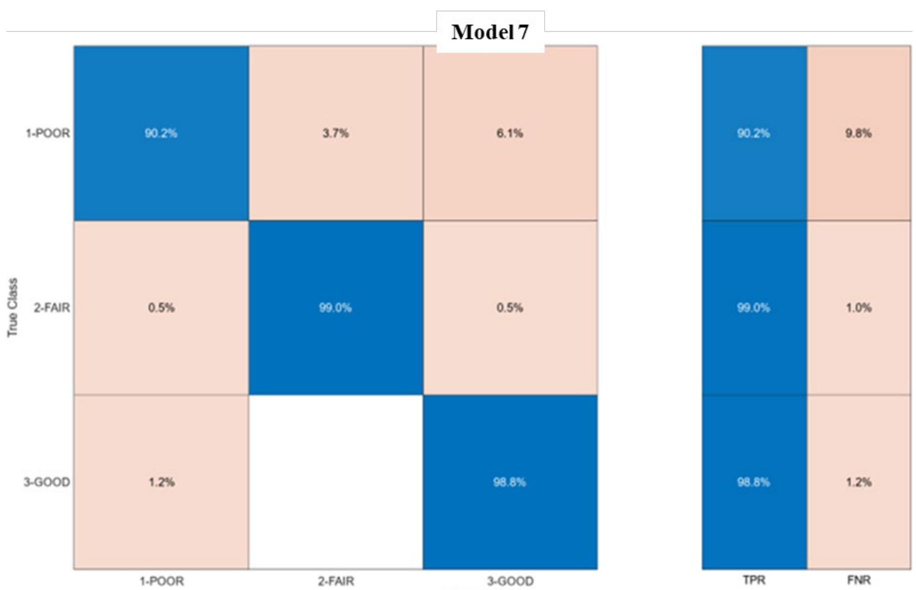


Figure 5.79. Substructure Model 7: Ensemble Classifier (98 %) Performance, True Positive Rates (TPR), False Negative Rates (FNR)

The most important of the explanatory variables, with the highest importance factor, was identified as Age (Figure 5.80).

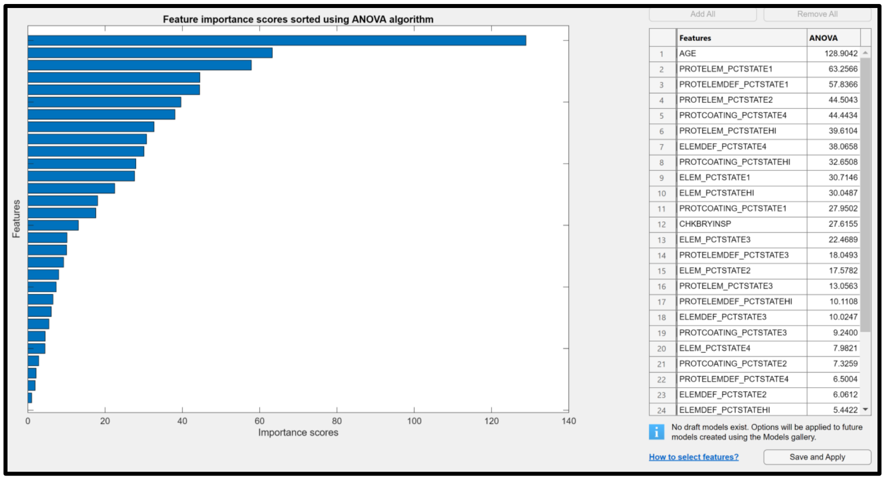


Figure 5.80. ANOVA feature ranking result for Substructure Model 7.

5.3.3.4. Development of Channel NBI ML Translator Models

The Trial Translator Models for the Channel NBI rating are summarized in terms of the predictor and response variables in Table 5.29. For each of the trial translator models, the best four suitable machine learning (ML) algorithms were selected based on the accuracy of the results. Also shown are the most important predictor variable and the computing times for training the ML models. Table 5.30 further describes the details of the predictor variables and their inclusion on the different trial models.

Table 5.29. Summary of machine learning (ML) model results for Channel NBI Translator.

Trial Translator Models	ML Models	Accuracy (Validation) (%)	Most important predictor	Training time (sec.)
Model 1: Primary element data -- 5089 observations, 7 predictors, 9 response classes (NBI rating 0 to 9).	Ensemble	57.9	Primary element condition index	715.7
	Tree	57.0		
	Linear SVM	55.5		
	KNN	55.3		
Model 2: Primary element data -- 5089 observations, 7 predictors, 3 response classes (NBI Generalized ratings Good, Fair, and Poor).	Tree	78.2	Primary element condition index	26.1
	Linear SVM	78.2		
	Ensemble	78.1		
	KNN	77.9		

Table 5.30. Summary of Trial Models for Channel NBI Translator using the machine learning approach.

Variable	Description	Model 1	Model 2
ChkBrInsp	No. of inspections	*	*
ElemKey	Element key		
ElemType	Element type		
ElemMatl	Element material		
Age	Age of bridge at inspection	*	*
ElemPctState1	Percent in primary element condition state 1	*	*
ElemPctState2	Percent in primary element condition state 2	*	*
ElemPctState3	Percent in primary element condition state 3	*	*
ElemPctState4	Percent in primary element condition state 4	*	*
ElemPctStateHI	Health index of primary element	*	*
ChanRating#	NBI condition rating	*	
GenChanRating#	Generalized NBI condition rating (Good, Fair, Poor)		*

[#] *Dependent variables.*

Channel Model 1: Primary element data (NBI rating 0 to 9).

The seven predictor variables used include the following: Inspection count per bridge; Age; Element key; Primary element percent in condition state 1; Primary element percent in condition state 2; Primary element percent in condition state 3; Primary element percent in condition state 4; and Primary element health index. Some variables such as matkey were missing or constant for the inventory and were therefore removed.

The classification ensemble gives the best accuracy results. This model performed well for NBI predictions 2 and 7 (Figures 5.81 and 5.82)**.** However, if we consider a positive prediction as being within ±1 of the actual class, the majority of the prediction classes exceed 70%, which is a good result.

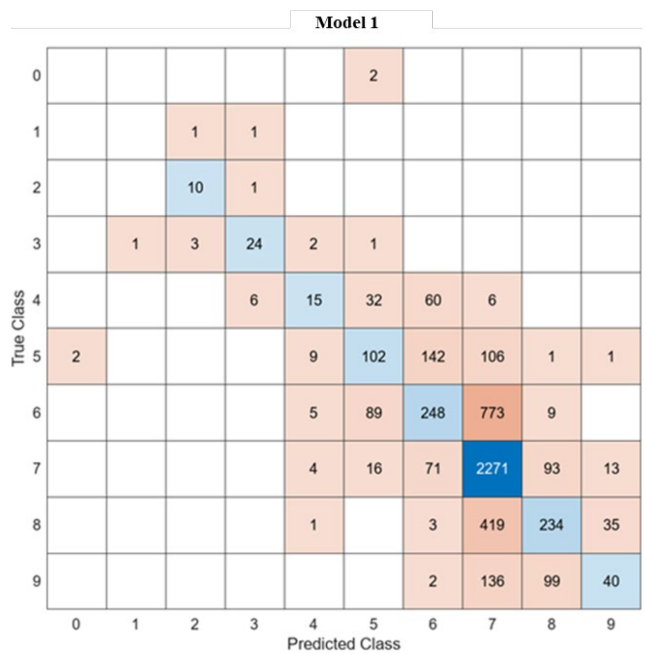


Figure 5.81. Channel Model 1: Ensemble Classifier (57.9%) Performance, Number of Observations

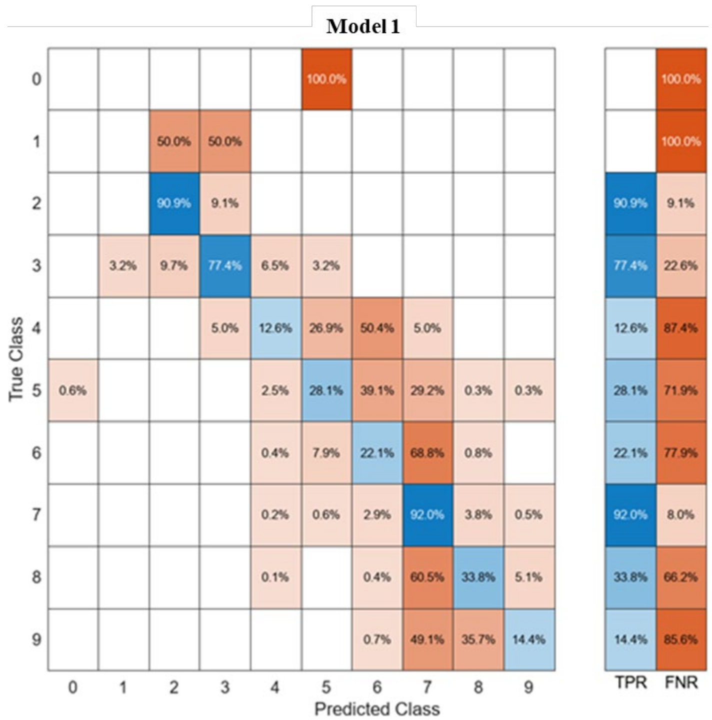


Figure 5.82. Channel Model 1: Ensemble Classifier (57.9%) Performance, True Positive Rates (TPR), False Negative Rates (FNR)

The most important of the explanatory variables, with the highest importance factor, was identified as the primary element health index (Figure 5.83).

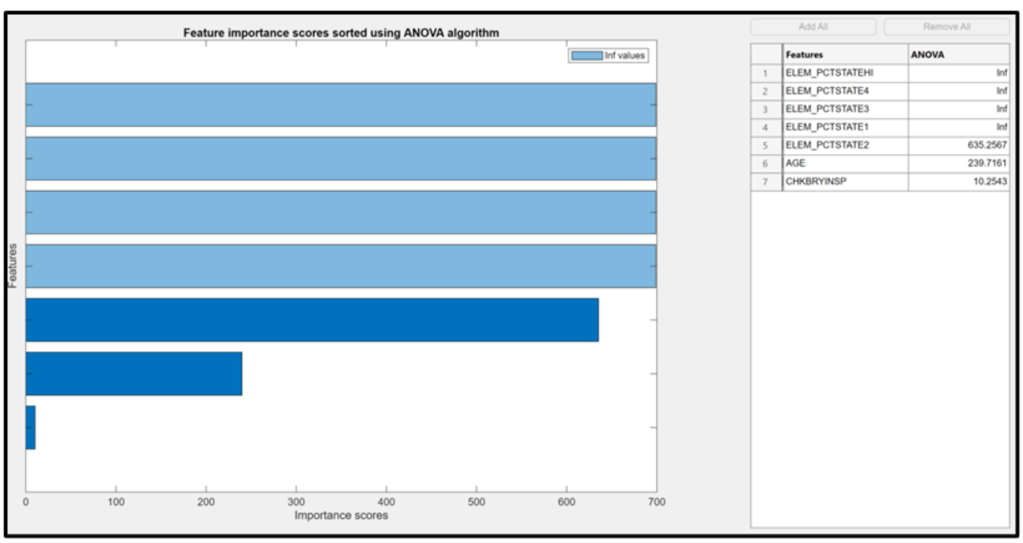


Figure 5.83. ANOVA feature ranking result for Channel Model 1.

Channel Model 2: Primary element data (NBI Generalized ratings Good, Fair, and Poor).

The seven predictor variables used include the following: Inspection count per bridge; Age; Element key; Primary element percent in condition state 1; Primary element percent in condition state 2; Primary element percent in condition state 3; Primary element percent in condition state 4; and Primary element health index. The classification decision tree produced the most results compared with other classifier models. This model performed well for prediction of the rating of Good (Figures 5.84 and 5.85).

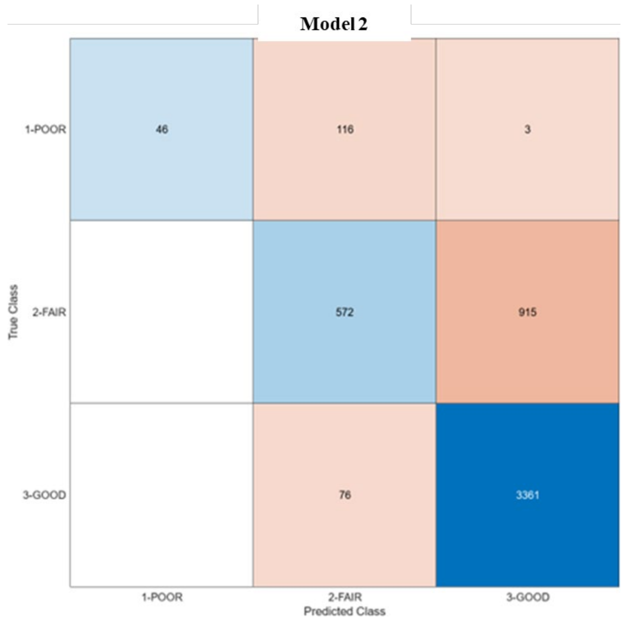


Figure 5.84. Channel Model 2: Decision Tree Classifier (78.2%) Performance, Number of Observations

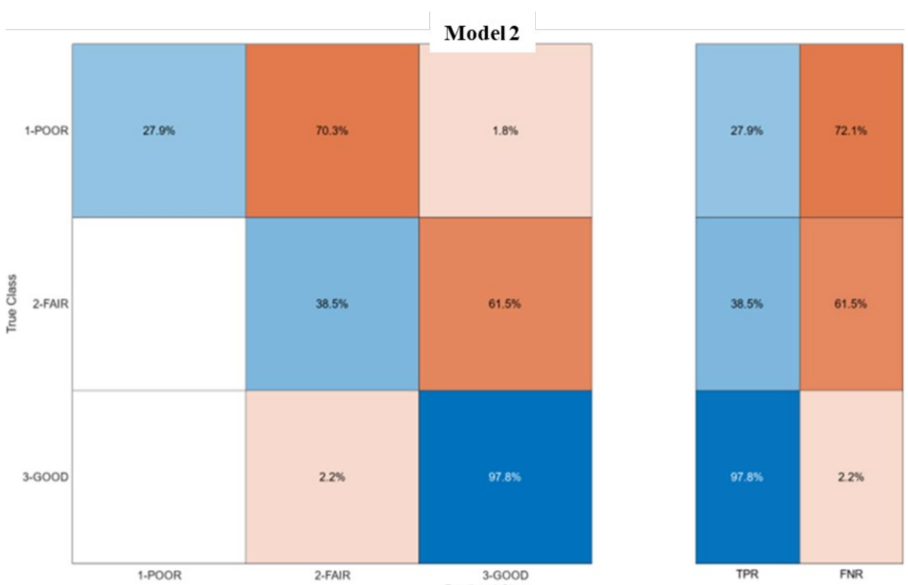


Figure 5.85. Channel Model 2: Decision Tree Classifier (78.2%) Performance, True Positive Rates (TPR), False Negative Rates (FNR).

The most important of the explanatory variables, with the highest importance factor, was identified as the primary element health index (Figure 5.86).

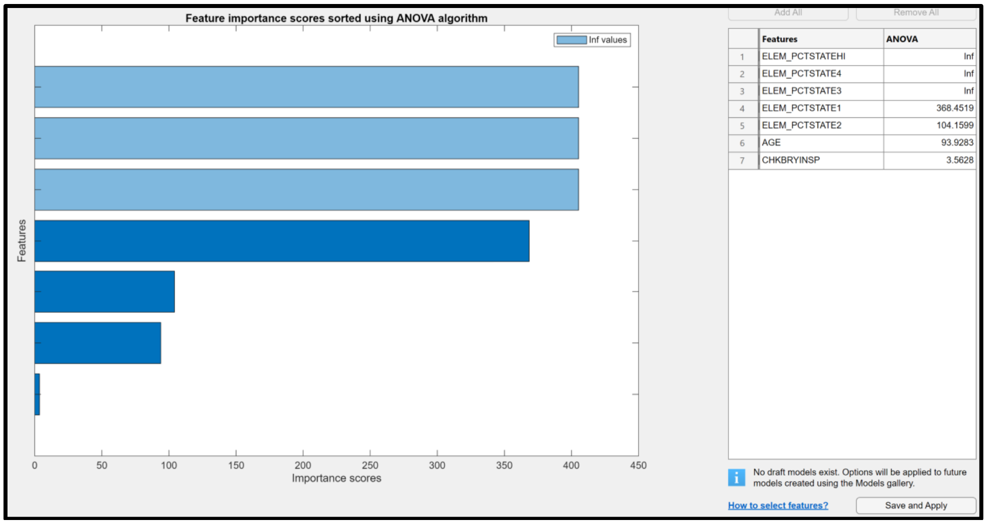


Figure 5.86. ANOVA feature ranking result for Channel Model 2.

5.3.3.5. Development of Culvert NBI ML Translator Models

The Trial Translator Models for the Culvert NBI rating are summarized in terms of the predictor and response variables in Table 5.31. For each of the trial translator models, the best four suitable machine learning (ML) algorithms were selected based on the accuracy of the results. Also shown are the most important predictor variable and the computing times for training the ML models. Table 5.32 further describes the details of the predictor variables and their inclusion on the different trial models.

Table 5.31. Summary of machine learning (ML) model results for Culvert NBI Translator.

Scenario	ML Model	Accuracy (Validation) (%)	Most important variable	Training time (sec.)
Model 1: Primary element data -- 1181 observations, 10 predictors, 7 response classes (NBI rating 0, 3 to 8).	Neural Network	61.6	Primary element % in condition state 4	48.5
	Ensemble	61.1		
	Tree	60.4		
	Kernel	56.6		
Model 2: Primary element data -- 1181 observations, 10 predictors, 3 response classes (NBI Generalized ratings Good, Fair, and Poor).	Logistic Regression	73.8	Primary element condition index	21.3
	Linear SVM	72.8		
	Ensemble	72.7		
	Tree	72.1		
Model 3: Primary element defect data -- 1181 observations, 10 predictors, 7 response classes (NBI rating 0, 3 to 8).	Ensemble	59.7	Primary element defect % in condition state 4	187.4
	Neural Network	58.4		
	Tree	56.7		
	SVM	56.7		
Model 4: Primary element defect data -- 1181 observations, 10 predictors, 3 response classes (NBI Generalized ratings Good, Fair, and Poor).	Ensemble	69.4	Primary element defect % in condition state 4	229.4
	Linear SVM	68.9		
	Neural Network	68.3		
	Tree	68.3		
Model 5: Primary element condition and defect data -- 1181 observations, 15 predictors, 7 response classes (NBI rating 0, 3 to 8).	Neural Network	62.0	Primary element % in condition state 4	899.3
	SVM	60.5		
	Tree	59.9		
	Kernel	59.1		
Model 6: Primary element condition and defect data -- 1181 observations, 15 predictors, 3 response classes (Generalized NBI ratings Good, Fair, and Poor).	Ensemble	73.7	Primary element condition index	234.7
	Neural Network	73.3		
	Tree	72.1		
	Kernel	71.7		

Table 5.32. Summary of Trial Models for Culvert NBI Translator using the machine learning approach.

Variable	**Description**	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
ChkBrInsp	No. of inspections	*	*	*	*	*	*
ElemKey	Element key	*	*	*	*	*	*
ElemType	Element type	*	*	*	*	*	*
ElemMatl	Element material	*	*	*	*	*	*
Age	Age of bridge at inspection	*	*	*	*	*	*
ElemPctState1	Percent in primary element condition state 1	*	*			*	*
ElemPctState2	Percent in primary element condition state 2	*	*			*	*
ElemPctState3	Percent in primary element condition state 3	*	*			*	*
ElemPctState4	Percent in primary element condition state 4	*	*			*	*
ElemPctStateHI	Health index of primary element	*	*			*	*
ElemDefPctState1	Percent in primary element defect condition state 1			*	*	*	*
ElemDefPctState2	Percent in primary element defect condition state 2			*	*	*	*
ElemDefPctState3	Percent in primary element defect condition state 3			*	*	*	*
ElemDefPctState4	Percent in primary element defect condition state 4			*	*	*	*
ElemDefPctStateHI	Health index of primary element defect			*	*	*	*
CulvRating#	NBI condition rating	*		*		*	
GenCulvRating#	Generalized NBI condition rating (Good, Fair, Poor)		*		*		*

Dependent variables.

Culvert Model 1: Primary element data (NBI rating 0, 3 to 8).

The 10 predictor variables used include the following: Inspection count per bridge; Age; Element key; Element Type Key; Element Material key; Primary element percent in condition state 1; Primary element percent in condition state 2; Primary element percent in condition state 3; Primary element percent in condition state 4; and Primary element health index. The neural network produced the most accurate results compared with other classifier models. This model performed very well for NBI predictions from 0, 3, 6, and 7 (Figures 5.87 and 5.88).

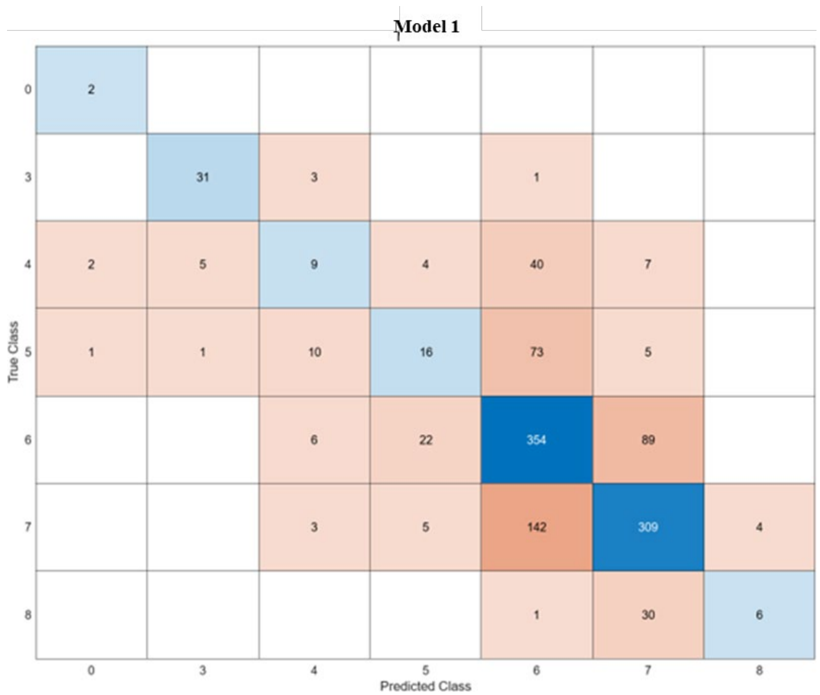


Figure 5.87. Culvert Model 1: Neural Network Classifier (61.6%) Performance, Number of Observations

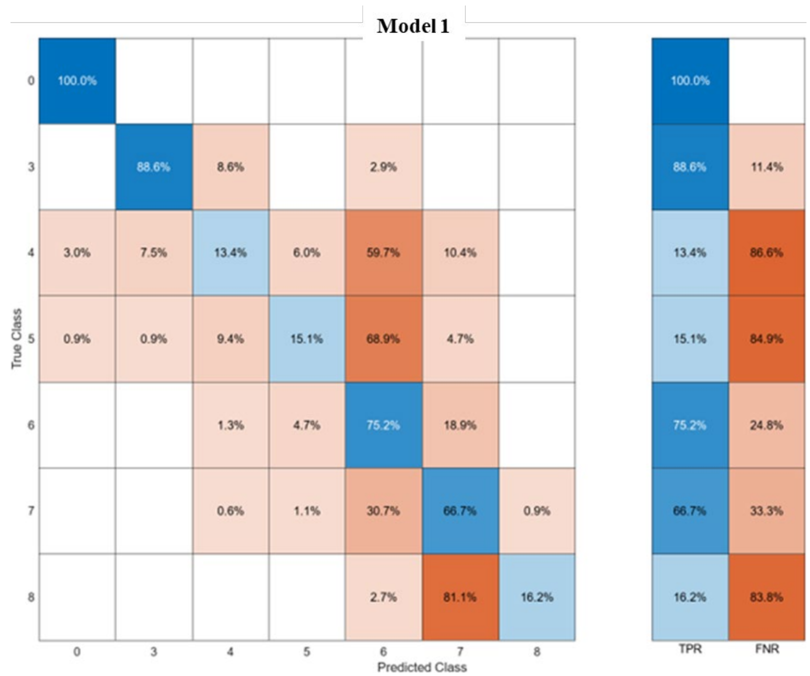


Figure 5.88. Culvert Model 1: Neural Network Classifier (61.6%) Performance, True Positive Rates (TPR), False Negative Rates (FNR)

The most important of the explanatory variables, with the highest importance factor, was identified as primary element percentage in state 4 (Figure 5.89).

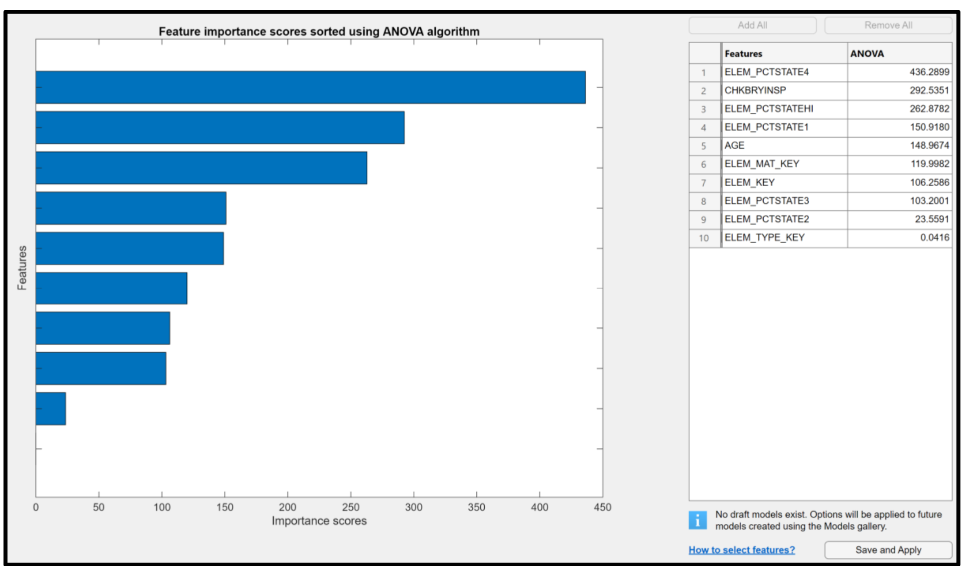


Figure 5.89. ANOVA feature ranking result for Culvert Model 1.

<u>Culvert Model 2: Primary element data (NBI Generalized ratings Good, Fair, and Poor).</u>

The 10 predictor variables used include the following: Inspection count per bridge; Age; Element key; Element Type Key; Element Material key; Primary element percent in condition state 1; Primary element percent in condition state 2; Primary element percent in condition state 3; Primary element percent in condition state 4; and Primary element health index.

The Efficient Logistic Regression Classifier produced the most accurate results compared with other classifier models. This model performed best for NBI predictions “Fair”, i.e. accuracy of more than 80% (Figures 5.90 and 5.91).

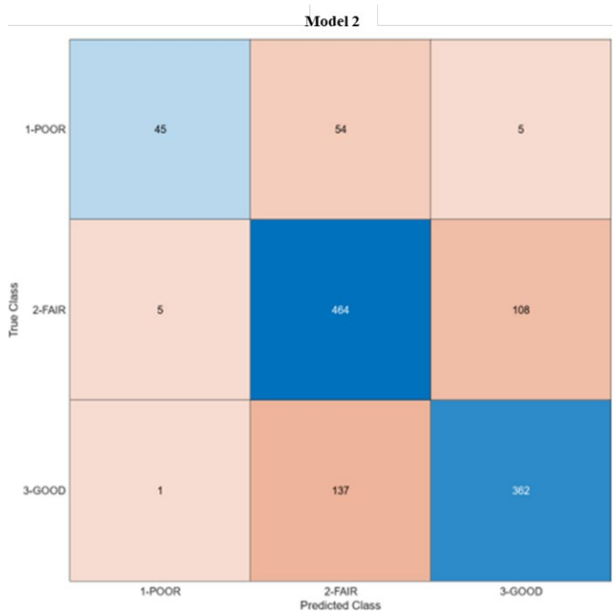


Figure 5.90. Culvert Model 2: Efficient Logistic Regression Classifier (73.8%) Performance, Number of Observations

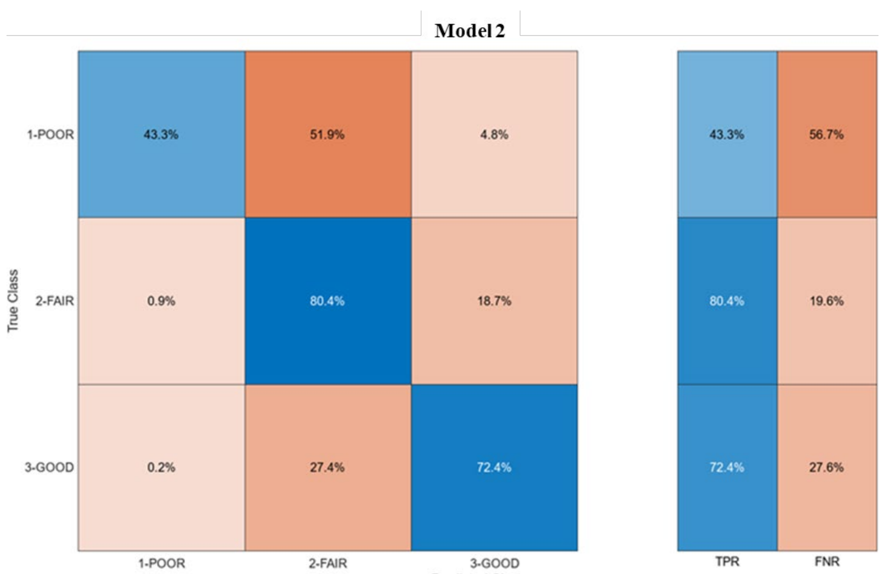


Figure 5.91. Culvert Model 2: Efficient Logistic Regression Classifier (73.8%) Performance, True Positive Rates (TPR), False Negative Rates (FNR).

The most important of the explanatory variables, with the highest importance factor, was identified as primary element health index (Figure 5.92).

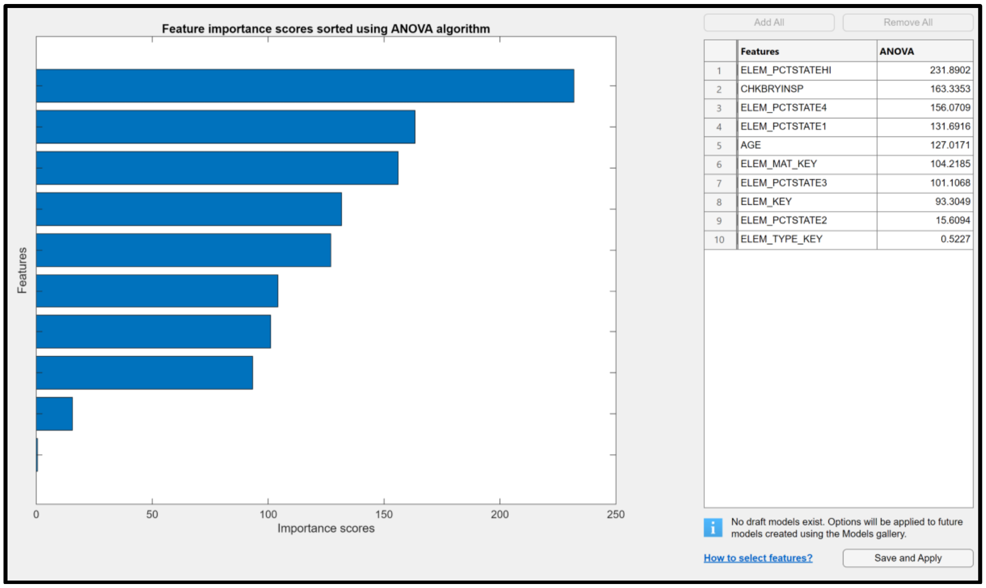


Figure 5.92. ANOVA feature ranking result for Culvert Model 2.

<u>Culvert Model 3: Primary element defect data (NBI rating 0, 3 to 8).</u>
The 10 predictor variables used include the following: Inspection count per bridge; Age; Element key; Element Type Key; Element Material key; Primary element percent in defect condition state 1; Primary element percent in defect condition state 2; Primary element percent in defect condition state 3; Primary element percent in defect condition state 4; and Primary element defect health index.

The classification ensemble produced the most accurate results compared with other classifier models. This model performed well for NBI predictions for ratings 0, 3, 6 and 7 (Figures 5.93 and 5.94).

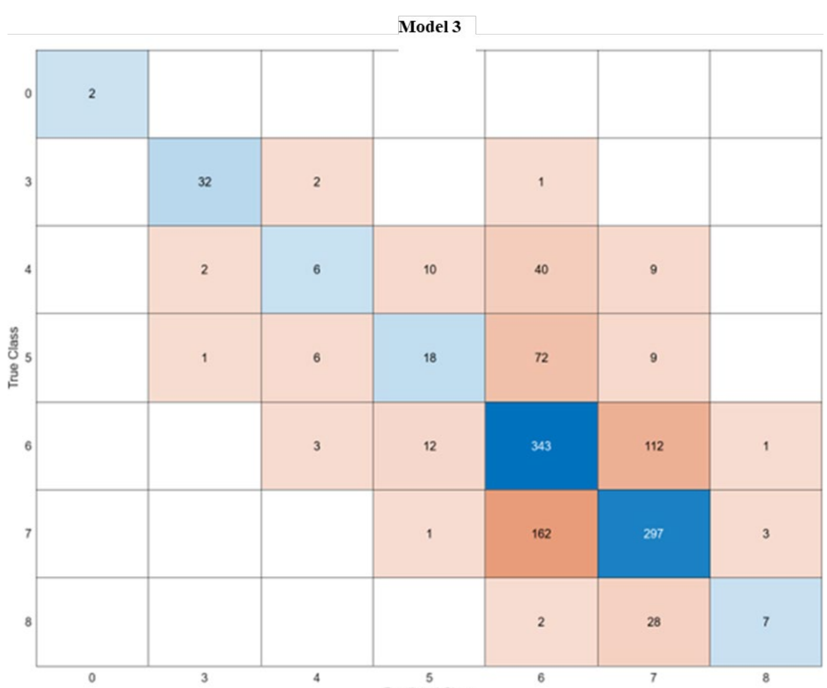


Figure 5.93. Culvert Model 3: Ensemble Classifier (59.7 %) Performance, Number of Observations.

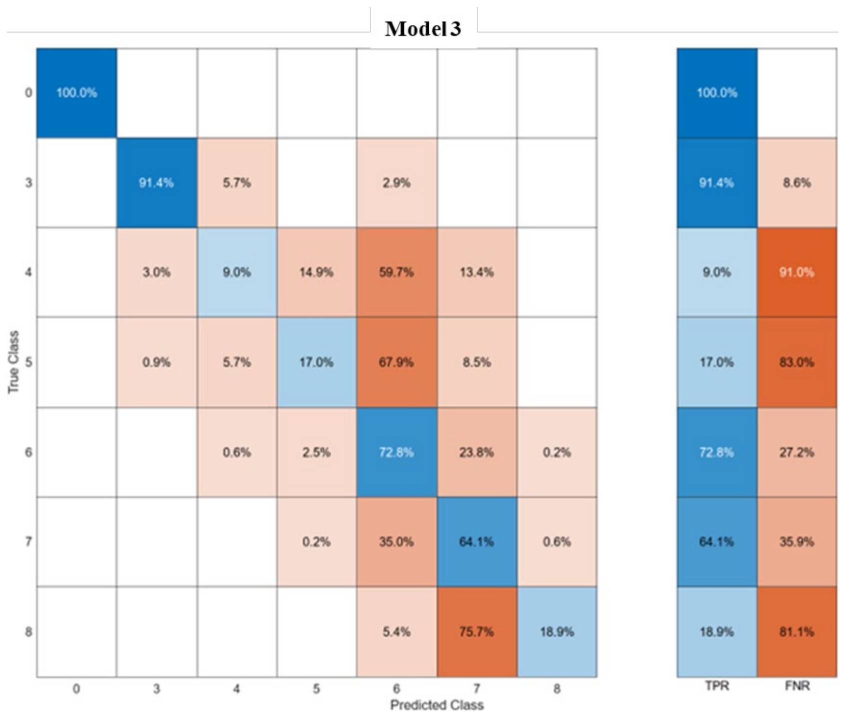


Figure 5.94. Culvert Model 3: Ensemble Classifier (59.7 %) Performance, True Positive Rates (TPR), False Negative Rates (FNR)

The most important of the explanatory variables, with the highest importance factor, was identified as the primary element percentage in defects state 4 (Figure 5.95).

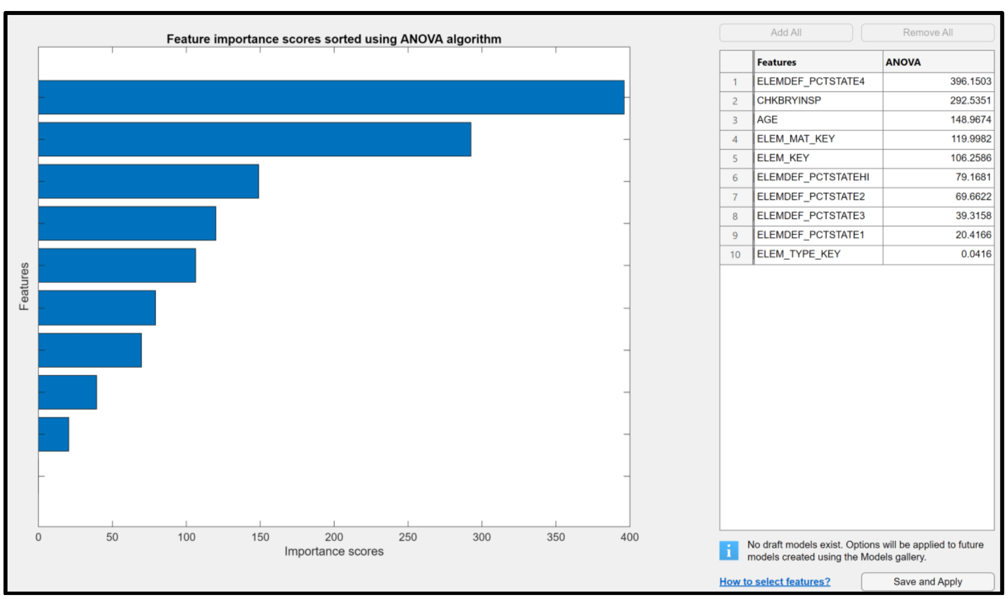


Figure 5.95. ANOVA feature ranking result for Culvert Model 3.

<u>Culvert Model 4: Primary element defect data (NBI Generalized ratings Good, Fair, and Poor).</u>

The 10 predictor variables used include the following: Inspection count per bridge; Age; Element key; Element Type Key; Element Material key; Primary element percent in defect condition state 1; Primary element percent in defect condition state 2; Primary element percent in defect condition state 3; Primary element percent in defect condition state 4; and Primary element defect health index.

The classification ensemble produced the most accurate results compared with other classifier models. This model performed best for NBI predictions of rating Fair, with an accuracy of more than 80% (Figures 5.96 and 5.97).

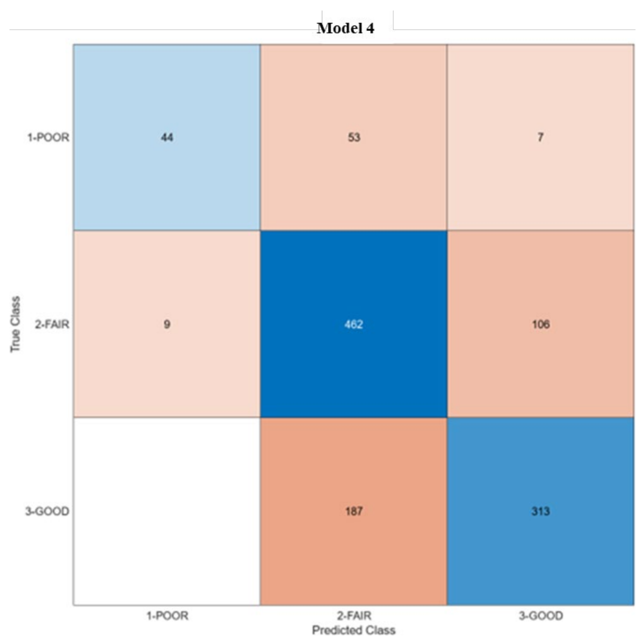


Figure 5.96. Culvert Model 4: Ensemble Classifier (69.3%) Performance, Number of Observations.

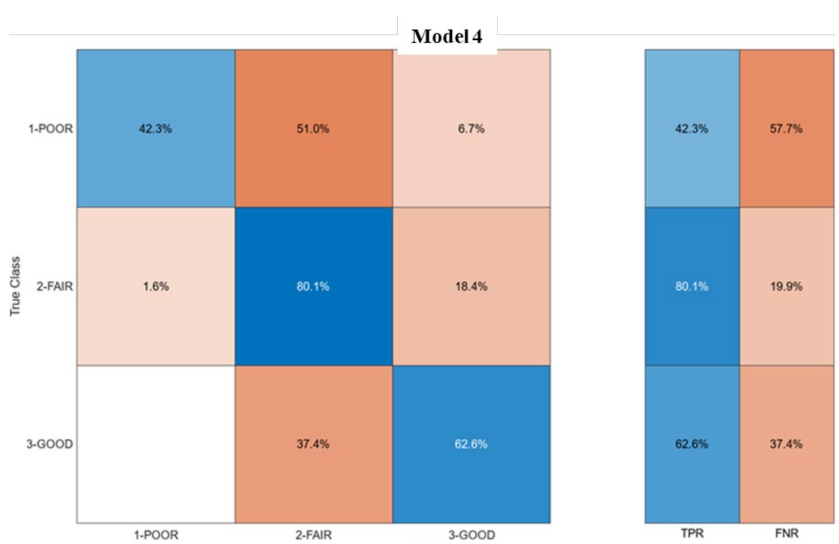


Figure 5.97. Culvert Model 4: Ensemble Classifier (69.3%) Performance, True Positive Rates (TPR), False Negative Rates (FNR).

The most important of the explanatory variables, with the highest importance factor, was identified as the primary element percentage in defects state 4 (Figure 5.98).

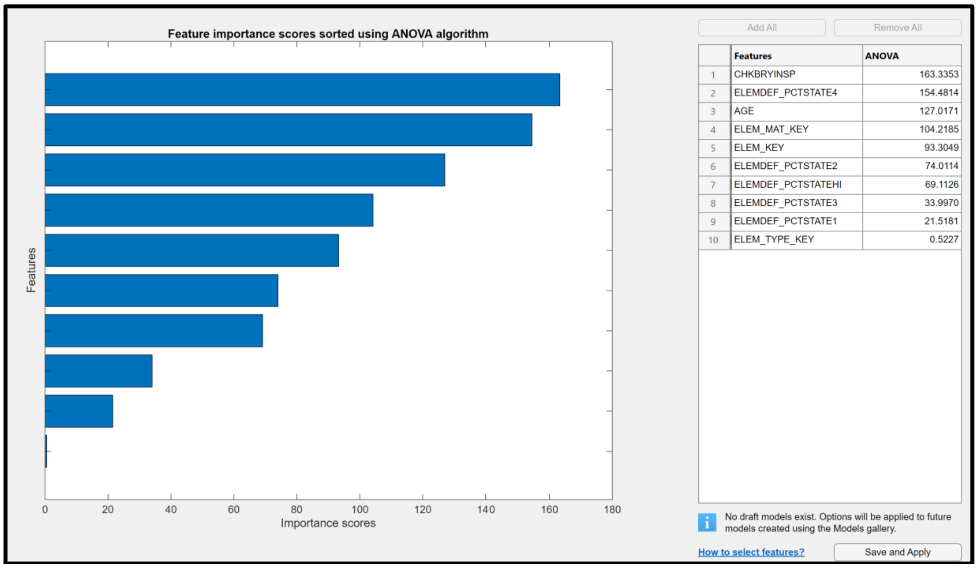


Figure 5.98. ANOVA feature ranking result for Culvert Model 4.

