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16. Abstract This project develops an environmentally informed, data-driven framework for evaluating bridge condition, with emphasis on precast concrete (PC) bridges. Structural, traffic, and environmental data from NBI, NBE, state traffic records, and environmental observations were integrated into a unified dataset. Multinomial logistic regression and neural network models were developed to estimate condition states using three-class and nine-class rating schemes. Results show that environmental variables contribute notably to condition classification and that PC bridges exhibit distinct deterioration tendencies compared with cast-in-place structures. Analyses using extended environmental input datasets illustrate how broader environmental conditions affect expected condition distributions. The methodology supports improved deterioration assessment, targeted maintenance planning, and long-horizon decision-making for PC bridge infrastructure.			
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**Transportation Infrastructure Precast Innovation Center
(TRANS-IPIC)**

University Transportation Center (UTC)

Environmentally-Informed, Data-Driven Precast Concrete Bridge Condition Modeling for Future-
Proof Transportation Infrastructure
UI-24-RP-03

FINAL REPORT

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Executive Summary:

Bridge infrastructure in the United States is aging, heavily utilized, and increasingly exposed to diverse environmental conditions. Understanding how environmental stressors, such as temperature variability, humidity, precipitation patterns, and freeze–thaw cycles, affect long-term bridge deterioration is essential for reliable asset management and for planning maintenance and rehabilitation activities. Yet current predictive models used by transportation agencies rely heavily on historical inspection data and typically do not evaluate deterioration under a range of environmental scenarios.

This project develops a comprehensive, environmentally-informed, data-driven model to estimate bridge conditions under a broader environmental conditions. The work focuses particularly on precast concrete (PC) bridges, a class widely used in U.S. transportation infrastructure. PC bridges provide significant construction and durability advantages but may be vulnerable to environmental fluctuations due to material properties related to thermal expansion, moisture sensitivity, joint behavior, and interface performance between precast segments.

The project integrates multiple data sources, including the National Bridge Inventory (NBI), National Bridge Elements (NBE), highway traffic data, and detailed environmental observations, to quantify how structural characteristics, traffic loads, and environmental conditions jointly influence bridge deterioration. A suite of statistical and machine learning models, including multinomial logistic regression, neural networks, and feature-selection-enhanced frameworks, were developed, validated, and applied. The models were then used to assess bridge condition states for the State of Illinois using a dataset of broad environmental data.

Results show that environmental stressors have statistically significant effects on deterioration; that PC bridges exhibit systematically higher vulnerability relative to cast-in-place bridges after controlling for other factors; and that condition distributions are sensitive to the environmental inputs supplied to the model. Analyses conducted using extended environmental datasets illustrate shifts in the distribution of bridges across condition categories, offering quantitative insight for identifying structures that may warrant closer attention in long-term asset management.

The project delivers the following key outcomes:

1. A validated bridge condition estimation model incorporating structural, traffic, and environmental variables.
2. A fully integrated database of Illinois bridges mapped to environmental datasets.
3. Analyses using extended environmental datasets that illustrate how long-term environmental effects may influence bridge condition distributions.
4. A set of methodological innovations, including AIC-based feature selection.
5. Recommendations for maintenance prioritization and infrastructure planning under a broad environmental scenarios.

Collectively, these contributions support the durability and resilience of transportation infrastructure and directly advance the mission of TRANS-IPIC to extend the life of precast concrete bridge systems.

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1. Problem description:

Bridge deterioration is strongly influenced by environmental conditions such as temperature fluctuations, humidity, precipitation variability, and freeze-thaw cycles. These stressors affect material performance and can accelerate deterioration processes, particularly in regions with substantial seasonal variability. Precast concrete (PC) bridges, which represent a large portion of the U.S. inventory, are susceptible to:

- thermal expansion and cracking
- moisture-related degradation
- accelerated corrosion
- fatigue accumulation during extreme temperature events

Most existing bridge condition models rely on historical inspection and traffic data and do not explicitly incorporate environmental factors or broad environmental conditions. As a result, deterioration rates estimated solely from past performance may underestimate the effects of environmental stressors.

This project addresses these limitations by developing a data-driven model that integrates environmental, structural, and traffic variables to produce more realistic assessments of bridge condition.

2. Background and literature review:

Research on bridge deterioration modeling has progressed over several decades, with methodologies evolving from empirical regression approaches to probabilistic frameworks and machine learning models. This section reviews key strands of work relevant to this project, identifies gaps, and motivates the methodological contributions of the research.