<u>Culvert Model 5: Primary element condition and defect data (NBI rating 0, 3 to 8).</u>

The 15 predictor variables used include the following: Inspection count per bridge; Age; Element key; Element Type Key; Element Material key; Primary element percent in condition state 1; Primary element percent in condition state 2; Primary element percent in condition state 3; Primary element percent in condition state 4; Primary element health index; Primary element percent in defect condition state 1; Primary element percent in defect condition state 2; Primary element percent in defect condition state 3; Primary element percent in defect condition state 4; and Primary element defect health index.

The classification ensemble produced the most accurate results compared with other classifier models. This model performed well for NBI predictions for ratings 0, 3, 6, and 7 (Figures 5.99 and 5.100).

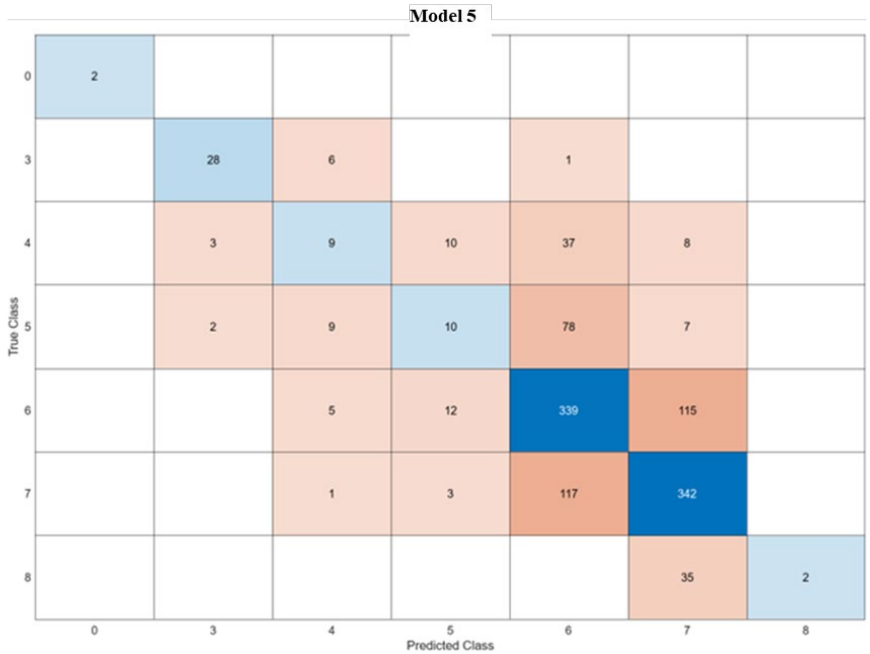


Figure 5.99. Culvert Model 5: Ensemble Classifier (62 %) Performance, Number of Observations.

Figure 5.100. Culvert Model 5: Ensemble Classifier (62 %) Performance, True Positive Rates (TPR), False Negative Rates (FNR).

The most important of the explanatory variables, with the highest importance factor, was identified as the primary element percentage in defects state 4 (Figure 5.101).

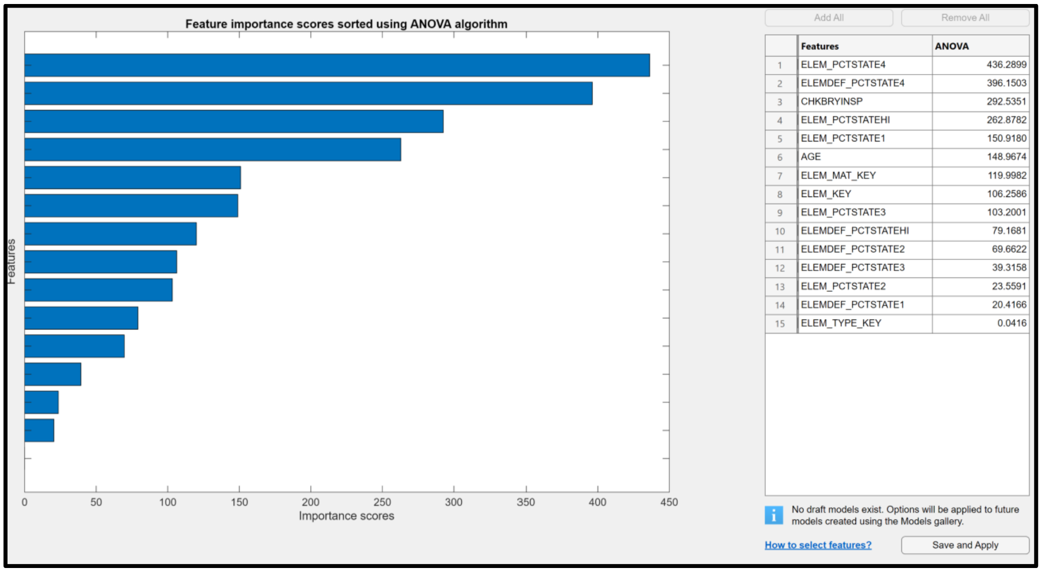


Figure 5.101. ANOVA feature ranking result for Culvert Model 5.

<u>Culvert Model 6: Primary element condition and defect data (Generalized NBI ratings Good, Fair, and Poor).</u>

The 15 predictor variables used include the following: Inspection count per bridge; Age; Element key; Element Type Key; Element Material key; Primary element percent in condition state 1; Primary element percent in condition state 2; Primary element percent in condition state 3; Primary element percent in condition state 4; Primary element health index; Primary element percent in defect condition state 1; Primary element percent in defect condition state 2; Primary element percent in defect condition state 3; Primary element percent in defect condition state 4; and Primary element defect health index.

The classification ensemble produced the most accurate results compared with other classifier models. This model performed best for NBI predictions for rating FAIR, i.e. accuracy of more than 80% (Figures 5.102 and 5.103).

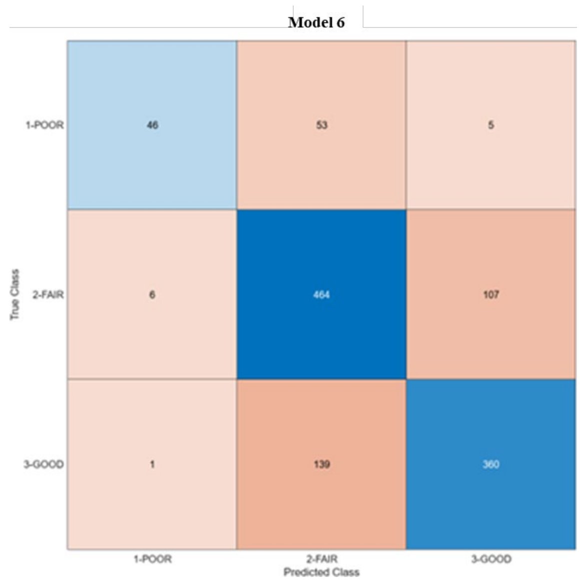


Figure 5.102. Culvert Model 6: Ensemble Classifier (73.7%) Performance, Number of Observations.

Figure 5.103. Culvert Model 6: Ensemble Classifier (73.7%) Performance, True Positive Rates (TPR), False Negative Rates (FNR).

The most important of the explanatory variables, with the highest importance factor, was identified as the primary element health index (Figure 5.104).

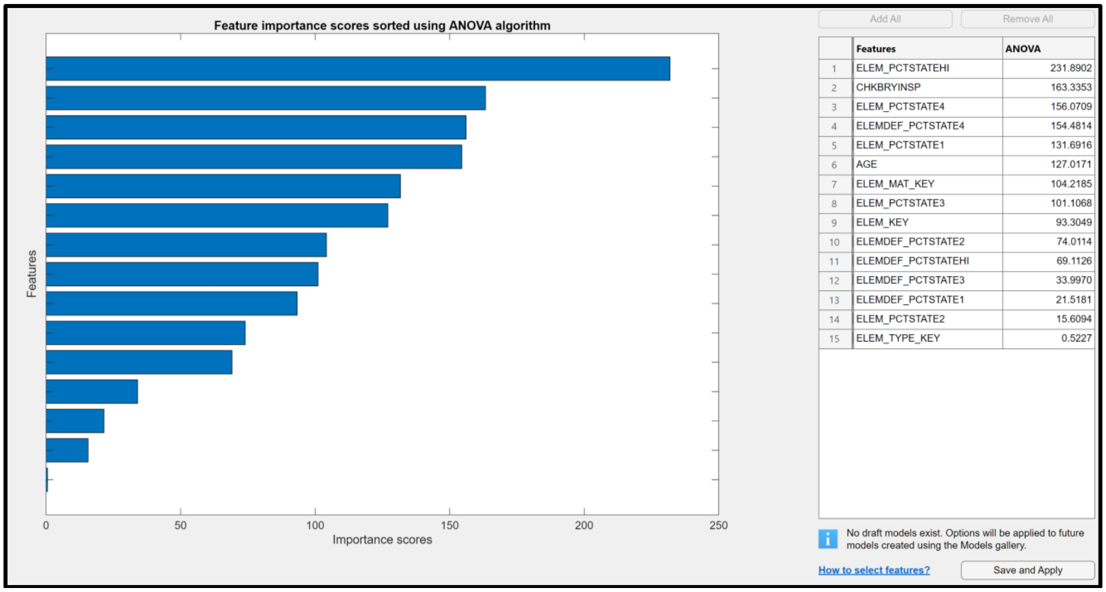


Figure 5.104. ANOVA feature ranking result for Culvert Model 6.

5.4. Conclusions

By exploring three approaches to developing an NBI Translator tool for the bridge deck, superstructure, substructure, culvert, and channel components, this study has discovered that considering more pertinent bridge attributes (age, ownership, structure type, etc.) and element data (primary element health index, percentages in condition states, etc. and similar data on defects, secondary, protection elements) improved the accuracy of the translated ratings. These three approaches were the multiple linear regression, multinomial logistic regression, and the Artificial intelligence (AI) in the form of machine learning. The selection of important explanatory variables was thoroughly done, before incorporation into the final prediction models. In addition to the typical NBI ratings (0 to 9), the Generalized NBI ratings, defined as the FHWA's ratings of Good, Fair, and Poor, which are aggregation of specific NBI ratings for each category, were also modeled in the Translator tool. Results from the three approaches have been presented in a comprehensive form, indicating the prediction accuracies and errors at the various condition ratings.

Overall the models showed that the accuracy was better for the Generalized NBI ratings than for the regular NBI ratings. Best predictions were obtained in almost all the bridge components for those at the rating of 7 in the regular NBI rating and Good for the Generalized NBI rating. The predictions at the NBI ratings 8 and 9 were reasonable but at ratings 0 to 4, there were large errors. But it should be noted that the FDOT state-maintained bridge inventory for these lower ratings (0 to 4) are very low. The multiple linear regression and the machine learning models of the NBI Translator indicated in many of the scenarios that the important explanatory variables included the primary element health index, percentage of the primary element in state 4, percentage of the primary element defects in state 4, and age. A slight modification was done to the initial linear regression models by using rules to impose NBI ratings of 9 on bridge components with age less than 5 years and also impose a minimum rating of 8 on 14 years (based on a histogram and average age of bridges with actual ratings of 8 and 9). While this slight modification improved the prediction of bridge components at rating 9, the accuracies at the other ratings were reduced as well as the overall prediction accuracy of the component.

The results from the multinomial logistic regression were slightly more accurate than those of the multiple linear regression but the implementation of the latter will be much easier and easy to understand. The machine learning also produced good results, and the accuracies on some bridge components are better than the accuracies from the linear and logistic regression models. The main shortcomings of the machine learning models are that some of the models will require an extremely high number of explanatory variables, and also the deployment of the models will be challenging due to tie development platform.

It is recommended that the multiple linear regression models be deployed for the FDOT BrM Translator models, as they will be coded as linear functions of the already-existing element and bridge data in the database. For future research, it is suggested that more studies be conducted on a bridge inventory that are dominated by bridges in the lower NBI ratings, i.e., less than 5. It is also recommended that as the machine learning technology become more accessible, that easily-deployable models be developed using the machine learning algorithms.

5.5. References

Al-Wazeer, Adel, Chris Nutakor, and Bobby Harris. (2007). Comparison of Neural Network Method Versus National Bridge Inventory Translator in Predicting Bridge Condition Ratings. Proceedings, Transportation Research Board 86th Annual Meeting, Washington DC. 23 pp.

Bektas, B. A., Carriquiry, A., & Smadi, O. (2013). Using Classification Trees for Predicting National Bridge Inventory Condition Ratings. Journal of Infrastructure Systems, 19(4), 425–433. https://doi.org/10.1061/(asce)is.1943-555x.0000143

Bektaş, B., & Smadi, O. (2008). A Discussion on the Efficiency of NBI Translator Algorithm. https://cornerstone.lib.mnsu.edu/me-cive-fac-pubs/8/

FHWA. (2017). National Performance Management Measures; Assessing Pavement Condition for the National Highway Performance Program and Bridge Condition for the National Highway Performance Program. 23 CFR Part 490 -- A Rule by the Federal Highway Administration (FHWA). Federal Register, The Daily Journal of the United States Government. Accessed August 2, 2024 from https://www.federalregister.gov/documents/2017/01/18/2017-00550/national-performance-management-measures-assessing-pavement-condition-for-the-national-highway.

Federal Highway Administration (FHWA). (2022). Specifications for the National Bridge Inventory.

FHWA. (1995). Recording and Coding Guide for Structure Inventory and Appraisal of the Nation's Bridges. Report No. FHWA-PD-96-001. U.S. Department of Transportation. Federal Highway Administration (FHWA). 124 pp.

Fiorillo, G., & Nassif, H. (2019). Application of Machine Learning Techniques for the Analysis of National Bridge Inventory and Bridge Element Data. Transportation Research Record, 2673(7), 99–110. https://doi.org/10.1177/0361198119853568

Hearn, G. , J. C. and D. M. Frangopol. (1997). Generation of NBI condition ratings from commonly recognized (CoRe) element data. Infrastructure Condition Assessment: Art, Science, and Practice, 41–50.

Sobanjo, J. O. & Thompson, P. D. (2011). Enhancement of the FDOT's Project Level and Network Level Bridge Management Analysis Tools. Final Report, Research Contract #BDK83 977-01, Florida Department of Transportation, Tallahassee, Florida, 303p.

Thompson, Paul D. (2021). StruPlan: Open Source long-range renewal planning for transportation structures. Users Manual, section 3.3. http://struplan.com/images/StruPlanManual.pdf.

FDOT. (2024). Bridge Condition Terminology. Bridge Information Documents. Florida Department of Transportation (FDOT). State Office of Maintenance. 4 pp. Accessed October 12, 2024, from https://www.fdot.gov/maintenance/bridgeinfo.shtm.

6. New cost estimating models for bridge MR&R activities

Despite the importance of applying the life cycle cost evaluation for decision making on transportation assets, there is a decreasing availability of records for pertinent bridge maintenance, repair and rehabilitation (MR&R) costs over the service lives of the infrastructure. Another challenge is the incompatibility of units in the available historical costs with the units of measure for the bridge MR&R activities. One of the earlier research efforts to address the latter problem was development of the framework of a national database which would enable the states to have a uniform format for collecting and maintaining the bridge maintenance data, including costs (Hearn et al. 2010). But this proposed framework has not been implemented in Florida or any other state. Another study presenting overall guidelines in the NCHRP 574 report for cost estimation of highway projects by Anderson et al. (2007) was reviewed and found not to be relevant for estimating the costs of bridge MR&R activities. The research team's experience from prior studies on the FDOT BMS had involved extensive analyses of historical costs (Sobanjo et al. 2002, and Sobanjo and Thompson 2011) but most of these costs could not be updated as they are no longer collected by the FDOT.

This research task explored existing bridge maintenance cost data at FDOT, including the Maintenance Management System (MMS) cost data, the historical bid cost data, and also developed a crew-based approach to estimating the bridge maintenance costs.

6.1. FDOT's Maintenance Management System (MMS) Costs

The FDOT's procedures for capturing and storing cost data on maintenance activities are described in the Maintenance Cost Handbook (FDOT 2012). These data are eventually stored in the FDOT's Maintenance Management System (MMS) database which provided a source of data for this research task. While the data captured for the MMS also include many categories of routine maintenance such as Routine Maintenance Activities (general for the highways, e.g., asphalt repair, road sweeping, etc.), and Emergency Maintenance Functions (fence repair, debris removal, etc.), this research task focused on the category labeled "Bridge Routine Maintenance Activities." The definitions of the specific bridge routine maintenance activities are listed in Table 1.

Bridge Work Order Library (BWOL) reports from the MMS database, showing the maintenance activity entries, were generated by FDOT for eight districts, and provided to the research team. Some clarifications were provided by the FDOT State Maintenance Office regarding the meaning of the data fields in the BWOL report. The *Datex* field (when the work order was created and loaded into the. BWOL), the *Comp*, *Compdate* and *Ccompdte* fields (indicating if the activity was completed and the completion date), were used to filter the pertinent data for analyses. Other important fields in the BWOL report include *Act* (Activity No.), *Instruct* (Description of activity), *Estunit* (Quantity of activity done), *Bridgeno* (bridge identification no.), and *Unitmeas* (unit of measure).

Another source of data were the statewide annual fiscal year reports generated from the MMS database, for fiscal years covering 2016 to 2022, provided by FDOT for the research team. For each fiscal year, one report covered activities done in-house, and the other report showed activities carried out by contract. These two reports are presented in two different formats, with the contract report having a field for the bridge identification, though the field very rarely had a value on the report.

Table 6.1. Definition of FDOT bridge routine maintenance activities (FDOT 2012).

Activity No.	Definition	Description	Unit of measure
805	Bridge Deck Joint Repair	Clean existing deck joint or deteriorated material and repair with new material.	LF
806	Bridge Deck Maintenance and Repair	Maintenance and/or repair to any bridge deck deficiency, such as spall, scale, crack repair, corrosion abatement, pothole patching, cleaning of joints, scuppers and gutters, replacement of deck material, securing connections and fasteners. Also to include sidewalk and catwalks.	SF
810	Bridge Rail Maintenance and Repair	Maintenance and/or repair to any bridge rail deficiency, such as spall, scale, crack repair, corrosion abatement, reconstruction. Does not include rail on movable spans.	LF
825	Superstructure Maintenance and Repair	Maintenance and/or repair of any superstructure deficiency. To include bearings, beams, girders, trusses, trestles, or suspension type construction. Not to include handrail, sidewalk, bridge railing, and catwalks.	MH
845	Substructure Maintenance and Repair	Maintenance and/or repair of any substructure deficiency.	MH
859	Channel Maintenance	Maintain and/or repair any channel or fender deficiency.	MH
861	Bridge Electrical Maintenance	Any maintenance or repair to the electrical system on a movable or fixed bridge. This can include electrical components on the fender system, traffic control devices, and control house.	MH
865	Movable Bridge Mechanical Maintenance	Any maintenance or repair to the mechanical system of a movable bridge. This includes greasing gears, alignment, shimming, adjusting or cleaning brakes, gears, bearings, shoes, buffers and locks, cable replacement and greasing, servicing traffic control devices, and any other mechanical components of the bridge.	MH
869	Movable Bridge Structural Maintenance	Maintenance and/or repair to the structural components of a bascule, swing, and lift bridge deck, superstructures and substructure. Activities include maintenance and repair to main girders, floor beams, stringers, trusses, connections, fasteners, steel grating, bascule, swing and lift piers, barriers, handrails, parapets, control house structures. Must not include maintenance and repair of fixed approach spans which are to be reported under other function numbers.	MH
888	Bridge Damage Repair	Repairs required on bridges due to factors other than natural deterioration.	MH
896	Ferry Slip Maintenance and Repair	Maintenance and repair to ferry slips to include boxed dolphins, slips, walls, mats, ramps, seawalls, gates, towers and electrical components.	MH
898	Tunnel Maintenance	Maintenance and repair to the tunnel. Includes cleaning the walls and ceilings, mechanical and electrical repairs, servicing and repairing of traffic control devices.	MH

As shown in Table 6.2 for the Fiscal Year 2021-2022, the statewide contract report indicates for the respective FDOT districts and the entire state, quantity of work done for each recorded MMS activity, the total and average unit cost, the engineered total and engineered unit cost, as well as the number of contracts done for the activity. The statewide In-house report is shown in Table 3 for the Fiscal Year 2021-2022, reflecting similar data but with more details in terms of the material, labor, and equipment cost.

The In-house report also shows the labor effort (Man Hour or MH) per unit measure of the MMS activity. It should be noted that as indicated in the activity definitions in Table 6.1, and in both types of report, most of the units of measure are Man-hours (MH) except for MMS Activity Nos. 805 Bridge Deck Joint Repair (LF), 806 Bridge Deck Maintenance and Repair (SF), and 810 Bridge Rail Maintenance and Repair (LF). Observations from the statewide reports (Tables 6.2 and 6.3) also show that most data were available for FDOT Districts 2 and 5, thus the research task focused on deriving cost estimates for these two districts.

The MMS activities listed in Table 6.1 are generic in terms of the definition for specific bridge MR&R activities, particularly MMS Activity No. 825 (Superstructure Maintenance and Repair) and MMS Activity No. 845 (Substructure Maintenance and Repair). So, one initial step was to refine the BWOL data, by filtering the instructions (activity descriptions) using keywords, to narrow down the data to more specific maintenance activities. For instance, the MMS Activity No. 845, Substructure Maintenance and Repair, was filtered with keywords “slope” and “protection” to extract the pertinent data for maintenance and repair of slope protection. Review and verification of the results showed example instructions such as “Remove vegetation from slope protection” and “Repair collapsed slope protection on southwest radius section.” Based on this filter approach, specific data were obtained for activities such as Clean and paint beam, Clean and paint bearing, Repair spalls on beam, Repair bent or pier cap, Clean and repair slope protection, and Repair footing. The refined BWOL data was then used for the analyses to obtain the required average costs.

Prior research projects have identified the incompatibility of the MMS units with Pontis and BrM bridge maintenance and repair activities. One approach taken to address this issue in this study was first to utilize a merge of the BWOL data with the BrM Bridge Table, extracting the deck area, to compute the labor effort in MH per bridge SF deck area. Then for each MMS activity, the derived MH/SF values were multiplied with the corresponding cost per MH (from statewide reports) to estimate the cost per SF deck area of the bridge. Tables 6.4 and 6.5 show the summary of the costs estimated based on this approach for FDOT Districts 2 and 5. Each table lists the MMS activities, and some specific activities where possible, along with the basic statistics of the labor effort or measure of the activity per bridge deck area. The first three MMS activities, Bridge Deck Joint Repair, Bridge Deck Maintenance and Repair, and Bridge Rail Maintenance and Repair, are measured in LF, SF, and LF, respectively, thus the mean numbers shown are for the average quantities of defects repaired in these units, relative to the bridge deck area. For the remaining MMS activities, which are measured in MH units in MMS, the mean values represent the MH per bridge deck area. So, in FDOT District 2, for the deck joint repair, on the average, 0.0110 LF of deck joint repairs are done per SF deck area of the entire bridge (Table 6.4).

Also, in general, maintenance and repair of the superstructure (MMS Activity No. 825) takes 0.0676 MH per bridge deck area to do, while specifically, for cleaning and painting beams, it takes 0.551MH/SF (small data size), and it takes 0.0118 MH/SF to repair spalls on beams. The statewide MMS contract cost report showed that for the 2021-2022 fiscal year, it costs $73.56/LF to do deck joint repairs, while the in-house statewide cost report shows $11.42/LF (Table 6.4). Multiplying each of the statewide report values with the mean LF/deck area SF values gives estimates of deck joint repairs as $0.81/deck area SF and $0.13/deck area SF, respectively, for using contract and in-house crews. For District 5, as shown in Table 6.5, similar computations indicate the mean LF/deck area SF estimates of deck joint repairs as $0.49/deck area SF and $0.10/deck area SF, respectively, for using contract and in-house crews. The variation in the estimated labor effort per bridge deck area (MH/SF) in FDOT Districts 2 and 5, are shown in Figures 6.1 and 6.2, respectively, for MMS Act 825 superstructure maintenance and repair, and MMS Act 845 substructure maintenance and repair. The figures indicate that for both districts, most of the values are less than or equal to 0.125 MH/SF. Figures 6.3 and 6.4 present the variation in the estimated costs per bridge SF deck area for FDOT Districts 2 and 5 bridges, for both the contract and in-house methods. The unit costs in FDOT District 5 are generally lower than those in District 2, with what appears to be a very high outlier value for bridge deck maintenance and repair unit cost of $205.35/SF in District 2 based on the contract method. For both districts, the contract unit costs were higher than those of the work done in-house.

Table 6.2. Summary of statewide MMS costs for contract bridge maintenance & repairs for (FY 2021 – 2022.

Bridge ID	MMS Activity No.	Unit	District	Units completed	Total cost	Average unit cost	Engineered cost	Engineered unit cost	No. of contracts
	805	LF	2	13072.50	$961,651.45	$73.56	$482,636.70	$36.92	6
			5	3972.00	$84,722.13	$21.33	$146,646.24	$36.92	1
			6	4321.59	$81,277.00	$18.81	$159,552.96	$36.92	4
			8	569.00	$105,817.50	$185.97	$21,007.48	$36.92	1
			ALL	21935.09	$1,233,468.08	$56.23	$809,843.38		12
	806	SF	2	605.75	$504,734.80	$833.24	$52,651.79	$86.92	6
			5	2124.00	$14,543.28	$6.85	$184,618.08	$86.92	2
			6	4574.17	$241,682.00	$52.84	$397,587.03	$86.92	3
			8	163.00	$98,840.00	$606.38	$14,167.96	$86.92	1
			ALL	7466.92	$859,800.08	$115.15	$649,024.86		12
	810	LF	2	544.00	$15,315.50	$28.15	$17,195.84	$31.61	4
			5	1230.00	$25,188.09	$20.48	$38,880.30	$31.61	1
			6	37.00	$1,628.00	$44.00	$1,169.57	$31.61	1
			ALL	1811.00	$42,131.59	$23.26	$57,245.71		6
	825	MH	2	391.50	$40,829.20	$104.29	$19,199.16	$49.04	5
790148			5	530.11	$46,155.95	$87.07	$25,996.59	$49.04	3
			6	1230.00	$615,000.00	$500.00	$60,319.20	$49.04	2
			8	2.00	$6,025.00	$3,012.50	$98.08	$49.04	1
			ALL	2153.61	$708,010.15	$328.76	$105,613.03		11
	845	MH	2	4597.00	$853,259.00	$185.61	$375,207.14	$81.62	7
			5	738.00	$21,896.53	$29.67	$60,235.56	$81.62	1
			8	136.00	$24,229.00	$178.15	$11,100.32	$81.62	1
			ALL	5471.00	$899,384.53	$164.39	$446,543.02		9
	859	MH	2	57.50	$4,000.20	$69.57	$5,303.80	$92.24	2
			6	14.00	$8,400.00	$600.00	$1,291.36	$92.24	1
			ALL	71.50	$12,400.20	$173.43	$6,595.16		3
	861	MH	2	18.00	$2,112.50	$117.36	$493.74	$27.43	1
	865	MH	2	549.50	$43,517.70	$79.20	$14,034.23	$25.64	4

Table 6.3. Summary of statewide MMS costs for In-house bridge maintenance and repairs for fiscal year 2021 – 2022.

MMS Activity No.	Unit	District	Total hours	Units completed	Labor cost	Labor unit cost	Equipment cost	Equipment unit cost	Material cost	Material unit cost	Total cost	Average unit cost	MH/Unit	Standard MH/Unit
805	LF	2	2188	7001	$54,274	$7.75	$25,648	$3.66	$0	$0.00	$79,922	$11.42	0.313	0.323
		4	52	100	$1,227	$11.58	$229	$2.16	$0	$0.00	$1,456	$13.74	0.491	0.323
		5	508	4521	$13,123	$2.90	$2,607	$0.58	$3,433	$0.76	$19,163	$4.24	0.112	0.323
		6	141	8	$2,858	$357.25	$2,174	$271.75	$0	$0.00	$5,032	$629.00	17.625	0.323
		ALL	2889	11636	$71,482	$6.14	$30,658	$2.63	$3,433	$0.30	$105,573	$9.07	0.248	0.323
		Engrd*				$10.53		$5.61		$5.21		$21.35		
806	SF	2	1994	8377	$48,070	$5.74	$21,394	$2.55	$0	$0.00	$69,464	$8.29	0.238	0.179
		4	105	282	$1,964	$6.96	$958	$3.40	$13	$0.05	$2,935	$10.41	0.372	0.179
		5	622	15996	$15,722	$0.98	$3,847	$0.24	$1,854	$0.12	$21,423	$1.34	0.039	0.179
		6	209	425	$4,295	$10.11	$4,461	$10.50	$0	$0.00	$8,756	$20.60	0.492	0.179
		ALL	2930	25080	$70,051	$2.79	$30,660	$1.22	$1,867	$0.07	$102,578	$4.09	0.117	0.179
		Engrd*				$6.20		$3.48		$0.68		$10.36		
810	LF	2	457	500	$11,748	$23.50	$1,418	$2.84	$0	$0.00	$13,166	$26.33	0.914	0.735
		3	15	180	$449	$2.49	$155	$0.86	$0	$0.00	$604	$3.36	0.083	0.735
		4	101	255	$2,320	$9.10	$950	$3.73	$0	$0.00	$3,270	$12.82	0.396	0.735
		5	91	1827	$2,260	$1.24	$513	$0.28	$0	$0.00	$2,773	$1.52	0.050	0.735
		6	17	23	$191	$8.30	$0	$0.00	$0	$0.00	$191	$8.30	0.739	0.735
		ALL	681	2785	$16,968	$6.09	$3,036	$1.09	$0	$0.00	$20,004	$7.18	0.245	0.735
		Engrd*				$12.66		$7.12		$0.69		$20.47		
825	MH	2	1950	1950	$51,055	$26.18	$25,994	$13.33	$0	$0.00	$77,049	$39.51	1.000	1.000
		4	21	21	$467	$22.24	$76	$3.62	$0	$0.00	$543	$25.86	1.000	1.000
		5	124	124	$3,370	$27.18	$741	$5.98	$131	$1.06	$4,242	$34.21	1.000	1.000
		ALL	2095	2095	$54,892	$26.20	$26,811	$12.80	$131	$0.06	$81,834	$39.06	1.000	1.000
		Engrd*				$23.48		$6.10		$0.62		$30.20		
845	MH	2	4727	4727	$106,161	$22.46	$39,748	$8.41	$215,930	$45.68	$361,839	$76.55	1.000	1.000
		4	109	109	$2,591	$23.77	$1,006	$9.23	$0	$0.00	$3,597	$33.00	1.000	1.000
		5	1941	1941	$46,122	$23.76	$9,363	$4.82	$4,637	$2.39	$60,122	$30.97	1.000	1.000
		6	260	260	$2,913	$11.20	$829	$3.19	$0	$0.00	$3,742	$14.39	1.000	1.000
		ALL	7037	7037	$157,787	$22.42	$50,946	$7.24	$220,567	$31.34	$429,300	$61.01	1.000	1.000
		Engrd*				$19.26		$6.97		$3.41		$29.64		

Engineered costs.

Table 6.3. Summary of statewide MMS costs for In-house bridge maintenance and repairs for fiscal year 2021 – 2022 (Cont'd).

MMS Activity No.	Unit	District	Total hours	Units completed	Labor cost	Labor unit cost	Equipment cost	Equipment unit cost	Material cost	Material unit cost	Total cost	Average unit cost	MH/Unit	Standard MH/Unit
859	MH	2	1086	1086	$26,174	$24.10	$8,918	$8.21	$0	$0.00	$35,092	$32.31	1.000	1.000
		4	2	2	$58	$29.00	$82	$41.00	$0	$0.00	$140	$70.00	1.000	1.000
		5	81	81	$2,267	$27.99	$428	$5.28	$0	$0.00	$2,695	$33.27	1.000	1.000
		ALL	1169	1169	$28,499	$24.38	$9,428	$8.07	$0	$0.00	$37,927	$32.44	1.000	1.000
		Engrd*				$18.67		$3.13		$1.03		$22.83		
861	MH	2	1396	1396	$41,835	$29.97	$8,790	$6.30	$0	$0.00	$50,625	$36.26	1.000	1.000
		ALL	1396	1396	$41,835	$29.97	$8,790	$6.30	$0	$0.00	$50,625	$36.26	1.000	1.000
		Engrd*				$17.55		$1.27		$6.88		$25.70		
865	MH	2	6097	6097	$186,116	$30.53	$26,244	$4.30	$0	$0.00	$212,360	$34.83	1.000	1.000
		ALL	6097	6097	$186,116	$30.53	$26,244	$4.30	$0	$0.00	$212,360	$34.83	1.000	1.000
		Engrd*				$20.24		$2.45		$3.39		$26.08		
869	MH	2	198	198	$6,053	$30.57	$466	$2.35	$0	$0.00	$6,519	$32.92	1.000	1.000
		ALL	198	198	$6,053	$30.57	$466	$2.35	$0	$0.00	$6,519	$32.92	1.000	1.000
		Engrd*				$20.55		$6.00		$2.86		$29.41		

**Engineered costs.*

Table 6.4. Summary of the costs and labor effort/bridge deck area estimates for bridge maintenance and repair activities in FDOT District 2[#].

MMS Activity No.	Description	Details	Mean	Median	Std. Dev.	Min.	Max.	Count	Contract costs (2021/2022)			In-House costs (2021/2022)		
									$/MH**	**$/SF***	$/Unit**	$/MH**	**$/SF***	$/Unit**
805	Bridge Deck Joint Repair	All	0.0110	0.0011	0.0409	0.00000	0.7391	1654		**$0.81**	$73.56		**$0.13**	$11.42
806	Bridge Deck Maintenance and Repair	All	0.2465	0.0010	1.3400	0.00001	10.7789	1376		**$205.35**	$833.24		**$2.04**	$8.29
810	Bridge Rail Maintenance and Repair	All	0.0422	0.0015	0.1298	0.00001	0.7384	356		**$1.19**	$28.15		**$1.11**	$26.33
825	Superstructure Maintenance and Repair	All	0.0676	0.0009	0.3582	0.00001	5.5829	628	$104.29	**$7.05**		$39.51	**$2.67**	
825	Superstructure Maintenance and Repair	Clean and paint beam	0.5510	0.0011	0.8673	0.00011	1.9045	6	$104.29	**$57.47**		$39.51	**$21.77**	
825	Superstructure Maintenance and Repair	Clean and paint bearing	0.0092	0.0095	0.0082	0.00004	0.0172	5	$104.29	**$0.96**		$39.51	**$0.36**	
825	Superstructure Maintenance and Repair	Repair spalls on beam	0.0118	0.0021	0.0378	0.00008	0.4170	139	$104.29	**$1.23**		$39.51	**$0.47**	
845	Substructure Maintenance and Repair	All	0.2299	0.0013	1.3281	0.00001	19.8045	2295	$185.61	**$42.67**		$76.55	**$17.60**	
845	Substructure Maintenance and Repair	Repair bent or pier cap	0.1829	0.0018	1.4626	0.00003	12.2431	70	$185.61	**$33.94**		$76.55	**$14.00**	
845	Substructure Maintenance and Repair	Clean and repair slope protection	0.1963	0.0018	1.2304	0.00007	13.2986	149	$185.61	**$36.44**		$76.55	**$15.03**	
845	Substructure Maintenance and Repair	Repair footing							$185.61			$76.55		
859	Channel Maintenance	All	0.0022	0.0004	0.0063	0.00001	0.0550	196	$69.57	**$0.15**		$32.31	**$0.07**	
861	Bridge Electrical Maintenance	All	0.0004	0.0002	0.0035	0.00001	0.0632	333	$117.36	**$0.04**		$36.26	**$0.01**	
865	Movable Bridge Mechanical Maintenance	All	0.0003	0.0002	0.0003	0.00008	0.0019	338	$79.20	**$0.02**		$34.83	**$0.01**	
869	Movable Bridge Structural Maintenance	All	0.0002	0.0002	0.0003	0.00001	0.0027	276				$32.92	**$0.01**	

 # Units are MH/SF deck area except for ACT 805 and 810 (LF of deck repair/deck area in SF) and ACT 806 (SF of deck repair/deck area in SF).

** SF of bridge deck area*

*** From statewide MMS annual report, based on unit of defect repair (LF for Act 805 and Act 810; SF for Act 806).*

Not available for district; use state average if available.

Table 6.5. Summary of the costs and labor effort/bridge deck area estimates for bridge maintenance and repair activities in FDOT District 5#.

MMS Activity No.	Description	Details	Mean	Median	Std. Dev.	Min.	Max.	Count	Contract costs (2021/2022)			In-House costs (2021/2022)		
									$/MH**	**$/SF***	$/Unit**	$/MH**	**$/SF***	$/Unit**
805	Bridge Deck Joint Repair	All	0.0228	0.0038	0.0482	0.00002	0.7349	1778		**$0.49**	$21.33		**$0.10**	$4.24
806	Bridge Deck Maintenance and Repair	All	0.2045	0.0020	0.9911	0.00002	10.7639	1789		**$1.40**	$6.85		**$0.27**	$1.34
810	Bridge Rail Maintenance and Repair	All	0.0773	0.0021	0.1615	0.00003	1.5016	836		**$1.58**	$20.48		**$0.12**	$1.52
825	Superstructure Maintenance and Repair	All	0.0223	0.0020	0.2204	0.00002	4.3075	786	$87.07	**$1.94**		$34.21	**$0.76**	
825	Superstructure Maintenance and Repair	Clean and paint beam	0.0073	0.0019	0.0103	0.00022	0.0379	44	$87.07	**$0.63**		$34.21	**$0.25**	
825	Superstructure Maintenance and Repair	Clean and paint bearing	0.0204	0.0078	0.0312	0.00022	0.1664	78	$87.07	**$1.78**		$34.21	**$0.70**	
825	Superstructure Maintenance and Repair	Repair spalls on beam	0.0096	0.0041	0.0150	0.00007	0.1158	144	$87.07	**$0.83**		$34.21	**$0.33**	
845	Substructure Maintenance and Repair	All	0.0071	0.0028	0.0197	0.00002	0.5825	2939	$29.67	**$0.21**		$30.97	**$0.22**	
845	Substructure Maintenance and Repair	Repair bent or pier cap	0.0082	0.0010	0.0213	0.00007	0.1347	140	$29.67	**$0.24**		$30.97	**$0.25**	
845	Substructure Maintenance and Repair	Clean and repair slope protection	0.0080	0.0034	0.0155	0.00005	0.1771	1067	$29.67	**$0.24**		$30.97	**$0.25**	
845	Substructure Maintenance and Repair	Repair footing	0.0006	0.0002	0.0008	0.00005	0.0027	11	$29.67	**$0.02**		$30.97	**$0.02**	
859	Channel Maintenance	All	0.0367	0.0013	0.3325	0.00004	4.0375	151	$69.57	**$2.55**		$33.27	**$1.22**	
861	Bridge Electrical Maintenance	All	0.0011	0.0006	0.0032	0.00006	0.0379	141	$117.36	**$0.13**		$36.26	**$0.04**	
865	Movable Bridge Mechanical Maintenance	All	0.0029	0.0011	0.0050	0.00014	0.0304	111	$79.20	**$0.23**		$34.83	**$0.10**	
869	Movable Bridge Structural Maintenance	All	0.0062	0.0010	0.0165	0.00014	0.1167	121				$32.92	**$0.21**	

 # Units are MH/SF deck area except for ACT 805 and 810 (LF of deck repair/deck area in SF) and ACT 806 (SF of deck repair/deck area in SF).

** SF of bridge deck area*

*** From statewide MMS annual report, based on unit of defect repair (LF for Act 805 and Act 810; SF for Act 806).*

Not available for district; use state average if available.

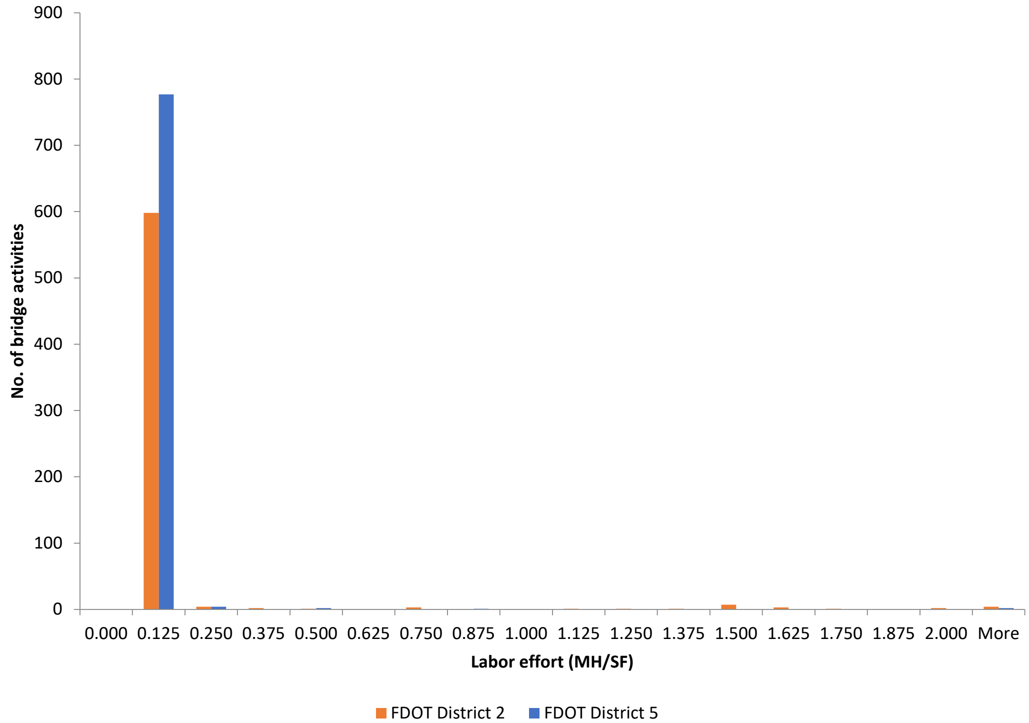


Figure 6.1. Labor effort per bridge deck area in Districts 2 & 5 for superstructure maintenance and repair.

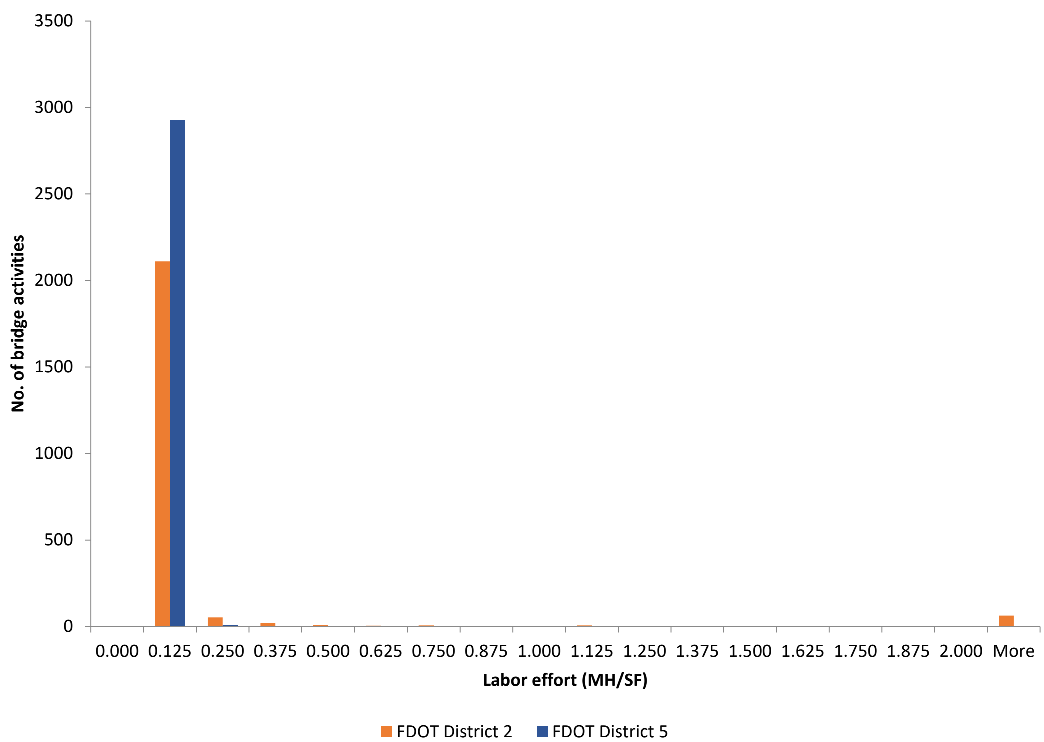


Figure 6.2. Labor effort per bridge deck area in Districts 2 & 5 for substructure maintenance and repair.

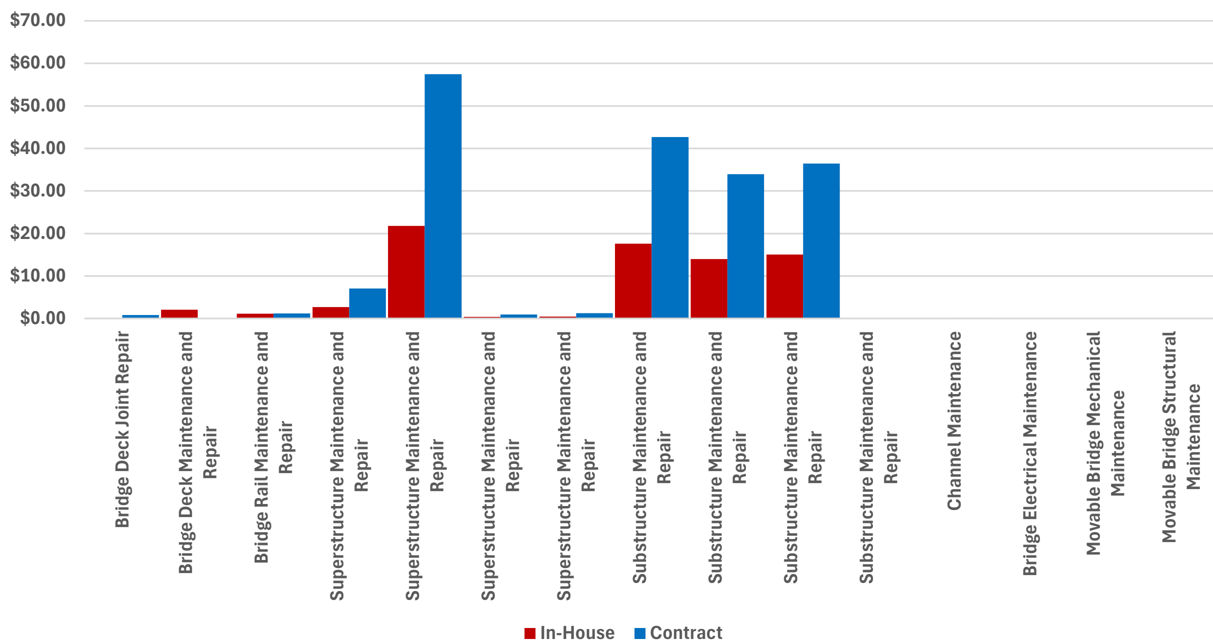


Figure 6.3. FDOT District 2’s bridge maintenance and repair unit costs ($/deck area SF) without $205/SF outlier.

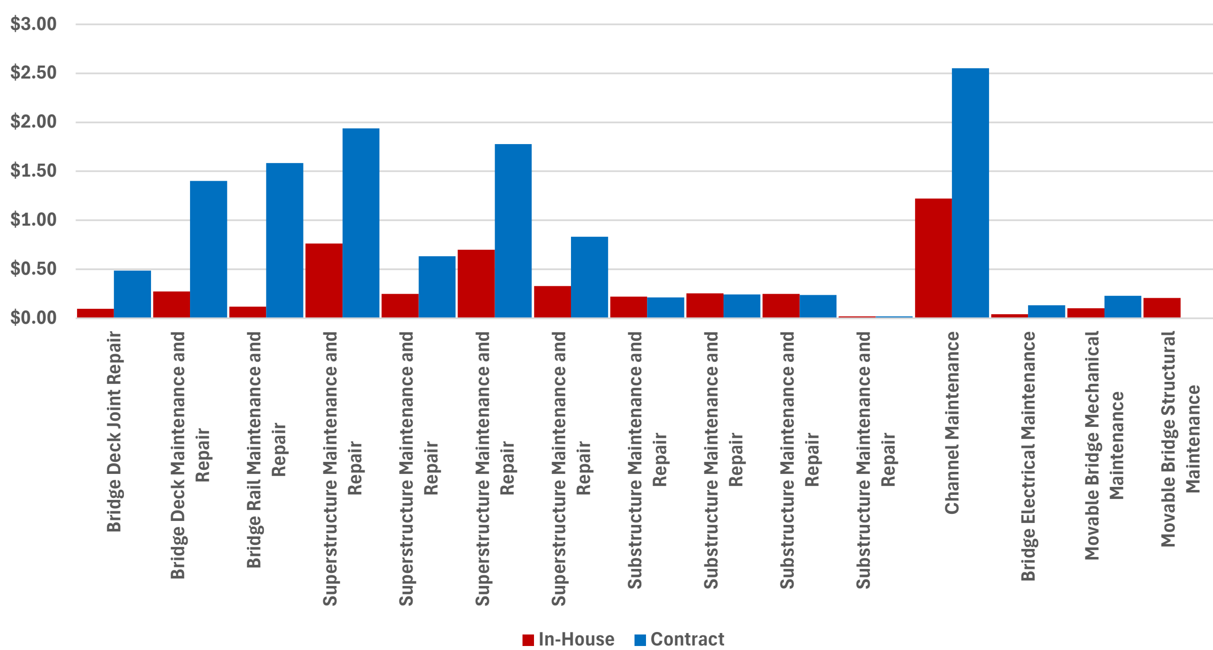


Figure 6.4. FDOT District 5’s bridge maintenance and repair unit costs ($/deck area SF).

6.2. FDOT's Historical Bid Costs

The most recent historical bid data for FDOT was downloaded from the FDOT's Office of Forecasting and Performance, indicating the Years 2021 to 2023 (FDOT 2024). Based on the pay item descriptions in the data, a list of bridge MR&R activities was developed and matched to the corresponding Pay Item Nos., as illustrated in Figure 6.5 for sample activities. This mapping can be used to automate the generation of bridge MR&R data from the FDOT bid historical costs. The bid cost data was finally filtered to remove pay items that are not related to bridge MR&R activities.

FDOT Historical Bid Cost Database

Bridge MR&R activity

Beam repair

Pay Item No.	Description	Unit of Measure
0450 82	BEAM REPAIR	LF
0450 83 1	BEAM REPAIR, STRAND SPLICES	EA
0450 83 2	BEAM REPAIR, BAR SPLICES	EA

Cathodic protection

Pay Item No.	Description	Unit of Measure
0400 60 3	CATHODIC PROTECTION-ELECT WORK, CODUIT,	LF
0400 60 4	CATHODIC PROTECTION-ELECT WORK, EQUIP,	LS
0400142 3	CATHODIC PROTECTION SYSTEM, ZINC ALUM SP	SF
0400142 3	CATHODIC PROTECTION SYSTEM, ZINC ALUM SP	SF
0400142 7	CATHODIC PROTECTION SYSTEM,TITANIUM MESH	SF
0400142 9	CATHODIC PROTECTION SYSTEM,OTHER MATRL	SF
0455 81102	CATHODIC PROT,F&I,PILE,ZINC ANODE ASSEM	EA
0455 81106	CATHODIC PROT,F&I,PIER,OTHER MATERIAL	EA
0457 2121	CATH PROT INTE PILE JA, NON-STR, 16.1-30	LF
0457 2211	CATH PROT INTE PILE JA, STR,UP TO 16	LF
0457 2221	CATH PROT INTE PILE JA, STR, 16.1-30	LF
0457 2231	CATH PROT INT PILE JKT, >30", GALV SYS	LF

Deck joint rehab, repair or replacement

Pay Item No.	Description	Unit of Measure
0400 32	CONCRETE FOR JOINT REPAIR	CY
0458 1 11	BRIDGE DECK EXPANSION JNT,NEW,POURED	LF
0458 1 12	BRIDGE DECK EXPANSION JNT,NEW,STRIP SEAL	LF
0458 1 13	BRIDGE DECK EXPANSION JNT,NEW,MODULAR	LF
0458 1 14	BRIDGE DECK EXPANSION JNT,NEW,FINGER JNT	LF
0458 1 21	BRIDGE DECK EXPANSION JNT, REHAB,POURED	LF
0458 1 22	BRIDGE DECK EXPANSION JNT, REHAB,STRIP	LF
0458 1 24	BRIDGE DECK EXPAN JNT,REHAB,FINGER JNT	LF
0458 1 25	BRIDGE DECK EXPAN JNT, REHAB,COMPRESSION	LF
0458 1 28	BRIDGE DECK EXP JNT,REHAB,POURED W/O ROD	LF

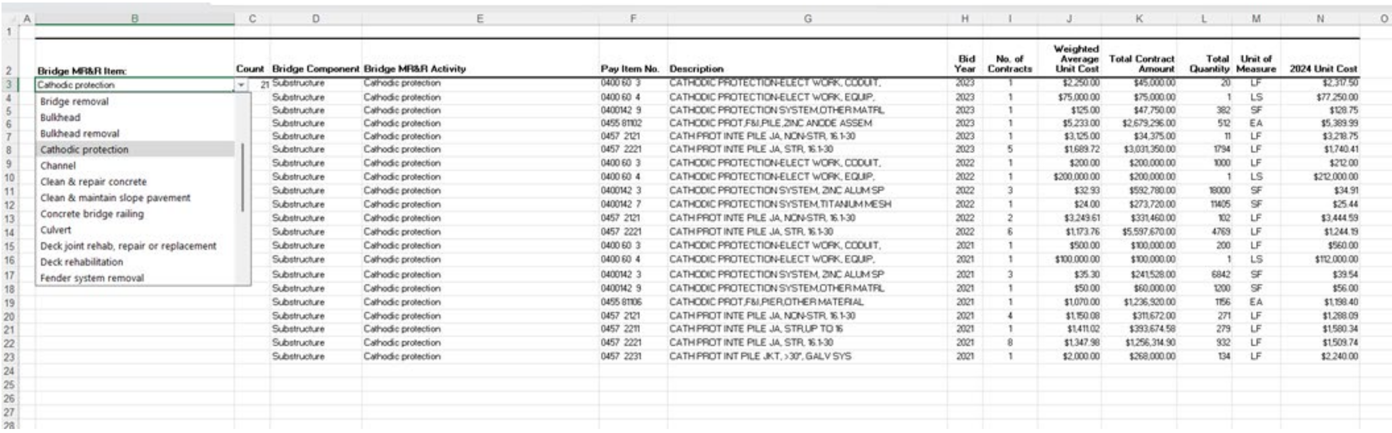
Figure 6.5. Sample mapping of Bridge MR&R activity to FDOT Pay Item Nos.

The resulting data was analyzed to estimate the mean unit costs, with the results summarized as shown in Table 6.6, separating the estimates based on the different units of measure with each bridge MR&R activity; an example of the item description is also shown in the table for each activity and unit of measure. The historical bid cost for each record in the database was converted to 2024 dollars to account for inflation, using the consumer price indexes shown in Table 6.7 for the Florida transportation industry (BLS 2024). The complete list of historical cost bid costs, for the bridge MR&R activities, broken down by categories, is shown in Appendix D Tables D1 to D5.

Table 6.6. Summary of bridge maintenance & repair unit costs from FDOT bid cost database (2021 – 2023).

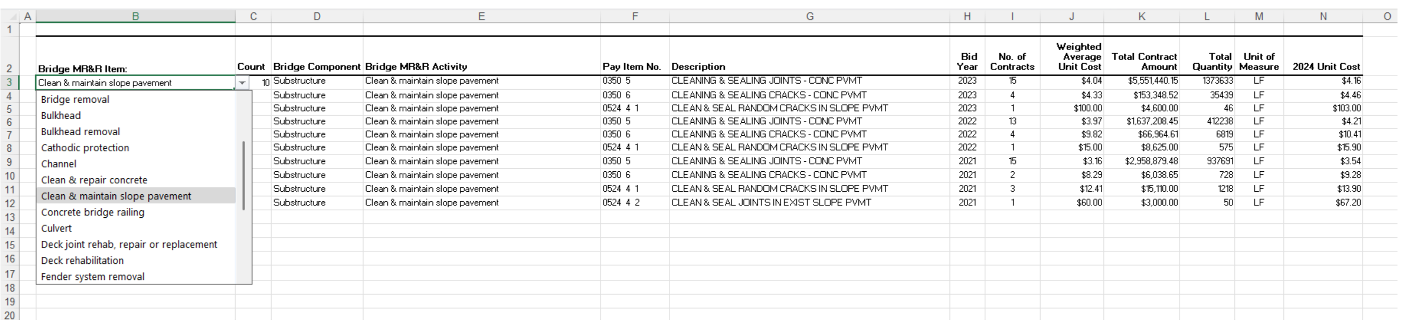
Bridge MR&R Activity	Unit of Measure	2024 Mean Unit Cost	Example of Pay Item in Unit
Approach slab	CY	$650.98	CONC CLASS II, APPROACH SLABS
	LB	$1.53	REINF STEEL- APPROACH SLABS
	LF	$137.84	BRIDGE APPR EXP JOINT FOR CONC PVMT
Beam repair	EA	$2,432.14	BEAM REPAIR, STRAND SPLICES
	LF	$782.69	BEAM REPAIR
Bearing pad	CF	$1,525.72	COMPOSITE NEOPRENE PADS
	EA	$8,176.02	NEOPRENE PAD REPLACEMENT, BENT/PIER
Bridge drains	EA	$4,919.03	BRIDGE DRAINS
	LF	$311.64	BRIDGE DRAINAGE PIPE
Bridge monitoring	LS	$17,782.90	MONITOR EXISTING STRUCTURES- VIBRA
Bridge removal	MB	$3,497.93	REMOVE & DISPOSE OF STRUCTURAL TIMBER
	SF	$45.78	REMOVAL OF EXISTING STRUCTURES/BRIDGES
Bulkhead removal	LF	$269.39	REMOVE EXISTING BULKHEAD
Cathodic protection	EA	$3,294.20	CATHODIC PROT,F&I,PILE,ZINC ANODE ASSEM
	LF	$11,890.51	CATHODIC PROTECTION-ELECT WORK, CODUIT,
	LS	$25,774.81	CATHODIC PROTECTION-ELECT WORK, EQUIP,
	SF	$71.16	CATHODIC PROTECTION SYSTEM,TITANIUM MESH
Channel	CY	$57.02	CHANNEL EXCAVATION
Clean & maintain slope pavement	LF	$23.61	CLEANING & SEALING CRACKS - CONC PVMT
Clean & repair concrete	CF	$491.84	RESTORE SPALLED AREAS, EPOXY
	SF	$4.60	CLEAN & COAT CONCRETE SURF , CLASS 5
Concrete bridge railing	EA	$6,880.34	CONC TRAF RAIL- BRG, RETRO-POST & BEAM
	LF	$406.83	CONC TRAF RAIL- BRG, 32" VERT FACE
Culvert	CY	$1,701.04	CONC CLASS II, CULVERTS
Deck joint rehab, repair or replacement	CY	$14,689.15	CONCRETE FOR JOINT REPAIR
	LF	$554.92	BRIDGE DECK EXPANSION JNT,NEW,POURED
Deck rehabilitation	CY	$4,187.48	CONC CLASS IV, PRECAST DECK OVERLAY
	SY	$12.00	BRIDGE DECK GROOVING
Deck removal	SF	$376.30	REMOVAL OF EXIST CONC BRIDGE DECK
Fender system removal	LF	$359.34	BRIDGE FENDER SYSTEM, REMOVAL & DISPOSAL
Movable bridge maintenance and repair	AS	$70,846.12	MOV BRDG MACH & CAST-REHAB,F&I,SPAN LOCK
	DA	$476.94	MOVABLE BRIDGE OPERATOR
	EA	$81,526.73	MOV BRDG MACH & CAST-REHAB,F&I,HYDRAULIC
	LS	$854,077.52	MOV BRDG MACH & CAST-REHAB,F&I,SPEED
Pedestrian bridge	SF	$570.55	PREFABRICATED STEEL PED BRIDGE
Prestressed beam	LF	$486.29	PREST BEAMS: FLORIDA-I BEAM 36"
Replace slope pavement	CY	$1,015.55	CONC PAVT SLAB REPLACEMENT
	SY	$149.56	CONC SLOPE PAVT, NR, 4"
Structural steel	LB	$13.58	STRUCT STEEL REHAB-BOLT, NUT, WASH & PLT
	LF	$4,770.00	STRUCT STEEL - REHAB, MISC.
Substructure concrete material	CY	$1,612.17	CONC CLASS II, BRIDGE SUBSTRUCTURE
Substructure reinf steel material	LB	$1.77	REINF STEEL- SUBSTRUCTURE
Superstructure concrete material	CY	$1,187.13	CONC CLASS II, BRIDGE SUPERSTRUCTURE
Superstructure reinf steel material	LB	$1.53	REINF STEEL- SUPERSTRUCTURE

To enhance a quick browsing of the bid historical cost data on bridge MR&R, a simple record filter worksheet was developed in Microsoft Excel with screenshots shown in 6, in this case, showing the data for cathodic protection, selected through a pull-down menu. The 21 records for cathodic protection in the database are shown, including their pertinent attributes. Also as shown in Figure 6.6, for the activity "Clean and maintain slope protection" there are 10 records on the database, with the various contributing information in terms of the Pay item numbers, bid year, etc.



Bridge Component	Bridge MR&R Activity	Pay Item No.	Description	Bid Year	No. of Contracts	Weighted Average Unit Cost	Total Contract Amount	Total Quantity	Unit of Measure	2024 Unit Cost
Substructure	Cathodic protection	0400 60 3	CATHODIC PROTECTION-ELECT WORK, CODUIT,	2023	1	$2,250.00	$45,000.00	20	LF	$2,317.50
Substructure	Cathodic protection	0400 60 4	CATHODIC PROTECTION-ELECT WORK, EQUIP,	2023	1	$75,000.00	$75,000.00	1	LS	$77,250.00
Substructure	Cathodic protection	0400142 9	CATHODIC PROTECTION SYSTEM,OTHER MATRL	2023	1	$125.00	$47,750.00	382	SF	$128.75
Substructure	Cathodic protection	0455 81102	CATHODIC PROT,F&I,PILE,ZINC ANODE ASSEM	2023	1	$5,233.00	$2,679,296.00	512	EA	$5,389.99
Substructure	Cathodic protection	0457 2121	CATH PROT INTE PILE JA, NON-STR, 16.1-30	2023	1	$3,125.00	$34,375.00	11	LF	$3,218.75
Substructure	Cathodic protection	0457 2221	CATH PROT INTE PILE JA, STR, 16.1-30	2023	5	$1,689.72	$3,031,350.00	1794	LF	$1,740.41
Substructure	Cathodic protection	0400 60 3	CATHODIC PROTECTION-ELECT WORK, CODUIT,	2022	1	$200.00	$200,000.00	1000	LF	$212.00
Substructure	Cathodic protection	0400 60 4	CATHODIC PROTECTION-ELECT WORK, EQUIP,	2022	1	$200,000.00	$200,000.00	1	LS	$212,000.00
Substructure	Cathodic protection	0400142 3	CATHODIC PROTECTION SYSTEM, ZINC ALUM SP	2022	3	$32.93	$592,780.00	18000	SF	$34.91
Substructure	Cathodic protection	0400142 7	CATHODIC PROTECTION SYSTEM,TITANIUM MESH	2022	1	$24.00	$273,720.00	11405	SF	$25.44
Substructure	Cathodic protection	0457 2121	CATH PROT INTE PILE JA, NON-STR, 16.1-30	2022	2	$3,249.61	$331,460.00	102	LF	$3,444.59
Substructure	Cathodic protection	0457 2221	CATH PROT INTE PILE JA, STR, 16.1-30	2022	6	$1,173.76	$5,597,670.00	4769	LF	$1,244.19
Substructure	Cathodic protection	0400 60 3	CATHODIC PROTECTION-ELECT WORK, CODUIT,	2021	1	$500.00	$100,000.00	200	LF	$560.00
Substructure	Cathodic protection	0400 60 4	CATHODIC PROTECTION-ELECT WORK, EQUIP,	2021	1	$100,000.00	$100,000.00	1	LS	$112,000.00
Substructure	Cathodic protection	0400142 3	CATHODIC PROTECTION SYSTEM, ZINC ALUM SP	2021	3	$35.30	$241,528.00	6842	SF	$39.54
Substructure	Cathodic protection	0400142 9	CATHODIC PROTECTION SYSTEM,OTHER MATRL	2021	1	$50.00	$60,000.00	1200	SF	$56.00
Substructure	Cathodic protection	0455 81106	CATHODIC PROT,F&I,PIER,OTHER MATERIAL	2021	1	$1,070.00	$1,236,920.00	1156	EA	$1,198.40
Substructure	Cathodic protection	0457 2121	CATH PROT INTE PILE JA, NON-STR, 16.1-30	2021	4	$1,150.08	$311,672.00	271	LF	$1,288.09
Substructure	Cathodic protection	0457 2211	CATH PROT INTE PILE JA, STR,UP TO 16	2021	1	$1,411.02	$393,674.58	279	LF	$1,580.34
Substructure	Cathodic protection	0457 2221	CATH PROT INTE PILE JA, STR, 16.1-30	2021	8	$1,347.98	$1,256,314.90	932	LF	$1,509.74
Substructure	Cathodic protection	0457 2231	CATH PROT INT PILE JKT, >30", GALV SYS	2021	1	$2,000.00	$268,000.00	134	LF	$2,240.00

a. Cathodic protection



Bridge Component	Bridge MR&R Activity	Pay Item No.	Description	Bid Year	No. of Contracts	Weighted Average Unit Cost	Total Contract Amount	Total Quantity	Unit of Measure	2024 Unit Cost
Substructure	Clean & maintain slope pavement	0350 5	CLEANING & SEALING JOINTS - CONC PVMT	2023	15	$4.04	$5,551,440.15	1373633	LF	$4.16
Substructure	Clean & maintain slope pavement	0350 6	CLEANING & SEALING CRACKS - CONC PVMT	2023	4	$4.33	$153,348.52	35439	LF	$4.46
Substructure	Clean & maintain slope pavement	0524 4 1	CLEAN & SEAL RANDOM CRACKS IN SLOPE PVMT	2023	1	$100.00	$4,600.00	46	LF	$103.00
Substructure	Clean & maintain slope pavement	0350 5	CLEANING & SEALING JOINTS - CONC PVMT	2022	13	$3.97	$1,637,208.45	412238	LF	$4.21
Substructure	Clean & maintain slope pavement	0350 6	CLEANING & SEALING CRACKS - CONC PVMT	2022	4	$9.82	$66,964.61	6819	LF	$10.41
Substructure	Clean & maintain slope pavement	0524 4 1	CLEAN & SEAL RANDOM CRACKS IN SLOPE PVMT	2022	1	$15.00	$8,625.00	575	LF	$15.90
Substructure	Clean & maintain slope pavement	0350 5	CLEANING & SEALING JOINTS - CONC PVMT	2021	15	$3.16	$2,958,879.48	937691	LF	$3.54
Substructure	Clean & maintain slope pavement	0350 6	CLEANING & SEALING CRACKS - CONC PVMT	2021	2	$8.29	$6,038.65	728	LF	$9.28
Substructure	Clean & maintain slope pavement	0524 4 1	CLEAN & SEAL RANDOM CRACKS IN SLOPE PVMT	2021	3	$12.41	$15,110.00	1218	LF	$13.90
Substructure	Clean & maintain slope pavement	0524 4 2	CLEAN & SEAL JOINTS IN EXIST SLOPE PVMT	2021	1	$60.00	$3,000.00	50	LF	$67.20

b. Clean and maintain slope protection

Figure 6.6. Excel spreadsheet for filter and review of bridge MR&R bid costs.

Table 6.7. Consumer price indexes for the Florida transportation industry (BLS 2024).

Year	Jan	Dec	Jan_Factor	Dec_Factor
2014	1586.0	1645.7	1.26	1.23
2015	1648.2	1692.3	1.21	1.19
2016	1684.4	1723.3	1.19	1.17
2017	1725.2	1752.4	1.16	1.15
2018	1757.4	1780.1	1.14	1.14
2019	1789.0	1815.0	1.12	1.11
2020	1815.2	1760.9	1.10	1.15
2021	1785.7	1895.4	1.12	1.07
2022	1886.4	1941.8	1.06	1.04
2023	1945.4	1999.7	1.03	1.01
2024	1998.2	2020.9*	1.00	1.00

- *Preliminary/estimated.*

6.3. Crew-based Estimated Costs

The crew-based approach is a good method for estimating detailed costs of construction tasks and the project. Detailed cost estimates, as done for constructor's estimates while preparing bids, and also estimating the cost of change orders during construction, involves identifying the labor and equipment necessary to get the task done. This approach is appropriate for estimating the cost of bridge MR&R activities, since these activities also require the use of crews.

Crew-based cost estimating is the methodology employed by contractors in developing detailed cost estimates for competitive bids. In crew-based estimating, the labor composition is listed in terms of the specific trades needed (carpenters, concrete masons, cement finishers, steel workers, etc.), and the equipment required to perform the task (e.g., portable air compressor, gas, concrete mixer, steel grinder, welding equipment, etc.). The hourly cost rates of the labor trades and the daily costs of the equipment are needed to compute the daily costs of labor and equipment, respectively. It is necessary to know the crew's daily production rate, based on historical records or getting the information from published cost handbooks. The ratio of daily labor cost to the crew daily production rate estimates the labor unit cost for the task. Similarly, the unit cost of equipment can be estimated. The remaining component of the cost is the material cost. This can be obtained through quotes from vendors or from in-house inventory records. The estimated quantity of work to be done is applied to the labor and equipment unit costs, and added to the cost of materials, to obtain the total costs. It should be noted that the cost inputs described above reflect the typical direct costs; it will be necessary to add the overhead and indirect costs (materials sales taxes, transportation costs, labor fringe benefits, contingencies, etc.,) to obtain the final estimates.

6.3.1. RS Means Cost Data Application

A popular cost manual, the RS Means Cost Manual, utilizes the crew-based methodology for buildings and highway construction projects, but none specifically for bridge new construction or maintenance and repair work. The use of RS Means data for cost estimating has been demonstrated at federal agencies such as the Department of Energy (DOE) (Mewis and Keller 2022). While not specifically listed for bridge repairs, the concrete repair and cast-in-place activities from RS Means Heavy Construction Cost Data are used to illustrate the crew-based method as shown in Figures 6.7 to 6.9. The standard crew composition and costs are based on a data collection from 30 cities in the U.S. Thus the costs need to be adjusted using location indices for application to a specific Florida city. A rough adjustment of 50% will appear reasonable for Florida costs.

The methodology for using the RS Means cost data involves first identifying the maintenance activity, such as repairing concrete cracks by epoxy injection (ACI RAP-1), shown in Figure 6.8. The activity's line number is 03 01 30.71 1015 (CSI Masterformat code) when routing crack with v-notch chaser. The recommended crew for this activity is C-32, and the cost manual states that the crew can repair 600 LF per day. The bare (direct) unit cost of labor is calculated as the total daily labor cost divided by the crew daily production rate, i.e., (\$99.04 + \$93.15)/600 = \$1.45/LF. Similarly, the bare (direct) unit cost of equipment is the total daily equipment cost by the crew daily production rate, i.e., (\$467.60 + \$401.60)/600 = \$0.32/LF. The unit cost materials provided can be used directly or adjusted for location. Figures 6.7 and 6.9 show similar illustrations on estimating cost for concrete crack repair and casting concrete in place. In the latter two cases, the material costs will be added to the labor and equipment costs.

03 01 30.71 Concrete crack repair		Crew	Daily Prod. Rate	Unit	LaborHour /Unit	Material	Labor	Equipment	Total
	Structural repair of concrete cracks by epoxy injection (ACI RAP-1)								
	Suitable for horizontal, vertical and overhead repairs.								
1015	Rout crack with v-notch chaser, if needed.	**C-32**	**600**	**LF**	0.027	$0.03	$1.45	$0.32	$1.80
1020	Blow out crack with oil-free dry compressed air (1 pass).	C-28	**3000**	LF	0.005	$0.00	$0.16	$0.01	$0.17
1040	Cap crack at surface with epoxy gel (per side/face).	Cefi*	400	LF	0.020	$0.36	$1.17	$0.00	$1.53
1510	Pneumatic injection with 2-part bulk epoxy, excl. prep., up to 5/32" wide x 4" deep	C31	240	LF	0.033	$0.25	$1.95	$1.60	$3.80
	*Cefi = Cement finisher								

	RS Means Year 2025 (Bare costs -- Standard Crew)		
No.	Crew C-32	Hr. or Day*	Daily
1	Cement Finisher	$58.45	$467.60
1	Laborer	50.20	401.60
1	Crack Chaser Saw, Gas, 6 H.P.	99.04	99.04
1	Vacuum Pick-Up System	93.15	93.15
16	L.H., Daily Totals		
No.	Crew C-28	Hr. or Day*	Daily
1	Cement Finisher	$58.45	$467.60
1	Portable Air Compressor, Gas	36.95	36.95
16	L.H., Daily Totals		
No.	Cefi	Hr. or Day*	Daily
1	Cement Finisher	$58.45	$467.60
8	L.H., Daily Totals		
No.	Crew C-31	Hr. or Day*	Daily
1	Cement Finisher	$58.45	$467.60
1	Grout Pump	385.11	385.11
8	L.H., Daily Totals		
Hr. for Labor and Day for Equipment.			

Figure 6.7. Crew-based cost estimating of concrete crack repair based on RS Means Cost Data.

03 01 30.72 Concrete surface repairs		Crew	Daily Prod. Rate	Unit	LaborHour /Unit	Material	Labor	Equipment	Total
	Surface repair by Methacrylate flod coat (ACI RAP-13)								
	Large cracks must previously have been repaired or filled.								
9100	Shotblast entire surface to remove contaminants	**A-1A**	**4000**	**SF**	0.002		$0.13	$0.06	$0.19
9200	Blow off dusts and debris with oil-free compressed air	C-28	**16000**	SF	0.001		$0.03	$0.00	$0.03

	RS Means Year 2025 (Bare costs -- Standard Crew)		
No.	Crew A-1A	Hr. or Day*	Daily
1	Skilled Worker	$65.20	$521.60
1	Shot Blaster, 20"	248.63	248.63
8	L.H., Daily Totals		
No.	Crew C-28	Hr. or Day*	Daily
1	Cement Finisher	$58.45	$467.60
1	Portable Air Compressor, Gas	36.95	36.95
16	L.H., Daily Totals		
Hr. for Labor and Day for Equipment.			

Figure 6.8. Crew-based cost estimating of concrete surface repair based on RS Means Cost Data.

03 30 53.40 Concrete In Place		Crew	Daily Prod. Rate	Unit	LaborHour/Unit	Material	Labor	Equipment	Total
	Incl. forms, rebar, concrete, placement, and finishing.								
0300	Beams, (3500 psi), 5 kip/LF, 10' span	**C-14A**	**15.62**	**CY**	12.804	$340.00	$800.13	$59.69	$1,199.82
0700	Columns, square (4000 psi), 12" x 12" , up to 1% reinf.	C-14A	**11.96**	CY	16.722	$380.00	$1,044.98	$77.95	$1,502.94
5950	Pile caps (3000 psi), incl. forms and reinf., over 10 CY.	C-14C	75	CY	1.493	$175.00	$89.05	$0.43	$264.48
6350	Retaining walls (3000 psi), cantilever, level backfill loading, 16' high	C-14D	91	CY	2.198	$165.00	$136.29	$10.25	$311.53

RS Means Year 2025 (Bare costs -- Standard Crew)			
No.	Crew C-14A	Hr. or Day*	Daily
1	Carpenter Foreman (outside)	$64.40	$515.20
16	Carpenters	62.40	7987.20
4	Rodmen (reinf.)	68.40	2188.80
2	Laborers	50.20	803.20
1	Cement Finisher	58.45	467.60
1	Equip. Oper. (medium)	67.00	536.00
1	Gas Engine Vibrator	32.55	32.55
1	Concrete Pump (Small)	899.78	899.78
200	L.H., Daily Totals		
No.	Crew C-14C	Hr. or Day*	Daily
1	Carpenter Foreman (outside)	$64.40	515.20
6	Carpenters	62.40	2995.20
2	Rodmen (reinf.)	68.40	1094.40
4	Laborers	50.20	1606.40
1	Cement Finisher	58.45	467.60
1	Gas Engine Vibrator	32.55	32.55
112	L.H., Daily Totals		
No.	Crew C-14D	Hr. or Day*	Daily
1	Carpenter Foreman (outside)	$64.40	$515.20
18	Carpenters	62.40	8985.60
2	Rodmen (reinf.)	68.40	1094.40
2	Laborers	50.20	803.20
1	Cement Finisher	58.45	467.60
1	Equip. Oper. (medium)	67.00	536.00
1	Gas Engine Vibrator	32.55	32.55
1	Concrete Pump (Small)	899.78	899.78
200	L.H., Daily Totals		
** Hr. for Labor and Day for Equipment.*			

Figure 6.9. Crew-based cost estimating of casting concrete in place based on RS Means Cost Data.

6.3.2. Interactive Crew-Based Excel Template

The FDOT's Bridge Maintenance Reference Manual, an adapted FHWA publication, provides some valuable information on bridge maintenance activities, with listed instructions, including equipment, labor and materials. Illustration of this information is shown in the Appendix D Figures D6 and D7, and the information served as a primary source of data for sample crews and materials for common bridge maintenance activities. Using these data, and developing based on the crew data driven methodology, an interactive Microsoft Excel spreadsheet was developed to utilize a list of custom data on the following: crew and daily production rate, labor and hourly cost; equipment and daily cost, and materials. The user interface screen allows the user to select the desired activity, and the crew production rate is shown on the screen. The user selects the equipment and labor needed from a list of options shown in Figure 6.10, with pull down menus (Figure 6.11). Each of these options has associated costs. The materials list is also provided for the user to select but the costs have to be provided by the user. In a similar approach to the

RS Means crew-based methodology illustrated earlier, the unit cost and total cost of the bridge maintenance activity are calculated and shown on the screen. This tool is useful due to the convenience of being provided with a choice of input data, but it should be considered a preliminary tool as this stage because the user has to provide and maintain the data behind the user interface.

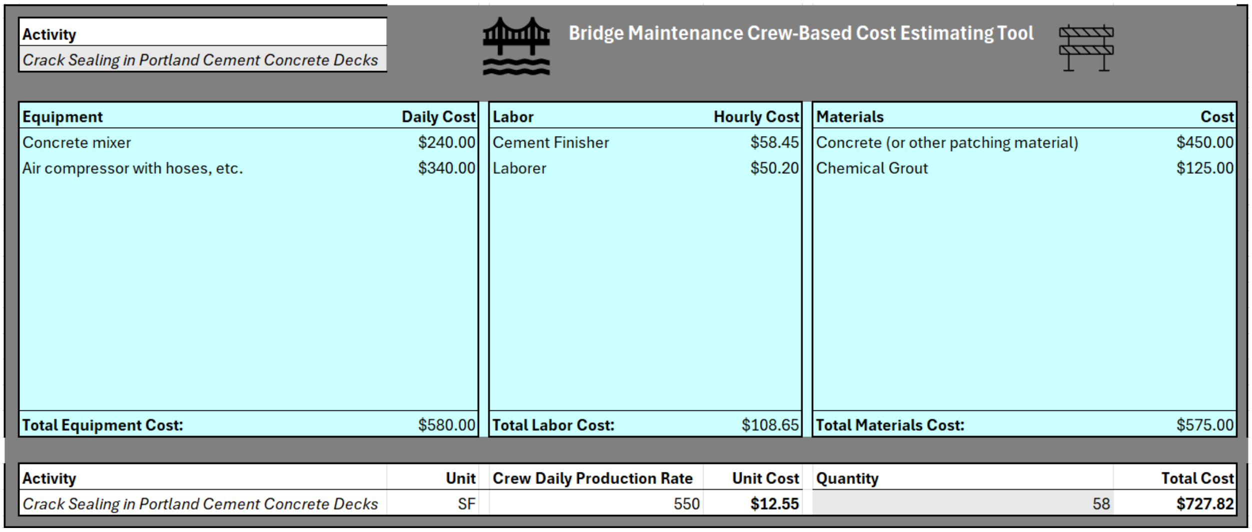


Figure 6.10. Screenshot of the Interactive Crew-based Cost Estimating Excel Tool

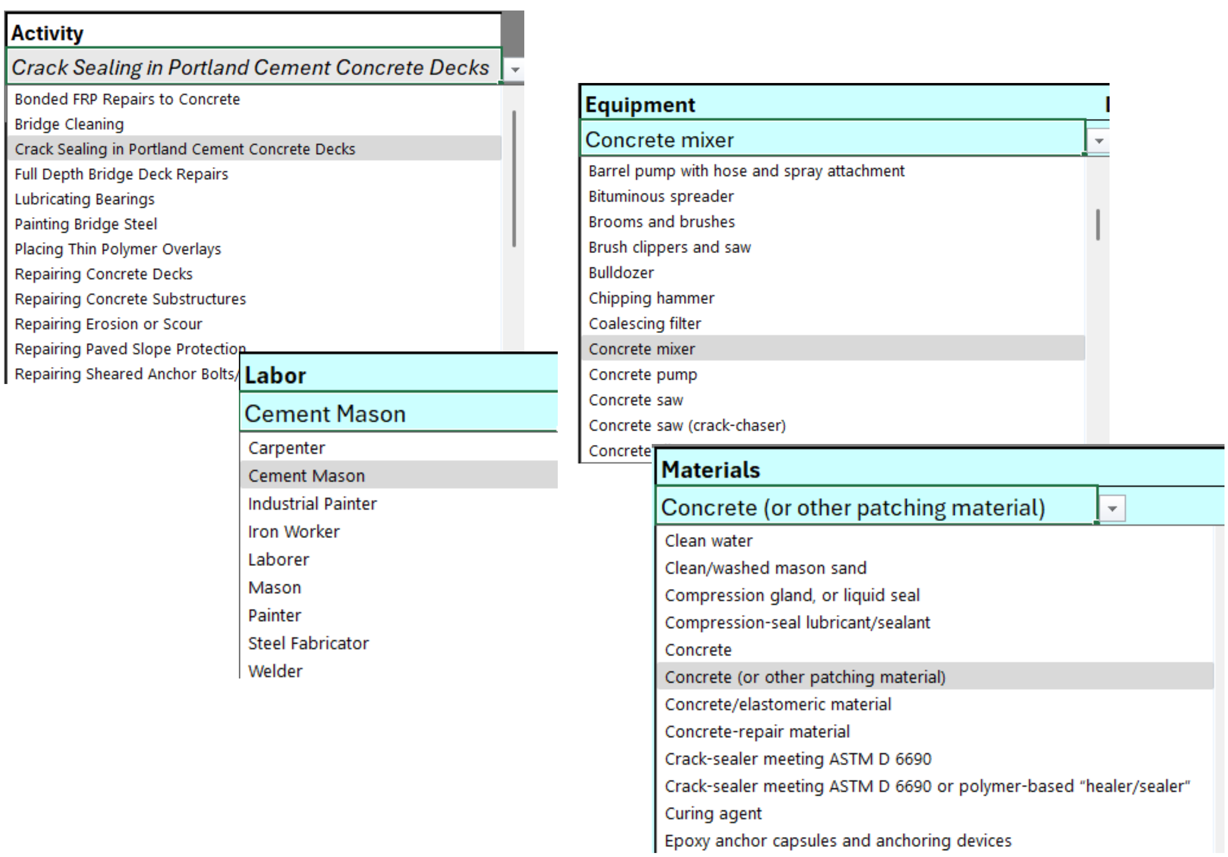


Figure 6.10. Screenshots of user entries with pull-down menus for options.

6.4. Conclusions

The recent challenges in estimating costs of bridge MR&R activities has been explored in this study as presented in this report. There is a lack of FDOT data to adequately estimate the bridge MR&R costs, but the research team utilized the available data to derive cost estimates, as well as presenting the crew-based approach to estimating costs. The research utilized the available historical costs, specifically, the FDOT's Maintenance Management System (MMS) database and the FDOT's historical bid costs to estimate the costs. In addition, a methodology for developing crew-based cost estimates was presented, using typical crew data and production rates.

Most bridge MR&R activities costs from the FDOT's Maintenance Management System (MMS) database are recorded in labor effort (MH) units that are not compatible with the BrM units for the activities. This is a nationally-recognized problem. One approach was successfully applied in this study, where the estimates of labor effort (MH) per SF deck area were computed and combined with average costs per MH, to derive estimates of various activities, in terms of dollar per bridge SF deck area. This approach will enable FDOT to estimate unit costs of bridge MR& activities using the data currently available.

The FDOT's historical bid costs, which is available for all pay items used on FDOT construction bids, provided a useful source of unit costs for bridge MR&R activities. Further classification of the bid cost data enabled the estimation of unit costs for specific bridge MR&R activities, e.g., cathodic protection, clean and maintain slope protection, etc. A mapping structure was established for classification of the data, which will be useful for future processing of FDOT historical bid reports.

Lastly, a crew-based approach was presented where for bridge MR&R activities, the crew (required labor and equipment) can be selected, and the information on costs and crew production rate, are used to estimate the installation costs. The materials costs can then be added to complete the cost estimates. The use of RS Means Cost data was demonstrated as a useful source for implementing the crew-based cost estimates of bridge MR&R activities. In addition, the study utilized the materials and crew data for bridge MR&R activities from the FDOT Bridge Maintenance Reference Manual to develop a preliminary version of a Microsoft Excel spreadsheet for the crew based cost estimating methodology.