2.1 Historical Approaches to Bridge Deterioration Modeling

2.1.1 Markov Chain–Based Models

Markov models represent one of the earliest and most widely applied approaches to bridge deterioration modeling. These models characterize deterioration as transitions between discrete condition states (e.g., Good → Fair → Poor), with transition probabilities estimated from inspection histories. Notable early studies include the work by Mishalani and Madanat (2002), followed by enhancements incorporating Bayesian updating, hierarchical structures, and element-level modeling.

Markov models provide intuitive interpretations and computational tractability, which explains their widespread adoption in state DOT management systems. However, they rely heavily on historical transition frequencies and assume stationary transition probabilities, meaning that the rate of deterioration is assumed to be constant over time. This assumption limits the usefulness of Markov models in situations where key influencing factors operate outside the model's state framework.

Additionally, Markov models may struggle when inspection intervals are irregular, when deterioration mechanisms are nonlinear, or when data exhibit strong dependencies on

unobserved variables. These limitations motivate the development of data-driven models that better integrate structural and environmental information.

2.2 Regression-Based and Statistical Models

Regression models represent the next stage in deterioration modeling. Linear, nonlinear, and ordinal regression formulations allow researchers to quantify relationships between condition ratings and explanatory variables, such as age, span length, traffic volume, and material type. Estes and Frangopol (2001), for example, established regression-based frameworks for predicting condition ratings and structural reliability indices.

Ordinal logistic regression, in particular, offers advantages for modeling condition ratings, which are typically ordered categorical variables. These models can incorporate multiple predictors, estimate the direction and magnitude of effects, and provide statistical significance testing. However, regression models often assume linear or monotonic relationships and may not sufficiently capture complex or interaction-based deterioration mechanisms.

2.3 Machine Learning Approaches

In the past decade, machine learning techniques have gained traction in bridge deterioration modeling. Methods such as neural networks, decision trees, random forests, and support vector machines allow for nonlinear relationships, interaction effects, and high-dimensional feature spaces. Studies such as Liu et al. (2018) and Liu & Zhang (2020) demonstrated that machine learning models often outperform traditional regression techniques.

Machine learning approaches are particularly useful when datasets are large or when deterioration patterns are influenced by many interdependent factors. However, they may exhibit challenges such as overfitting or limited interpretability. Therefore, this project employs a hybrid approach: interpretable statistical models supplemented by higher-performance machine learning models.

2.4 Importance of Environmental Conditions in Deterioration Modeling

Environmental stressors such as temperature, humidity, precipitation, and freeze-thaw cycles are known drivers of material degradation. Concrete structures exposed to repeated freeze-thaw cycles show increased cracking and scaling. Steel reinforcement corrodes more rapidly in environments with high moisture or chloride exposure. Temperature gradients induce thermal stresses and influence concrete creep and shrinkage.

Although these environmental effects are well-documented, only limited studies have integrated detailed environmental datasets into bridge deterioration models. Most existing work uses coarse regional environmental descriptors or relies on historical averages that do not reflect broad environmental conditions. This gap is particularly significant because variability in environmental conditions can meaningfully influence deterioration mechanisms.

2.5 Gaps in Existing Research

This project addresses several key gaps:

1. **Insufficient Integration of Environmental Variables:**
Most deterioration models lack granular environmental data and do not quantify the effects of temperature variability, humidity, or precipitation on condition ratings.
2. **Limited Use of Extended Environmental Data:**
Only a small number of studies incorporate environmental information beyond historical observations, leaving uncertainty about how environmental patterns are associated with bridge deterioration.
3. **Lack of Bridge Type-Specific Comparisons:**
Existing literature rarely distinguishes deterioration patterns between PC, RC, and steel bridges when analyzing environmental vulnerability.
4. **Need for Hybrid Statistical–Machine Learning Frameworks:**
Many studies use either interpretable models or predictive models, but not both.

This project responds to these gaps by developing an integrated, multi-model framework that incorporates detailed environmental features and long-term projections.

3. Research scope and objectives:

The purpose of this research is to develop a comprehensive, data-driven framework for understanding how structural, traffic, and environmental factors collectively influence bridge condition, with an emphasis on PC bridges. The work is motivated by the recognition that bridge deterioration is shaped by multiple interacting factors, and that predictive models relying solely on historical inspection data often fail to capture the role of environmental stressors or account for long-term environmental effect.

The research is structured around two primary objectives:

- (1) the development of an environmentally-informed bridge condition estimation model, and
- (2) the examination of how long-term environmental information may be incorporated to support extended-horizon condition assessments.

Together, these objectives support not only the methodological advancement of deterioration forecasting, but also practical needs in infrastructure planning, maintenance prioritization, and adaptation of asset-management strategies for precast concrete systems.

3.1 Objective 1: Environmentally-Informed Bridge Condition Estimation Model

The first objective focuses on building a predictive model that integrates bridge structural characteristics, traffic loading metrics, and environmental stressors. Traditional models commonly emphasize structural and age-related variables while excluding environmental features, despite well-documented effects of temperature fluctuations, humidity, precipitation, and freeze-thaw cycles on material degradation.

The goal is to quantify how these stressors, individually and in interaction, relate to observed bridge condition ratings. To achieve this, the project compiles diverse datasets, harmonizes them

into a unified analytical framework, and deploys statistical and machine learning models capable of capturing linear, nonlinear, and interaction-based deterioration mechanisms.

Two central **research questions** guide this objective:

1. *Which environmental variables are most influential in explaining variation in bridge condition?*
The expectation is that variables such as maximum annual temperature, daily or seasonal temperature swings, humidity levels, and precipitation intensity may contribute meaningfully to deterioration mechanisms observed in concrete and steel bridges. Identifying the magnitude and direction of these effects provides insight into which stressors are most critical to consider in predictive modeling.
2. *Do environmental influences differ across bridge types, particularly between PC and non-PC bridges?*

Precast concrete bridges possess characteristics that distinguish them from cast-in-place or steel structures, such as segmental connections, joint behaviors, and different thermal response profiles. This objective aims to quantify whether PC bridges demonstrate distinct sensitivity to environmental factors and whether structural type should be explicitly incorporated into predictive modeling.

The model development activities under Objective 1 encompass data preparation (Task 1.1), model formulation (Task 1.2), and model evaluation (Task 1.3). The output is a set of validated models capable of estimating bridge condition ratings from integrated structural, traffic, and environmental inputs.

3.2 Objective 2: Condition Analysis Using Long-Term Environmental Information

The second objective extends the modeling capacity developed in Objective 1 by incorporating long-term environmental datasets into condition evaluation. Unlike traditional deterioration models that rely exclusively on historic environmental conditions, this work introduces broader sets of environmental inputs. This work demonstrates how deterioration modeling frameworks can remain functional and informative when supplied with extended-horizon environmental information.

This objective is guided by three **research questions**:

1. *How does the inclusion of long-term environmental information influence expected condition distributions?*
This question examines whether model outputs shift meaningfully when environmental inputs reflect broader patterns than those observed historically. The goal is to understand how sensitive deterioration forecasts are to environmental inputs and whether it produces different condition distributions than purely historical datasets.
2. *How do patterns differ across bridge types?*
Changes in expected condition distributions may not be uniform across structural types. For example, PC bridges may exhibit greater sensitivity to variables such as freeze–thaw cycles or maximum annual temperatures, while steel structures may respond differently. This objective provides a basis for comparing bridge types under consistent analytical conditions.

3. *How can uncertainty in long-term environmental information be accommodated in deterioration modeling?*

Long-range environmental datasets often contain inherent variability due to differences in modeling methods or assumptions. Understanding how these uncertainties carry through to condition assessments supports more robust asset-management planning.

To address these questions, this objective involves selecting a case study region (Task 2.1) and applying the developed model to environmental datasets representing potential long-term patterns (Task 2.2). The resulting condition distributions offer insights into how structural, traffic, and environmental variables jointly influence expected condition states over extended planning horizons.

3.3 Alignment with TRANS-IPIC Mission

Both research objectives contribute directly to TRANS-IPIC's emphasis on improving the durability and extending the service life of precast concrete transportation infrastructure. By quantifying the role of environmental conditions in deterioration processes, identifying stressors that disproportionately affect PC structures, and exploring long-term performance considerations, this work enables more informed maintenance, planning, and design decisions. The resulting methodology supports technology transfer through its adaptability, data-driven nature, and applicability to a wide range of transportation agencies.