6.5. References

Anderson, Stuart; Molenaar, Keith; and Schexnayder, Cliff. (2007). Guidance for Cost Estimation and Management for Highway Projects During Planning, Programming, and Preconstruction, NCHRP Report 574, Transportation Research Board, Washington, D.C. 289 pp.

BLS. (2024). Consumer Price Index: Trade, Transportation, and Utilities. Bureau of Labor Statistics (BLS) of the US Department of Labor. Southeast Information Office. Available at https://www.bls.gov/regions/southeast/florida.htm.

FDOT. (2022). Detailed Unit Cost - By Activity: Fiscal Year 2021-22 (01JUL21 – 30JUN22). Maintenance Management System (MMS), Florida Department of Transportation (FDOT), Office of State Maintenance. Report published Nov. 16, 2022. 9 pp.

FDOT. (2022). Statewide Contract Summary By Activity, District - Year-To-Date: Fiscal Year 2021-22 (Does not include asset maintenance). Maintenance Management System (MMS), Florida Department of Transportation (FDOT), Office of State Maintenance. Report published Nov. 16, 2022. 8 pp.

FDOT. (2017). Statewide Contract Summary By Activity, District - Year-To-Date: Fiscal Year 2016-17 (Does not include asset maintenance). Maintenance Management System (MMS), Florida Department of Transportation (FDOT), Office of State Maintenance. Report published Oct. 4, 2017. 10 pp.

FDOT. (2024). Historical Item Average Cost Reports: Annual (Bid) Averages for 2021 to 2023. Accessed Nov. 11, 2024, from https://www.fdot.gov/programmanagement/estimates/reports/historical-item-average-cost-reports.

FDOT. (2012). Maintenance Cost Handbook, Florida Department of Transportation (FDOT), Office of State Maintenance. Report published March 27, 2012. 42 pp. Accessed Oct. 2, 2024 from https://www.fdot.gov/maintenance/asset-maintenance-guides.

FDOT. (2015). Bridge Maintenance Reference Manual. Florida Department of Transportation (FDOT), Office of State Maintenance. Original FHWA Publication No. FHWA-NHI-14-050. Published May 2015. Accessed Oct. 2, 2024, from https://www.fdot.gov/maintenance/bmrm.shtm.

Hearn, George; Thompson, Paul D.; Mystkowski, Walter; and Hyman, William. (2010). Framework for a National Database System for Maintenance Actions on Highway Bridges, NCHRP Report 668, Transportation Research Board, Washington, D.C. 93 pp.

Sobanjo, J.; Thompson, PD; Lewis, M; and Kerr, R. (2002). Estimating Agency Cost of Maintenance, Repair, and Rehabilitation for Florida Bridges, Transportation Research Record 1795, Transportation Research Board, pp 66-73.

Sobanjo, John, and Thompson, Paul. (2011). Enhancement of the FDOT's Project Level and Network Level Bridge Management Analysis Tools, Final Report, Research Contract #BDK83 977-01, Florida Department of Transportation, Tallahassee, Florida, 303p.

Mewis, Bob and Keller, Scott. (2022). RS Means Data for DOE. Presentation at the Department of Energy (DOE). Gordian/RSMeans. 46 pp. Accessed 3/10/2025 from https://fims.doe.gov/caisinfo/Meetings/2022/Presentations/RSM_Presentation.pdf.

Appendix A: Environmental classification

Table A1. List of bridges with environmental classes of Superstructure Extremely Aggressive and Substructure Extremely Aggressive

ROADWAY	ROAD_SIDE	STRUCTURE	DISTRICT	COUNTY	COUNTY	MNG	Material	pH	Chloride	Sulfate	Resistivity
03010000	C	030062	1	03	Collier	1	Water	8.2	8875		75
87061000	L	875000	6	87	Miami-	6	Water	8.3	18638	450	30
87080000	L	870082	6	87	Miami-	6	Water	7.7	10047	922.1	61
03010000	C	030057	1	03	Collier	1	Water	8.1	11005		62
03010000	C	030050	1	03	Collier	1	Water	8.1	11005		50
87080000	L	870084	6	87	Miami-	6	Water	7.4	16700	2660	30
01050000	L	010104	1	01	Charlotte	1	Water	7.8	14000	700	37000
17080000	C	170060	1	17	Sarasota	1	Water	7.5	19498	3200	26
01050000	R	010035	1	01	Charlotte	1	Water	7.8	14000	700	37000
17020000	R	170037	1	17	Sarasota	1	Water	7.6	15244	2200	35
03070000	C	030122	1	03	Collier	1	Water	7.7	19880		27
03010000	C	030058	1	03	Collier	1	Water	8.1	12070		61
17080000	C	170061	1	17	Sarasota	1	Water	8.36	21393	3439	21
17030000	R	170022	1	17	Sarasota	1	Water	8.19	19594	7157.7	21.5
03010000	C	030061	1	03	Collier	1	Water	8.3	9585		76
87061000	R	875001	6	87	Miami-	6	Water	8.3	18638	450	30
03010000	L	030145	1	03	Collier	1	Water	8	10650		76
03010000	C	030069	1	03	Collier	1	Water	8.2	7455		76
87004022	C	870375	6	87	Miami-	6	Water	7.7	21300	3600	27
08000021	C	080016	7	08	Hernando	7	Water	7.7	6877	1275	50
87060000	C	870077	6	87	Miami-	6	Water	8.3	18638	450	30
03010000	C	030066	1	03	Collier	1	Water	8.1	11715		56
87004000	C	870302	6	87	Miami-	6	Water	6.8	19880	3200	27
17020000	R	170169	1	17	Sarasota	1	Water	8.3	60000	18	30
03010000	C	030070	1	03	Collier	1	Water	8.3	7455		82
87080000	R	870550	6	87	Miami-	6	Water	7.4	16700	2660	30
17020000	C	170142	1	17	Sarasota	1	Water	8.16	21293	3148.4	21.5
17020000	C	170172	1	17	Sarasota	1	Water	7.8	17193	2800	23
01010000	R	010033	1	01	Charlotte	1	Water	7.5	12403	1900	30
17110000	R	170052	1	17	Sarasota	1	Water	7.7	17512	3200	26
03010000	C	030047	1	03	Collier	1	Water	7.8	16330		39
87080000	L	870085	6	87	Miami-	6	Water	7.7	10047	922.1	61
03010000	C	030048	1	03	Collier	1	Water	7.8	14200		42
87060000	C	870071	6	87	Miami-	6	Water	7.9	17902	2720	22
01010000	L	010056	1	01	Charlotte	1	Water	7.5	12403	1900	30
17010000	L	170168	1	17	Sarasota	1	Water	8.2	26200	8	10

Table A1. List of bridges with environmental classes of Superstructure Extremely Aggressive and Substructure Extremely Aggressive (Cont'd)

ROADWAY	ROAD_SIDE	STRUCTURE	DISTRICT	COUNTY	COUNTY	MNG	Material	pH	Chloride	Sulfate	Resistivity
87060000	L	870771	6	87	Miami-	6	Water	7.9	22000	2700	230
03010000	C	030071	1	03	Collier	1	Water	8.2	9585		80
17020000	C	170068	1	17	Sarasota	1	Water	7.4	17867	2600	23
03010000	C	030074	1	03	Collier	1	Water	8.2	9585		66
17502000	C	170054	1	17	Sarasota	1	Water	7	17116	2250	25
87080000	R	870549	6	87	Miami-	6	Water	7.4	16700	2660	30
03518000	C	030149	1	03	Collier	1	Water	7.9	24495		20
01000024	C	015005	1	01	Charlotte	1	Water	7.2	14000	24	60
03010000	C	030059	1	03	Collier	1	Water	8.3	11715		62
03010000	R	030017	1	03	Collier	1	Water	8.4	8520	0	88
01050001	C	010029	1	01	Charlotte	1	Water	7.5	24531		23
87080000	R	870554	6	87	Miami-	6	Water	7.7	10047	922.1	61
01010101	C	010050	1	01	Charlotte	1	Water	7	13840	2384	94
17020000	L	170015	1	17	Sarasota	1	Water	7.5	11486	2000	30
03010000	C	030073	1	03	Collier	1	Water	8.2	9940		80
87080000	R	870551	6	87	Miami-	6	Water	7.7	10047	922.1	61
01075000	C	010106	1	01	Charlotte	1	Water	7.4	14000	26	36
03010000	C	030054	1	03	Collier	1	Water	8	8875		94
17100000	C	170057	1	17	Sarasota	1	Water	7.7	17725	2650	23
87004000	C	870301	6	87	Miami-	6	Water	8.13	19194	149.9	20
17020000	L	170170	1	17	Sarasota	1	Water	8.3	60000	18	30
03010000	C	030055	1	03	Collier	1	Water	8	20590		95
03010000	C	030049	1	03	Collier	1	Water	7.8	18460		50
01010000	C	010092	1	01	Charlotte	1	Water	7	13840	2384	94
03030000	L	030293	1	03	Collier	1	Water	8	19095.69	2484.81	21
87004000	C	870314	6	87	Miami-	6	Water	7.3	18080	4900	20
17020000	L	170014	1	17	Sarasota	1	Water	7.6	15244	2200	35
17030000	L	170120	1	17	Sarasota	1	Water	8	18257	2850	23
87030000	C	870019	6	87	Miami-	6	Water	7.4	14820	2482	46
03040000	C	030076	1	03	Collier	1	Water	7.6	8165		14
03010000	C	030068	1	03	Collier	1	Water	8.2	8520		2000
03010000	C	030302	1	03	Collier	1	Water	7.5	7810		3100
03010000	L	030306	1	03	Collier	1	Water	8.4	8520		88
17030000	L	170951	1	17	Sarasota	1	Water	8.19	19594	7157.7	21.5
17030000	R	170141	1	17	Sarasota	1	Water	8	18257	2850	23
03010000	C	030045	1	03	Collier	1	Water	7.8	25205		27
03010000	C	030044	1	03	Collier	1	Water	7.7	21655		29
03010000	C	030060	1	03	Collier	1	Water	7.9	9940		76

Table A1. List of bridges with environmental classes of Superstructure Extremely Aggressive and Substructure Extremely Aggressive (Cont'd)

ROADWAY	ROAD_SIDE	STRUCTURE	DISTRICT	COUNTY	COUNTY	MNG	Material	pH	Chloride	Sulfate	Resistivity
03010000	C	030065	1	03	Collier	1	Water	8	11715		54
17020000	C	170171	1	17	Sarasota	1	Water	7.8	17193	2500	23
87080000	L	870083	6	87	Miami-Dade	6	Water	7.4	16700	2660	30
17010000	R	170167	1	17	Sarasota	1	Water	8.2	26200	8	10
03010000	C	030075	1	03	Collier	1	Water	8.1	11715		88
17100000	C	170064	1	17	Sarasota	1	Water	7.7	19369		20
03010000	C	030064	1	03	Collier	1	Water	8.2	11005		68
03010000	C	030072	1	03	Collier	1	Water	8.2	23075		3000
17080000	C	170059	1	17	Sarasota	1	Water	7.5	18080	2800	28
01010000	C	010042	1	01	Charlotte	1	Water	7.4	12053	1800	30
87060000	R	870772	6	87	Miami-Dade	6	Water	7.9	22000	2700	230
17030201	C	170176	1	17	Sarasota	1	Water	7.9	19994	3600	22
17110000	L	170065	1	17	Sarasota	1	Water	7.7	17512	3200	26
03030000	R	030148	1	03	Collier	1	Water	8	19095.69	2484.81	21
87004023	C	870376	6	87	Miami-Dade	6	Water	7.7	21300	3600	27
03010000	R	030146	1	03	Collier	1	Water	8	10650		76
03010000	C	030052	1	03	Collier	1	Water	8	12070		53
90020000	C	900091	6	90	Monroe	6	Water	8.1	18600	2890	27
79010000	L	790157	5	79	Volusia	5	Water	7.7	17158	285	23
70080000	R	700117	5	70	Brevard	5	Water	8.1	17000	2730	28
70050000	L	700174	5	70	Brevard	5	Water	7.96	12046	3383	20
10110000	L	100080	7	10	Hillsborough	7	Water	7	15265		37
70100000	R	700220	5	70	Brevard	5	Water	7.8	14393	1400	26
90030000	C	900104	6	90	Monroe	6	Water	8	24495	3230	26
70050000	L	700233	5	70	Brevard	5	Water	8.1	20590		31
57518000	C	570091	3	57	Okaloosa	3	Water	7.84	8997	1226.8	39
57030000	C	570034	3	57	Okaloosa	3	Water	7.32	15045	1800	22
79010000	R	790162	5	79	Volusia	5	Water	7.8	16874	190	25
70004000	R	700148	5	70	Brevard	5	Water	7.5	10360	3200	40
34070000	C	340001	2	34	Levy	2	Water	7.9	16496	1924.6	42
70004000	L	700081	5	70	Brevard	5	Water	7.5	10360	3200	40
90030000	C	900105	6	90	Monroe	6	Water	8	24495	3190	20
90020000	C	900108	6	90	Monroe	6	Water	7.9	17583	2600	21
89015000	L	890151	4	89	Martin	4	Water	7.5	31072.2	1887.25	25
90060000	C	900076	6	90	Monroe	6	Water	8.1	17950	2790	24
70070000	R	700221	5	70	Brevard	5	Water	8	13397	1756.5	34
88070000	C	880005	4	88	Indian River	4	Water	8.1	18296	2354.1	27
10000090	C	105504	7	10	Hillsborough	7	Water	7.7	11396	1739.3	32.5

Table A1. List of bridges with environmental classes of Superstructure Extremely Aggressive and Substructure Extremely Aggressive (Cont'd)

ROADWAY	ROAD_SIDE	STRUCTURE	DISTRICT	COUNTY	COUNTY	MNG	Material	pH	Chloride	Sulfate	Resistivity
70010000	C	700224	5	70	Brevard	5	Water	8	24850		26
79220002	C	790174	5	79	Volusia	5	Water	7.5	13467.6	1157.09	35
57040000	C	570017	3	57	Okaloosa	3	Water	7.3	9855		40
70050000	R	700181	5	70	Brevard	5	Water	7.96	12046	3383	20
90003000	C	900054	6	90	Monroe	6	Water	7.76	17545	2390.4	24
90509000	C	904982	6	90	Monroe	6	Water	7.67	20894	2682.4	21
90050000	C	900097	6	90	Monroe	6	Water	8	20839.7	5054	85
79080001	R	790188	5	79	Volusia	5	Water	7.5	13467.6	1157.09	35
70100000	C	700137	5	70	Brevard	5	Water	8	16500	2650	25
87200120	C	870453	6	87	Miami-Dade	6	Water	7.7	6745	30	340
88050000	C	880051	4	88	Indian River	4	Water	7.77	15045	2253.8	30
70050000	R	700234	5	70	Brevard	5	Water	8.1	20590		31
10130001	R	100300	7	10	Hillsborough	7	Water	7.8	13886.3	1370.81	27
90030000	L	900016	6	90	Monroe	6	Water	8.1	23923.2	2671.55	20
79010000	L	790155	5	79	Volusia	5	Water	7.8	16450	280	23
88050000	C	880050	4	88	Indian River	4	Water	7.77	15045	2253.8	30
70070000	R	700115	5	70	Brevard	5	Water	8	13797	1719.2	33
90010000	L	900125	6	90	Monroe	6	Water	7.9	23992.56	2174.83	18
70070000	L	700025	5	70	Brevard	5	Water	7.2	23815.9	1657.56	33
70004000	R	700144	5	70	Brevard	5	Water	7.47	17495	2857.7	29
70140000	R	700201	5	70	Brevard	5	Water	7.8	15656	30	
79010000	R	790156	5	79	Volusia	5	Water	7.8	16450	280	23
34650000	C	340013	2	34	Levy	2	Water	7.5	13490		1200
90020000	R	900074	6	90	Monroe	6	Water	7.7	19000	2600	21
79280500	C	794004	5	79	Volusia	5	Water	7.5	13467.6	1157.09	35
90060114	C	900132	6	90	Monroe	6	Water	8.1	17200	2720	24
70120000	C	700183	5	70	Brevard	5	Water	8.17	13846	1811.7	29
70004000	R	700147	5	70	Brevard	5	Water	7.5	10360	3200	40
70004000	L	700077	5	70	Brevard	5	Water	7.47	17495	2857.7	29
90060000	C	900089	6	90	Monroe	6	Water	8.1	18600	2890	27
70004000	L	700082	5	70	Brevard	5	Water	7.5	10360	3200	40
89030000	C	890146	4	89	Martin	4	Water	7.73	16795	2340	20
70100000	C	700192	5	70	Brevard	5	Water	8.1	14393	1400	26
90060000	C	900095	6	90	Monroe	6	Water	8.3	34452.1	2571.55	18.5
78090000	C	780090	2	78	St. Johns	2	Water	7.94	23293	2392.2	21.5
10250000	R	100338	7	10	Hillsborough	7	Water	7.8	11911	1850	30
89000062	C	890149	4	89	Martin	4	Water	7.7	16685	2390	220
79100000	R	790163	5	79	Volusia	5	Water	7.4	17371	62	1900

Table A1. List of bridges with environmental classes of Superstructure Extremely Aggressive and Substructure Extremely Aggressive (Cont'd)

ROADWAY	ROAD_SIDE	STRUCTURE	DISTRICT	COUNTY	COUNTY	MNG	Material	pH	Chloride	Sulfate	Resistivity
70070000	L	700110	5	70	Brevard	5	Water	8	13397	1756.5	34
90509000	C	904990	6	90	Monroe	6	Water	7.96	19394	2914.4	22.5
70100000	C	700208	5	70	Brevard	5	Water	8	14393	1600	26
90060000	L	900130	6	90	Monroe	6	Water	8	18100	2800	20
57030000	R	570082	3	57	Okaloosa	3	Water	7.5	7374	1000	48
34100000	C	340012	2	34	Levy	2	Water	8	6035		320
70100001	C	700061	5	70	Brevard	5	Water	8	16500	2650	25
10110000	R	100081	7	10	Hillsborough	7	Water	7	15265		37
89040000	C	890150	4	89	Martin	4	Water	8	17595	2264.8	20
90050000	C	900094	6	90	Monroe	6	Water	8.3	36633.7	2652.88	19
70070000	L	700028	5	70	Brevard	5	Water	8	13797	1719.2	33
90010000	R	900086	6	90	Monroe	6	Water	7.9	23992.56	2174.83	18
70080000	L	700030	5	70	Brevard	5	Water	8.1	17000	2730	28
70004000	R	700142	5	70	Brevard	5	Water	7.47	17495	2857.7	29
79170000	C	790150	5	79	Volusia	5	Water	7.83	17250	2382	18
89015000	R	890152	4	89	Martin	4	Water	7.5	31072.2	1887.25	25
79010000	L	790159	5	79	Volusia	5	Water	7.9	14747	215	23
70080120	C	700031	5	70	Brevard	5	Water	8.1	17000	2730	28
90030000	C	900106	6	90	Monroe	6	Water	8.1	41095.7	2783.6	19
57030000	L	570054	3	57	Okaloosa	3	Water	7.5	7374	1000	48
79010000	L	790161	5	79	Volusia	5	Water	7.8	16874	190	25
87270000	L	870356	6	87	Miami-Dade	6	Water	7.6	12780	30	350
90020000	C	900117	6	90	Monroe	6	Water	7.88	20294	2857.3	21
34070000	C	340003	2	34	Levy	2	Water	8	16796	2260.7	44
90000531	C	904320	6	90	Monroe	6	Water	8.02	18894	2974.4	22
34070000	C	340002	2	34	Levy	2	Water	7.9	18396	2204.7	44
90060000	C	900096	6	90	Monroe	6	Water	8	24495	2860	23
87270000	R	870453	6	87	Miami-Dade	6	Water	7.7	6745	30	340
10130001	L	100585	7	10	Hillsborough	7	Water	7.8	13886.3	1370.81	27
70004000	R	700146	5	70	Brevard	5	Water	7.5	10360	3200	40
70100000	C	700193	5	70	Brevard	5	Water	8.4	15265		29
90030000	C	900103	6	90	Monroe	6	Water	8.1	24495	3140	22
70100000	L	700219	5	70	Brevard	5	Water	7.8	14393	1400	26
10080000	C	100100	7	10	Hillsborough	7	Water	7.5	9075	1350	47
10250000	L	100299	7	10	Hillsborough	7	Water	7.8	11911	1850	30
90030000	R	900045	6	90	Monroe	6	Water	8.1	23923.2	2671.55	20
79010000	L	790217	5	79	Volusia	5	Water	7.2	13797	1401.7	32
70004000	L	700076	5	70	Brevard	5	Water	7.47	17495	2857.7	29

Table A1. List of bridges with environmental classes of Superstructure Extremely Aggressive and Substructure Extremely Aggressive (Cont'd)

ROADWAY	ROAD_SIDE	STRUCTURE	DISTRICT	COUNTY	COUNTY	MNG	Material	pH	Chloride	Sulfate	Resistivity
70070000	L	700027	5	70	Brevard	5	Water	8.5	24850		25
90020000	C	900102	6	90	Monroe	6	Water	8.1	16650	168	20
89030000	C	890145	4	89	Martin	4	Water	7.73	16795	2340	20
90060000	R	900073	6	90	Monroe	6	Water	8	18100	2800	20
70050000	C	700235	5	70	Brevard	5	Water	8.1	22720		34
90509000	C	904984	6	90	Monroe	6	Water	7.73	19394	3012.8	22
79220001	C	790175	5	79	Volusia	5	Water	7.5	13467.6	1157.09	35
34500000	C	344010	2	34	Levy	2	Water	7.9	50000	3700	25
70020000	C	700008	5	70	Brevard	5	Water	7.7	12796	2921.2	36.5
70004000	L	700080	5	70	Brevard	5	Water	7.5	10360	3200	40
90060000	C	900088	6	90	Monroe	6	Water	8	17950	2790	27
70120000	C	700184	5	70	Brevard	5	Water	7.4	13862	1500	38
90060000	C	900077	6	90	Monroe	6	Water	8	25205	3440	22
79080001	L	790187	5	79	Volusia	5	Water	7.5	13467.6	1157.09	35
70070000	R	700112	5	70	Brevard	5	Water	7.2	23815.9	1657.56	33
79170000	C	790149	5	79	Volusia	5	Water	7.79	18350	2301.2	19
10140000	C	100301	7	10	Hillsborough	7	Water		12522		31
70004000	L	700078	5	70	Brevard	5	Water	7.47	17495	2857.7	29
12000094	C	124115	1	12	Lee	1	Water	7.73	18294	2321.2	20
70070000	R	700109	5	70	Brevard	5	Water	8	36565		25
90010000	C	900128	6	90	Monroe	6	Water	7.5	16520	2800	22
34070000	C	340053	2	34	Levy	2	Water	8.25	14425	1952	25.01
86130000	C	860157	4	86	Broward	4	Water	7.9	17340	2734	22
30591000	C	300043	2	30	Dixie	2	Water	7.8	6745		150
15110000	L	150053	7	15	Pinellas	7	Water	8.15	22145	3086.2	19
49580100	C	490100	3	49	Franklin	3	Water	7.69	9247	1195.2	40
78070000	C	780091	2	78	St. Johns	2	Water	7	20795	2522.2	24
49010000	C	490023	3	49	Franklin	3	Water	7.4	14555		47
48050000	C	480118	3	48	Escambia	3	Water	8	30530		25
15150098	C	150020	7	15	Pinellas	7	Water	7.74	15895	1964.3	27
15020000	C	150046	7	15	Pinellas	7	Water	7.9	17938	2600	21
49010000	C	490012	3	49	Franklin	3	Water	7	15265	18	42
15010000	R	150074	7	15	Pinellas	7	Water	7.3	16300	2800	24
15090500	C	157109	7	15	Pinellas	7	Water	7.5	16023	3200	23
78002000	R	780089	2	78	St. Johns	2	Water	7.87	18092	2715	19
60660100	C	600078	3	60	Walton	3	Water	7.3	11360		52
93180000	L	930104	4	93	Palm Beach	4	Water	7.93	18944	2575	20.9
10060000	R	100107	7	10	Hillsborough	7	Water	7.2	7232	650	50

Table A1. List of bridges with environmental classes of Superstructure Extremely Aggressive and Substructure Extremely Aggressive (Cont'd)

ROADWAY	ROAD_SIDE	STRUCTURE	DISTRICT	COUNTY	COUNTY	MNG	Material	pH	Chloride	Sulfate	Resistivity
93280000	L	930506	4	93	Palm Beach	4	Water	8.1	26270		27
10060000	L	100045	7	10	Hillsborough	7	Water	7.2	7232	650	50
15100000	L	150253	7	15	Pinellas	7	Water	8	19852	3500	20
58170000	C	580065	3	58	Santa Rosa	3	Water	7.2	15265		47
15020000	C	150006	7	15	Pinellas	7	Water	7	7150	1090	49
93040000	R	930543	4	93	Palm Beach	4	Water	7.4	10580	1500	24
86180000	L	860623	4	86	Broward	4	Water	7.7	17480	2748	21
93040000	R	930541	4	93	Palm Beach	4	Water	7.3	9156	1230	180
10060000	C	100049	7	10	Hillsborough	7	Water	7.1	9784	800	36
78040000	C	780119	2	78	St. Johns	2	Water	7.9	52000	5670	22000
78002000	L	780100	2	78	St. Johns	2	Water	7.87	18092	2715	19
15120000	R	150112	7	15	Pinellas	7	Water	7.9	19000	3200	20
93040000	L	930544	4	93	Palm Beach	4	Water	7.4	10580	1500	24
10060000	L	100039	7	10	Hillsborough	7	Water	7.77	12296	1505.2	27.48
10320000	C	100218	7	10	Hillsborough	7	Water	7.6	17016	380	200
93710000	R	934161	4	93	Palm Beach	4	Water	7.9	24850	63	30
78030000	C	780071	2	78	St. Johns	2	Water	7	20795	2522.2	24
93509001	C	930214	4	93	Palm Beach	4	Water	8.1	29465	170	23
49010000	C	490032	3	49	Franklin	3	Water	7.35	12746	1567.8	36
15050005	C	150009	7	15	Pinellas	7	Water	6.9	11769	2000	32
15110000	L	150030	7	15	Pinellas	7	Water	7.8	19356	3300	20
15050007	C	150013	7	15	Pinellas	7	Water	7.8	9220	1500	38
15110000	R	150137	7	15	Pinellas	7	Water	8.15	22145	3086.2	19
15000183	C	154371	7	15	Pinellas	7	Water	7.68	12196	1246.2	28
93040000	L	930542	4	93	Palm Beach	4	Water	7.7	13561	202	25
58170000	C	580028	3	58	Santa Rosa	3	Water	7.2	19525		38
15010000	L	150001	7	15	Pinellas	7	Water	7.3	16300	2800	24
93180000	R	930318	4	93	Palm Beach	4	Water	7.93	18944	2575	20.9
48230000	R	480139	3	48	Escambia	3	Water	7.32	15045	1800	22
15110000	L	150054	7	15	Pinellas	7	Water	8.15	22145	3086.2	19
15100000	R	150254	7	15	Pinellas	7	Water	8	19852	3500	20
15040000	C	150138	7	15	Pinellas	7	Water	7.8	14180	2400	20
60660100	C	600089	3	60	Walton	3	Water	7.4	12780		53
10060000	R	100104	7	10	Hillsborough	7	Water	7.77	12296	1505.2	27.48
15110000	R	150135	7	15	Pinellas	7	Water	7.8	19356	3300	20
86170500	C	864071	4	86	Broward	4	Water	7.73	7460	1025.1	46
93090000	C	930339	4	93	Palm Beach	4	Water	7.2	8336	1112	260
78040000	C	780097	2	78	St. Johns	2	Water	7.8	20580	5000	20

Table A1. List of bridges with environmental classes of Superstructure Extremely Aggressive and Substructure Extremely Aggressive (Cont'd)

ROADWAY	ROAD_SIDE	STRUCTURE	DISTRICT	COUNTY	COUNTY	MNG	Material	pH	Chloride	Sulfate	Resistivity
30508000	C	300015	2	30	Dixie	2	Water	8	19880		32
78010027	C	780003	2	78	St. Johns	2	Water	7.9	14325	11600	25
93280000	R	930507	4	93	Palm	4	Water	8.1	26270		27
86200000	L	860619	4	86	Broward	4	Water	7.9	30175		20
15045000	C	150244	7	15	Pinellas	7	Water	8.2	14180	2400	27
49502000	C	490002	3	49	Franklin	3	Water	7.4	12070		62
93002000	R	930226	4	93	Palm	4	Water	8	7810	160	23
78040000	C	780074	2	78	St. Johns	2	Water	7.9	19196	2428.8	23
15120000	C	150255	7	15	Pinellas	7	Water	7	7090	1200	49
48080060	C	480215	3	48	Escambia	3	Water	6.5	8662		40
78030001	C	780099	2	78	St. Johns	2	Water	7.8	18505	12000	22
48230000	L	480123	3	48	Escambia	3	Water	7.32	15045	1800	22
15110000	R	150136	7	15	Pinellas	7	Water	8.15	22145	3086.2	19
86200000	R	860618	4	86	Broward	4	Water	7.9	30175		20
49010001	C	490031	3	49	Franklin	3	Water	7.5	13490	292	180
86180000	R	860622	4	86	Broward	4	Water	7.7	17480	2748	21
86230000	C	860043	4	86	Broward	4	Water	7.6	17480	2748	22
30508000	C	300014	2	30	Dixie	2	Water	7.6	12425		46
15100000	C	150028	7	15	Pinellas	7	Water	7.6	18859	3300	20
72090000	R	720281	2	72	Duval	2	Water	7.9	13525	2345	300
15240000	R	150108	7	15	Pinellas	7	Water	7.8	9825	1260	36
72260000	C	720692	2	72	Duval	2	Water	8	23293	3803.7	22.5
13130017	C	130141	1	13	Manatee	1	Water	8.29	18194	2874.5	21.5
72080000	L	720017	2	72	Duval	2	Water	7	8413		56
72002000	L	720474	2	72	Duval	2	Water		13000	1000	
72040000	C	720076	2	72	Duval	2	Water	7.2	8998	1102.9	40.7
15500000	C	150067	7	15	Pinellas	7	Water	8.04	17994	2392.5	21
46020000	C	460073	3	46	Bay	3	Water	7.8	25560		25
15170000	L	150213	7	15	Pinellas	7	Water	8.19	19144	2954.7	20
72260000	C	720072	2	72	Duval	2	Water	7.5	23093	3878	23
72020066	C	720632	2	72	Duval	2	Water	7.58	9697	1435.3	33
15520000	C	150020	7	15	Pinellas	7	Water	7.74	15895	1964.3	27
14030000	C	140005	7	14	Pasco	7	Water	8	8721	1500	42
72250452	C	720146	2	72	Duval	2	Water	7.6	16000	2590	35
15520000	C	150021	7	15	Pinellas	7	Water	7.4	8012	1800	45
46000009	C	460053	3	46	Bay	3	Water	8.1	26625		26
46020000	C	460019	3	46	Bay	3	Water	8	13684	2100	30
72100408	C	720366	2	72	Duval	2	Water	8.1	17800	2900	27

Table A1. List of bridges with environmental classes of Superstructure Extremely Aggressive and Substructure Extremely Aggressive (Cont'd)

ROADWAY	ROAD_SIDE	STRUCTURE	DISTRICT	COUNTY	COUNTY	MNG	Material	pH	Chloride	Sulfate	Resistivity
72250000	C	720059	2	72	Duval	2	Water	8	14695	2488	24
15200001	L	150052	7	15	Pinellas	7	Water	8.18	20294	3149.4	20.5
72100000	R	720044	2	72	Duval	2	Water	7.3	7427.9	1068.72	40
72020000	C	720629	2	72	Duval	2	Water	7.58	9697	1435.3	33
13150000	C	130153	1	13	Manatee	1	Water	8	12000	19	19
15200001	L	150951	7	15	Pinellas	7	Water	8.18	20294	3149.4	20.5
12530000	C	120028	1	12	Lee	1	Water	8.1	18080	2850	22
86040000	C	860230	4	86	Broward	4	Water	7.7	17348	2734	22
72070000	C	720022	2	72	Duval	2	Water	7.1	21126.2	1186.97	38
72240000	C	720077	2	72	Duval	2	Water	7.7	7200	650	80
12060000	C	124134	1	12	Lee	1	Water	7.6	16300	2500	25
15500000	C	150068	7	15	Pinellas	7	Water	8.2	20207	3000	20
74130001	C	740105	2	74	Nassau	2	Water	8	23393	4713.3	21.5
12530000	C	120055	1	12	Lee	1	Water	7.6	17000	2700	25
13075000	L	130101	1	13	Manatee	1	Water	7.6	10934		38
94060000	C	940045	4	94	St. Lucie	4	Water	7.96	14763	2584	20
15190000	L	150210	7	15	Pinellas	7	Water	7.9	15196	1775.2	27
15200001	C	150223	7	15	Pinellas	7	Water	8.22	19144	2914.8	21.5
74060000	R	740088	2	74	Nassau	2	Water	7.2	18576	3750	20
86050000	C	860011	4	86	Broward	4	Water	8.09	18894	2369.4	19.96
13075000	R	130102	1	13	Manatee	1	Water	7.6	10934		38
72060000	L	720012	2	72	Duval	2	Water		8350	1000	
72001000	L	720370	2	72	Duval	2	Water	7.6	6700	350	72
72160448	R	720571	2	72	Duval	2	Water	7.2	8998	1102.9	40.7
72250000	L	720569	2	72	Duval	2	Water	8	14695	2488	24
72090000	L	720110	2	72	Duval	2	Water	7.9	13525	2345	300
46010100	R	460112	3	46	Bay	3	Water	7.8	19844	2622.5	23
72060000	C	720688	2	72	Duval	2	Water	7.3	10785	296	36
72100000	L	720690	2	72	Duval	2	Water	7.3	7427.9	1068.72	40
15220000	C	150043	7	15	Pinellas	7	Water	7.9	19356	3600	21
46510000	C	460003	3	46	Bay	3	Water	7.9	24140	23	
72190000	R	720730	2	72	Duval	2	Water	7.2	10280	1408	35
72020000	C	720627	2	72	Duval	2	Water	7.58	9697	1435.3	33
94050000	C	940094	4	94	St. Lucie	4	Water	7.78	19994	2501.6	27
15200000	C	150243	7	15	Pinellas	7	Water	7.9	18344	2131.2	19
46030000	C	460121	3	46	Bay	3	Water	7.5	23785		28
13130000	C	130053	1	13	Manatee	1	Water	7.68	20039	2049	23
12540000	C	120043	1	12	Lee	1	Water	8	16800	2600	24

Table A1. List of bridges with environmental classes of Superstructure Extremely Aggressive and Substructure Extremely Aggressive (Cont'd)

ROADWAY	ROAD_SIDE	STRUCTURE	DISTRICT	COUNTY	COUNTY	MNG	Material	pH	Chloride	Sulfate	Resistivity
12090000	C	120064	1	12	Lee	1	Water	7.7	10295		68
72150000	R	720272	2	72	Duval	2	Water	7.65	9559	1207	42
15170000	L	150038	7	15	Pinellas	7	Water	8.29	19244	3090.6	21.5
46070000	C	460052	3	46	Bay	3	Water	7.2	16685		88
72250000	L	720757	2	72	Duval	2	Water	8	7698	1776.7	58
12530000	C	120026	1	12	Lee	1	Water	7.6	14550	2650	28
15190000	R	150107	7	15	Pinellas	7	Water	7.9	15196	1775.2	27
13550000	C	130007	1	13	Manatee	1	Water	7.3	11344	1700	33
13150000	C	130054	1	13	Manatee	1	Water	7.6	18930	3000	20
15190000	C	150252	7	15	Pinellas	7	Water	7.3	9926	1500	40
72150000	L	720032	2	72	Duval	2	Water	7.65	9559	1207	42
15200001	R	150200	7	15	Pinellas	7	Water	8.18	20294	3149.4	20.5
15170000	R	150214	7	15	Pinellas	7	Water	8.19	19144	2954.7	20
13130000	L	130151	1	13	Manatee	1	Water	7.8	16023	2400	24
86060000	L	860018	4	86	Broward	4	Water	7.97	14346	2094.5	27
46600000	C	460020	3	46	Bay	3	Water	7.5	18800		36
46630000	C	460024	3	46	Bay	3	Water	7.6	16330		36
86014000	C	860144	4	86	Broward	4	Water	7.4	15660	2566	36
72020065	C	720633	2	72	Duval	2	Water	7.58	9697	1435.3	33
74060000	L	740087	2	74	Nassau	2	Water	7.2	18576	3750	20
13130000	R	130019	1	13	Manatee	1	Water	7.8	16023	2400	24
46140001	C	460075	3	46	Bay	3	Water	7.6	24140		26
72260000	C	720063	2	72	Duval	2	Water	7.8	18894	3694.5	28.5
72020064	C	720628	2	72	Duval	2	Water	7.58	9697	1435.3	33
15170001	C	150189	7	15	Pinellas	7	Water	8.21	19744	3033.2	22
46070000	C	460051	3	46	Bay	3	Water	7.1	8165		120
72292000	L	720442	2	72	Duval	2	Water	7.4	7846		50
72002000	R	720473	2	72	Duval	2	Water		13000	1000	
15240000	L	150014	7	15	Pinellas	7	Water	7.8	14180	2300	26
13075000	R	130104	1	13	Manatee	1	Water	7.5	12141		35
86005000	R	860467	4	86	Broward	4	Water	7.8	10281	1500	33
72292000	R	720509	2	72	Duval	2	Water	7.4	7846		50
15200001	R	150201	7	15	Pinellas	7	Water	8.18	20294	3149.4	20.5
72190000	L	720729	2	72	Duval	2	Water	6.9	10280	1380	34
12004000	C	120089	1	12	Lee	1	Water	7.8	19283.6	2503.49	21
86005000	L	860466	4	86	Broward	4	Water	7.8	10281	1500	33
72001000	R	720371	2	72	Duval	2	Water	7.6	6700	350	72
72160448	L	720570	2	72	Duval	2	Water	7.2	8998	1102.9	40.7

Table A1. List of bridges with environmental classes of Superstructure Extremely Aggressive and Substructure Extremely Aggressive (Cont'd)

ROADWAY	ROAD_SIDE	STRUCTURE	DISTRICT	COUNTY	COUNTY	MNG	Material	pH	Chloride	Sulfate	Resistivity
72250000	R	720758	2	72	Duval	2	Water	8	7698	1776.7	58
15170000	R	150211	7	15	Pinellas	7	Water	8.29	19244	3090.6	21.5
72250000	R	720568	2	72	Duval	2	Water	8	14695	2488	24
13130000	R	130139	1	13	Manatee	1	Water	8.29	18194	2874.5	21.5
46010100	L	460113	3	46	Bay	3	Water	7.8	19844	2622.5	23
86030005	C	860230	4	86	Broward	4	Water	7.7	17348	2734	22
74611000	C	740070	2	74	Nassau	2	Water	7.2	18292	3800	20
46090000	L	460077	3	46	Bay	3	Water	7.4	17040		47
72150000	C	720033	2	72	Duval	2	Water	7.6	8800	1400	52
13130000	L	130951	1	13	Manatee	1	Water	8.29	18194	2874.5	21.5
13040000	C	130006	1	13	Manatee	1	Water	8.2	21393	3476.6	21.5
13080000	C	130057	1	13	Manatee	1	Water	8.13	20594	3227.7	21
12530000	C	120022	1	12	Lee	1	Water	7.7	17000	2770	21
72250000	C	720060	2	72	Duval	2	Water	7.8	14296	2430	3500
51570000	C	510020	3	51	Gulf	3	Water	7.4	19525		37
51502000	C	510047	3	51	Gulf	3	Water	7.3	14200		47
51502000	C	510046	3	51	Gulf	3	Water	5.5	13135		39
87016000	C	870055	6	87	Miami-	6	Water	7.8	22010	2980	24
03634001	C	030125	1	03	Collier	1	Water	8.1	24495		22
87037000	C	870670	6	87	Miami-	6	Water	7.8	17196	2260.7	33
90000004	C	904980	6	90	Monroe	6	Water	7.81	19394	2779.3	22.5
90020000	L	900003	6	90	Monroe	6	Water	7.7	19000	2600	21
70140000	L	700072	5	70	Brevard	5	Water	7.8	15656		30
90060000	C	900131	6	90	Monroe	6	Water	8.1	17200	2720	24
79100000	L	790027	5	79	Volusia	5	Water	7.4	17371	62	1900
70070000	L	700015	5	70	Brevard	5	Water	8	35565		25
70004000	R	700143	5	70	Brevard	5	Water	7.47	17495	2857.7	29
48050001	C	480191	3	48	Escambia	3	Water	7.4	19525		39
49040000	C	490030	3	49	Franklin	3	Water	7.62	19394	3138.5	29
15120000	L	150225	7	15	Pinellas	7	Water	7.9	19000	3200	20
72090000	C	720107	2	72	Duval	2	Water	7.9	15300	2510	74
46030000	C	460025	3	46	Bay	3	Water	7.5	7100		58
72020000	C	720630	2	72	Duval	2	Water	7.58	9697	1435.3	33
94050000	C	940084	4	94	St. Lucie	4	Water	7.8	21195	2652.9	20
72500002	C	720359	2	72	Duval	2	Water	6.8	13700	2370	120
72060000	R	720095	2	72	Duval	2	Water		8350	1000	
86050000	C	860018	4	86	Broward	4	Water	7.97	14346	2094.5	27

Table A2. List of recommended assigned values for local environmental factors*.

Elem No.	Elem category key	Bridge component	Elem description	Elem Unit	With Deck Joint	Without Deck Joint	Marine Structure	Non-marine Structure
12	6	Decks and slabs	Reinforced Concrete Deck	sq feet				
13	6	Decks and slabs	Prestressed Concrete Deck	sq feet				
15	6	Decks and slabs	Prestressed Concrete Top Flange	sq feet				
16	6	Decks and slabs	Reinforced Concrete Top Flange	sq feet				
28	6	Decks and slabs	Steel Deck With Open Grid	sq feet				
29	6	Decks and slabs	Steel Deck with Concrete Filled Grid	sq feet				
30	6	Decks and slabs	Steel Deck Corrugated/Orthotropic/Etc.	sq feet				
31	6	Decks and slabs	Timber Deck	sq feet				
38	6	Decks and slabs	Reinforced Concrete Slab	sq feet				
54	6	Decks and slabs	Timber Slab	sq feet				
60	6	Decks and slabs	Other Deck	sq feet				
65	6	Decks and slabs	Other Slab	sq feet				
8097	6	Decks and slabs	PS Conc Slab (Hybrid)					
8098	6	Decks and slabs	Conc Deck on PC Panel					
8099	6	Decks and slabs	PS Conc Slab (Sonovoid)					
102	1	Superstructure	Steel Closed Web/Box Girder	feet			**Moderate**	**Benign**
104	1	Superstructure	Prestressed Concrete Closed Web/Box Girder	feet			**Moderate**	**Benign**
105	1	Superstructure	Reinforced Concrete Closed Web/Box Girder	feet			**Moderate**	**Benign**
106	1	Superstructure	Other Closed Web/Box Girder	feet			**Moderate**	**Benign**
107	1	Superstructure	Steel Open Girder/Beam	feet			**Moderate**	**Benign**
109	1	Superstructure	Prestressed Concrete Open Girder/Beam	feet	**Moderate**	**Benign**	**Moderate**	**Benign**
110	1	Superstructure	Reinforced Concrete Open Girder/Beam	feet	**Moderate**	**Benign**	**Moderate**	**Benign**
111	1	Superstructure	Timber Open Girder/Beam	feet	**Moderate**	**Benign**	**Moderate**	**Benign**
112	1	Superstructure	Other Open Girder/Beam	feet			**Moderate**	**Benign**
113	1	Superstructure	Steel Stringer	feet			**Moderate**	**Benign**
115	1	Superstructure	Prestressed Concrete Stringer	feet	**Moderate**	**Benign**	**Moderate**	**Benign**
116	1	Superstructure	Reinforced Concrete Stringer	feet	**Moderate**	**Benign**	**Moderate**	**Benign**
117	1	Superstructure	Timber Stringer	feet			**Moderate**	**Benign**
118	1	Superstructure	Other Stringer	feet			**Moderate**	**Benign**
120	1	Superstructure	Steel Truss	feet			**Moderate**	**Benign**
135	1	Superstructure	Timber Truss	feet			**Moderate**	**Benign**
136	1	Superstructure	Other Truss	feet			**Moderate**	**Benign**
141	1	Superstructure	Steel Arch	feet				
142	1	Superstructure	Other Arch	feet				
143	1	Superstructure	Prestressed Concrete Arch	feet				
144	1	Superstructure	Reinforced Concrete Arch	feet				
145	1	Superstructure	Masonry Arch	feet				

Table A2. List of recommended assigned values for local environmental factors* (Cont'd).