4. Research description:

This section describes the complete methodological framework developed in the study. It outlines the selection, processing, and integration of data sources; the design and implementation of statistical and machine learning models; the feature engineering and selection techniques used to enhance model performance; the procedures used to handle imbalanced condition ratings; and the process of applying the models to a case study region using extended environmental input data.

The research design was guided by the dual goals of (1) achieving interpretability and transparency in the modeling process, and (2) ensuring that the models were sufficiently flexible to capture complex deterioration mechanisms influenced by structural, traffic, and environmental factors.

4.1 Data Collection and Preparation (Task 1.1)

The initial phase of the research involved assembling a comprehensive, multi-source dataset capturing bridge characteristics, inspection outcomes, traffic loading, and environmental conditions. Because deterioration processes are multifactorial, careful integration of these data sources was essential for meaningful modeling.

Data sources included:

1. National Bridge Inventory (NBI) records for Illinois, containing information such as bridge age, structural material, deck type, superstructure and substructure ratings, span configuration, geometric characteristics, and functional classifications.
2. Traffic data obtained from state DOTs, including Annual Average Daily Traffic (AADT), truck AADT, and percentage heavy vehicle traffic for each bridge.

3. Environmental observations obtained from NOAA weather stations nearest each bridge. These observations included temperature (mean, maximum, minimum), humidity, precipitation (rainfall, snowfall), and freeze-thaw indicators derived from daily records.

4.1.1 Environmental Data Aggregation

Environmental data are essential to characterize stressors that may influence material deterioration. Four NOAA weather stations distributed across Illinois were used to represent a range of environmental conditions within the state. Hourly and daily records were aggregated into annual descriptors such as:

- Annual mean temperature
- Annual maximum temperature
- Annual minimum temperature
- Annual total precipitation
- Annual average humidity
- Annual snowfall
- Heating Degree Days (HDD) and Cooling Degree Days (CDD)

These aggregated variables provide an annual-level environmental profile for each bridge. Each bridge was mapped to the nearest weather station using geographic coordinates. In a few cases where structures were located approximately equidistant between stations, ties were resolved by choosing the station with closer climatological similarity based on long-term averages.

4.1.2 Structural and Traffic Data Integration

Structural and traffic data from NBI and state DOT sources were standardized to ensure consistency across datasets. This process included:

- Harmonizing variable names and formats
- Standardizing units (e.g., converting feet to meters where applicable)
- Cleaning typographical inconsistencies and resolving duplicated or invalid records
- Filling non-critical missing data using established NBI imputation rules (e.g., functional class code harmonization)

Traffic data were merged by matching NBI route identifiers and geographic coordinates. Particular care was taken to align bridges with correct traffic volumes, as traffic loading is a critical predictor of deterioration.

4.1.3 Final Dataset Structure

After integration, the dataset included over 2,400 bridges with 37 initial explanatory variables spanning:

- Structural characteristics (e.g., deck type, material type, age, span count)
- Traffic metrics (AADT, truck percentages)
- Environmental descriptors (temperature, humidity, precipitation, HDD, CDD)
- Condition ratings (NBI ratings, element states for NBE)

This fully integrated dataset served as the foundation for model development (Task 1.2).

4.2 Model Development Framework (Task 1.2)

Predictive modeling in this work involves both statistical and machine learning methods. The rationale for using multiple modeling techniques is twofold:

1. Interpretability:
Statistical models such as ordinal or multinomial logistic regression provide insight into the direction and magnitude of predictor effects, especially valuable for understanding environmental influences.
2. Predictive Performance:
Machine learning models capture complex nonlinearities and interactions among variables, enhancing predictive accuracy.

The outcome variable for modeling was the bridge’s overall NBI condition rating, which was analyzed using both the full nine-point NBI scale and a derived three-class categorization (Good, Fair, Poor). The nine-point scale preserves the full granularity of NBI inspections, while the three-class version reflects commonly used asset-management groupings and provides improved class balance for certain modeling tasks. Using both formulations allows the analysis to capture detailed condition differences while also assessing model performance under a more operationally focused classification structure.

4.3 Statistical Model Formulation

Statistical models were employed to retain interpretability, ensuring the ability to quantify how structural, traffic, and environmental variables influence condition states.

Multinomial logistic regression was selected because condition state is a discrete, unordered categorical variable when reduced to the three-class scheme. The model estimates the log-odds of each condition class relative to a chosen baseline.