Elem No.	Elem category key	Bridge component	Elem description	Elem Unit	With Deck Joint	Without Deck Joint	Marine Structure	Non-marine Structure
146	1	Superstructure	Timber Arch	feet				
147	1	Superstructure	Steel Main Cables	feet			**Moderate**	**Benign**
148	1	Superstructure	Secondary Steel Cables	feet			**Moderate**	**Benign**
149	1	Superstructure	Other Secondary Cable	feet			**Moderate**	**Benign**
152	1	Superstructure	Steel Floor Beam	feet			**Moderate**	**Benign**
154	1	Superstructure	Prestressed Concrete Floor Beam	feet			**Moderate**	**Benign**
155	1	Superstructure	Reinforced Concrete Floor Beam	feet			**Moderate**	**Benign**
156	1	Superstructure	Timber Floor Beam	feet			**Moderate**	**Benign**
157	1	Superstructure	Other Floor Beam	feet			**Moderate**	**Benign**
161	1	Superstructure	Steel Pin and Pin & Hanger Assembly or both	each			**Moderate**	**Benign**
162	1	Superstructure	Steel Gusset Plate	each			**Moderate**	**Benign**
330	1	Railings	Metal Bridge Railing	feet				
331	1	Railings	Reinforced Concrete Bridge Railing	feet				
332	1	Railings	Timber Bridge Railing	feet				
333	1	Railings	Other Bridge Railing	feet				
334	1	Railings	Masonry Bridge Railing	feet				
202	2	Substructure	Steel Column	each	**Severe**	**Benign**	**Severe**	**Benign**
203	2	Substructure	Other Column	each				
204	2	Substructure	Prestressed Concrete Column	each	**Moderate**	**Benign**	**Moderate**	**Benign**
205	2	Substructure	Reinforced Concrete Column	each	**Moderate**	**Benign**	**Moderate**	**Benign**
206	2	Substructure	Timber Column	each	**Severe**	**Benign**	**Severe**	**Benign**
207	2	Substructure	Steel Tower	each	**Severe**	**Benign**	**Severe**	**Benign**
208	2	Substructure	Timber Trestle	each	**Severe**	**Benign**	**Severe**	**Benign**
210	2	Substructure	Reinforced Concrete Pier Wall	feet	**Moderate**	**Benign**	**Moderate**	**Benign**
211	2	Substructure	Other Pier Wall	feet	**Moderate**	**Benign**	**Moderate**	**Benign**
212	2	Substructure	Timber Pier Wall	feet	**Severe**	**Benign**	**Severe**	**Benign**
213	2	Substructure	Masonry Pier Wall	feet	**Moderate**	**Benign**	**Moderate**	**Benign**
215	2	Substructure	Reinforced Concrete Abutment	feet	**Moderate**	**Benign**	**Moderate**	**Benign**
216	2	Substructure	Timber Abutment	feet	**Severe**	**Benign**	**Severe**	**Benign**
217	2	Substructure	Masonry Abutment	feet	**Moderate**	**Benign**	**Moderate**	**Benign**
218	2	Substructure	Other Abutments	feet				
219	2	Substructure	Steel Abutment	feet	**Severe**	**Benign**	**Severe**	**Benign**
220	2	Substructure	Reinforced Concrete Pile Cap/Footing	each	**Moderate**	**Benign**	**Moderate**	**Benign**
225	2	Substructure	Steel Pile	each				
226	2	Substructure	Prestressed Concrete Pile	each				
227	2	Substructure	Reinforced Concrete Pile	each				
228	2	Substructure	Timber Pile	each				

Table A2. List of recommended assigned values for local environmental factors* (Cont'd).

Elem No.	Elem category key	Bridge component	Elem description	Elem Unit	With Deck Joint	Without Deck Joint	Marine Structure	Non-marine Structure
229	2	Substructure	Other Pile	feet				
231	2	Substructure	Steel Pier Cap	feet				
233	2	Substructure	Prestressed Concrete Pier Cap	feet	**Moderate**	**Benign**	**Moderate**	**Benign**
234	2	Substructure	Reinforced Concrete Pier Cap	feet				
235	2	Substructure	Timber Pier Cap	feet	**Moderate**	**Benign**	**Moderate**	**Benign**
236	2	Substructure	Other Pier Cap	feet	**Severe**	**Benign**	**Severe**	**Benign**
8207	2	Substructure	Hollow Core Pile					
8298	2	Substructure	Pile Jacket Bare					
8386	2	Substructure	Fender Dolphin System Metal Uncoated					
8387	2	Substructure	Fender Dolphin System Prestressed Concrete					
8388	2	Substructure	Fender Dolphin System Reinforced Concrete					
8389	2	Substructure	Fender Dolphin System Timber					
8390	2	Substructure	Fender Dolphin System Other Material					
8393	2	Substructure	Bulkhead/Seawall Any Material					
8394	2	Substructure	Abutment Slope Protection Reinforced					
8395	2	Substructure	Abutment Slope Protection Timber					
8396	2	Substructure	Abutment Slope Protection Other Material					
240	2	Culvert	Steel Culvert	feet				
241	2	Culvert	Reinforced Concrete Culvert	feet				
242	2	Culvert	Timber Culvert	feet				
243	2	Culvert	Other Culvert	feet				
244	2	Culvert	Masonry Culvert	feet				
245	2	Culvert	Prestressed Concrete Culvert	feet				
300	3	Deck joints	Strip Seal Expansion Joint	feet				
301	3	Deck joints	Pourable Joint Seal	feet				
302	3	Deck joints	Compression Joint Seal	feet				
303	3	Deck joints	Assembly Joint With Seal	feet				
304	3	Deck joints	Open Expansion Joint	feet				
305	3	Deck joints	Assembly Joint Without Seal	feet				
306	3	Deck joints	Other Joint	feet				
310	4	Bearings	Elastomeric Bearing	each	**Moderate**	**Benign**	**Moderate**	**Benign**
311	4	Bearings	Movable Bearing	each	**Moderate**	**Benign**	**Moderate**	**Benign**
312	4	Bearings	Enclosed/Concealed Bearing	each				
313	4	Bearings	Fixed Bearing	each	**Moderate**	**Benign**	**Moderate**	**Benign**
314	4	Bearings	Pot Bearing	each	**Moderate**	**Benign**	**Moderate**	**Benign**
315	4	Bearings	Disk Bearing	each	**Moderate**	**Benign**	**Moderate**	**Benign**
316	4	Bearings	Other Bearing	each	**Moderate**	**Benign**	**Moderate**	**Benign**

Table A2. List of recommended assigned values for local environmental factors* (Cont'd).

Elem No.	Elem category key	Bridge component	Elem description	Elem Unit	With Deck Joint	Without Deck Joint	Marine Structure	Non-marine Structure
1000	7	Defects	Corrosion	each				
1010	7	Defects	Cracking	each				
1020	7	Defects	Connection	each				
1080	7	Defects	Delamination/Spall/Patched Area	each				
1090	7	Defects	Exposed Rebar	each				
1100	7	Defects	Exposed Prestressing	each				
1110	7	Defects	Cracking (PSC)	each				
1120	7	Defects	Efflorescence/Rust Staining	each				
1130	7	Defects	Cracking (RC and Other)	each				
1140	7	Defects	Decay/Section Loss	each				
1150	7	Defects	Check/Shake	each				
1160	7	Defects	Crack (Timber)	each				
1170	7	Defects	Split/Delamination (Timber)	each				
1180	7	Defects	Abrasion/Wear (Timber)	each				
1190	7	Defects	Abrasion/Wear(PSC/RC)	each				
1220	7	Defects	Deterioration (Other)	each				
1610	7	Defects	Mortar Breakdown (Masonry)	each				
1620	7	Defects	Split/Spall (Masonry)	each				
1630	7	Defects	Patched Area (Masonry)	each				
1640	7	Defects	Masonry Displacement	each				
1900	7	Defects	Distortion	each				
2210	7	Defects	Movement	each				
2220	7	Defects	Alignment	each				
2230	7	Defects	Bulging, Splitting or Tearing	each				
2240	7	Defects	Loss of Bearing Area	each				
2310	7	Defects	Leakage	each				
2320	7	Defects	Seal Adhesion	each				
2330	7	Defects	Seal Damage	each				
2340	7	Defects	Seal Cracking	each				
2350	7	Defects	Debris Impaction	each				
2360	7	Defects	Adjacent Deck or Header	each				
2370	7	Defects	Metal Deterioration or Damage	each				
3210	7	Defects	Delamination/Spall/Patched Area/Pothole	each				
3220	7	Defects	Crack (Wearing Surface)	each				
3230	7	Defects	Effectiveness (Wearing Surface)	each				
3410	7	Defects	Chalking (Steel Protective Coatings)	each				
3420	7	Defects	Peeling/Bubbling/Cracking (Steel Protective	each				

Table A2. List of recommended assigned values for local environmental factors* (Cont'd).

Elem No.	Elem category key	Bridge component	Elem description	Elem Unit	With Deck Joint	Without Deck Joint	Marine Structure	Non-marine Structure
3430	7	Defects	Oxide Film Degradation Color/Texture	each				
3440	7	Defects	Effectiveness (Steel Protective Coatings)	each				
3510	7	Defects	Wear (Concrete Protective Coatings)	each				
3540	7	Defects	Effectiveness (Concrete Protective Coatings)	each				
3600	7	Defects	Effectiveness - Protective System (e.g.	each				
4000	7	Defects	Settlement	each				
6000	7	Defects	Scour	each				
7000	7	Defects	Damage	each				
7356	7	Defects	Steel Cracking/Fatigue					
7357	7	Defects	Pack Rust					
7358	7	Defects	Concrete Cracking					
7359	7	Defects	Concrete Efflorescence					
7360	7	Defects	Settlement					
7361	7	Defects	Scour					
7362	7	Defects	Superstructure Traffic Impact					
7363	7	Defects	Steel Section Loss					
7364	7	Defects	Steel Out-of-Plane Compression Members					
7366	7	Defects	Deck Traffic Impact					
7367	7	Defects	Substructure Traffic Impact					
7368	7	Defects	Barrel Distortion					
7369	7	Defects	Substructure Section Loss					
7370	7	Defects	Alert					
8290	C	Channel	Channel					
8516	0	Protective systems	Painted Steel					
8517	0	Protective systems	Weathering Steel					
8518	0	Protective systems	Galvanized Steel					
8519	0	Protective systems	Other Steel Coatings					
8540	8	Movable bridge elements	Open Gearing					
8541	8	Movable bridge elements	Speed Reducers					
8542	8	Movable bridge elements	Shafts					
8543	8	Movable bridge elements	Shaft Bearings and Shaft Couplings					
8544	8	Movable bridge elements	Brakes					
8545	8	Movable bridge elements	Emergency Drive and Back Up Power System					
8546	8	Movable bridge elements	Span Drive Motors					
8547	8	Movable bridge elements	Hydraulic Power Units					
8548	8	Movable bridge elements	Hydraulic Piping System					
8549	8	Movable bridge elements	Hydraulic Cylinders/Motors/Rotary Actuators					

Table A2. List of recommended assigned values for local environmental factors* (Cont'd).

Elem No.	Elem category key	Bridge component	Elem description	Elem Unit	With Deck Joint	Without Deck Joint	Marine Structure	Non-marine Structure
8550	8	Movable bridge elements	Hopkins Frame					
8560	8	Movable bridge elements	Span Locks/Toe Locks/Heel Stops/Tail Locks					
8561	8	Movable bridge elements	Live Load Shoes/Strike Plates/Buffer Cylinders					
8562	8	Movable bridge elements	Counterweight Support					
8563	8	Movable bridge elements	Access Ladder & Platforms					
8564	8	Movable bridge elements	Counterweight					
8565	8	Movable bridge elements	Trunnion/Straight and Curved Track					
8570	8	Movable bridge elements	Transformers & Thyristors					
8571	8	Movable bridge elements	Submarine Cable					
8572	8	Movable bridge elements	Conduit & Junction Boxes					
8573	8	Movable bridge elements	Programmable Logic Controllers					
8574	8	Movable bridge elements	Control Console					
8580	8	Movable bridge elements	Navigational Light System					
8581	8	Movable bridge elements	Operator Facilities					
8582	8	Movable bridge elements	Lift Bridge Specific Equipment					
8583	8	Movable bridge elements	Swing Bridge Specific Equipment					
8590	8	Movable bridge elements	Resistance Barriers					
8591	8	Movable bridge elements	Warning Gates					
8592	8	Movable bridge elements	Traffic Signal					
320	5	Other	Prestress Concrete Approach Slab	sq feet				
321	5	Other	Reinforced Concrete Approach Slab	sq feet				
510	5	Other	Wearing Surfaces	sq feet				
515	5	Other	Steel Protective Coating	sq feet				
520	5	Other	Concrete Reinforcing Steel Protective System	sq feet				
521	5	Other	Concrete Protective Coating	sq feet				
8199	0	Other	External Post Tensioning Duct					
8397	1	Other	Drainage System Metal Coated					
8398	1	Other	Drainage System Other Material					
8474	5	Other	Metal Wall					
8475	5	Other	Wingwall/Retaining Wall Reinforced Concrete					
8476	5	Other	Wingwall/Retaining Wall Timber					
8477	5	Other	Wingwall/Retaining Wall Other Material					
8478	5	Other	Mechanically Stabilized Earth Wall					
8480	5	Other	Mast Arm Foundations					
8481	5	Other	Metal Mast Arm Vertical Member					
8483	5	Other	Rein Conc Mast Arm Vertical Member					
8484	5	Other	Metal Mast Arm Horizontal Member					

Table A2. List of recommended assigned values for local environmental factors* (Cont'd).

Elem No.	Elem category key	Bridge component	Elem description	Elem Unit	With Deck Joint	Without Deck Joint	Marine Structure	Non-marine Structure
8487	5	Other	Overlane Sign Structure Horizontal Member					
8488	5	Other	Overlane Sign Structure Vertical Member					
8489	5	Other	Overlane Sign Structure Foundation					
8491	5	Other	RC Overlane Sign Vertical					
8496	5	Other	High Mast Light Pole					
8499	5	Other	High Mast Light Pole Foundations					
9000		Other	Lubrication					
9010		Other	Mechanical Alignment					
9020		Other	Operation					
9030		Other	Clearances					
9040		Other	Mechanical Wear/Abrasion					
9050		Other	Outer Insulation (Sub Cable)					
9060		Other	Cable Geometry (Submarine Cable)					
9100		Other	Channel Alignment					
9110		Other	Migration					
9120		Other	Degradation					
9130		Other	Aggradation					
9140		Other	Debris					
9150		Other	Bank Erosion/Scour					
9160		Other	Blockage and Leakage					

* Local environmental factors: Benign (2.0); Low (1.5); Moderate (1.0); and Severe (0.7).

Appendix B: Development of an improved NBI Translator (Multiple Linear Regression)

Table B1. Assignment of bridge elements to NBI components

ELEM KEY	ELEM_SHORTNAME	ELEM_LONGNAME	Component
12	Re Concrete Deck	Reinforced Concrete Deck	Deck
13	Pre Concrete Deck	Prestressed Concrete Deck	Deck
15	Pre Concrete Top Flange	Prestressed Concrete Top Flange	Deck
16	Re Conc Top Flange	Reinforced Concrete Top Flange	Deck
28	Steel Deck - Open Grid	Steel Deck With Open Grid	Deck
29	Steel Deck - Conc Fill Grid	Steel Deck with Concrete Filled Grid	Deck
30	Steel Deck - Orthotropic	Steel Deck Corrugated/Orthotropic/Etc.	Deck
31	Timber Deck	Timber Deck	Deck
38	Re Concrete Slab	Reinforced Concrete Slab	Deck
54	Timber Slab	Timber Slab	Deck
60	Other Deck	Other Deck	Deck
65	Other Slab	Other Slab	Deck
102	Steel Clsd Box Gird	Steel Closed Web/Box Girder	Superstructure
104	Pre Clsd Box Girder	Prestressed Concrete Closed Web/Box Girder	Superstructure
105	Re Clsd Box Girder	Reinforced Concrete Closed Web/Box Girder	Superstructure
106	Othr Clsd Web/Box Girder	Other Closed Web/Box Girder	Superstructure
107	Steel Opn Girder/Beam	Steel Open Girder/Beam	Superstructure
109	Pre Opn Conc Girder/Beam	Prestressed Concrete Open Girder/Beam	Superstructure
110	Re Conc Opn Girder/Beam	Reinforced Concrete Open Girder/Beam	Superstructure
111	Timber Open Girder	Timber Open Girder/Beam	Superstructure
112	Other Open Girder/Beam	Other Open Girder/Beam	Superstructure
113	Steel Stringer	Steel Stringer	Superstructure_Support
115	Pre Conc Stringer	Prestressed Concrete Stringer	Superstructure_Support
116	Re Conc Stringer	Reinforced Concrete Stringer	Superstructure_Support
117	Timber Stringer	Timber Stringer	Superstructure_Support
118	Other Stringer	Other Stringer	Superstructure_Support
120	Steel Truss	Steel Truss	Superstructure
135	Timber Truss	Timber Truss	Superstructure
136	Other Truss	Other Truss	Superstructure
141	Stl Arch	Steel Arch	Superstructure
142	Other Arch	Other Arch	Superstructure
143	Pre Conc Arch	Prestressed Concrete Arch	Superstructure
144	Re Conc Arch	Reinforced Concrete Arch	Superstructure
145	Masonry Arch	Masonry Arch	Superstructure
146	Timber Arch	Timber Arch	Superstructure
147	Stl Main Cables	Steel Main Cables	Superstructure_Support
148	Sec Steel Cables	Secondary Steel Cables	Superstructure_Support
149	Otr Secondary Cable	Other Secondary Cable	Superstructure_Support

Table B1 Assignment of bridge elements to NBI components (Cont'd)

ELEM KEY	ELEM_SHORTNAME	ELEM_LONGNAME	Component
152	Steel Floor Beam	Steel Floor Beam	Superstructure_Support
154	Prestress Floor Beam	Prestressed Concrete Floor Beam	Superstructure_Support
155	Re Conc Floor Beam	Reinforced Concrete Floor Beam	Superstructure_Support
156	Timber Floor Beam	Timber Floor Beam	Superstructure_Support
157	Other Floor Beam	Other Floor Beam	Superstructure_Support
161	Stl Pin Pin/Han both	Steel Pin and Pin & Hanger Assembly or both	Superstructure_Support
162	Stl Gus Plate	Steel Gusset Plate	Superstructure_Support
202	Steel Column	Steel Column	Substructure
203	Other Column	Other Column	Substructure
204	Pre Conc Column	Prestressed Concrete Column	Substructure
205	Re Conc Column	Reinforced Concrete Column	Substructure
206	Timber Column	Timber Column	Substructure
207	Stl Tower	Steel Tower	Substructure
208	Timber Trestle	Timber Trestle	Substructure
210	Re Conc Pier Wall	Reinforced Concrete Pier Wall	Substructure
211	Other Pier Wall	Other Pier Wall	Substructure
212	Timber Pier Wall	Timber Pier Wall	Substructure
213	Masonry Pier Wall	Masonry Pier Wall	Substructure
215	Re Conc Abutment	Reinforced Concrete Abutment	Substructure
216	Timber Abutment	Timber Abutment	Substructure
217	Masonry Abutment	Masonry Abutment	Substructure
218	Other Abutments	Other Abutments	Substructure
219	Stl Abutment	Steel Abutment	Substructure
220	Re Conc Pile Cap/Ftg	Reinforced Concrete Pile Cap/Footing	Substructure
225	Steel Pile	Steel Pile	Substructure
226	Pre Conc Pile	Prestressed Concrete Pile	Substructure
227	Re Conc Pile	Reinforced Concrete Pile	Substructure
228	Timber Pile	Timber Pile	Substructure
229	Other Pile	Other Pile	Substructure
231	Steel Pier Cap	Steel Pier Cap	Substructure
233	Pre Conc Pier Cap	Prestressed Concrete Pier Cap	Substructure
234	Re Conc Pier Cap	Reinforced Concrete Pier Cap	Substructure
235	Timber Pier Cap	Timber Pier Cap	Substructure
236	Other Pier Cap	Other Pier Cap	Substructure
240	Steel Culvert	Steel Culvert	Substructure
241	Re Conc Culvert	Reinforced Concrete Culvert	Substructure
242	Timber Culvert	Timber Culvert	Substructure
243	Other Culvert	Other Culvert	Substructure
244	Masonry Culvert	Masonry Culvert	Substructure
245	Pre Concrete Culvert	Prestressed Concrete Culvert	Substructure

Table B1 Assignment of bridge elements to NBI components (Cont'd)

ELEM KEY	ELEM_SHORTNAME	ELEM_LONGNAME	Component
300	Strip Seal Exp Joint	Strip Seal Expansion Joint	Deck_Support
301	Pourable Joint Seal	Pourable Joint Seal	Deck_Support
302	Compressn Joint Seal	Compression Joint Seal	Deck_Support
303	Assem Jnt With Seal	Assembly Joint With Seal	Deck_Support
304	Open Expansion Joint	Open Expansion Joint	Deck_Support
305	Assem Jnt Wthut Seal	Assembly Joint Without Seal	Deck_Support
306	Other Joint	Other Joint	Deck_Support
310	Elastomeric Bearing	Elastomeric Bearing	Superstructure_Support
311	Moveable Bearing	Movable Bearing	Superstructure_Support
312	Enclosed Bearing	Enclosed/Concealed Bearing	Superstructure_Support
313	Fixed Bearing	Fixed Bearing	Superstructure_Support
314	Pot Bearing	Pot Bearing	Superstructure_Support
315	Disk Bearing	Disk Bearing	Superstructure_Support
316	Other Bearing	Other Bearing	Superstructure_Support
320	Pre Conc Appr Slab	Prestress Concrete Approach Slab	Deck_Support
321	Re Conc Approach Slab	Reinforced Concrete Approach Slab	Deck_Support
330	Metal Bridge Railing	Metal Bridge Railing	Superstructure_Support
331	Re Conc Bridge Railing	Reinforced Concrete Bridge Railing	Superstructure_Support
332	Timb Bridge Railing	Timber Bridge Railing	Superstructure_Support
333	Other Bridge Railing	Other Bridge Railing	Superstructure_Support
334	Masry Bdge Rling	Masonry Bridge Railing	Superstructure_Support
510	Wearing Surfaces	Wearing Surfaces	Protection
515	Steel Protective Coating	Steel Protective Coating	Protection
520	Conc Re Prot Sys	Concrete Reinforcing Steel Protective System	Protection
521	Conc Prot Coating	Concrete Protective Coating	Protection
1000	Corrosion	Corrosion	Defect
1010	Cracking	Cracking	Defect
1020	Connection	Connection	Defect
1080	Delamination/Spall/Patched Area	Delamination/Spall/Patched Area	Defect
1090	Exposed Rebar	Exposed Rebar	Defect
1100	Exposed Prestressing	Exposed Prestressing	Defect
1110	Cracking (PSC)	Cracking (PSC)	Defect
1120	Efflorescence/Rust Staining	Efflorescence/Rust Staining	Defect
1130	Cracking (RC and Other)	Cracking (RC and Other)	Defect

Table B1 Assignment of bridge elements to NBI components (Cont'd)

ELEM KEY	ELEM_SHORTNAME	ELEM_LONGNAME	Component
1140	Decay/Section Loss	Decay/Section Loss	Defect
1150	Check/Shake	Check/Shake	Defect
1160	Crack (Timber)	Crack (Timber)	Defect
1170	Split/Delamination (Timber)	Split/Delamination (Timber)	Defect
1180	Abrasion	Abrasion/Wear (Timber)	Defect
1190	Abrasion(PSC/RC)	Abrasion/Wear(PSC/RC)	Defect
1220	Deterioration (Other)	Deterioration (Other)	Defect
1610	Mortar Breakdown (Masonry)	Mortar Breakdown (Masonry)	Defect
1620	Split/Spall (Masonry)	Split/Spall (Masonry)	Defect
1630	Patched Area (Masonry)	Patched Area (Masonry)	Defect
1640	Masonry Displacement	Masonry Displacement	Defect
1900	Distortion	Distortion	Defect
2210	Movement	Movement	Defect
2220	Alignment	Alignment	Defect
2230	Bulging, Splitting or Tearing	Bulging, Splitting or Tearing	Defect
2240	Loss of Bearing Area	Loss of Bearing Area	Defect
2310	Leakage	Leakage	Defect
2320	Seal Adhesion	Seal Adhesion	Defect
2330	Seal Damage	Seal Damage	Defect
2340	Seal Cracking	Seal Cracking	Defect
2350	Debris Impaction	Debris Impaction	Defect
2360	Adjacent Deck or Header	Adjacent Deck or Header	Defect
2370	Metal Deterioration or Damage	Metal Deterioration or Damage	Defect
3210	Del/Spall/Patch/Pot(Wear Surf)	Delamination/Spall/Patched Area/Pothole (Wearing Surfaces)	Defect
3220	Crack (Wearing Surface)	Crack (Wearing Surface)	Defect
3230	Effectiveness (Wearing Surface)	Effectiveness (Wearing Surface)	Defect
3410	Chalk(Steel Protect Coatings)	Chalking (Steel Protective Coatings)	Defect
3420	Peel/Bub/Crack(Stl Protect Coat)	Peeling/Bubbling/Cracking (Steel Protective Coatings)	Defect
3430	Ox Flm/Txt Adhr(Stl Prot Coat)	Oxide Film Degradation Color/Texture Adherence(Stl Protect Coat)	Defect
3440	Eff (Stl Protect Coat)	Effectiveness (Steel Protective Coatings)	Defect
3510	Wear (Concrete Protect Coat)	Wear (Concrete Protective Coatings)	Defect
3540	Eff(Crete Protect Coat)	Effectiveness (Concrete Protective Coatings)	Defect
3600	Eff - Protect Sys(e.g. cathodic)	Effectiveness - Protective System (e.g. cathodic)	Defect
4000	Settlement	Settlement	Defect
6000	Scour	Scour	Defect

Table B1 Assignment of bridge elements to NBI components (Cont'd)

ELEM KEY	ELEM_SHORTNAME	ELEM_LONGNAME	Component
7000	Damage	Damage	Defect
7356	Steel Cracking/Fatigue	Steel Cracking/Fatigue	Defect
7357	Pack Rust	Pack Rust	Defect
7358	Concrete Cracking	Concrete Cracking	Defect
7359	Concrete Efflorescence	Concrete Efflorescence	Defect
7360	Settlement	Settlement	Defect
7361	Scour	Scour	Defect
7362	Superstructure Traffic Impact	Superstructure Traffic Impact	Defect
7363	Steel Section Loss	Steel Section Loss	Defect
7364	Steel Out-of-Plane Comp. Member	Steel Out-of-Plane Compression Members	Defect
7366	Deck Traffic Impact	Deck Traffic Impact	Defect
7367	Substructure Traffic Impact	Substructure Traffic Impact	Defect
7368	Barrel Distortion	Barrel Distortion	Defect
7369	Sub.Sect Loss SmFlag	Substructure Section Loss	Defect
7370	Alert Smart Flag	Alert	Defect
8097	PS Conc Slab (Hybrid)	PS Conc Slab (Hybrid)	Deck
8098	Conc Deck on PC Panel	Conc Deck on PC Panel	Deck
8099	PS Conc Slab (Sonovoid)	PS Conc Slab (Sonovoid)	Deck
8199	External Post Tensioning Duct	External Post Tensioning Duct	Protection
8207	Hollow Core Pile	Hollow Core Pile	Substructure
8290	Channel	Channel	Channel
8298	Pile Jacket Bare	Pile Jacket Bare	Substructure
8386	Fender/Dolphin Uncoa	Fender Dolphin System Metal Uncoated	Substructure
8387	PS Fender/Dolphin	Fender Dolphin System Prestressed Concrete	Substructure
8388	Rein Conc Fender/Dolphin	Fender Dolphin System Reinforced Concrete	Substructure
8389	Timber Fender/Dolphin	Fender Dolphin System Timber	Substructure
8390	Other Fender/Dolphin	Fender Dolphin System Other Material	Substructure
8393	Bulkhead Seawall Any Material	Bulkhead/Seawall Any Material	Substructure
8394	R/Conc Abut Slope Protection	Abutment Slope Protection Reinforced Concrete	Substructure
8395	Timber Abutment Slope Protection	Abutment Slope Protection Timber	Substructure
8396	Other Abutment Slope Protection	Abutment Slope Protection Other Material	Substructure
8397	Drainage System - Metal	Drainage System Metal Coated	Superstructure
8398	Drainage System - Other	Drainage Sytem Other Material	Superstructure
8474	Metal Wall	Metal Wall	Substructure
8475	R/Conc Walls	Wingwall/Retaining Wall Reinforced Concrete	Substructure

Table B1 Assignment of bridge elements to NBI components (Cont'd)

ELEM KEY	ELEM_SHORTNAME	ELEM_LONGNAME	Component
8476	Timber Walls	Wingwall/Retaining Wall Timber	Substructure
8477	Other Wingwall/Retaining Wall	Wingwall/Retaining Wall Other Material	Substructure
8478	MSE Walls	Mechanically Stabilized Earth Wall	Substructure
8480	Mast Arm Foundation	Mast Arm Foundations	Signstructure
8481	Metal Mast Arm Vertical	Metal Mast Arm Vertical Member	Signstructure
8483	R/Conc Mast Arm Vertical	Rein Conc Mast Arm Vertical Member	Signstructure
8484	Metal Mast Arm Horizontal	Metal Mast Arm Horizontal Member	Signstructure
8487	Sign Member - Horizontal	Overlane Sign Structure Horizontal Member Metal Co	Signstructure
8488	Sign Member - Vertical	Overlane Sign Structure Vertical Member Metal Coat	Signstructure
8489	Sign Foundation	Overlane Sign Structure Foundation	Signstructure
8491	R/Conc Overlane Sign - Vertical	RC Overlane Sign Vertical	Signstructure
8496	High Mast Light Pole	High Mast Light Pole	Signstructure
8499	HMLP Foundation	High Mast Light Pole Foundations	Signstructure
8516	Painted Steel	Painted Steel	Protection
8517	Weathering Steel	Weathering Steel	Protection
8518	Galvanized Steel	Galvanized Steel	Protection
8519	Other Steel Coatings	Other Steel Coatings	Protection
8540	Open Gearing	Open Gearing	Movable bridge
8541	Speed Reducers	Speed Reducers	Movable bridge
8542	Shafts	Shafts	Movable bridge
8543	Shaft Bearings and Couplings	Shaft Bearings and Shaft Couplings	Movable bridge
8544	Brakes	Brakes	Movable bridge
8545	Emergency Drive	Emergency Drive and Back Up Power System	Movable bridge
8546	Span Drive Motors	Span Drive Motors	Movable bridge
8547	Hydraulic Power Unit	Hydraulic Power Units	Movable bridge
8548	Hydraulic Piping System	Hydraulic Piping System	Movable bridge
8549	Hydraulic Cylinders	Hydraulic Cylinders/Motors/Rotary Actuators	Movable bridge
8550	Hopkins Frame	Hopkins Frame	Movable bridge
8560	Locks	Span Locks/Toe Locks/Heel Stops/Tail Locks	Movable bridge
8561	Live Load Shoes	Live Load Shoes/Strike Plates/Buffer Cylinders	Movable bridge
8562	Counterweight Support	Counterweight Support	Movable bridge
8563	Access Ladder & Platform	Access Ladder & Platforms	Movable bridge
8564	Counterweight	Counterweight	Movable bridge
8565	Trunnion/Straight & Curved Track	Trunnion/Straight and Curved Track	Movable bridge
8570	Transformers	Transformers & Thyristors	Movable bridge
8571	Submarine Cable	Submarine Cable	Movable bridge
8572	Conduit & Junction Box	Conduit & Junction Boxes	Movable bridge
8573	PLCs	Programmable Logic Controllers	Movable bridge
8574	Control Console	Control Console	Movable bridge

Table B1 Assignment of bridge elements to NBI components (Cont'd)

ELEM KEY	ELEM_SHORTNAME	ELEM_LONGNAME	Component
8580	Navigational Lights	Navigational Light System	Movable bridge
8581	Operator Facilities	Operator Facilities	Movable bridge
8582	Lift Bridge Special Equipment	Lift Bridge Specific Equipment	Movable bridge
8583	Swing Bridge Special Equipment	Swing Bridge Specific Equipment	Movable bridge
8590	Resistance Barriers	Resistance Barriers	Movable bridge
8591	Warning Gates	Warning Gates	Movable bridge
8592	Traffic Signals	Traffic Signal	Movable bridge
9000	Lubrication	Lubrication	Movable bridge
9010	Mechanical Alignment	Mechanical Alignment	Movable bridge
9020	Operation	Operation	Movable bridge
9030	Clearances	Clearances	Miscellaneous
9040	Mechanical Wear/Abrasion	Mechanical Wear/Abrasion	Defect
9050	Outer Insulation (Sub Cable)	Outer Insulation (Sub Cable)	Movable bridge
9060	Cable Geometry (Submarine Cable)	Cable Geometry (Submarine Cable)	Miscellaneous
9100	Channel Alignment	Channel Alignment	Defect
9110	Migration	Migration	Defect
9120	Degradation	Degradation	Defect
9130	Aggradation	Aggradation	Defect
9140	Debris	Debris	Defect
9150	Bank Erosion	Bank Erosion/Scour	Defect
9160	Blockage and Leakage	Blockage and Leakage	Defect

	NoOfDeck	NoOfDeck	NoOfDeck	NoOfDeck	DeckHI	DeckSupp	DeckProtH	DeckDefH	PercentDe	PercentDe	PercentDe	PercentDe	PercentDe	PercentDe	PercentDe	PercentDe	PercentDe	PercentDe	PercentDe	PercentDe	PercentDe	PercentDe	PercentDe	PercentDe	PercentDe	PercentDe	PercentDe	PercentDe	Owner	StructureK	StructureT	Age	DeckNBI
NoOfDeckElem	1.000																																
NoOfDeckSupport	0.312	1.000																															
NoOfDeckProtection	0.330	-0.156	1.000																														
NoOfDeckDefects	0.433	0.205	0.077	1.000																													
DeckHI	0.147	0.294	0.086	-0.214	1.000																												
DeckSuppHI	0.096	0.708	-0.128	-0.045	0.425	1.000																											
DeckProtHI	0.170	-0.164	0.909	-0.004	0.147	-0.081	1.000																										
DeckDefHI	0.095	0.052	-0.045	0.590	-0.110	-0.065	-0.080	1.000																									
PercentDeckSt1	0.098	0.293	0.092	-0.313	0.900	0.437	0.161	-0.252	1.000																								
PercentDeckSt2	-0.042	-0.240	-0.076	0.326	-0.548	-0.355	-0.135	0.344	-0.846	1.000																							
PercentDeckSt3	-0.004	-0.064	-0.036	0.122	-0.591	-0.142	-0.069	-0.008	-0.432	-0.020	1.000																						
PercentDeckSt4	-0.003	-0.087	0.045	0.004	-0.218	-0.105	0.027	-0.059	-0.099	-0.015	0.002	1.000																					
PercentDeckSuppSt1	0.080	0.604	-0.078	-0.104	0.422	0.945	-0.028	-0.115	0.446	-0.371	-0.151	-0.090	1.000																				
PercentDeckSuppSt2	0.023	0.193	-0.137	0.154	-0.041	0.065	-0.146	0.150	-0.082	0.101	0.018	-0.027	-0.239	1.000																			
PercentDeckSuppSt3	0.032	0.070	-0.004	0.112	-0.048	-0.132	-0.030	0.053	-0.050	0.022	0.089	-0.015	-0.232	-0.058	1.000																		
PercentDeckSuppSt4	-0.023	0.020	-0.030	0.097	-0.102	-0.273	-0.019	0.035	-0.115	0.087	0.094	0.029	-0.240	-0.054	-0.018	1.000																	
PercentDeckProtSt1	0.171	-0.089	0.857	-0.007	0.198	0.010	0.971	-0.096	0.224	-0.196	-0.084	-0.012	0.054	-0.131	-0.033	-0.014	1.000																
PercentDeckProtSt2	0.005	-0.296	0.258	0.004	-0.188	-0.348	0.202	0.060	-0.236	0.237	0.039	0.154	-0.310	-0.067	0.000	-0.027	-0.025	1.000															
PercentDeckProtSt3	0.031	-0.148	0.277	0.033	-0.034	-0.158	0.182	0.001	-0.029	0.010	0.041	0.056	-0.139	-0.048	0.030	0.018	0.108	0.007	1.000														
PercentDeckProtSt4	0.003	-0.184	0.128	0.040	-0.160	-0.208	-0.028	0.033	-0.200	0.185	0.093	-0.002	-0.180	-0.052	-0.013	-0.027	-0.029	-0.005	0.023	1.000													
PercentDeckDefSt1	0.054	0.056	0.052	0.048	0.007	0.011	0.048	0.071	0.013	-0.016	0.000	0.025	0.007	0.013	0.002	-0.008	0.051	-0.009	0.008	-0.006	1.000												
PercentDeckDefSt2	0.030	0.041	-0.110	0.429	-0.046	-0.041	-0.138	0.910	-0.204	0.354	-0.157	-0.047	-0.085	0.148	0.009	0.007	-0.152	0.053	-0.028	0.009	-0.024	1.000											
PercentDeckDefSt3	0.133	0.006	0.158	0.288	-0.141	-0.052	0.146	0.037	-0.081	-0.078	0.370	-0.025	-0.054	-0.023	0.099	0.065	0.143	0.010	0.070	0.055	-0.008	-0.370	1.000										
PercentDeckDefSt4	0.002	-0.056	0.045	0.027	-0.151	-0.083	0.034	-0.078	-0.067	-0.012	-0.001	0.712	-0.067	-0.034	-0.008	0.049	0.007	0.103	0.056	-0.004	0.029	-0.064	-0.029	1.000									
PercentDeckNonSt1	-0.040	-0.252	-0.079	0.347	-0.787	-0.394	-0.149	0.296	-0.964	0.878	0.448	0.103	-0.410	0.095	0.059	0.124	-0.214	0.246	0.035	0.207	-0.011	0.236	0.100	0.071	1.000								
PercentDeckSuppNonSt1	0.022	0.185	-0.114	0.223	-0.111	-0.178	-0.128	0.154	-0.147	0.130	0.114	-0.011	-0.428	0.632	0.514	0.497	-0.118	-0.062	-0.006	-0.058	0.006	0.112	0.076	-0.002	0.167	1.000							
PercentDeckProtNonSt1	0.021	-0.372	0.386	0.036	-0.224	-0.427	0.233	0.059	-0.274	0.259	0.088	0.144	-0.377	-0.096	0.010	-0.022	0.024	0.755	0.519	0.416	-0.005	0.029	0.065	0.104	0.288	-0.073	1.000						
PercentDeckDefNonSt1	0.134	0.038	0.023	0.649	-0.176	-0.091	-0.015	0.907	-0.271	0.282	0.139	0.027	-0.135	0.122	0.086	0.065	-0.035	0.072	0.035	0.051	-0.026	0.675	0.425	0.045	0.318	0.169	0.093	1.000					
Owner	-0.078	0.052	-0.183	-0.132	0.107	0.126	-0.193	-0.092	0.123	-0.106	-0.055	-0.014	0.152	-0.075	-0.075	-0.071	-0.180	-0.065	-0.052	0.016	-0.021	-0.061	-0.056	-0.027	-0.122	-0.133	-0.069	-0.107	1.000				
StructureKind	-0.114	-0.105	-0.034	-0.123	-0.067	-0.120	-0.042	-0.057	-0.079	0.080	-0.003	0.054	-0.079	-0.067	-0.113	-0.149	-0.095	0.207	0.044	-0.014	-0.017	-0.024	-0.068	0.059	0.076	-0.192	0.173	-0.070	0.114	1.000			
StructureType	0.276	0.045	0.091	0.095	-0.012	-0.056	0.038	-0.037	0.018	-0.039	-0.008	-0.011	-0.058	0.018	-0.004	0.004	0.047	-0.024	-0.024	0.077	0.018	-0.049	0.032	-0.023	-0.040	0.012	0.001	-0.026	-0.038	-0.007	1.000		
Age	0.137	-0.049	0.314	0.355	**-0.164**	-0.079	0.335	0.222	-0.214	0.194	0.132	-0.006	-0.091	0.016	0.091	0.094	0.340	0.000	0.070	-0.044	0.055	0.117	0.210	0.006	0.233	0.114	0.018	0.281	-0.164	-0.205	-0.021	1.000	
DeckNBI	-0.078	0.156	-0.271	-0.432	0.339	0.266	-0.248	-0.265	0.351	-0.255	-0.234	-0.218	0.270	-0.010	-0.115	-0.134	-0.206	-0.141	-0.211	-0.088	-0.021	-0.127	-0.292	-0.277	-0.361	-0.145	-0.249	-0.390	0.183	-0.009	0.029	-0.392	1.000

Figure B1. Pearson correlation matrix for Deck NBI ratings and bridge variables.