Let Y_i denote the condition class for bridge i , and let X_i denote the vector of predictor variables. The probability of belonging to class k is modeled as:

$$P(Y_i = k | X_i) = \frac{\exp(\beta_{k0} + \beta_k^T X_i)}{\sum_{j=1}^C \exp(\beta_{j0} + \beta_j^T X_i)},$$

where C is the number of condition categories (here, $C = 3$ or 9), β_k and β_{k0} are class-specific coefficients.

Interpretation of coefficients follows the usual log-odds framework. For example, a positive coefficient for annual maximum temperature in the “Poor” class indicates that increases in maximum temperature are associated with higher odds of the structure being classified as Poor.

4.4 Machine Learning Model Formulation

Machine learning (ML) models complement statistical models by capturing nonlinear and interaction effects. Neural Network approach was explored, which capture multi-variate nonlinear patterns. A fully connected feedforward neural network was constructed and hyperparameters were tuned, balancing performance and computational cost. The resulting architecture is presented in Table 4.1.

Table 4.1 Neural Network Architecture

Layer	Size	Activation function
Input Layer	10	N/A
Dense Layer 1	25	sigmoid
Dense layer 2	10	Rectified linear unit
Output layer	Number of classes	Softmax

4.5 Feature Engineering and AIC-Based Selection

Initial modeling revealed that not all 37 variables were equally informative. To reduce noise and improve interpretability, stepwise backward elimination based on the Akaike Information Criterion (AIC) was employed. The procedure retained variables whose removal increased the AIC, indicating loss of model quality.

This process reduced the feature set from 37 to 10 key predictors, including:

- Total annual precipitation
- Snowfall
- Design load
- Skew
- Structure length
- Vertical clearance
- Operating rating
- Inventory rating
- Scour critical

This refinement improved model generalization and reduced overfitting in both statistical and ML models.

4.6 Handling Class Imbalance in Condition Ratings

Bridge condition data are inherently imbalanced because most bridges fall into Good or Fair condition categories. Imbalance can bias models toward predicting the majority classes, reducing sensitivity to minority (Poor) class observations.

Several strategies were evaluated:

1. Oversampling:
Synthetic Minority Oversampling Technique (SMOTE) generated synthetic Poor-class samples.
2. Undersampling:
Random reduction of majority classes to reduce imbalance.
3. Class weights:
Assigning higher penalty to errors in minority classes during training.

Class weighting produced the best balance of accuracy and reliability and was adopted as the primary strategy.

4.7 Case Study Location Selection (Task 2.1)

Illinois was selected as the case study region because:

- It exhibits diverse environmental patterns across its geography.
- It maintains comprehensive NBI inspection records.
- Traffic datasets were readily integrated at the bridge level.
- The distribution of PC bridges provided adequate sample size for type-specific modeling.

This combination enabled a robust evaluation of deterioration mechanisms and model performance.

4.8 Application Using Extended Environmental Input Data (Task 2.2)

The final component of the research involved applying the models to condition evaluations informed by extended environmental data. These data represent long-horizon environmental information.

The procedure included:

1. Substituting extended environmental inputs (e.g., expanded temperature ranges, humidity patterns, precipitation trends) into the trained model.
2. Computing resulting condition classifications under these extended inputs.
3. Evaluating shifts in condition distributions to understand sensitivity to environmental variability.

This exercise does not assign causal interpretation to environmental time periods but instead demonstrates how the modeling framework can remain functional under a wider diversity of environmental conditions than those observed historically.

5. Project results:

This section presents the results of the modeling framework described earlier, including: (1) the statistical model findings, (2) the machine learning model findings, (3) comparative condition assessments across structural types, with special attention to PC bridges, and (4)

analyses performed using extended environmental input data to examine how broader environmental patterns relate to expected condition distributions.

The results demonstrate that structural, traffic, and environmental variables all contribute meaningfully to condition classification; that PC bridges exhibit distinct deterioration tendencies relative to cast-in-place structures; and that condition distributions shift when models are evaluated under extended environmental conditions. Each subsection here provides a detailed narrative of these findings.

5.1 Descriptive Statistics of Bridge Condition Data

The integrated dataset used for modeling includes 2,400+ Illinois bridges with structural, traffic, and environmental attributes mapped to each location. For the 2022 reference dataset:

- Good condition bridges numbered 1,491
- Fair condition bridges numbered 705
- Poor condition bridges numbered 179

This distribution is typical of statewide bridge inventories in the U.S., where maintenance and inspection programs keep the majority of structures in adequate or better condition. However, the imbalance poses modeling challenges, as statistical and machine learning algorithms perform best when all classes have sufficient representation. These challenges were addressed through class-weighting and synthetic oversampling techniques, as described in Section 4.

5.2 Statistical Model Findings

Multinomial logistic regression was used to examine how bridge characteristics and environmental indicators relate to the probability of belonging to each condition class (Good, Fair, Poor). The final model, refined using AIC-based feature selection, retained a subset of structural, operational, and environmental predictors.

Tables 5.1 and 5.2 summarize the estimated regression coefficients for each condition class. Several predictors show systematic associations with bridge condition. Structural and operational attributes, such as year built, design load, structure length, vertical clearance, and operating and inventory ratings, were significant contributors. As expected, older bridges and those with lower operating or inventory ratings exhibited higher odds of being classified as Fair or Poor.

Environmental factors retained in the final model, including total precipitation and total snowfall, also showed measurable associations with condition class. These results highlight that deterioration outcomes reflect a combination of structural characteristics, operational performance, and environmental exposure.

Table 5.1. Regression Coefficients for the 3-Class Bridge Condition Multinomial Logistic Model

	YEAR_B UILT_0 27	DESIGN_ LOAD_03 1	DEGREES _SKEW_03 4	STRUCTURE _LEN_MT_04 9	VERT_CLR_ UND_054B	OPERATING_R ATING_064	INVENTORY_ RATING_066	SCOUR_C RITICAL_ 113	PrecipitationT otal	TotalSnowfall	Intercept
	-0.009	-0.28	0.159386	0.03403	-0.113986	-0.012363	0.232458	-0.14851	0.017061	-0.008858	0.342566
	1.6808	0.13212	-0.0003	-0.29153	0.049756	-0.618329	0.886281	0.24798	-0.276129	0.277316	0.394083
	-0.103	-0.0002	-0.03742	0.014253	-0.064845	1.601171	-2.118739	-0.01912	-0.000929	-0.120453	-0.736649

Table 5.2. Regression Coefficients for the 9-Class Bridge Condition Multinomial Logistic Model

	YEAR_B UITL_0 27	DESIGN_ LOAD_03 1	DEGREES_ SKEW_03 4	STRUCTURE_ LEN_MT_04 9	VERT_CLR_ UND_054B	OPERATING_R ATING_064	INVENTORY_ RATING_066	SCOUR_C RITICAL_ 113	PrecipitationT otal	TotalSnowfall	Intercept
	0.1322	-1.9076	3.932195	0.112421	0.005474	-4.787342	-3.676742	3.91576	2.224022	-0.009095	-29.871765
	-0.426	0.76399	-1.05412	-1.38044	0.568455	2.054392	-1.996585	-1.46116	-0.054936	0.659215	3.723923
	-0.283	-0.5719	0.107767	0.289303	-0.197866	2.755306	-2.169413	-0.14329	-0.117413	0.010576	4.464356
	-1.163	0.05386	-0.07185	0.045781	-0.104799	2.482982	-1.508299	-0.66784	-0.607086	-0.14152	4.918415
	-1.048	-0.3988	0.13208	0.249639	0.086023	0.012563	1.179911	-0.49191	-0.117983	-0.267045	6.06965
	-1.011	-0.6316	0.080785	0.321195	0.029794	0.060379	1.349811	-0.49424	-0.216054	-0.299586	5.996843
	-0.498	0.17833	-0.00351	0.101453	0.26991	-0.518505	1.911372	-0.15198	-0.316369	-0.082396	6.30135
	0.4054	0.29218	-0.02765	-0.283064	-0.000142	-0.903898	2.101321	0.2956	-0.496574	0.138295	5.601738
	7.3272	1.45447	0.001139	-0.352781	0	0.001115	1.808623	0.05199	-0.00763	0.091135	-7.204509