	NoOfSupst	NoOfSupst	NoOfSusps	NoOfSupst	SupstrHI	SupstrSup	SupstrProt	SupstrDefH	PercentSu	PercentSu	PercentSu	PercentSu	PercentSu	PercentSu	PercentSu	PercentSu	PercentSu	PercentSu	PercentSu	PercentSu	PercentSu	PercentSu	PercentSu	PercentSu	PercentSu	PercentSu	PercentSu	PercentSu	Owner	StructureK	StructureT	Age	SusptrNBI
NoOfSupstrElem	1.000																																
NoOfSupstrSupport	0.556	1.000																															
NoOfSuspstrProtection	0.490	0.503	1.000																														
NoOfSupstrDefects	0.485	0.324	0.272	1.000																													
SupstrHI	0.097	0.173	-0.142	-0.152	1.000																												
SupstrSuppHI	0.116	0.290	-0.055	-0.177	0.526	1.000																											
SupstrProtHI	0.401	0.431	0.898	0.152	-0.031	0.019	1.000																										
SupstrDefHI	0.201	0.074	0.106	0.572	0.006	-0.113	0.070	1.000																									
PercentSupstrSt1	0.013	0.186	-0.189	-0.256	0.894	0.595	-0.059	-0.159	1.000																								
PercentSupstrSt2	0.052	-0.174	0.106	0.244	-0.354	-0.469	0.040	0.315	-0.714	1.000																							
PercentSupstrSt3	0.144	0.052	0.281	0.249	-0.499	-0.189	0.121	0.066	-0.500	0.030	1.000																						
PercentSupstrSt4	0.136	-0.025	0.019	0.097	-0.315	-0.141	0.009	-0.066	-0.202	0.002	-0.005	1.000																					
PercentSupstrSuppSt1	0.076	0.201	-0.153	-0.221	0.487	0.899	-0.054	-0.165	0.576	-0.457	-0.267	-0.102	1.000																				
PercentSupstrSuppSt2	0.004	0.004	0.158	0.123	-0.088	-0.158	0.114	0.151	-0.166	0.182	0.128	-0.020	-0.555	1.000																			
PercentSupstrSuppSt3	0.102	0.195	0.298	0.202	-0.236	-0.282	0.148	0.081	-0.250	0.049	0.452	-0.011	-0.366	0.009	1.000																		
PercentSupstrSuppSt4	-0.003	0.007	0.035	-0.001	-0.043	-0.079	0.033	0.003	-0.046	0.008	0.090	-0.005	-0.083	0.033	0.049	1.000																	
PercentSupstrProtSt1	0.363	0.396	0.827	0.123	0.000	0.031	0.966	0.040	-0.016	0.003	0.086	0.002	-0.028	0.084	0.115	0.029	1.000																
PercentSupstrProtSt2	0.179	0.171	0.328	0.109	-0.073	-0.022	0.239	0.107	-0.112	0.104	0.089	0.018	-0.068	0.083	0.109	0.012	-0.011	1.000															
PercentSupstrProtSt3	0.083	0.081	0.233	0.086	-0.186	-0.078	0.083	0.075	-0.240	0.171	0.232	0.045	-0.155	0.171	0.147	0.027	0.004	0.046	1.000														
PercentSupstrProtSt4	0.018	-0.026	0.267	0.091	-0.321	-0.222	0.017	0.056	-0.367	0.150	0.534	0.011	-0.314	0.176	0.460	0.029	0.000	0.021	0.166	1.000													
PercentSupstrDefSt1	0.030	0.017	-0.003	0.021	0.015	0.023	-0.005	0.097	0.018	-0.012	-0.015	0.011	0.028	-0.019	-0.012	-0.003	-0.007	-0.003	0.031	-0.009	1.000												
PercentSupstrDefSt2	0.142	0.025	0.104	0.375	0.030	-0.107	0.099	0.876	-0.130	0.343	-0.097	-0.052	-0.147	0.145	0.002	0.006	0.071	0.111	0.050	-0.007	-0.033	1.000											
PercentSupstrDefSt3	0.101	0.094	-0.001	0.370	-0.055	-0.012	-0.065	0.163	-0.054	-0.079	0.342	-0.029	-0.035	0.008	0.165	-0.006	-0.066	-0.013	0.038	0.133	-0.024	-0.314	1.000										
PercentSupstrDefSt4	0.149	-0.041	0.033	0.113	-0.259	-0.143	0.022	-0.082	-0.199	0.070	-0.003	0.759	-0.110	-0.005	-0.011	0.000	0.016	0.018	0.035	0.021	0.037	-0.061	-0.050	1.000									
PercentSupstrNonSt1	0.150	-0.115	0.242	0.351	-0.624	-0.507	0.099	0.269	-0.883	0.807	0.568	0.229	-0.530	0.209	0.283	0.054	0.049	0.134	0.272	0.412	-0.015	0.207	0.118	0.229	1.000								
PercentSupstrSuppNonSt1	0.058	0.108	0.294	0.211	-0.203	-0.289	0.176	0.169	-0.275	0.179	0.355	-0.023	-0.663	0.839	0.548	0.119	0.134	0.129	0.223	0.395	-0.022	0.122	0.095	-0.010	0.329	1.000							
PercentSupstrProtNonSt1	0.161	0.131	0.454	0.155	-0.295	-0.166	0.200	0.131	-0.366	0.216	0.440	0.035	-0.276	0.216	0.382	0.034	-0.006	0.701	0.493	0.627	0.005	0.089	0.078	0.036	0.418	0.387	1.000						
PercentSupstrDefNonSt1	0.234	0.093	0.093	0.653	-0.067	-0.132	0.032	0.884	-0.197	0.249	0.198	0.080	-0.181	0.134	0.133	0.000	0.004	0.089	0.083	0.109	-0.043	0.602	0.541	0.102	0.323	0.183	0.151	1.000					
Owner	-0.062	-0.087	-0.048	-0.143	0.094	0.117	-0.019	-0.138	0.122	-0.108	-0.061	-0.030	0.130	-0.062	-0.078	-0.020	-0.008	-0.036	-0.037	-0.026	-0.018	-0.117	-0.029	-0.035	-0.125	-0.095	-0.052	-0.147	1.000				
StructureKind	-0.104	-0.264	-0.421	0.039	0.059	-0.243	-0.419	0.057	-0.011	0.155	-0.153	0.066	-0.190	0.040	-0.140	-0.013	-0.388	-0.149	-0.099	-0.101	0.003	0.056	-0.003	0.071	0.054	-0.042	-0.193	0.065	0.033	1.000			
StructureType	0.219	0.191	0.138	0.294	-0.145	-0.009	0.081	0.154	-0.129	0.019	0.162	-0.021	-0.044	0.055	0.093	-0.004	0.075	0.029	0.020	0.038	-0.019	0.106	0.096	-0.024	0.099	0.095	0.048	0.161	-0.112	-0.232	1.000		
Age	0.039	0.144	0.055	0.255	-0.068	-0.049	0.004	0.194	-0.092	0.053	0.139	0.007	-0.103	0.089	0.187	0.052	-0.010	0.034	0.076	0.040	0.000	0.073	0.242	-0.006	0.119	0.178	0.073	0.260	-0.175	-0.192	0.033	1.000	
SusptrNBI	-0.047	0.019	-0.177	-0.446	0.410	0.407	-0.066	-0.303	0.480	-0.322	-0.373	-0.176	0.432	-0.157	-0.309	-0.071	-0.039	-0.071	-0.158	-0.299	-0.006	-0.170	-0.258	-0.229	-0.498	-0.301	-0.271	-0.402	0.188	0.032	-0.147	-0.391	1.000

Figure B2. Pearson correlation matrix for Superstructure NBI ratings and bridge variables.

	NoOfSubE	NoOfSubP	NoOfSubD	SubHI	SubProtHI	SubDefHI	PercentSu	PercentSu	PercentSu	PercentSu	PercentSu	PercentSu	PercentSu	PercentSu	PercentSu	PercentSu	PercentSu	PercentSu	PercentSu	PercentSu	PercentSu	Owner	StructureK	StructureT	Age	SubNBI
NoOfSubElem	1.000																									
NoOfSubProtection	0.314	1.000																								
NoOfSubDefects	0.579	0.258	1.000																							
SubHI	0.106	-0.083	-0.358	1.000																						
SubProtHI	0.322	0.860	0.239	-0.039	1.000																					
SubDefHI	0.212	0.040	0.346	-0.009	0.049	1.000																				
PercentSubSt1	0.031	-0.088	-0.481	0.906	-0.043	-0.172	1.000																			
PercentSubSt2	0.032	0.038	0.430	-0.478	0.016	0.336	-0.789	1.000																		
PercentSubSt3	0.096	0.137	0.407	-0.586	0.084	0.021	-0.574	0.159	1.000																	
PercentSubSt4	0.022	0.038	0.124	-0.301	0.015	-0.045	-0.220	0.064	0.088	1.000																
PercentSubProtSt1	0.308	0.823	0.223	-0.032	0.980	0.045	-0.034	0.008	0.076	0.017	1.000															
PercentSubProtSt2	0.104	0.245	0.089	-0.014	0.210	0.025	-0.024	0.026	0.019	-0.010	0.026	1.000														
PercentSubProtSt3	0.064	0.229	0.091	-0.070	0.128	0.012	-0.081	0.051	0.099	0.003	0.054	0.031	1.000													
PercentSubProtSt4	0.040	0.351	0.077	-0.104	0.116	0.025	-0.118	0.078	0.127	0.041	0.107	0.016	0.126	1.000												
PercentSubDefSt1	0.002	-0.005	-0.013	0.020	0.000	0.122	0.025	-0.022	-0.015	0.007	0.001	-0.005	-0.005	-0.006	1.000											
PercentSubDefSt2	0.107	0.009	0.191	0.040	0.021	0.870	-0.121	0.353	-0.174	-0.044	0.017	0.025	-0.007	0.013	-0.041	1.000										
PercentSubDefSt3	0.167	0.057	0.244	-0.109	0.047	-0.031	-0.071	-0.117	0.416	0.009	0.046	-0.003	0.039	0.020	-0.045	-0.490	1.000									
PercentSubDefSt4	0.026	0.027	0.086	-0.150	0.001	-0.094	-0.104	0.024	0.031	0.570	0.000	0.006	-0.004	0.025	-0.011	-0.066	-0.032	1.000								
PercentSubNonSt1	0.075	0.102	0.548	-0.699	0.056	0.262	-0.920	0.856	0.627	0.237	0.046	0.028	0.088	0.128	-0.023	0.179	0.116	0.116	1.000							
PercentSubProtNonSt1	0.117	0.452	0.141	-0.099	0.254	0.035	-0.118	0.083	0.128	0.018	0.100	0.643	0.562	0.615	-0.009	0.019	0.028	0.015	0.129	1.000						
PercentSubDefNonSt1	0.274	0.068	0.444	-0.089	0.067	0.843	-0.210	0.252	0.226	0.058	0.062	0.023	0.030	0.037	-0.087	0.540	0.455	0.070	0.313	0.049	1.000					
Owner	-0.125	-0.072	-0.158	0.141	-0.070	-0.096	0.169	-0.134	-0.140	-0.040	-0.069	-0.010	-0.019	-0.036	-0.026	-0.032	-0.103	-0.006	-0.178	-0.035	-0.132	1.000				
StructureKind	-0.005	-0.106	-0.032	0.033	-0.110	-0.034	0.020	0.036	-0.119	-0.020	-0.106	-0.025	-0.038	-0.022	0.011	0.014	-0.098	0.036	-0.033	-0.046	-0.074	0.114	1.000			
StructureType	0.110	0.202	0.119	-0.052	0.212	-0.023	-0.026	-0.014	0.019	-0.012	0.206	0.046	0.051	0.064	0.022	-0.032	0.018	-0.015	-0.003	0.087	-0.018	-0.038	-0.017	1.000		
Age	0.203	0.078	0.334	-0.205	0.084	0.244	-0.259	0.203	0.268	0.070	0.075	0.040	0.048	-0.003	0.003	0.129	0.179	0.050	0.298	0.046	0.312	-0.164	-0.211	-0.015	1.000	
SubNBI	-0.195	-0.151	-0.515	0.485	-0.127	-0.229	0.558	-0.419	-0.463	-0.333	-0.118	-0.045	-0.072	-0.106	0.013	-0.113	-0.193	-0.200	-0.598	-0.120	-0.334	0.192	0.082	0.008	-0.440	1.000

Figure B3. Pearson correlation matrix for Substructure NBI ratings and bridge variables.

	NoOfCulv	NoOfCulvF	NoOfCulvD	CulvHI	CulvProtHI	CulvDefHI	PercentCu	PercentCu	PercentCu	PercentCu	PercentCu	PercentCu	PercentCu	PercentCu	PercentCu	PercentCu	PercentCu	PercentCu	PercentCu	PercentCu	PercentCu	Owner22	StructureK	StructureT	Age	CulvNBI
NoOfCulvElem	1.000																									
NoOfCulvProtection	0.087	1.000																								
NoOfCulvDefects	0.205	-0.234	1.000																							
CulvHI	0.269	-0.226	-0.138	1.000																						
CulvProtHI	0.061	0.903	-0.190	-0.114	1.000																					
CulvDefHI	0.270	-0.217	0.357	0.283	-0.150	1.000																				
PercentCulvSt1	0.061	-0.042	-0.384	0.807	0.019	-0.138	1.000																			
PercentCulvSt2	0.117	-0.218	0.408	0.003	-0.191	0.576	-0.561	1.000																		
PercentCulvSt3	0.061	0.195	0.043	-0.673	0.155	-0.320	-0.384	-0.466	1.000																	
PercentCulvSt4	0.011	0.342	-0.101	-0.352	0.167	-0.324	-0.101	-0.126	-0.075	1.000																
PercentCulvProtSt1	0.061	0.837	-0.164	-0.091	0.972	-0.146	0.030	-0.177	0.128	0.157	1.000															
PercentCulvProtSt2	0.008	0.302	-0.101	-0.064	0.232	-0.018	-0.013	-0.067	0.072	0.069	0.027	1.000														
PercentCulvProtSt3	0.010	0.352	-0.107	-0.119	0.176	-0.059	-0.068	-0.071	0.151	0.025	0.055	0.060	1.000													
PercentCulvProtSt4	0.098	0.555	-0.156	-0.295	0.195	-0.233	-0.117	-0.135	0.111	0.532	0.174	0.086	0.096	1.000												
PercentCulvDefSt1	0.003	-0.016	-0.022	0.049	-0.014	0.091	0.056	-0.025	-0.028	-0.006	-0.013	-0.005	-0.006	-0.009	1.000											
PercentCulvDefSt2	0.140	-0.186	0.168	0.385	-0.137	0.876	-0.026	0.624	-0.594	-0.161	-0.128	-0.022	-0.086	-0.163	-0.034	1.000										
PercentCulvDefSt3	0.109	0.063	0.184	-0.375	0.062	-0.336	-0.161	-0.414	0.739	-0.144	0.050	0.019	0.088	-0.006	-0.034	-0.735	1.000									
PercentCulvDefSt4	0.011	0.351	-0.095	-0.346	0.181	-0.327	-0.097	-0.125	-0.076	0.991	0.171	0.068	0.025	0.529	-0.006	-0.164	-0.143	1.000								
PercentCulvNonSt1	0.181	0.053	0.434	-0.714	-0.009	0.212	-0.963	0.582	0.399	0.103	-0.021	0.016	0.071	0.121	-0.054	0.062	0.195	0.100	1.000							
PercentCulvProtNonSt1	0.075	0.672	-0.199	-0.285	0.314	-0.194	-0.118	-0.154	0.177	0.405	0.156	0.508	0.560	0.765	-0.011	-0.161	0.045	0.402	0.123	1.000						
PercentCulvDefNonSt1	0.382	-0.010	0.485	-0.157	-0.024	0.658	-0.331	0.259	0.174	0.038	-0.033	0.030	0.016	0.009	-0.106	0.326	0.321	0.040	0.439	0.026	1.000					
Owner22	-0.131	-0.061	-0.132	0.098	-0.057	-0.093	0.142	-0.068	-0.112	-0.016	-0.053	-0.021	-0.022	-0.028	0.015	-0.023	-0.092	-0.017	-0.177	-0.038	-0.182	1.000				
StructureKind43A	-0.176	0.422	-0.263	-0.111	0.361	-0.204	0.047	-0.170	0.020	0.184	0.331	0.130	0.152	0.275	-0.014	-0.110	-0.071	0.186	-0.103	0.314	-0.180	0.008	1.000			
StructureType-43B	0.356	-0.143	0.151	0.171	-0.136	0.208	0.023	0.119	-0.012	-0.097	-0.117	-0.111	-0.009	-0.072	0.007	0.133	0.031	-0.095	0.084	-0.100	0.201	0.001	-0.342	1.000		
Age	0.054	0.064	0.253	-0.390	0.040	0.067	-0.467	0.215	0.261	0.038	0.025	0.038	0.072	0.046	-0.007	-0.041	0.182	0.034	0.473	0.082	0.229	-0.149	-0.044	0.066	1.000	
CulvNBI	0.005	-0.341	-0.195	0.565	-0.236	0.146	0.456	-0.004	-0.366	-0.357	-0.197	-0.168	-0.119	-0.324	0.036	0.230	-0.260	-0.369	-0.444	-0.348	-0.230	0.126	-0.184	0.116	-0.420	1.000

Figure B4. Pearson correlation matrix for Culvert NBI ratings and bridge variables.

	NoOfChanElem	NoOfChanDe	ChanHI	ChanDefHI	PercentChan	PercentChan	PercentChan	PercentChan	PercentChan	PercentChan	PercentChan	PercentChan	PercentChan	PercentChan	Owner	StructureKind	StructureType	Age	ChanNBI
NoOfChanElem	1.000																		
NoOfChanDefects	0.150	1.000																	
ChanHI	0.287	-0.705	1.000																
ChanDefHI	0.137	0.905	-0.409	1.000															
PercentChanSt1	0.065	-0.949	0.801	-0.857	1.000														
PercentChanSt2	0.102	0.693	-0.146	0.912	-0.693	1.000													
PercentChanSt3	0.036	0.258	-0.645	-0.118	-0.258	-0.464	1.000												
PercentChanSt4	0.008	0.062	-0.283	-0.132	-0.059	-0.106	-0.040	1.000											
PercentChanDefSt1	0.002	0.016	0.031	0.048	0.039	-0.027	-0.010	-0.002	1.000										
PercentChanDefSt2	0.110	0.717	-0.144	0.934	-0.682	0.983	-0.456	-0.105	-0.027	1.000									
PercentChanDefSt3	0.036	0.268	-0.639	-0.111	-0.256	-0.460	0.991	-0.039	-0.010	-0.453	1.000								
PercentChanDefSt4	0.008	0.062	-0.283	-0.132	-0.059	-0.106	-0.040	1.000	-0.002	-0.105	-0.039	1.000							
PercentChanNonSt1	0.142	0.974	-0.723	0.880	-0.974	0.712	0.265	0.061	-0.038	0.700	0.263	0.061	1.000						
PercentChanDefNonSt1	0.150	0.999	-0.706	0.902	-0.950	0.694	0.258	0.062	-0.037	0.718	0.269	0.062	0.975	1.000					
Owner	-0.001	-0.053	0.050	-0.041	0.057	-0.033	-0.026	-0.020	-0.002	-0.028	-0.024	-0.020	-0.060	-0.053	1.000				
StructureKind	-0.066	-0.104	0.048	-0.096	0.089	-0.079	-0.020	-0.011	0.011	-0.080	-0.019	-0.011	-0.105	-0.104	0.106	1.000			
StructureType	-0.023	0.123	-0.135	0.091	-0.132	0.052	0.085	0.010	0.001	0.052	0.084	0.010	0.126	0.123	-0.059	-0.445	1.000		
Age	0.082	0.160	-0.128	0.115	-0.144	0.066	0.108	0.036	-0.008	0.066	0.106	0.036	0.164	0.161	-0.092	-0.242	0.124	1.000	
ChanNBI	-0.037	-0.500	0.635	-0.254	0.500	-0.049	-0.499	-0.293	0.005	-0.052	-0.499	-0.293	-0.505	-0.500	0.054	0.082	-0.116	-0.264	1.000

Figure B5. Pearson correlation matrix for Channel NBI ratings and bridge variables.

Table B2. Classification table for predicted NBI ratings for bridge deck (Linear regression).

PREDICTED

ACTUAL	0	1	2	3	4	5	6	7	8	9	*Accuracy*	*Total Count*	*Zero Error*	*+/- 1 Error*	*+/- 1 Accuracy*
0	0	0	0	0	0	1	5	2	0	0	0.0%	8	0	0	0.0%
1	0	0	0	0	0	0	7	3	1	0	0.0%	11	0	0	0.0%
2	0	0	0	0	0	0	2	0	0	0	0.0%	2	0	0	0.0%
3	0	0	0	0	0	3	18	10	0	0	0.0%	31	0	0	0.0%
4	0	0	0	0	0	9	113	37	0	0	0.0%	159	0	9	5.7%
5	0	0	0	0	0	29	193	109	0	0	8.8%	331	29	222	67.1%
6	0	0	0	0	1	72	632	345	1	0	60.1%	1051	632	1049	99.8%
7	0	0	0	0	0	18	695	2609	112	0	76.0%	3434	2609	3416	99.5%
8	0	0	0	0	0	0	23	465	406	0	45.4%	894	406	871	97.4%
9	0	0	0	0	0	0	6	8	72	0	0.0%	86	0	72	83.7%
	0	0	0	0	1	132	1694	3588	592	0	**61.2%**	6007	3676	5639	93.9%

Table B3. Classification table for predicted NBI ratings for bridge superstructure (Linear regression).

PREDICTED

ACTUAL	0	1	2	3	4	5	6	7	8	9	*Accuracy*	*Total Count*	*Zero Error*	*+/- 1 Error*	*+/- 1 Accuracy*
0	0	0	0	0	1	4	2	0	1	0	*0.0%*	8	0	0	*0.0%*
1	0	0	0	0	0	7	2	0	0	0	*0.0%*	9	0	0	*0.0%*
2	0	0	0	0	0	10	1	0	0	0	*0.0%*	11	0	0	*0.0%*
3	0	0	0	0	0	2	20	2	0	0	*0.0%*	24	0	0	*0.0%*
4	0	0	0	0	3	26	71	7	0	0	*2.8%*	107	3	29	*27.1%*
5	0	0	0	2	8	55	133	56	0	0	*21.7%*	254	55	196	*77.2%*
6	0	0	0	0	4	53	269	199	8	0	*50.5%*	533	269	521	*97.7%*
7	0	0	0	0	3	31	354	1636	245	0	*72.1%*	2269	1636	2235	*98.5%*
8	0	0	0	0	0	5	12	316	541	0	*61.9%*	874	541	857	*98.1%*
9	0	0	0	0	0	0	11	10	64	0	*0.0%*	85	0	64	*75.3%*
	0	0	0	2	19	193	875	2226	859	0	***60.0%***	4174	2504	3902	*93.5%*

Table B4. Classification table for predicted NBI ratings for bridge substructure (Linear regression).

PREDICTED

ACTUAL	0	1	2	3	4	5	6	7	8	9	*Accuracy*	*Total Count*	*Zero Error*	*+/- 1 Error*	*+/- 1 Accuracy*
0	0	0	0	0	0	1	2	2	0	0	*0.0%*	5	0	0	*0.0%*
1	0	0	0	0	0	8	17	0	0	0	*0.0%*	25	0	0	*0.0%*
2	0	0	0	0	0	1	2	0	0	0	*0.0%*	3	0	0	*0.0%*
3	0	0	0	0	0	11	0	3	0	0	*0.0%*	14	0	0	*0.0%*
4	0	0	0	0	3	50	0	13	0	0	*4.5%*	66	3	53	*80.3%*
5	0	0	0	0	4	59	0	33	0	0	*61.5%*	96	59	63	*65.6%*
6	0	0	0	0	6	80	0	304	2	0	*0.0%*	392	0	384	*98.0%*
7	0	0	0	0	5	28	0	2657	282	0	*89.4%*	2972	2657	2939	*98.9%*
8	0	0	0	0	0	0	4	441	686	0	*60.7%*	1131	686	1127	*99.6%*
9	0	0	0	0	0	0	4	7	92	0	*0.0%*	103	0	92	*89.3%*
	0	0	0	0	18	238	29	3460	1062	0	***70.8%***	4807	3405	4658	*96.9%*

Table B5. Classification table for predicted NBI ratings for bridge culvert (Linear regression).

PREDICTED

ACTUAL	0	1	2	3	4	5	6	7	8	9	*Accuracy*	*Total Count*	*Zero Error*	*+/- 1 Error*	*+/- 1 Accuracy*
0	0	0	0	0	0	2	0	0	0	0	0.0%	2	0	0	0.0%
1	0	0	0	0	0	0	0	0	0	0	0.0%	0	0	0	0.0%
2	0	0	0	0	0	0	0	0	0	0	0.0%	0	0	0	0.0%
3	0	0	0	0	0	24	6	0	0	0	0.0%	30	0	0	0.0%
4	0	0	0	0	1	31	33	4	0	0	1.4%	69	1	32	46.4%
5	0	0	0	0	0	29	69	9	0	0	27.1%	107	29	98	91.6%
6	0	0	0	0	0	87	323	65	0	0	68.0%	475	323	475	100.0%
7	0	0	0	0	1	18	198	273	0	0	55.7%	490	273	471	96.1%
8	0	0	0	0	0	2	1	66	0	0	0.0%	69	0	66	95.7%
9	0	0	0	0	0	0	0	3	0	0	0.0%	3	0	0	0.0%
	0	0	0	0	2	193	630	420	0	0	**50.3%**	1245	626	1142	91.7%

Table B6. Classification table for predicted NBI ratings for bridge channel (Linear regression).

ACTUAL \ PREDICTED	0	1	2	3	4	5	6	7	8	9	*Accuracy*	*Total Count*	*Zero Error*	*+/- 1 Error*	*+/- 1 Accuracy*
0	0	0	0	0	0	0	2	0	0	0	0.0%	2	0	0	0.0%
1	0	0	0	0	0	3	0	0	0	0	0.0%	3	0	0	0.0%
2	0	0	0	0	0	7	0	1	0	0	0.0%	8	0	0	0.0%
3	0	0	0	0	0	21	2	0	0	0	0.0%	23	0	0	0.0%
4	0	0	0	0	0	10	104	6	2	0	0.0%	122	0	10	8.2%
5	0	0	0	0	0	5	253	107	3	0	1.4%	368	5	258	70.1%
6	0	0	0	0	0	10	320	730	71	0	28.3%	1131	320	1060	93.7%
7	0	0	0	0	0	14	69	1800	590	0	72.8%	2473	1800	2459	99.4%
8	0	0	0	0	0	23	4	195	492	0	68.9%	714	492	687	96.2%
9	0	0	0	0	0	7	2	9	265	0	0.0%	283	0	265	93.6%
	0	0	0	0	0	100	756	2848	1423	0	**51.0%**	5127	2617	4739	92.4%

Table B7. Classification table for age-based predicted NBI ratings for bridge deck (Linear regression).

ACTUAL \ PREDICTED	0	1	2	3	4	5	6	7	8	9	*Accuracy*	*Total Count*	*Zero Error*	*+/- 1 Error*	*+/- 1 Accuracy*
0	0	0	0	0	0	1	3	1	2	1	0.0%	8	0	0	0.0%
1	0	0	0	0	0	0	7	1	1	2	0.0%	11	0	0	0.0%
2	0	0	0	0	0	0	2	0	0	0	0.0%	2	0	0	0.0%
3	0	0	0	0	0	3	18	10	0	0	0.0%	31	0	0	0.0%
4	0	0	0	0	0	9	111	37	1	1	0.0%	159	0	9	5.7%
5	0	0	0	0	0	29	189	105	4	4	8.8%	331	29	218	65.9%
6	0	0	0	0	1	72	625	306	34	13	59.5%	1051	625	1003	95.4%
7	0	0	0	0	0	18	688	2398	254	76	69.8%	3434	2398	3340	97.3%
8	0	0	0	0	0	0	14	341	279	260	31.2%	894	279	880	98.4%
9	0	0	0	0	0	0	0	2	22	62	72.1%	86	62	84	97.7%
	0	0	0	0	1	132	1657	3201	597	419	**56.5%**	6007	3393	5534	92.1%

Table B8. Classification table for age-based predicted NBI ratings for bridge superstructure (Linear regression).

	PREDICTED														
	0	1	2	3	4	5	6	7	8	9	*Accuracy*	*Total Count*	*Zero Error*	*+/- 1 Error*	*+/- 1 Accuracy*
0	0	0	0	0	1	2	2	0	2	1	0.0%	8	0	0	0.0%
1	0	0	0	0	0	7	1	0	1	0	0.0%	9	0	0	0.0%
2	0	0	0	0	0	7	1	0	3	0	0.0%	11	0	0	0.0%
3	0	0	0	0	0	2	20	2	0	0	0.0%	24	0	0	0.0%
4	0	0	0	0	3	26	68	6	4	0	2.8%	107	3	29	27.1%
5	0	0	0	2	8	55	129	53	3	4	21.7%	254	55	192	75.6%
6	0	0	0	0	4	53	261	185	25	5	49.0%	533	261	499	93.6%
7	0	0	0	0	3	31	348	1503	290	94	66.2%	2269	1503	2141	94.4%
8	0	0	0	0	0	4	10	268	425	167	48.6%	874	425	860	98.4%
9	0	0	0	0	0	0	0	2	24	59	69.4%	85	59	83	97.6%
	0	0	0	2	19	187	840	2019	777	330	**55.2%**	4174	2306	3804	91.1%

Table B9. Classification table for age-based predicted NBI ratings for bridge substructure (Linear regression).

	PREDICTED														
	0	1	2	3	4	5	6	7	8	9	*Accuracy*	*Total Count*	*Zero Error*	*+/- 1 Error*	*+/- 1 Accuracy*
0	0	0	0	0	0	1	2	1	2	1	0.0%	7	0	0	0.0%
1	0	0	0	0	0	8	2	0	0	0	0.0%	10	0	0	0.0%
2	0	0	0	0	0	1	5	0	0	0	0.0%	6	0	0	0.0%
3	0	0	0	0	0	9	26	3	0	2	0.0%	40	0	0	0.0%
4	0	0	0	0	3	49	69	10	5	2	2.2%	138	3	52	37.7%
5	0	0	0	0	4	58	173	32	2	1	21.5%	270	58	235	87.0%
6	0	0	0	0	6	78	470	288	20	9	54.0%	871	470	836	96.0%
7	0	0	0	0	5	28	449	2524	346	75	73.7%	3427	2524	3319	96.8%
8	0	0	0	0	0	0	14	386	492	252	43.0%	1144	492	1130	98.8%
9	0	0	0	0	0	0	2	3	31	77	68.1%	113	77	108	95.6%
	0	0	0	0	18	232	1212	3247	898	419	**60.1%**	6026	3624	5680	94.3%

Table B10. Classification table for age-based predicted NBI ratings for bridge culvert (Linear regression).

	PREDICTED														
	0	1	2	3	4	5	6	7	8	9	*Accuracy*	*Total Count*	*Zero Error*	*+/- 1 Error*	*+/- 1 Accuracy*
0	0	0	0	0	0	2	0	0	0	0	0.0%	2	0	0	0.0%
1	0	0	0	0	0	0	0	0	0	0	0.0%	0	0	0	0.0%
2	0	0	0	0	0	0	0	0	0	0	0.0%	0	0	0	0.0%
3	0	0	0	0	0	24	6	0	0	0	0.0%	30	0	0	0.0%
4	0	0	0	0	1	31	33	2	1	1	1.4%	69	1	32	46.4%
5	0	0	0	0	0	29	69	9	0	0	27.1%	107	29	98	91.6%
6	0	0	0	0	0	86	322	58	3	6	67.8%	475	322	466	98.1%
7	0	0	0	0	1	17	198	182	79	14	37.1%	491	182	459	93.5%
8	0	0	0	0	0	1	1	14	24	29	34.8%	69	24	67	97.1%
9	0	0	0	0	0	0	0	0	0	3	100.0%	3	3	3	100.0%
	0	0	0	0	2	190	629	265	107	53	**45.0%**	1246	561	1125	90.3%

Table B11. Classification table for age-based predicted NBI ratings for bridge channel (Linear regression).

	PREDICTED														
	0	1	2	3	4	5	6	7	8	9	*Accuracy*	*Total Count*	*Zero Error*	*+/- 1 Error*	*+/- 1 Accuracy*
0	0	0	0	0	0	0	2	0	0	0	0.0%	2	0	0	0.0%
1	0	0	0	0	0	1	0	0	2	0	0.0%	3	0	0	0.0%
2	0	0	0	0	0	7	0	1	0	0	0.0%	8	0	0	0.0%
3	0	0	0	0	0	20	2	0	1	0	0.0%	23	0	0	0.0%
4	0	0	0	0	0	10	98	4	9	1	0.0%	122	0	10	8.2%
5	0	0	0	0	0	5	238	101	19	5	1.4%	368	5	243	66.0%
6	0	0	0	0	0	10	306	688	115	12	27.1%	1131	306	1004	88.8%
7	0	0	0	0	0	8	59	1625	712	69	65.7%	2473	1625	2396	96.9%
8	0	0	0	0	0	16	4	140	466	88	65.3%	714	466	694	97.2%
9	0	0	0	0	0	1	2	5	221	54	19.1%	283	54	275	97.2%
	0	0	0	0	0	78	711	2564	1545	229	**47.9%**	5127	2456	4622	90.2%

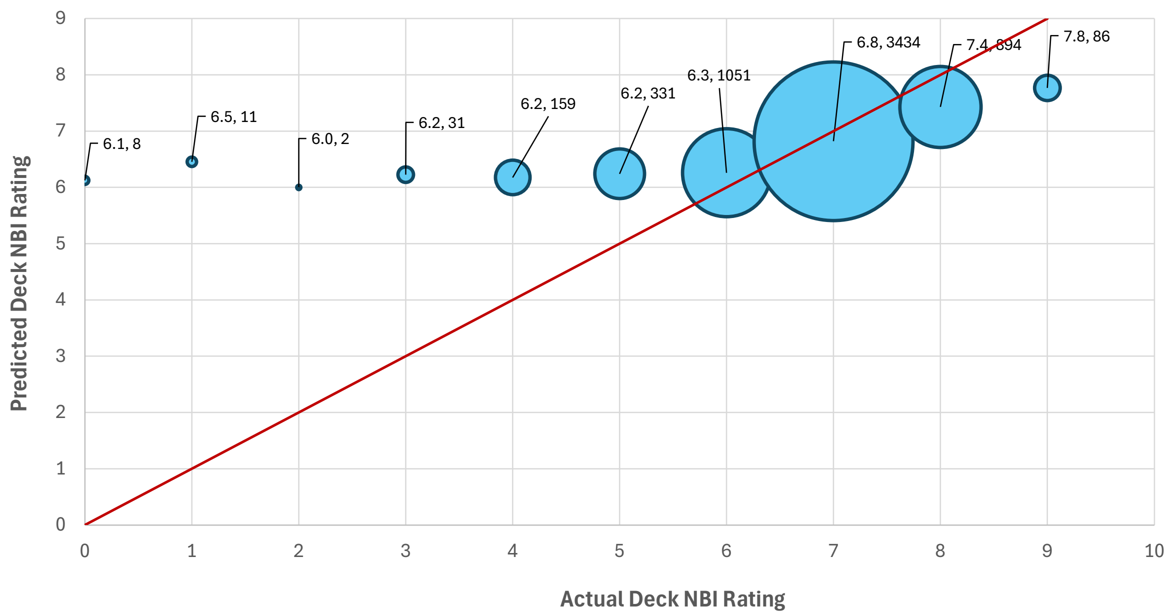


Figure B6. Means of predicted Deck NBI rating and number of bridges at each actual rating.

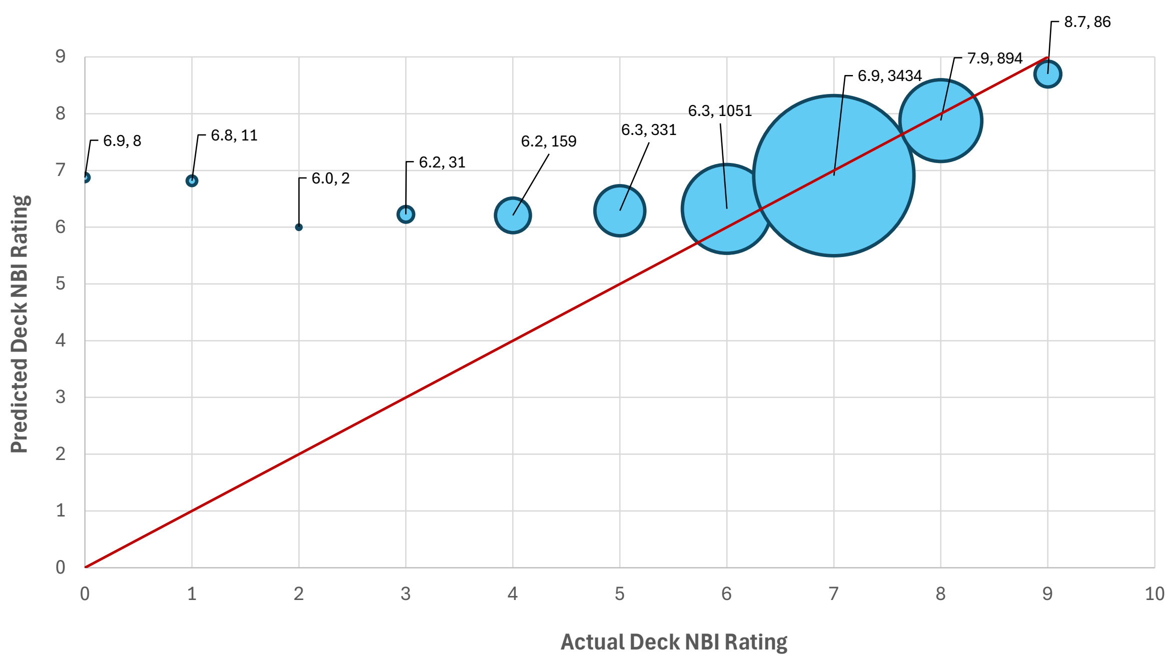


Figure B7. Means of age-based predicted Deck NBI rating and number of bridges at each actual rating.

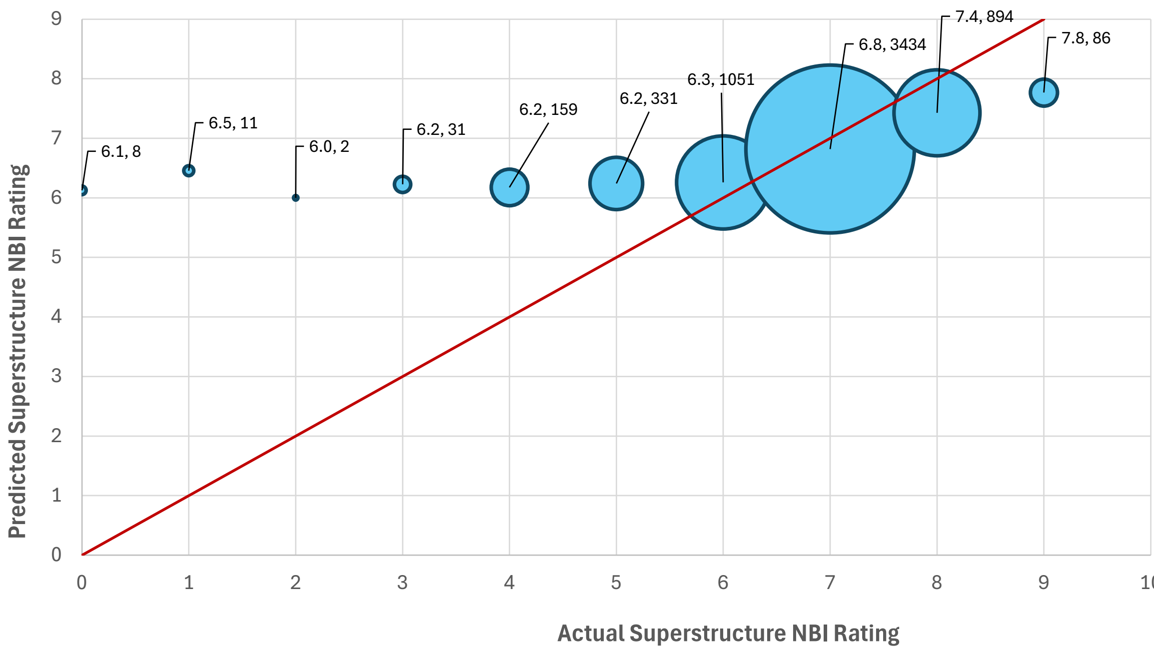


Figure B8. Means of predicted Superstructure NBI rating and number of bridges at each actual rating.

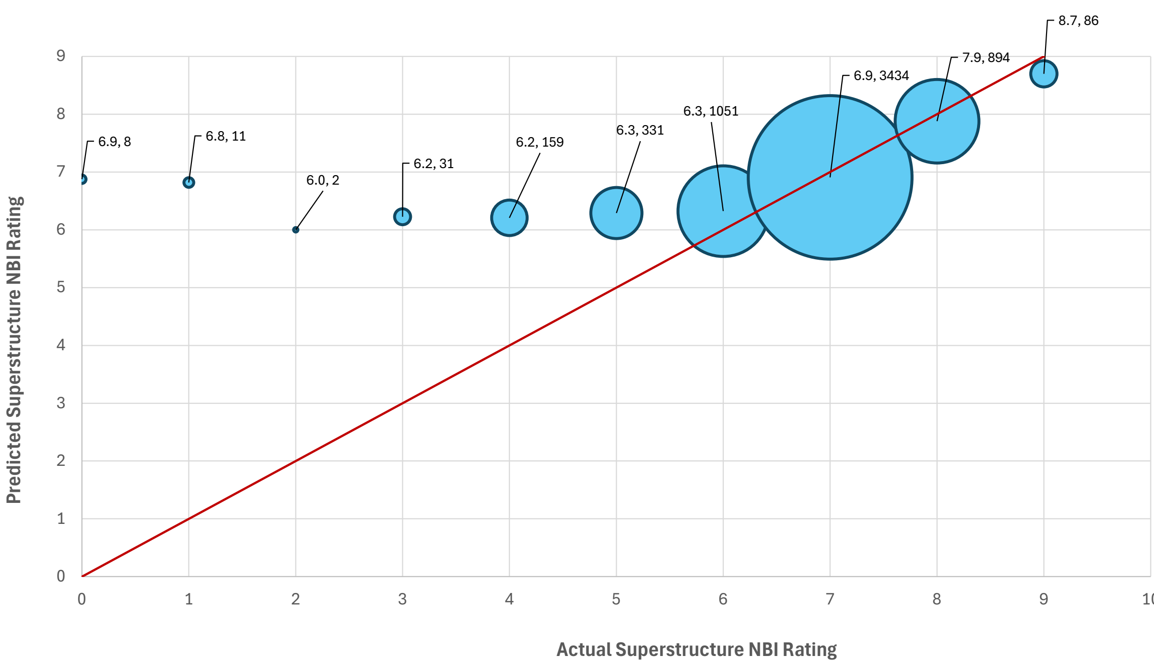


Figure B9. Means of age-based predicted Superstructure NBI rating and number of bridges at each actual rating.

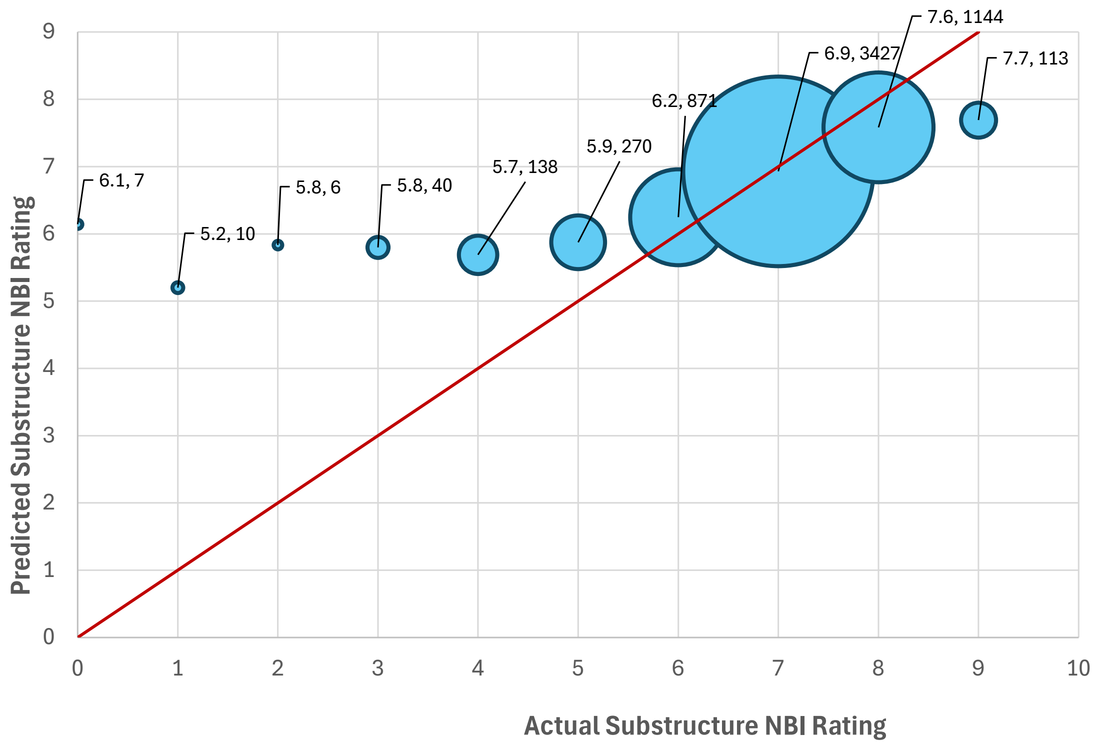


Figure B10. Means of predicted Substructure NBI rating and number of bridges at each actual rating.

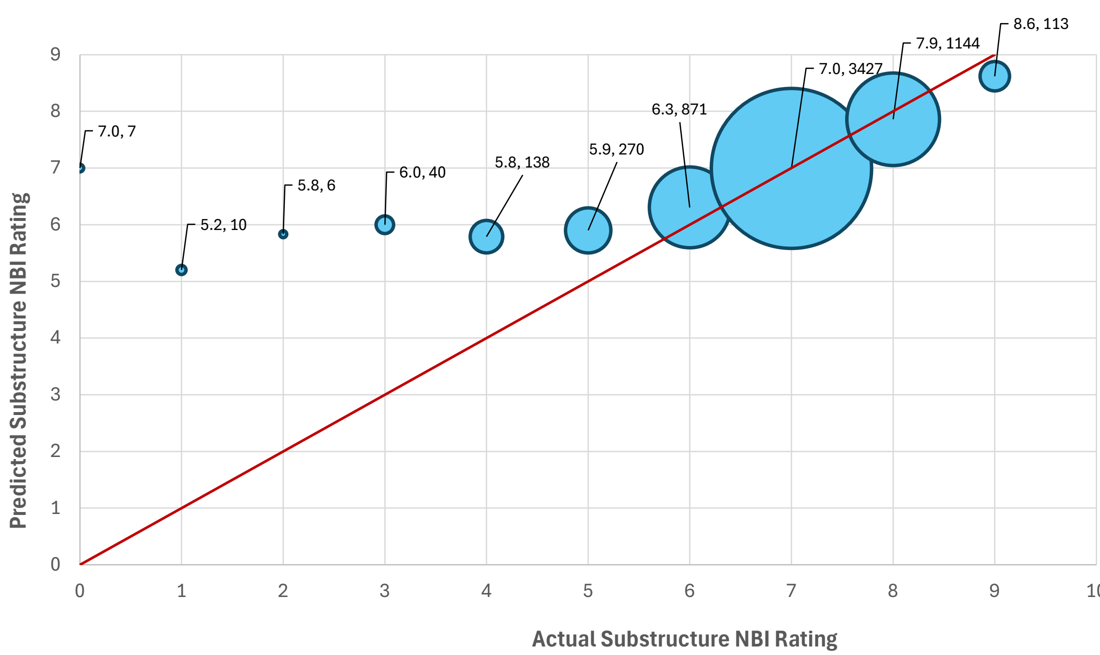


Figure B11. Means of age-based predicted Substructure NBI rating and number of bridges at each actual rating.

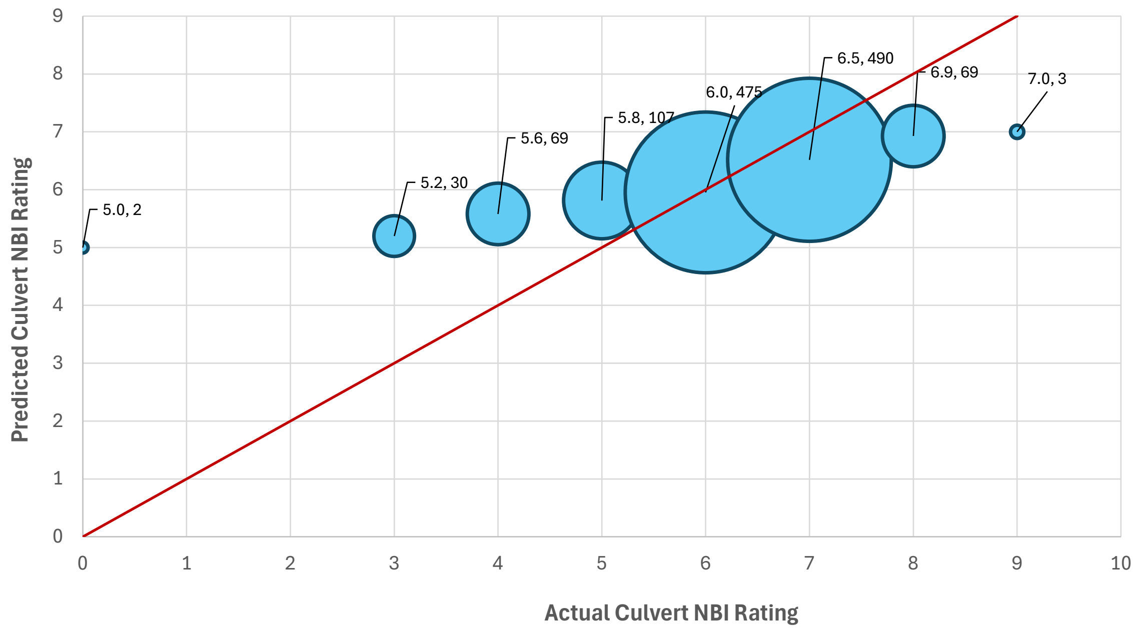


Figure B12. Means of predicted Culvert NBI rating and number of bridges at each actual rating.

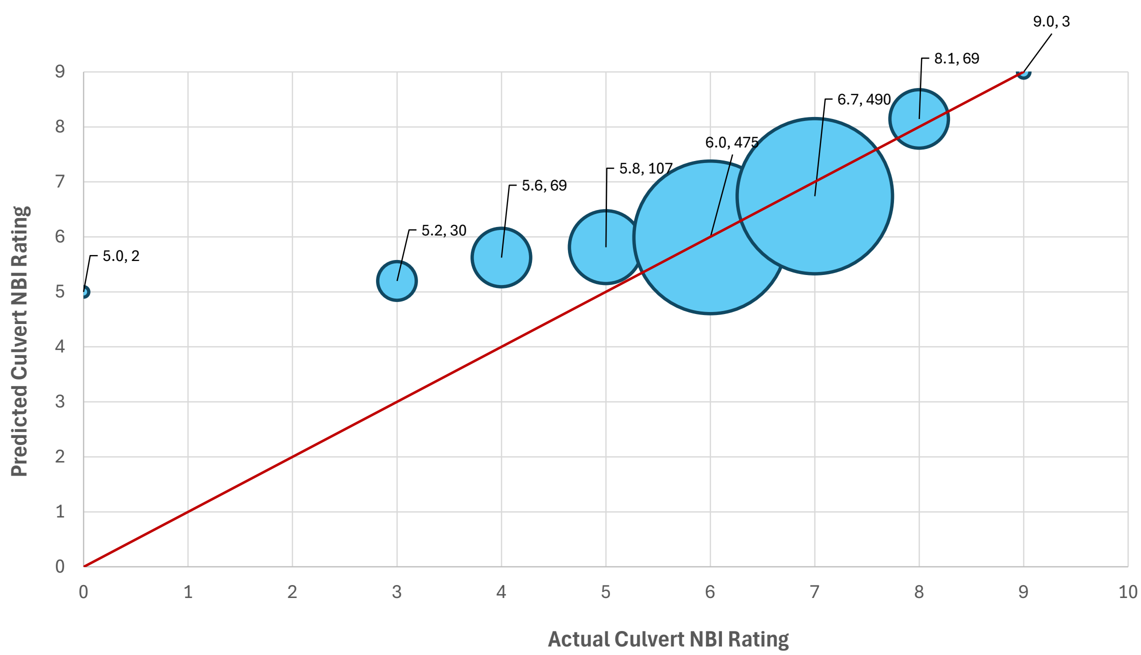


Figure B13. Means of age-based predicted Culvert NBI rating and number of bridges at each actual rating.

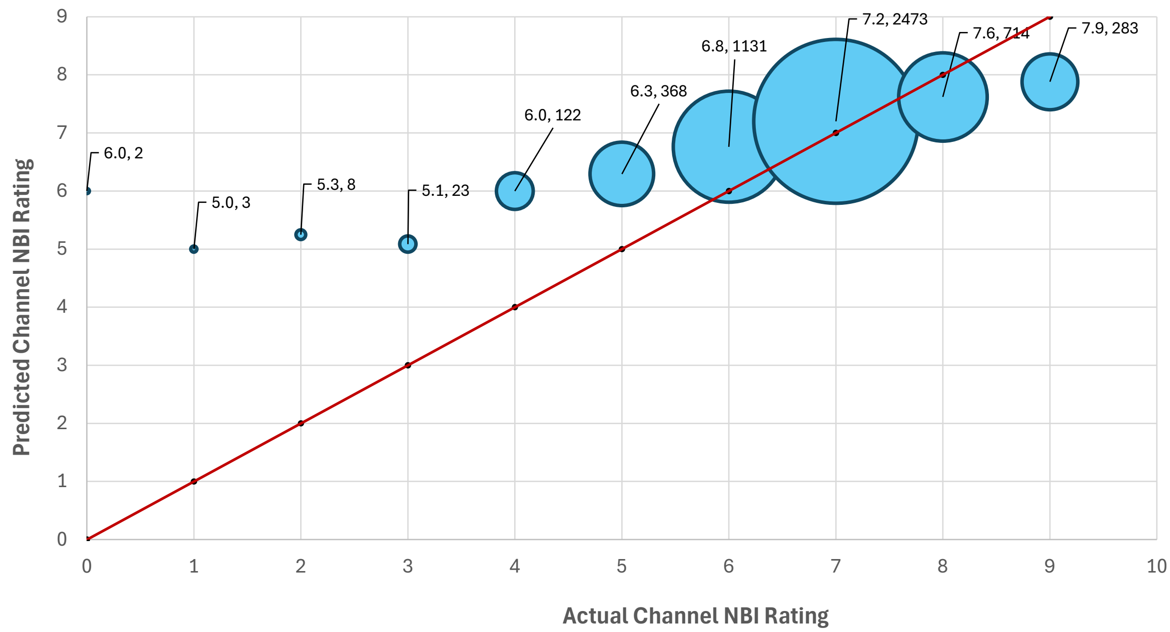


Figure B14. Means of predicted Channel NBI rating and number of bridges at each actual rating.

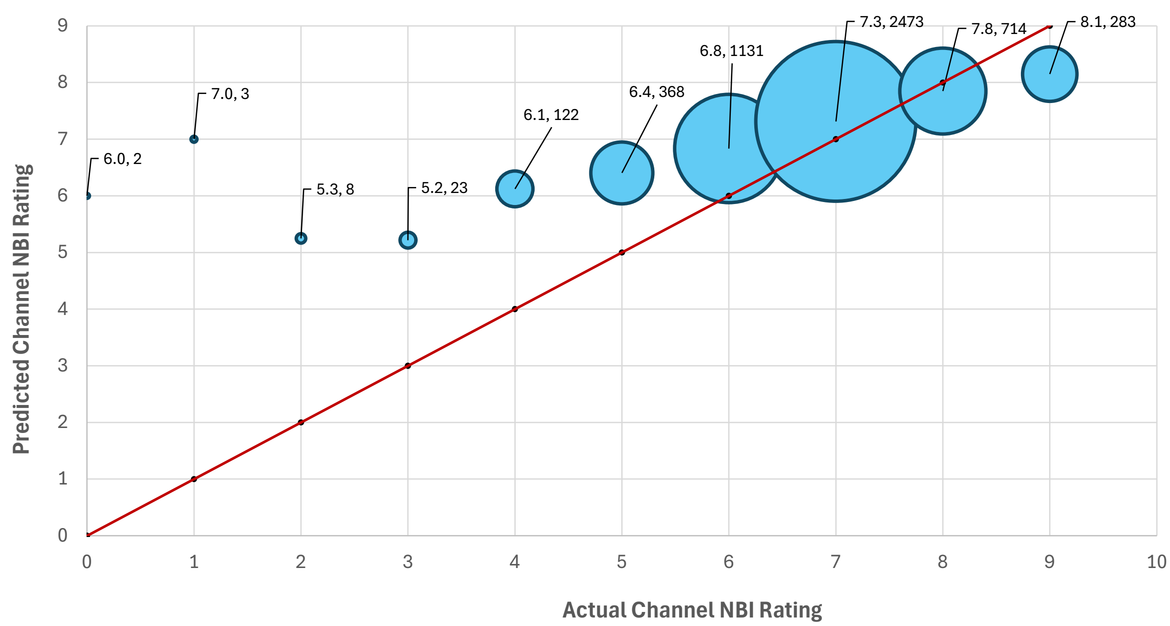


Figure B15. Means of predicted Channel NBI rating and number of bridges at each actual rating.

Appendix C: Development of an improved NBI Translator (Multinomial Logistic Regression)

Table C1. Multinomial logistic regression equations for Deck NBI Translator

Deck NBI Ratings:
$S_1 = e^{(-2.435737+2.402414*\mathbf{NoOfDeckDefects}+1.367506*\mathbf{DeckHI}-1.436090*\mathbf{PercentDeckSt1}+0.215022*\mathbf{Age})}$
$S_2 = e^{(-2.507459+2.386925*\mathbf{NoOfDeckDefects}+1.406220*\mathbf{DeckHI}-1.461093*\mathbf{PercentDeckSt1}+0.187186*\mathbf{Age})}$
$S_3 = e^{(-12.026500+2.665328*\mathbf{NoOfDeckDefects}+1.495361*\mathbf{DeckHI}-1.483974*\mathbf{PercentDeckSt1}+0.229287*\mathbf{Age})}$
$S_4 = e^{(-4.708682+2.321792*\mathbf{NoOfDeckDefects}+1.389477*\mathbf{DeckHI}-1.417630*\mathbf{PercentDeckSt1}+0.260668*\mathbf{Age})}$
$S_5 = e^{(-3.390757+2.425679*\mathbf{NoOfDeckDefects}+1.390369*\mathbf{DeckHI}-1.412856*\mathbf{PercentDeckSt1}+0.252957*\mathbf{Age})}$
$S_6 = e^{(-3.469492+2.269725*\mathbf{NoOfDeckDefects}+1.419919*\mathbf{DeckHI}-1.435790*\mathbf{PercentDeckSt1}+0.259298*\mathbf{Age})}$
$S_7 = e^{(-1.934867+2.229060*\mathbf{NoOfDeckDefects}+1.431273*\mathbf{DeckHI}-1.449525*\mathbf{PercentDeckSt1}+0.250848*\mathbf{Age})}$
$S_8 = e^{(-3.064101+1.736166*\mathbf{NoOfDeckDefects}+1.468438*\mathbf{DeckHI}-1.441579*\mathbf{PercentDeckSt1}+0.235107*\mathbf{Age})}$
$S_9 = e^{(-0.250177+0.805281*\mathbf{NoOfDeckDefects}+1.355653*\mathbf{DeckHI}-1.343485*\mathbf{PercentDeckSt1}+0.162321*\mathbf{Age})}$
$S_{10}=1+\sum_{j=1...9} S_j$
$Pr(i) = S_i/S_{10}$, i=1...9
$Pr(DeckNBI=9) = 1 - \sum_{i=1...9} Pr(i)$
Generalized Deck NBI Ratings:
S(1) = Exp(-1.895754+0.670070***NoOfDeckDefects**-0.041224***DeckHI**+0.021300***PercentDeckDefSt3**+0.015031***Age**)
S(2) = Exp(0.740959+0.554844***NoOfDeckDefects**-0.045738***DeckHI**+0.010962***PercentDeckDefSt3**+0.022938***Age**)
S(3)=1+Sum[j=1...2] S(j)
Pr(i) = S(i)/S(3), i=1...2
Pr(DeckNBIGen=3) = 1 - Sum[i=1...2] Pr(i)

Table C2. Multinomial logistic regression equations for Superstructure NBI Translator

Superstructure NBI Ratings:
S(1) = Exp(-3.331470+2.420455*NoOfSupstrDefects-0.029209*SupstrHI-0.046018*SupstrSuppHI+0.241294*Age)
S(2) = Exp(-3.262471+2.777051*NoOfSupstrDefects-0.049163*SupstrHI-0.050636*SupstrSuppHI+0.251063*Age)
S(3) = Exp(-4.244948+3.095214*NoOfSupstrDefects-0.028918*SupstrHI-0.051193*SupstrSuppHI+0.246147*Age)
S(4) = Exp(-5.469080+2.867422*NoOfSupstrDefects-0.030638*SupstrHI-0.015095*SupstrSuppHI+0.273096*Age)
S(5) = Exp(-2.648091+2.910613*NoOfSupstrDefects-0.036632*SupstrHI-0.019362*SupstrSuppHI+0.257760*Age)
S(6) = Exp(-3.742727+2.881898*NoOfSupstrDefects-0.022217*SupstrHI-0.014367*SupstrSuppHI+0.271545*Age)
S(7) = Exp(-2.899357+2.699168*NoOfSupstrDefects-0.004675*SupstrHI-0.016264*SupstrSuppHI+0.252177*Age)
S(8) = Exp(-2.940160+2.080205*NoOfSupstrDefects+0.017306*SupstrHI+0.003490*SupstrSuppHI+0.224406*Age)
S(9) = Exp(-2.954143+0.616837*NoOfSupstrDefects+0.020682*SupstrHI+0.017167*SupstrSuppHI+0.168344*Age)
S(10)=1+Sum[j=1...9] S(j)
Pr(i) = S(i)/S(10), i=1...9
Pr(SusptrNBI=9) = 1 - Sum[i=1...9] Pr(i)
Generalized Superstructure NBI Ratings:
S(1) = Exp(0.086343+0.895288*NoOfSupstrDefects-0.048761*SupstrHI-0.027740*SupstrSuppHI+0.039709*Age)
S(2) = Exp(-0.246302+0.785263*NoOfSupstrDefects-0.025375*SupstrHI-0.020033*SupstrSuppHI+0.039644*Age)
S(3)=1+Sum[j=1...2] S(j)
Pr(i) = S(i)/S(3), i=1...2
Pr(SupstrNBIGen=3) = 1 - Sum[i=1...2] Pr(i)

Table C3. Multinomial logistic regression equations for Substructure NBI Translator

Substructure NBI Ratings:
S(1) = Exp(-3.106887+1.128650*NoOfSubDefects-0.057333*SubHI+0.211307*PercentSubSt3+0.144270*Age)
S(2) = Exp(-3.618636+1.360773*NoOfSubDefects-0.092881*SubHI+0.233914*PercentSubSt3+0.175001*Age)
S(3) = Exp(-4.601344+1.317418*NoOfSubDefects-0.066380*SubHI+0.238669*PercentSubSt3+0.157932*Age)
S(4) = Exp(-4.431296+1.242863*NoOfSubDefects-0.055652*SubHI+0.232150*PercentSubSt3+0.201436*Age)
S(5) = Exp(-4.667410+1.206848*NoOfSubDefects-0.043697*SubHI+0.257971*PercentSubSt3+0.208761*Age)
S(6) = Exp(-4.621501+1.206994*NoOfSubDefects-0.031318*SubHI+0.253074*PercentSubSt3+0.205359*Age)
S(7) = Exp(-3.633744+1.134387*NoOfSubDefects-0.014671*SubHI+0.238091*PercentSubSt3+0.197249*Age)
S(8) = Exp(-3.905321+0.899252*NoOfSubDefects+0.031796*SubHI+0.208214*PercentSubSt3+0.170138*Age)
S(9) = Exp(-1.539212+0.412423*NoOfSubDefects+0.025582*SubHI+0.108145*PercentSubSt3+0.109890*Age)
S(10)=1+Sum[j=1...9] S(j)
Pr(i) = S(i)/S(10), i=1...9
Pr(SubNBI=9) = 1 - Sum[i=1...9] Pr(i)
Generalized Substructure NBI Ratings:
S(1) = Exp(0.300373+0.382880*NoOfSubDefects-0.084838*SubHI+0.042187*Age)
S(2) = Exp(0.507996+0.311216*NoOfSubDefects-0.053877*SubHI+0.036068*Age)
S(3)=1+Sum[j=1...2] S(j)
Pr(i) = S(i)/S(3), i=1...2
Pr(SubNBIGen=3) = 1 - Sum[i=1...2] Pr(i)

Table C4. Multinomial logistic regression equations for Culvert NBI Translator

Culvert NBI Ratings:
S(1) = Exp(533.905109-5.457556*CulvHI+0.645343*Age)
S(2) = Exp(537.703858-5.488018*CulvHI+0.640204*Age)
S(3) = Exp(537.089792-5.432344*CulvHI+0.634704*Age)
S(4) = Exp(535.710708-5.410357*CulvHI+0.646804*Age)
S(5) = Exp(537.948959-5.403098*CulvHI+0.627019*Age)
S(6) = Exp(536.673532-5.364172*CulvHI+0.598464*Age)
S(7) = Exp(532.457462-5.320872*CulvHI+0.525717*Age)
S(8)=1+Sum[j=1...7] S(j)
Pr(i) = S(i)/S(8), i=1...7
Pr(CulvNBI=9) = 1 - Sum[i=1...7] Pr(i)
Generalized Culvert NBI Ratings:
S(1) = Exp(1.319274-0.083125*CulvHI+0.037812*Age)
S(2) = Exp(1.285781-0.041401*CulvHI+0.034468*Age)
S(3)=1+Sum[j=1...2] S(j)
Pr(i) = S(i)/S(3), i=1...2
Pr(CulvNBIGen=3) = 1 - Sum[i=1...2] Pr(i)

Table C5. Multinomial logistic regression equations for Channel NBI Translator

Channel NBI Ratings:
S(1) = Exp(-28.241667+32.924935*NoOfChanDefects-0.125896*ChanHI)
S(2) = Exp(-1.380705+8.385417*NoOfChanDefects-0.655116*ChanHI)
S(3) = Exp(-28.636159+36.741143*NoOfChanDefects-0.222279*ChanHI)
S(4) = Exp(-28.718157+38.074387*NoOfChanDefects-0.259603*ChanHI)
S(5) = Exp(0.401176+8.076324*NoOfChanDefects-0.118108*ChanHI)
S(6) = Exp(0.761441+7.409833*NoOfChanDefects-0.081641*ChanHI)
S(7) = Exp(1.694352+5.010086*NoOfChanDefects-0.032143*ChanHI)
S(8) = Exp(-0.998785+5.136825*NoOfChanDefects+0.018559*ChanHI)
S(9) = Exp(1.057053+2.245124*NoOfChanDefects-0.004188*ChanHI)
S(10)=1+Sum[j=1...9] S(j)
Pr(i) = S(i)/S(10), i=1...9
Pr(ChanNBI=9) = 1 - Sum[i=1...9] Pr(i)
Generalized Channel NBI Ratings:
S(1) = Exp(-0.053034+4.046643*NoOfChanDefects-0.135125*ChanHI)
S(2) = Exp(1.692785+1.018994*NoOfChanDefects-0.051235*ChanHI)
S(3)=1+Sum[j=1...2] S(j)
Pr(i) = S(i)/S(3), i=1...2
Pr(ChanNBIGen=3) = 1 - Sum[i=1...2] Pr(i)

Table C6. Classification table for predicted NBI ratings for bridge deck (Logistic regression).

PREDICTED

ACTUAL	0	1	2	3	4	5	6	7	8	9	*Accuracy*	*Total Count*	*Zero Error*	*+/- 1 Error*	*+/- 1 Accuracy*
0	0	0	0	0	0	0	6	2	0	0	0.0%	8	0	0	0.0%
1	0	0	0	0	0	0	7	3	1	0	0.0%	11	0	0	0.0%
2	0	0	0	0	0	0	1	1	0	0	0.0%	2	0	0	0.0%
3	0	0	0	0	0	0	11	20	0	0	0.0%	31	0	0	0.0%
4	0	0	0	0	0	0	36	123	0	0	0.0%	159	0	0	0.0%
5	0	0	0	0	0	0	106	225	0	0	0.0%	331	0	106	32.0%
6	0	0	0	0	2	0	439	604	6	0	41.8%	1051	439	1043	99.2%
7	0	0	0	0	1	0	233	3001	199	0	87.4%	3434	3001	3433	100.0%
8	0	0	0	0	0	0	2	393	497	2	55.6%	894	497	892	99.8%
9	0	0	0	0	0	0	0	4	78	4	4.7%	86	4	82	95.3%
	0	0	0	0	3	0	841	4376	781	6	**65.6%**	6007	3941	5556	92.5%

Table C7. Classification table for predicted NBI ratings for bridge superstructure (Logistic regression).

PREDICTED

ACTUAL	0	1	2	3	4	5	6	7	8	9	*Accuracy*	*Total Count*	*Zero Error*	*+/- 1 Error*	*+/- 1 Accuracy*
0	0	0	0	0	5	0	1	1	1	0	0.0%	8	0	0	0.0%
1	0	0	0	0	6	0	2	1	0	0	0.0%	9	0	0	0.0%
2	0	0	0	0	1	1	8	1	0	0	0.0%	11	0	0	0.0%
3	0	0	0	0	0	3	11	10	0	0	0.0%	24	0	0	0.0%
4	0	0	0	0	2	13	47	45	0	0	1.9%	107	2	15	14.0%
5	0	0	0	0	3	47	59	144	1	0	18.5%	254	47	109	42.9%
6	0	0	0	0	10	26	98	394	5	0	18.4%	533	98	518	97.2%
7	0	0	0	0	11	16	74	1926	241	1	84.9%	2269	1926	2241	98.8%
8	0	0	0	0	4	0	0	326	539	5	61.7%	874	539	870	99.5%
9	0	0	0	0	0	0	0	10	60	15	17.6%	85	15	75	88.2%
	0	0	0	0	42	106	300	2858	847	21	**62.9%**	4174	2627	3828	91.7%

Table C8. Classification table for predicted NBI ratings for bridge substructure (Logistic regression).

PREDICTED

ACTUAL	0	1	2	3	4	5	6	7	8	9	*Accuracy*	*Total Count*	*Zero Error*	*+/- 1 Error*	*+/- 1 Accuracy*
0	0	0	0	0	0	0	4	2	0	1	0.0%	7	0	0	0.0%
1	0	0	0	0	0	0	8	2	0	0	0.0%	10	0	0	0.0%
2	0	0	0	0	0	0	6	0	0	0	0.0%	6	0	0	0.0%
3	0	0	0	0	0	1	28	11	0	0	0.0%	40	0	0	0.0%
4	0	0	0	0	3	4	90	41	0	0	2.2%	138	3	7	5.1%
5	0	0	0	0	0	12	141	117	0	0	4.4%	270	12	153	56.7%
6	0	0	0	0	3	7	269	590	2	0	30.9%	871	269	866	99.4%
7	0	0	0	0	2	5	169	2991	259	1	87.3%	3427	2991	3419	99.8%
8	0	0	0	0	0	0	9	466	666	3	58.2%	1144	666	1135	99.2%
9	0	0	0	0	0	0	1	9	91	12	10.6%	113	12	103	91.2%
	0	0	0	0	8	29	725	4229	1018	17	**65.6%**	6026	3953	5683	94.3%

Table C9. Classification table for predicted NBI ratings for bridge culvert (Logistic regression).

PREDICTED

ACTUAL	0	1	2	3	4	5	6	7	8	9	*Accuracy*	*Total Count*	*Zero Error*	*+/- 1 Error*	*+/- 1 Accuracy*
0	0	0	0	0	0	0	2	0	0	0	0.0%	2	0	0	0.0%
1	0	0	0	0	0	0	0	0	0	0	0.0%	0	0	0	0.0%
2	0	0	0	0	0	0	0	0	0	0	0.0%	0	0	0	0.0%
3	16	0	0	0	0	0	12	2	0	0	0.0%	30	0	0	0.0%
4	7	0	0	0	0	0	53	9	0	0	0.0%	69	0	0	0.0%
5	2	0	0	0	0	0	94	11	0	0	0.0%	107	0	94	87.9%
6	5	0	0	0	0	0	370	100	0	0	77.9%	475	370	470	98.9%
7	6	0	0	0	0	0	139	346	0	0	70.5%	491	346	485	98.8%
8	2	0	0	0	0	0	0	59	8	0	11.6%	69	8	67	97.1%
9	0	0	0	0	0	0	0	1	2	0	0.0%	3	0	2	66.7%
	38	0	0	0	0	0	670	528	10	0	**58.1%**	1246	724	1118	89.7%

Table C10. Classification table for predicted NBI ratings for bridge channel (Logistic regression).

PREDICTED

ACTUAL	0	1	2	3	4	5	6	7	8	9	*Accuracy*	*Total Count*	*Zero Error*	*+/- 1 Error*	*+/- 1 Accuracy*
0	0	0	0	0	0	0	2	0	0	0	0.0%	2	0	0	0.0%
1	0	0	0	2	0	0	1	0	0	0	0.0%	3	0	0	0.0%
2	0	0	0	7	0	0	0	1	0	0	0.0%	8	0	7	0.0%
3	0	0	0	21	0	0	2	0	0	0	91.3%	23	21	21	91.3%
4	0	0	0	8	0	0	104	8	2	0	0.0%	122	0	8	6.6%
5	0	0	0	2	0	0	254	109	3	0	0.0%	368	0	254	69.0%
6	0	0	0	5	0	0	325	790	11	0	28.7%	1131	325	1115	98.6%
7	0	0	0	1	0	0	76	2373	23	0	96.0%	2473	2373	2472	100.0%
8	0	0	0	0	0	0	27	676	11	0	1.5%	714	11	687	96.2%
9	0	0	0	0	0	0	8	273	2	0	0.0%	283	0	2	0.7%
	0	0	0	46	0	0	799	4230	52	0	**53.2%**	5127	2730	4566	89.1%

Table C11. Classification table for predicted Generalized NBI ratings (Logistic regression).

a. Deck

Actual \ Predicted	1	2	3	Total	% correct
1	0	96	115	211	0.00%
2	0	605	777	1382	43.78%
3	0	299	4115	4414	93.23%
Total	0	1000	5007	6007	**78.57%**

b. Superstructure

Actual \ Predicted	1	2	3	Total	% correct
1	13	102	44	159	8.18%
2	13	309	465	787	39.26%
3	28	145	3055	3228	94.64%
Total	54	556	3564	4174	**80.91%**

c. Substructure

Actual \ Predicted	1	2	3	Total	% correct
1	2	150	49	201	1.00%
2	3	486	652	1141	42.59%
3	11	236	4437	4684	94.73%
Total	16	872	5138	6026	**81.73%**

d. Culvert

Actual \ Predicted	1	2	3	Total	% correct
1	20	70	11	101	19.80%
2	7	470	105	582	80.76%
3	8	152	403	563	71.58%
Total	35	692	519	1246	**71.67%**

e. Channel

Actual \ Predicted	1	2	3	Total	% correct
1	38	109	11	158	24.05%
2	7	579	913	1499	38.63%
3	1	111	3358	3470	96.77%
Total	46	799	4282	5127	**77.53%**

Appendix D: New cost estimating models for bridge MR&R activities

Table D1. Historical bid unit costs for bridge deck removal, rehabilitation, deck joint maintenance, and repair activities

Bridge MR&R Activity	Pay Item No.	Description	Bid Year	No. of Contracts	Avg. Unit Cost	Total Quantity	Unit of Measure	2024 Unit Cost
Deck joint rehab, repair or replacement	0400 32	CONCRETE FOR JOINT REPAIR	2021	3	$13,637.64	8.900	CY	$15,274.16
	0400 32	CONCRETE FOR JOINT REPAIR	2022	3	$13,305.80	22.400	CY	$14,104.15
	0458 1 11	BRIDGE DECK EXPANSION JNT,NEW,POURED	2021	30	$58.70	8,691.000	LF	$65.74
	0458 1 11	BRIDGE DECK EXPANSION JNT,NEW,POURED	2022	19	$56.01	7,907.000	LF	$59.37
	0458 1 11	BRIDGE DECK EXPANSION JNT,NEW,POURED	2023	26	$81.92	12,081.000	LF	$84.38
	0458 1 12	BRIDGE DECK EXPANSION JNT,NEW,STRIP SEAL	2021	3	$263.41	462.000	LF	$295.02
	0458 1 12	BRIDGE DECK EXPANSION JNT,NEW,STRIP SEAL	2022	2	$777.12	764.000	LF	$823.75
	0458 1 12	BRIDGE DECK EXPANSION JNT,NEW,STRIP SEAL	2023	2	$630.87	396.000	LF	$649.80
	0458 1 13	BRIDGE DECK EXPANSION JNT,NEW,MODULAR	2021	1	$1,727.48	675.000	LF	$1,934.78
	0458 1 13	BRIDGE DECK EXPANSION JNT,NEW,MODULAR	2023	1	$356.69	48.000	LF	$367.39
	0458 1 14	BRIDGE DECK EXPANSION JNT,NEW,FINGER JNT	2023	1	$1,056.69	147.000	LF	$1,088.39
	0458 1 21	BRIDGE DECK EXPANSION JNT, REHAB,POURED	2021	26	$48.37	13,605.000	LF	$54.17
	0458 1 21	BRIDGE DECK EXPANSION JNT, REHAB,POURED	2022	46	$76.11	30,969.000	LF	$80.68
	0458 1 21	BRIDGE DECK EXPANSION JNT, REHAB,POURED	2023	49	$79.12	23,940.000	LF	$81.49
	0458 1 22	BRIDGE DECK EXPANSION JNT, REHAB,STRIP	2021	5	$152.05	1,618.000	LF	$170.30
	0458 1 22	BRIDGE DECK EXPANSION JNT, REHAB,STRIP	2022	3	$581.90	179.000	LF	$616.81
	0458 1 22	BRIDGE DECK EXPANSION JNT, REHAB,STRIP	2023	1	$925.00	127.000	LF	$952.75
	0458 1 24	BRIDGE DECK EXPAN JNT,REHAB,FINGER JNT	2022	2	$1,926.42	624.000	LF	$2,042.01
	0458 1 25	BRIDGE DECK EXPAN JNT, REHAB,COMPRESSION	2022	2	$136.82	367.000	LF	$145.03
	0458 1 25	BRIDGE DECK EXPAN JNT, REHAB,COMPRESSION	2023	1	$295.00	81.000	LF	$303.85
	0458 1 28	BRIDGE DECK EXP JNT,REHAB,POURED W/O ROD	2023	2	$57.86	526.000	LF	$59.60
Deck rehabilitation	0400 4 41	CONC CLASS IV, PRECAST DECK OVERLAY	2021	1	$3,738.82	13.000	CY	$4,187.48
	0400 7 1	BRIDGE DECK GROOVING	2021	27	$5.03	118,004.000	SY	$5.63
	0400 7 1	BRIDGE DECK GROOVING	2022	20	$8.74	96,522.000	SY	$9.26
	0400 7 1	BRIDGE DECK GROOVING	2023	25	$8.66	108,812.000	SY	$8.92
	0400 9 1	BRIDGE DECK PLANING	2021	20	$6.24	105,478.000	SY	$6.99
	0400 9 1	BRIDGE DECK PLANING	2022	10	$6.97	92,052.000	SY	$7.39
	0400 9 1	BRIDGE DECK PLANING	2023	16	$9.06	103,593.000	SY	$9.33
	0400 20	GRINDING BRIDGE DECK- REHABILITATION	2023	1	$35.40	1,163.000	SY	$36.46
	0403 2100	RESTORE SPALL AREA CONC BRIDGE DECKS	2022	2	$692.41	237.000	CF	$733.95
Deck removal	0110 3 1	REMOVAL OF EXIST CONC BRIDGE DECK	2022	1	$355.00	110.000	SF	$376.30

Table D2. Historical bid unit costs for bridge superstructure maintenance and repair activities

Bridge MR&R Activity	Pay Item No.	Description	Bid Year	No. of Contracts	Avg. Unit Cost	Total Quantity	Unit of Measure	2024 Unit Cost
Beam repair	0450 82	BEAM REPAIR	2021	1	$500.00	277.000	LF	$560.00
	0450 82	BEAM REPAIR	2023	2	$976.09	92.000	LF	$1,005.37
	0450 83 1	BEAM REPAIR, STRAND SPLICES	2021	3	$2,916.67	12.000	EA	$3,266.67
	0450 83 1	BEAM REPAIR, STRAND SPLICES	2023	2	$2,825.00	20.000	EA	$2,909.75
	0450 83 2	BEAM REPAIR, BAR SPLICES	2021	2	$1,000.00	2.000	EA	$1,120.00
Bearing pad	0400147	COMPOSITE NEOPRENE PADS	2021	17	$1,100.55	894.900	CF	$1,232.62
	0400147	COMPOSITE NEOPRENE PADS	2022	12	$1,219.66	558.000	CF	$1,292.84
	0400147	COMPOSITE NEOPRENE PADS	2023	14	$1,291.91	933.100	CF	$1,330.67
	0400148	PLAIN NEOPRENE BEARING PADS	2021	14	$975.03	202.100	CF	$1,092.03
	0400148	PLAIN NEOPRENE BEARING PADS	2022	7	$2,330.65	76.000	CF	$2,470.49
	0400148	PLAIN NEOPRENE BEARING PADS	2023	11	$1,685.11	199.100	CF	$1,735.66
	0400140 1	NEOPRENE PAD REPLACEMENT, BENT/PIER	2021	1	$3,000.00	10.000	EA	$3,360.00
	0400140 1	NEOPRENE PAD REPLACEMENT, BENT/PIER	2023	2	$12,613.64	22.000	EA	$12,992.05
Concrete bridge railing	0521 5 4	CONC TRAF RAIL- BRG, 32" VERT FACE	2022	3	$229.64	298.000	LF	$243.42
	0521 5 4	CONC TRAF RAIL- BRG, 32" VERT FACE	2023	1	$200.00	304.000	LF	$206.00
	0521 5 4	CONC TRAF RAIL- BRG, 32" VERT FACE	2021	4	$100.04	1,845.000	LF	$112.04
	0521 5 5	CONC TRAF RAIL- BRG, 42" VERT FACE	2023	1	$169.40	800.000	LF	$174.48
	0521 5 8	CONC TRAF RAIL- BRG, RETRO-VERT FACE	2022	2	$2,146.00	40.000	LF	$2,274.76
	0521 5 8	CONC TRAF RAIL- BRG, RETRO-VERT FACE	2023	1	$765.00	60.000	LF	$787.95
	0521 5 10	CONC TRAF RAIL- BRG, REPAIR EXISTING	2022	1	$800.00	20.000	LF	$848.00
	0521 5 11	CONC TRAF RAIL- BRG, RETRO-POST & BEAM	2023	3	$6,679.94	13.000	EA	$6,880.34
	0521 5 12	CONC TRAF RAIL- BRG, 36" MED SING SLOPE	2021	2	$102.88	1,374.000	LF	$115.23
	0521 5 12	CONC TRAF RAIL- BRG, 36" MED SING SLOPE	2022	5	$153.20	2,158.000	LF	$162.39
	0521 5 12	CONC TRAF RAIL- BRG, 36" MED SING SLOPE	2023	4	$155.84	2,689.000	LF	$160.52
	0521 5 13	CONC TRAF RAIL- BRIDGE, 36" SING SLOPE	2021	23	$107.32	39,438.000	LF	$120.20
	0521 5 13	CONC TRAF RAIL- BRIDGE, 36" SING SLOPE	2022	16	$119.17	34,432.000	LF	$126.32
	0521 5 13	CONC TRAF RAIL- BRIDGE, 36" SING SLOPE	2023	22	$167.49	35,974.000	LF	$172.51
	0521 5 14	CONC TRAF RAIL- BRIDGE, 14" SINGLE SLOPE	2021	1	$140.00	2,253.000	LF	$156.80
	0521 5 14	CONC TRAF RAIL- BRIDGE, 14" SINGLE SLOPE	2022	2	$139.31	3,211.000	LF	$147.67
	0521 5 14	CONC TRAF RAIL- BRIDGE, 14" SINGLE SLOPE	2023	3	$162.85	7,883.000	LF	$167.74
	0521 5 22	CONC TRAF RAIL- BRIDGE, 8' NOISE WALL	2021	1	$390.00	2,217.000	LF	$436.80

Table D2. Historical bid unit costs for bridge superstructure maintenance and repair activities (Cont'd)

Bridge MR&R Activity	Pay Item No.	Description	Bid Year	No. of Contracts	Avg. Unit Cost	Total Quantity	Unit of Measure	2024 Unit Cost
Concrete bridge railing	0521 5 22	CONC TRAF RAIL- BRIDGE, 8' NOISE WALL	2023	2	$566.52	1,093.000	LF	$583.52
	0521 5100	CONC TRAF RAIL- BRG, 32" F	2023	1	$712.00	61.000	LF	$733.36
Prestressed beam	0450 1 1	PREST BEAMS, TYPE II	2021	6	$194.26	13,251.000	LF	$217.57
	0450 1 1	PREST BEAMS, TYPE II	2022	2	$203.99	3,243.000	LF	$216.23
	0450 1 1	PREST BEAMS, TYPE II	2023	2	$194.58	6,924.000	LF	$200.42
	0450 1201	PREST BEAMS, TYPE II, MODIFIED	2023	1	$309.93	432.000	LF	$319.23
	0450 2 36	PREST BEAMS: FLORIDA-I BEAM 36"	2021	5	$324.03	10,784.000	LF	$362.91
	0450 2 36	PREST BEAMS: FLORIDA-I BEAM 36"	2022	6	$400.44	8,931.000	LF	$424.47
	0450 2 36	PREST BEAMS: FLORIDA-I BEAM 36"	2023	6	$419.24	10,987.000	LF	$431.82
	0450 2 45	PREST BEAMS: FLORIDA-I BEAM 45"	2021	3	$310.99	4,664.000	LF	$348.31
	0450 2 45	PREST BEAMS: FLORIDA-I BEAM 45"	2022	2	$388.98	5,009.000	LF	$412.32
	0450 2 45	PREST BEAMS: FLORIDA-I BEAM 45"	2023	3	$372.22	10,053.000	LF	$383.39
	0450 2 54	PREST BEAMS: FLORIDA-I BEAM 54"	2021	3	$388.95	4,937.000	LF	$435.62
	0450 2 54	PREST BEAMS: FLORIDA-I BEAM 54"	2022	4	$403.00	11,714.000	LF	$427.18
	0450 2 54	PREST BEAMS: FLORIDA-I BEAM 54"	2023	3	$381.49	18,476.000	LF	$392.93
	0450 2 63	PREST BEAMS: FLORIDA-I BEAM 63"	2021	1	$500.00	2,962.000	LF	$560.00
	0450 2 63	PREST BEAMS: FLORIDA-I BEAM 63"	2022	1	$360.00	6,291.000	LF	$381.60
	0450 2 63	PREST BEAMS: FLORIDA-I BEAM 63"	2023	2	$414.50	4,424.000	LF	$426.94
	0450 2 72	PREST BEAMS: FLORIDA-I BEAM 72"	2021	2	$405.86	4,848.000	LF	$454.56
	0450 2 72	PREST BEAMS: FLORIDA-I BEAM 72"	2022	2	$432.32	5,842.000	LF	$458.26
	0450 2 72	PREST BEAMS: FLORIDA-I BEAM 72"	2023	4	$417.42	28,773.000	LF	$429.94
	0450 2 78	PREST BEAMS: FLORIDA-I BEAM 78"	2021	3	$455.16	44,556.000	LF	$509.78
	0450 2 78	PREST BEAMS: FLORIDA-I BEAM 78"	2023	3	$407.96	4,978.000	LF	$420.20
	0450 2 84	PREST BEAMS: FLORIDA-I BEAM 84"	2021	2	$364.97	9,176.000	LF	$408.77
	0450 2 84	PREST BEAMS: FLORIDA-I BEAM 84"	2022	2	$556.17	29,398.000	LF	$589.54
	0450 2 84	PREST BEAMS: FLORIDA-I BEAM 84"	2023	1	$445.06	6,111.000	LF	$458.41
	0450 2 96	PREST BEAMS: FLORIDA-I BEAM 96"	2021	2	$563.03	9,781.000	LF	$630.59
	0450 4 1	PREST BEAM- FL U-BEAM, 48"	2021	1	$868.00	208.000	LF	$972.16
	0450 8 12	PREST BEAM: FL SLAB BEAM,12" C,52-54" W	2021	1	$250.00	1,047.000	LF	$280.00
	0450 8 12	PREST BEAM: FL SLAB BEAM,12" C,52-54" W	2023	1	$725.00	406.000	LF	$746.75
	0450 8 13	PREST BEAM: FL SLAB BEAM,12" C,55-57" W	2023	2	$488.65	1,339.000	LF	$503.31

Table D2. Historical bid unit costs for bridge superstructure maintenance and repair activities (Cont'd)

Bridge MR&R Activity	Pay Item No.	Description	Bid Year	No. of Contracts	Avg. Unit Cost	Total Quantity	Unit of Measure	2024 Unit Cost
Prestressed beam	0450 8 21	PREST BEAM: FL SLAB BEAM,15" C,48-51" W	2021	2	$271.51	1,856.000	LF	$304.09
	0450 8 23	PREST BEAM: FL SLAB BEAM,15" C,55-57" W	2021	1	$283.00	1,978.000	LF	$316.96
	0450 8 23	PREST BEAM: FL SLAB BEAM,15" C,55-57" W	2023	2	$531.49	1,703.000	LF	$547.43
	0450 8 24	PREST BEAM: FL SLAB BEAM,15" C,58-60" W	2021	1	$300.00	1,740.000	LF	$336.00
	0450 8 31	PREST BEAM: FL SLAB BEAM,18" C,48-51" W	2021	1	$555.51	294.000	LF	$622.17
	0450 8 53	PREST BEAM: FL SLAB BEAM,12" CF,55-57" W	2023	1	$1,030.75	870.000	LF	$1,061.67
	0450 8 54	PREST BEAM: FL SLAB BEAM,12" CF,58-60" W	2023	1	$1,000.00	435.000	LF	$1,030.00
	0450 8 61	PREST BEAM: FL SLAB BEAM,15" CF,48-51" W	2023	1	$705.00	7,329.000	LF	$726.15
	0450 8 62	PREST BEAM: FL SLAB BEAM,15" CF,52-54" W	2023	1	$710.00	3,477.000	LF	$731.30
Structural steel	0460 1 2	STRUCT STEEL - REHAB, LOW ALLOY	2021	1	$28.00	3,046.000	LB	$31.36
	0460 1 5	STRUCT STEEL-REHAB, BASCULE LEAVES	2021	1	$8.95	71,304.000	LB	$10.02
	0460 1 6	STRUCT STEEL-REHAB, BASCULE PIERS	2021	1	$8.99	7,231.000	LB	$10.07
	0460 1 13	STRUCT STEEL REHAB-BOLT, NUT, WASH & PLT	2021	9	$23.11	36,270.000	LB	$25.88
	0460 1 13	STRUCT STEEL REHAB-BOLT, NUT, WASH & PLT	2022	7	$36.50	8,437.000	LB	$38.69
	0460 1 15	STRUCT STEEL - REHAB, MISC.	2021	5	$19.74	223,450.000	LB	$22.11
	0460 1 15	STRUCT STEEL - REHAB, MISC.	2022	4	$16.15	67,445.000	LB	$17.12
	0460 2 1	STRUCT STEEL, CARBON	2021	1	$4.57	192,627.000	LB	$5.12
	0460 2 2	STRUCT STEEL, LOW ALLOY	2021	5	$3.23	4,267,115.000	LB	$3.62
	0460 2 2	STRUCT STEEL, LOW ALLOY	2022	3	$3.92	3,058,062.000	LB	$4.16
	0460 2 5	STRUCT STEEL, BASCULE LEAVES	2021	1	$5.36	2,189,180.000	LB	$6.00
	0460 2 6	STRUCT STEEL, BASCULE PIERS	2021	1	$11.11	72,018.000	LB	$12.44
	0460 2 15	STRUCT STEEL, MISCELLANEOUS	2021	4	$8.80	46,730.000	LB	$9.86
	0460 2 15	STRUCT STEEL, MISCELLANEOUS	2022	2	$3.82	53,251.000	LB	$4.05
	0460 2 20	STRUCT STEEL - NEW/WIDENING, WEATHERING	2022	2	$3.06	4,690,934.000	LB	$3.24
	0460 94	STRUCTURAL STEEL REPAIR- WELDS	2022	1	$4,500.00	4.000	LF	$4,770.00
Superstructure concrete material	0400 2 4	CONC CLASS II, BRIDGE SUPERSTRUCTURE	2021	17	$832.06	14,716.500	CY	$931.91
	0400 2 4	CONC CLASS II, BRIDGE SUPERSTRUCTURE	2022	15	$1,016.03	16,814.800	CY	$1,076.99
	0400 2 4	CONC CLASS II, BRIDGE SUPERSTRUCTURE	2023	17	$1,345.46	26,444.100	CY	$1,385.82
	0400 4 4	CONC CLASS IV, SUPERSTRUCTURE	2021	14	$882.30	18,813.300	CY	$988.18

Table D2. Historical bid unit costs for bridge superstructure maintenance and repair activities (Cont'd)

Bridge MR&R Activity	Pay Item No.	Description	Bid Year	No. of Contracts	Avg. Unit Cost	Total Quantity	Unit of Measure	2024 Unit Cost
Superstructure concrete material	0400 4 4	CONC CLASS IV, SUPERSTRUCTURE	2022	8	$815.70	11,564.800	CY	$864.64
	0400 4 4	CONC CLASS IV, SUPERSTRUCTURE	2023	16	$1,559.61	3,258.400	CY	$1,606.40
	0400 4104	CONC CLASS IV, SUPERSTRUCTURE, LT-WT	2021	1	$1,300.00	415.000	CY	$1,456.00
Superstructure reinf steel material	0415 1 4	REINF STEEL- SUPERSTRUCTURE	2021	32	$1.16	8,563,101.000	LB	$1.30
	0415 1 4	REINF STEEL- SUPERSTRUCTURE	2022	23	$1.65	7,087,500.000	LB	$1.75
	0415 1 4	REINF STEEL- SUPERSTRUCTURE	2023	30	$1.50	6,764,123.000	LB	$1.55

Table D3. Historical bid unit costs for bridge substructure maintenance and repair activities

Bridge MR&R Activity	Pay Item No.	Description	Bid Year	No. of Contracts	Avg. Unit Cost	Total Quantity	Unit of Measure	2024 Unit Cost
Bulkhead	0400 72	PRECAST BULKHEAD PANELS	2023	1	$45.00	5,309.000	SF	$46.35
Bulkhead removal	0110 73	REMOVE EXISTING BULKHEAD	2021	3	$108.46	3,457.000	LF	$121.48
	0110 73	REMOVE EXISTING BULKHEAD	2022	3	$393.68	3,783.000	LF	$417.30
Cathodic protection	0400 60 3	CATHODIC PROTECTION-ELECT WORK, CODUIT,	2021	1	$500.00	200.000	LF	$560.00
	0400 60 3	CATHODIC PROTECTION-ELECT WORK, CODUIT,	2022	1	$200.00	1,000.000	LF	$212.00
	0400 60 3	CATHODIC PROTECTION-ELECT WORK, CODUIT,	2023	1	$2,250.00	20.000	LF	$2,317.50
	0400 60 4	CATHODIC PROTECTION-ELECT WORK, EQUIP,	2021	1	$100,000.00	1.000	LS	$112,000.00
	0400 60 4	CATHODIC PROTECTION-ELECT WORK, EQUIP,	2022	1	$200,000.00	1.000	LS	$212,000.00
	0400 60 4	CATHODIC PROTECTION-ELECT WORK, EQUIP,	2023	1	$75,000.00	1.000	LS	$77,250.00
	0400142 3	CATHODIC PROTECTION SYSTEM, ZINC ALUM SP	2021	3	$35.30	6,842.000	SF	$39.54
	0400142 3	CATHODIC PROTECTION SYSTEM, ZINC ALUM SP	2022	3	$32.93	18,000.000	SF	$34.91
	0400142 7	CATHODIC PROTECTION SYSTEM,TITANIUM MESH	2022	1	$24.00	11,405.000	SF	$25.44
	0400142 9	CATHODIC PROTECTION SYSTEM,OTHER MATRL	2021	1	$50.00	1,200.000	SF	$56.00
	0400142 9	CATHODIC PROTECTION SYSTEM,OTHER MATRL	2023	1	$125.00	382.000	SF	$128.75
	0455 81102	CATHODIC PROT,F&I,PILE,ZINC ANODE ASSEM	2023	1	$5,233.00	512.000	EA	$5,389.99
	0455 81106	CATHODIC PROT,F&I,PIER,OTHER MATERIAL	2021	1	$1,070.00	1,156.000	EA	$1,198.40
	0457 2121	CATH PROT INTE PILE JA, NON-STR, 16.1-30	2021	4	$1,150.08	271.000	LF	$1,288.09
	0457 2121	CATH PROT INTE PILE JA, NON-STR, 16.1-30	2022	2	$3,249.61	102.000	LF	$3,444.59
	0457 2121	CATH PROT INTE PILE JA, NON-STR, 16.1-30	2023	1	$3,125.00	11.000	LF	$3,218.75
	0457 2211	CATH PROT INTE PILE JA, STR,UP TO 16	2021	1	$1,411.02	279.000	LF	$1,580.34
	0457 2221	CATH PROT INTE PILE JA, STR, 16.1-30	2021	8	$1,347.98	932.000	LF	$1,509.74
	0457 2221	CATH PROT INTE PILE JA, STR, 16.1-30	2022	6	$1,173.76	4,769.000	LF	$1,244.19
	0457 2221	CATH PROT INTE PILE JA, STR, 16.1-30	2023	5	$1,689.72	1,794.000	LF	$1,740.41
	0457 2231	CATH PROT INT PILE JKT, >30", GALV SYS	2021	1	$2,000.00	134.000	LF	$2,240.00
Clean & maintain slope pavement	0350 5	CLEANING & SEALING JOINTS - CONC PVMT	2021	15	$3.16	937,691.000	LF	$3.54
	0350 5	CLEANING & SEALING JOINTS - CONC PVMT	2022	13	$3.97	412,238.000	LF	$4.21
	0350 5	CLEANING & SEALING JOINTS - CONC PVMT	2023	15	$4.04	1,373,633.000	LF	$4.16
	0350 6	CLEANING & SEALING CRACKS - CONC PVMT	2021	2	$8.29	728.000	LF	$9.28
	0350 6	CLEANING & SEALING CRACKS - CONC PVMT	2022	4	$9.82	6,819.000	LF	$10.41
	0350 6	CLEANING & SEALING CRACKS - CONC PVMT	2023	4	$4.33	35,439.000	LF	$4.46
	0524 4 1	CLEAN & SEAL RANDOM CRACKS IN SLOPE PVMT	2021	3	$12.41	1,218.000	LF	$13.90

Table D3. Historical bid unit costs for bridge substructure maintenance and repair activities (Cont'd)

Bridge MR&R Activity	Pay Item No.	Description	Bid Year	No. of Contracts	Avg. Unit Cost	Total Quantity	Unit of Measure	2024 Unit Cost
Clean & maintain slope pavement	0524 4 1	CLEAN & SEAL RANDOM CRACKS IN SLOPE PVMT	2022	1	$15.00	575.000	LF	$15.90
	0524 4 1	CLEAN & SEAL RANDOM CRACKS IN SLOPE PVMT	2023	1	$100.00	46.000	LF	$103.00
	0524 4 2	CLEAN & SEAL JOINTS IN EXIST SLOPE PVMT	2021	1	$60.00	50.000	LF	$67.20
Fender system removal	0110 71 1	BRIDGE FENDER SYSTEM, REMOVAL & DISPOSAL	2021	5	$324.76	1,422.000	LF	$363.73
	0110 71 1	BRIDGE FENDER SYSTEM, REMOVAL & DISPOSAL	2022	2	$317.08	653.000	LF	$336.10
	0110 71 1	BRIDGE FENDER SYSTEM, REMOVAL & DISPOSAL	2023	2	$367.16	271.000	LF	$378.17
Replace slope pavement	0524100	CONC SLOPE PAVE,NON R,VARIABLE THICKNESS	2022	1	$85.00	1,181.000	SY	$90.10
	0353 70	CONC PAVT SLAB REPLACEMENT	2021	5	$617.19	8,219.800	CY	$691.25
	0353 70	CONC PAVT SLAB REPLACEMENT	2022	4	$1,264.00	1,598.900	CY	$1,339.84
	0524 2 1	CONC SLOPE PAVT, NR, 3"	2021	1	$53.00	50.000	SY	$59.36
	0524 2 1	CONC SLOPE PAVT, NR, 3"	2022	4	$95.27	1,850.000	SY	$100.99
	0524 2 2	CONC SLOPE PAVT, NR, 4"	2021	14	$89.69	5,822.000	SY	$100.45
	0524 2 2	CONC SLOPE PAVT, NR, 4"	2022	19	$137.03	9,492.000	SY	$145.25
	0524 2 2	CONC SLOPE PAVT, NR, 4"	2023	14	$132.24	11,876.000	SY	$136.21
	0524 2 4	CONC SLOPE PAVT, NR, 6"	2022	3	$111.18	242.000	SY	$117.85
	0524 2 4	CONC SLOPE PAVT, NR, 6"	2023	3	$139.83	708.000	SY	$144.02
	0524 2 29	CONC SLOPE PAVT, 4", REINFORCED	2022	1	$144.00	50.000	SY	$152.64
	0524 2 29	CONC SLOPE PAVT, 4", REINFORCED	2023	1	$89.00	50.000	SY	$91.67
	0524 2 49	CONC SLOPE PAVT, 6", REINFORCED	2021	3	$480.61	42.000	SY	$538.28
	0524 2 49	CONC SLOPE PAVT, 6", REINFORCED	2022	2	$165.88	17.000	SY	$175.83
	0524 2 49	CONC SLOPE PAVT, 6", REINFORCED	2023	1	$89.00	100.000	SY	$91.67
Retaining wall	0521 6 34	CONC PARAPET, RETAINING WALL SYS, CURB	2021	1	$145.00	2,409.000	LF	$162.40
	0548 12	RET WALL SYSTEM, PERM, EX BARRIER	2021	11	$40.10	756,910.000	SF	$44.91
	0548 12	RET WALL SYSTEM, PERM, EX BARRIER	2022	12	$44.51	1,337,850.000	SF	$47.18
	0548 13	RETAINING WALL SYSTEM,TEMP, EXC BAR.	2021	8	$12.57	385,580.000	SF	$14.08
	0548 13	RETAINING WALL SYSTEM,TEMP, EXC BAR.	2022	8	$18.05	294,918.000	SF	$19.13
	0548 14	RETAINING WALL SYSTEM,PERM-WID, ATTACHED	2021	1	$65.40	5,263.000	SF	$73.25
	0548 14	RETAINING WALL SYSTEM,PERM-WID, ATTACHED	2022	4	$56.28	40,140.000	SF	$59.66
	0548 15	RETAINING WALL SYSTEM, RETROFIT SEAL	2022	1	$80.00	350.000	LF	$84.80
Substructure concrete material	0400 2 5	CONC CLASS II, BRIDGE SUBSTRUCTURE	2021	8	$1,599.25	563.000	CY	$1,791.16
	0400 2 5	CONC CLASS II, BRIDGE SUBSTRUCTURE	2022	6	$1,989.39	1,089.500	CY	$2,108.75

Table D3. Historical bid unit costs for bridge substructure maintenance and repair activities (Cont'd)

Bridge MR&R Activity	Pay Item No.	Description	Bid Year	No. of Contracts	Avg. Unit Cost	Total Quantity	Unit of Measure	2024 Unit Cost
Substructure concrete material	0400 2 5	CONC CLASS II, BRIDGE SUBSTRUCTURE	2023	3	$1,594.05	1,212.100	CY	$1,641.87
	0400 2 8	CONC CLASS II, BULKHEAD	2021	3	$2,000.69	74.500	CY	$2,240.77
	0400 2 11	CONC CLASS II, RETAINING WALLS	2021	5	$564.74	576.400	CY	$632.51
	0400 2 11	CONC CLASS II, RETAINING WALLS	2022	6	$770.93	1,408.700	CY	$817.19
	0400 2 11	CONC CLASS II, RETAINING WALLS	2023	6	$1,663.36	905.800	CY	$1,713.26
	0400 2 25	CONC CLASS II, MASS, BRIDGE SUBSTRUCTURE	2021	3	$733.70	631.500	CY	$821.74
	0400 2 25	CONC CLASS II, MASS, BRIDGE SUBSTRUCTURE	2022	4	$1,492.29	984.500	CY	$1,581.83
	0400 2 25	CONC CLASS II, MASS, BRIDGE SUBSTRUCTURE	2023	2	$991.05	201.100	CY	$1,020.78
	0400 3 45	CONC CLASS III, PRECAST SUBSTRUCTURE	2021	1	$750.00	2,301.000	CY	$840.00
	0400 4 5	CONC CLASS IV, SUBSTRUCTURE	2021	28	$1,320.05	10,567.800	CY	$1,478.46
	0400 4 5	CONC CLASS IV, SUBSTRUCTURE	2023	27	$1,744.60	9,566.200	CY	$1,796.94
	0400 4 5	CONC CLASS IV, SUBSTRUCTURE	2022	18	$1,897.97	3,671.500	CY	$2,011.85
	0400 4 8	CONC CLASS IV, BULKHEAD	2021	7	$902.95	422.700	CY	$1,011.30
	0400 4 8	CONC CLASS IV, BULKHEAD	2022	9	$938.55	4,190.800	CY	$994.86
	0400 4 8	CONC CLASS IV, BULKHEAD	2023	4	$1,156.49	2,155.000	CY	$1,191.18
	0400 4 11	CONC CLASS IV, RETAINING WALLS	2021	10	$953.53	4,757.300	CY	$1,067.95
	0400 4 11	CONC CLASS IV, RETAINING WALLS	2022	11	$1,783.38	1,369.800	CY	$1,890.38
	0400 4 11	CONC CLASS IV, RETAINING WALLS	2023	8	$1,153.04	8,879.400	CY	$1,187.63
	0400 4 25	CONC CLASS IV, MASS, SUBSTRUCTURE	2021	7	$707.15	43,534.800	CY	$792.01
	0400 4 25	CONC CLASS IV, MASS, SUBSTRUCTURE	2022	7	$916.15	24,463.800	CY	$971.12
	0400 8 5	CONC CLASS V, SUBSTRUCTURE	2022	1	$3,800.00	66.000	CY	$4,028.00
	0400 8 25	CONC CLASS V, MASS - SUBSTRUCTURE	2022	1	$995.00	583.600	CY	$1,054.70
	0400 16 25	CONC CLASS VI, MASS, SUBSTRUCTURE	2022	1	$5,300.00	62.400	CY	$5,618.00
Substructure reinf steel material	0415 1 3	REINF STEEL- RETAINING WALL	2021	12	$1.05	547,725.000	LB	$1.18
	0415 1 3	REINF STEEL- RETAINING WALL	2022	14	$1.89	317,192.000	LB	$2.00
	0415 1 3	REINF STEEL- RETAINING WALL	2023	9	$2.09	1,265,576.000	LB	$2.15
	0415 1 5	REINF STEEL- SUBSTRUCTURE	2021	36	$1.27	12,072,071.000	LB	$1.42
	0415 1 5	REINF STEEL- SUBSTRUCTURE	2022	22	$1.71	7,563,923.000	LB	$1.81
	0415 1 5	REINF STEEL- SUBSTRUCTURE	2023	26	$1.67	6,148,851.000	LB	$1.72
	0415 1 8	REINF STEEL- BULKHEAD	2021	9	$1.86	50,399.000	LB	$2.08
	0415 1 8	REINF STEEL- BULKHEAD	2022	7	$1.67	136,107.000	LB	$1.77
	0415 1 8	REINF STEEL- BULKHEAD	2023	4	$1.70	196,935.000	LB	$1.75

Table D4. Historical bid unit costs for movable bridge maintenance and repair activities

Bridge MR&R Activity	Pay Item No.	Description	Bid Year	No. of Contracts	Avg. Unit Cost	Total Quantity	Unit of Measure	2024 Unit Cost
Movable bridge maintenance and repair	0400 4 6	CONC CLASS IV, COUNTERWEIGHT	2021	1	$300.00	596.000	CY	$336.00
	0460 1 5	STRUCT STEEL-REHAB, BASCULE LEAVES	2022	1	$28.00	3,344.000	LB	$29.68
	0460 1 5	STRUCT STEEL-REHAB, BASCULE LEAVES	2023	1	$100.00	187.000	LB	$103.00
	0465 1	MOV BRDG - MECH EQUIPMENT	2021	1	$15,790,000.00	1.000	LS	$17,684,800.00
	0465 2101	MOV BRDG MACH & CAST-REHAB,F&I,SPEED	2023	1	$230,000.00	1.000	LS	$236,900.00
	0465 2105	MOV BRDG MACH & CAST-REHAB,F&I,SPAN LOCK	2021	3	$202,121.20	10.000	AS	$226,375.74
	0465 2108	MOV BRDG MACH & CAST-REHAB,F&I,LIVE LOAD	2021	2	$49,000.00	2.000	LS	$54,880.00
	0465 2152	MOV BRDG MACH & CAST-REHAB,F&I,HYD CYL	2021	1	$128,325.00	8.000	EA	$143,724.00
	0465 2152	MOV BRDG MACH & CAST-REHAB,F&I,HYD CYL	2022	1	$155,000.00	4.000	EA	$164,300.00
	0465 2154	MOV BRDG MACH & CAST-REHAB,F&I,HYDRAULIC	2021	2	$283,332.33	6.000	EA	$317,332.21
	0465 2155	MOV BRDG MACH & CAST-REHAB,F&I,HYDRAULIC	2021	2	$305,000.00	2.000	EA	$341,600.00
	0465 2160	MOV BRDG MACH & CAST-REHAB,F&I OTHER	2023	1	$160,000.00	1.000	LS	$164,800.00
	0465 2401	MOV BRDG MACH & CAST-REHAB,REC, SPEED	2021	2	$60,400.00	4.000	LS	$67,648.00
	0465 2401	MOV BRDG MACH & CAST-REHAB,REC, SPEED	2023	1	$65,000.00	1.000	LS	$66,950.00
	0465 2404	MOV BRDG MACH & CAST-REHAB,REC,TRUNION	2021	1	$4,750.00	4.000	EA	$5,320.00
	0465 2405	MOV BRDG MACH & CAST-REHAB,REHAB,SPAN LK	2021	2	$80,666.67	6.000	AS	$90,346.67
	0465 2410	MOV BRDG MACH & CAST-REHAB,RECONDITION	2022	1	$20,000.00	4.000	EA	$21,200.00
	0465 2452	MOV BRDG MACH & CAST-REHAB,REC,HYDRLIC	2021	1	$2,000.00	8.000	EA	$2,240.00
	0465 2454	MOV BRDG MACH & CAST-REHAB,REC, HYD POWR	2021	1	$80,000.00	4.000	EA	$89,600.00
	0465 2460	MOV BRDG MACH & CAST-REHAB,RECOND, OTHER	2023	1	$513,000.00	1.000	LS	$528,390.00
	0465 2505	MOV BRDG MACH & CAST-REHAB,REC, ADJ/MOD,	2023	2	$55,000.00	4.000	AS	$56,650.00
	0465 2508	MOV BRDG MACH & CAST-REHAB,REC, ADJ/MOD,	2021	3	$25,250.00	8.000	LS	$28,280.00
	0465 2508	MOV BRDG MACH & CAST-REHAB,REC, ADJ/MOD,	2023	1	$25,000.00	1.000	LS	$25,750.00
	0465 2605	MOV BRDG MACH & CAST-REHAB,R&D,SPAN LOCK	2021	4	$3,071.43	14.000	AS	$3,440.00
	0465 2608	MOV BRDG MACH & CAST-REHAB,R&D,LIVE LOAD	2021	1	$6,500.00	1.000	LS	$7,280.00
	0465 2652	MOV BRDG MACH & CAST-REHAB,REM, HYD CYL	2021	1	$1,000.00	8.000	EA	$1,120.00
	0465 2652	MOV BRDG MACH & CAST-REHAB,REM, HYD CYL	2022	1	$30,000.00	4.000	EA	$31,800.00
	0465 2654	MOV BRDG MACH & CAST-REHAB,R&D,HYDRLC	2021	2	$4,833.33	6.000	EA	$5,413.33
	0465 2708	MOV BRDG MACH & CAST-REHAB,R&S,LLSHOES	2021	1	$20,000.00	1.000	LS	$22,400.00
	0465 3 14	MOVABLE BRIDGE COUNTERWEIGHT, F&I,BUMPER	2021	2	$5,437.50	16.000	EA	$6,090.00
	0465 3 17	MOVABLE BRIDGE COUNTERWEIGHT, F&I,BAL BL	2021	3	$165.68	3,030.000	EA	$185.56

Table D4. Historical bid unit costs for movable bridge maintenance and repair activities (Cont'd)

Bridge MR&R Activity	Pay Item No.	Description	Bid Year	No. of Contracts	Avg. Unit Cost	Total Quantity	Unit of Measure	2024 Unit Cost
Movable bridge maintenance and repair	0465 3 17	MOVABLE BRIDGE COUNTERWEIGHT, F&I,BAL BL	2022	1	$200.00	20.000	EA	$212.00
	0465 3 17	MOVABLE BRIDGE COUNTERWEIGHT, F&I,BAL BL	2023	1	$135.00	200.000	EA	$139.05
	0465 3 19	MOVABLE BRIDGE COUNTERWEIGHT, F&I,STEEL	2021	1	$3,100.00	523.000	TN	$3,472.00
	0465 3 50	MOVABLE BRIDGE COUNTERWEIGHT, ADJ	2021	7	$28,393.33	21.000	EA	$31,800.53
	0465 3 50	MOVABLE BRIDGE COUNTERWEIGHT, ADJ	2022	3	$8,111.11	9.000	EA	$8,597.78
	0465 3 50	MOVABLE BRIDGE COUNTERWEIGHT, ADJ	2023	2	$11,600.00	10.000	EA	$11,948.00
	0465 20	MOVABLE BRIDGE- PREV MAINT & ROUT REPAIR	2021	10	$189.14	3,566.000	DA	$211.84
	0465 20	MOVABLE BRIDGE- PREV MAINT & ROUT REPAIR	2022	4	$412.85	2,381.000	DA	$437.62
	0465 20	MOVABLE BRIDGE- PREV MAINT & ROUT REPAIR	2023	3	$109.34	814.000	DA	$112.62
	0465 21	MOVABLE BRIDGE OPERATOR	2021	10	$569.57	3,278.000	DA	$637.92
	0465 21	MOVABLE BRIDGE OPERATOR	2022	4	$739.54	2,074.000	DA	$783.91
	0465 21	MOVABLE BRIDGE OPERATOR	2023	3	$657.98	467.000	DA	$677.72
	0465 71 1	MOVEABLE BRIDGE FUNCTIONAL CHKOUT, PH A	2021	1	$40,000.00	1.000	LS	$44,800.00
	0465 71 2	MOVEABLE BRIDGE FUNCTIONAL CHKOUT, PH B	2021	1	$40,000.00	1.000	LS	$44,800.00
	0465 71 3	MOVABLE BRIDGE FUNCTIONAL CHECKOUT,PH C	2021	9	$24,690.64	11.000	LS	$27,653.52
	0465 71 3	MOVABLE BRIDGE FUNCTIONAL CHECKOUT,PH C	2022	2	$27,500.00	2.000	LS	$29,150.00
	0465 71 3	MOVABLE BRIDGE FUNCTIONAL CHECKOUT,PH C	2023	1	$26,000.00	2.000	LS	$26,780.00
	0508 2 1	MOVABLE BRIDGE GATE, F&I	2021	1	$31,250.00	4.000	AS	$35,000.00
	0508 3 5	MOVABLE BRIDGE - SIGNAL,ADJ /MOD/ REHAB	2021	1	$2,500.00	1.000	AS	$2,800.00
	0508 3 6	MOVABLE BRIDGE - SIGNAL, REMOVE & DISPO	2021	1	$6,500.00	2.000	AS	$7,280.00
	0508 4	MOVABLE BRIDGE ELECTRICAL EQUIP, REHAB	2021	6	$545,659.22	9.000	LS	$611,138.33
	0508 4	MOVABLE BRIDGE ELECTRICAL EQUIP, REHAB	2023	1	$533,727.60	1.000	LS	$549,739.43
	0508 72 1	MOVABLE BRIDGE EMERGENCY GENERATOR ,F&I	2021	2	$200,031.67	3.000	AS	$224,035.47
	0508 72 4	MOVABLE BRIDGE EMERGENCY GENERATOR , REM	2021	2	$10,000.00	2.000	AS	$11,200.00
	0508 76 1	MOVABLE BRIDGE-REHAB,SPAN MOTORS,F&I	2021	2	$139,999.33	3.000	LS	$156,799.25
	0508 76 4	MOVABLE BRIDGE-REHAB,SPAN MOTORS,REM	2021	2	$18,033.33	3.000	LS	$20,197.33
	0508 77 1	MOVABLE BRIDGE-REHAB,PROG LOGIC,F&I	2021	3	$290,150.00	4.000	EA	$324,968.00
	0508 77 4	MOVABLE BRIDGE-REHAB,PROG LOGIC,REMOVE	2021	1	$11,000.00	1.000	EA	$12,320.00
	0508 77 5	MOVABLE BRIDGE-REHAB,PROG LOGIC	2021	2	$67,100.00	2.000	EA	$75,152.00
	0508 78 1	MOVABLE BRIDGE-REHAB,LIMIT SWITCH,F&I	2021	2	$48,486.67	3.000	LS	$54,305.07

Table D4. Historical bid unit costs for movable bridge maintenance and repair activities (Cont'd)

Bridge MR&R Activity	Pay Item No.	Description	Bid Year	No. of Contracts	Avg. Unit Cost	Total Quantity	Unit of Measure	2024 Unit Cost
Movable bridge maintenance and repair	0508 78 4	MOVABLE BRIDGE-REHAB,LIMIT SWITCH	2021	2	$4,360.00	3.000	LS	$4,883.20
	0508 79 1	MOVABLE BRIDGE-REHAB,CONTROL CONSOLE,F&I	2021	3	$304,347.75	4.000	EA	$340,869.48
	0508 79 4	MOVABLE BRIDGE-REHAB,CONTROL CONSOLE,REM	2021	2	$18,166.75	3.000	EA	$20,346.76
	0508 80 1	MOVABLE BRIDGE-REHAB,BRAKE SYS,F&I	2021	1	$17,500.00	8.000	EA	$19,600.00
	0508 80 4	MOVABLE BRIDGE-REHAB,BRAKE SYS,REM	2021	1	$1,200.00	4.000	EA	$1,344.00
	0508 82 1	MOVABLE BRIDGE-REHAB,CONTROL PANEL,F&I	2021	1	$164,999.00	1.000	EA	$184,798.88
	0508 83101	MOVABLE BR INTGR DR SYS,F&I,25 KW OR <	2021	1	$45,833.33	12.000	AS	$51,333.33
	0510 1 1	NAV LIGHTS- FIXED BRIDGE, SYSTEM, SOLAR	2022	1	$99,000.00	1.000	LS	$104,940.00
	0512 1	MOVABLE BRIDGE-CONTROL HOUSE, NEW	2021	1	$400,000.00	1.000	LS	$448,000.00
	0512 1 1	MOVABLE BRIDGE-CONTROL HOUSE,RENOVATE	2021	4	$304,173.20	5.000	LS	$340,673.98
	0512 71 1	MOVABLE BRIDGE PLUMBING SYSTEM, F&I	2021	2	$35,000.00	2.000	EA	$39,200.00

Table D5. Historical bid unit costs for other bridge maintenance and repair activities

Bridge MR&R Activity	Pay Item No.	Description	Bid Year	No. of Contracts	Avg. Unit Cost	Total Quantity	Unit of Measure	2024 Unit Cost
Approach slab	0370 1	BRIDGE APPR EXP JOINT FOR CONC PVMT	2021	1	$71.90	1,079.000	LF	$80.53
	0370 1	BRIDGE APPR EXP JOINT FOR CONC PVMT	2022	2	$33.31	561.000	LF	$35.31
	0370 1	BRIDGE APPR EXP JOINT FOR CONC PVMT	2023	1	$289.00	4,711.000	LF	$297.67
	0400 2 10	CONC CLASS II, APPROACH SLABS	2021	25	$413.56	7,518.600	CY	$463.19
	0400 2 10	CONC CLASS II, APPROACH SLABS	2022	22	$638.26	7,041.100	CY	$676.56
	0400 2 10	CONC CLASS II, APPROACH SLABS	2023	27	$789.51	9,934.200	CY	$813.20
	0415 1 9	REINF STEEL- APPROACH SLABS	2021	25	$1.17	1,479,043.000	LB	$1.31
	0415 1 9	REINF STEEL- APPROACH SLABS	2022	22	$1.62	1,355,132.000	LB	$1.72
	0415 1 9	REINF STEEL- APPROACH SLABS	2023	25	$1.53	1,940,191.000	LB	$1.58
	0536 8123	APPROACH TRANS CONN TO RIGID BA, F&I, ET	2021	19	$2,397.24	44.000	EA	$2,684.91
Channel	0120 5	CHANNEL EXCAVATION	2021	11	$42.22	31,593.300	CY	$47.29
	0120 5	CHANNEL EXCAVATION	2023	8	$50.59	13,720.000	CY	$52.11
	0120 5	CHANNEL EXCAVATION	2022	10	$67.62	4,189.500	CY	$71.68
Culvert	0400 2 1	CONC CLASS II, CULVERTS	2021	7	$1,463.01	1,472.500	CY	$1,638.57
	0400 2 1	CONC CLASS II, CULVERTS	2022	11	$1,544.04	1,785.200	CY	$1,636.68
	0400 2 1	CONC CLASS II, CULVERTS	2023	17	$1,459.24	5,560.800	CY	$1,503.02
	0400 3 1	CONC CLASS III, CULVERTS	2022	1	$2,200.00	10.000	CY	$2,332.00
	0400 3 1	CONC CLASS III, CULVERTS	2023	1	$1,500.00	10.000	CY	$1,545.00
	0400 4 1	CONC CLASS IV, CULVERTS	2021	15	$1,430.39	3,851.600	CY	$1,602.04
	0400 4 1	CONC CLASS IV, CULVERTS	2022	9	$1,616.87	4,162.700	CY	$1,713.88
	0400 4 1	CONC CLASS IV, CULVERTS	2023	14	$1,589.47	3,605.500	CY	$1,637.15
Clean & repair concrete	0400143	CLEAN & COAT CONCRETE SURF , CLASS 5	2021	15	$.78	1,588,786.000	SF	$0.87
	0400143	CLEAN & COAT CONCRETE SURF , CLASS 5	2022	18	$1.64	1,424,786.000	SF	$1.74
	0400143	CLEAN & COAT CONCRETE SURF , CLASS 5	2023	15	$2.03	547,579.000	SF	$2.09
	0400145	CLEANING CONC SURFACE	2021	8	$.14	2,853,023.000	SF	$0.16
	0400145	CLEANING CONC SURFACE	2022	4	$.16	529,021.000	SF	$0.17
	0400145	CLEANING CONC SURFACE	2023	9	$.13	1,190,708.000	SF	$0.13
	0400150	CLEANING AND SEALING EXISTING CONCRETE	2021	1	$35.00	93.000	SF	$39.20
	0400150	CLEANING AND SEALING EXISTING CONCRETE	2022	1	$1.50	1,515.000	SF	$1.59
	0413154	CLEAN & SEAL CONC- PENETR OR METHACR	2021	12	$1.20	892,865.000	SF	$1.34
	0413154	CLEAN & SEAL CONC- PENETR OR METHACR	2022	9	$1.65	1,054,518.000	SF	$1.75

Table D5. Historical bid unit costs for other bridge maintenance and repair activities (Cont'd)

Bridge MR&R Activity	Pay Item No.	Description	Bid Year	No. of Contracts	Avg. Unit Cost	Total Quantity	Unit of Measure	2024 Unit Cost
Clean & repair concrete	0413154	CLEAN & SEAL CONC- PENETR OR METHACR	2023	17	$1.53	3,066,355.000	SF	$1.58
	0401 70 1	RESTORE SPALLED AREAS, EPOXY	2022	1	$428.00	100.000	CF	$453.68
	0401 70 2	RESTORE SPALL AREA,LATX MOD MTR,STY-BUT	2021	5	$476.70	427.400	CF	$533.90
	0401 70 2	RESTORE SPALL AREA,LATX MOD MTR,STY-BUT	2022	7	$373.53	452.200	CF	$395.94
	0401 70 3	RESTORE SPALL AREA,LATX MOD MTR, ACRYLC	2021	12	$454.41	1,277.100	CF	$508.94
	0401 70 3	RESTORE SPALL AREA,LATX MOD MTR, ACRYLC	2022	10	$981.29	271.400	CF	$1,040.17
	0401 70 4	RESTORE SPALLED AREAS,PORTLND CEM GROUT	2021	11	$494.97	966.500	CF	$554.37
	0401 70 4	RESTORE SPALLED AREAS,PORTLND CEM GROUT	2022	7	$685.74	296.600	CF	$726.88
	0401 70 7	RESTORE SPALLED AREAS, SHOTCRETE	2021	4	$170.07	3,986.600	CF	$190.48
	0401 70 7	RESTORE SPALLED AREAS, SHOTCRETE	2022	7	$252.45	15,083.600	CF	$267.60
	0401 71 11	RESTORE SPALLED AREAS- MAINT CONTR ONLY	2021	1	$220.00	8.750	CF	$246.40
Bridge (fixed) navigational lights	0510 1	NAVIGATION LIGHTS- FIXED BRIDGE, SYSTEM	2022	3	$38,333.33	3.000	LS	$40,633.33
Bridge drains	0506 2	BRIDGE DRAINAGE PIPE	2021	3	$375.60	593.000	LF	$420.67
	0506 2	BRIDGE DRAINAGE PIPE	2022	4	$186.89	1,909.000	LF	$198.10
	0506 2	BRIDGE DRAINAGE PIPE	2023	1	$306.95	1,448.000	LF	$316.16
	0506 3	BRIDGE DRAINS	2021	3	$548.16	212.000	EA	$613.94
	0506 3	BRIDGE DRAINS	2022	3	$4,431.82	22.000	EA	$4,697.73
	0506 3	BRIDGE DRAINS	2023	2	$5,974.42	16.000	EA	$6,153.65
	0506 72	BRIDGE DRAINS- POWER CLEAN	2022	1	$7,746.04	1.000	EA	$8,210.80
Bridge monitoring	0108 1	MONITOR EXISTING STRUCTURES- SETTL	2022	74	$15,609.37	92.000	LS	$16,545.93
	0108 1	MONITOR EXISTING STRUCTURES- SETTL	2023	80	$15,645.75	95.000	LS	$16,115.12
	0108 2	MONITOR EXISTING STRUCTURES- VIBRA	2022	49	$16,103.75	62.000	LS	$17,069.98
	0108 2	MONITOR EXISTING STRUCTURES- VIBRA	2023	61	$18,211.21	73.000	LS	$18,757.55
	0108 3	MONITOR EXISTING STRUCTURES- GROUN	2022	5	$7,988.28	7.000	LS	$8,467.58
	0108 3	MONITOR EXISTING STRUCTURES- GROUN	2023	2	$28,875.00	4.000	LS	$29,741.25
Bridge removal	0110 3	REMOVAL OF EXISTING STRUCTURES/BRIDGES	2021	36	$37.27	547,993.000	SF	$41.74
	0110 3	REMOVAL OF EXISTING STRUCTURES/BRIDGES	2022	26	$46.99	200,335.000	SF	$49.81
	0110 82	REMOVE & DISPOSE OF STRUCTURAL TIMBER	2021	3	$1,738.94	85.900	MB	$1,947.61
	0110 82	REMOVE & DISPOSE OF STRUCTURAL TIMBER	2022	2	$4,762.49	19.500	MB	$5,048.24
Pedestrian bridge	0460 7	PREFABRICATED STEEL PED BRIDGE	2021	2	$436.32	6,760.000	SF	$488.68
	0460 7	PREFABRICATED STEEL PED BRIDGE	2022	4	$601.89	11,412.000	SF	$638.00
	0460 7	PREFABRICATED STEEL PED BRIDGE	2023	3	$860.89	5,446.000	SF	$886.72
	0751 49	TIMBER PEDESTRIAN BRIDGE	2021	1	$240.00	8,227.000	SF	$268.80

Bridge Maintenance Course Series Reference Manual

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Figure D6. List of bridge maintenance activities from FHWA manual (FDOT 2015)

Bridge Maintenance Course Series Reference Manual

A.3 Crack Sealing in Portland Cement Concrete Decks

Description

Applying ASTM D 6690 Joint and Crack sealant to cracks in concrete bridge decks. Also, applying epoxy injection and sealers such as HMWM.

Project Objectives

Minimize or eliminate water and chlorides entering the structure through these cracks. Extend the service life of the existing bridge deck.

Labor Skills

Physical labor

Materials

- Crack-sealer meeting ASTM D 6690
- Blasting sand

Equipment

- Crack-sealer heater/melter
- Wand, hoses, and nozzles
- Air compressor with hoses, etc.
- Shovels and brooms
- Walk behind concrete router
- Sandblaster
- Personal safety equipment
- Grinder and putty knife

Procedure

- Prepare work-zone (i.e., traffic control, environmental protection, equipment).
- Clean deck by sweeping and/or using compressed air.
- Clean cracks and joints using water or compressed air, and a grinder or putty knife to scrape out larger deposits or old joint material.
- Using concrete router, route channel along existing crack to a depth of +/- 1 inch.

Figure A.3 Crack Sealing in Concrete Decks

- Remove debris from routing operation.
- Sandblast routed crack, clean up sandblasting debris.
- Surface must be clean, dry, and temperatures must be correct.

Figure D7. Instructions for crack sealing on concrete decks (FDOT 2015)