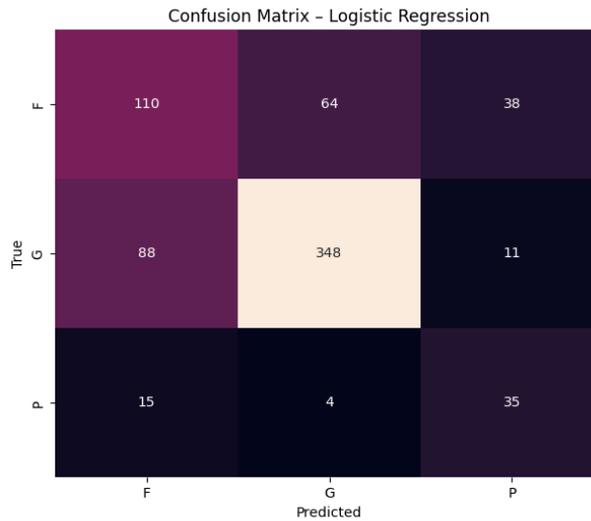


Figure 5.1. Confusion matrix for the 3-class multinomial logistic regression model (accuracy = 69%).

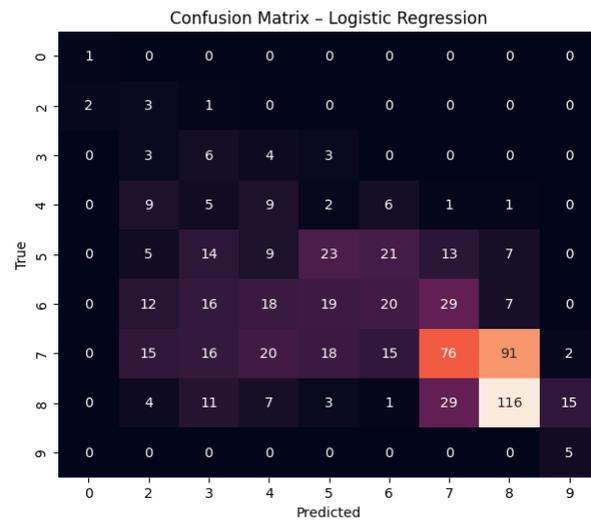


Figure 5.2. Confusion matrix for the 9-class multinomial logistic regression model (accuracy = 36%).

Model performance for both the 3-class and 9-class formulations was evaluated using overall accuracy and confusion matrices. The 3-class multinomial logistic regression achieved an accuracy of 69%, with most misclassifications occurring between Good and Fair. In contrast, the 9-class model attained an accuracy of 36%, reflecting the increased difficulty of differentiating fine-grained NBI condition ratings. The confusion matrices for both formulations are presented in Figures 5.1 and 5.2.

5.3 Comparative Results for Precast and Cast-in-Place Bridges

An important component of this research is the evaluation of deterioration tendencies across bridge types. The study examined differences between PC and cast-in-place (CIP) concrete bridges, using CIP as the reference category in the multinomial logistic regression.

The coefficient patterns show the following tendencies:

- For the Good condition class:
The exponentiated coefficient (odds ratio) was approximately 0.85, indicating that PC bridges were 15% less likely than CIP bridges to be classified as Good when controlling for other predictors.
- For the Fair condition class:
The odds ratio was close to 1.00, indicating effectively no meaningful difference between bridge types for the Fair condition category.
- For the Poor condition class:
The odds ratio was approximately 1.145, meaning PC bridges were 14.5% more likely to fall into the Poor category relative to CIP structures, holding all other variables constant.

These findings suggest that PC bridges exhibit somewhat higher vulnerability to certain deterioration mechanisms captured by the integrated dataset. While many factors could account for these differences, including joint behavior, thermal compatibility between precast segments, or moisture sensitivity, this study's focus remains observational rather than causal. Nonetheless, these quantitative comparisons provide useful guidance for asset-management strategies prioritizing PC structures for monitoring and maintenance.

5.4 Machine Learning Model Findings

Machine learning (ML) analyses provide complementary insights by capturing nonlinear relationships and complex interactions that logistic regression may not fully represent.

The neural network model achieved the strongest overall performance among the machine-learning models tested, providing the most balanced classification across the Good, Fair, and Poor categories. Although absolute accuracy remains constrained by class imbalance, particularly for the Poor class, the neural network reduced misclassification rates relative to the baseline statistical models.

For the 3-class formulation, the neural network achieved an overall accuracy of 68%. As shown in Figure 5.3, most misclassifications occurred between the Good and Fair classes, with the Poor class identified with moderate reliability. For the 9-class formulation, the neural network achieved an accuracy of 37%. The confusion matrix in Figure 5.4 indicates that errors were primarily concentrated among adjacent NBI condition levels, reflecting the challenge of resolving finer-scale distinctions.

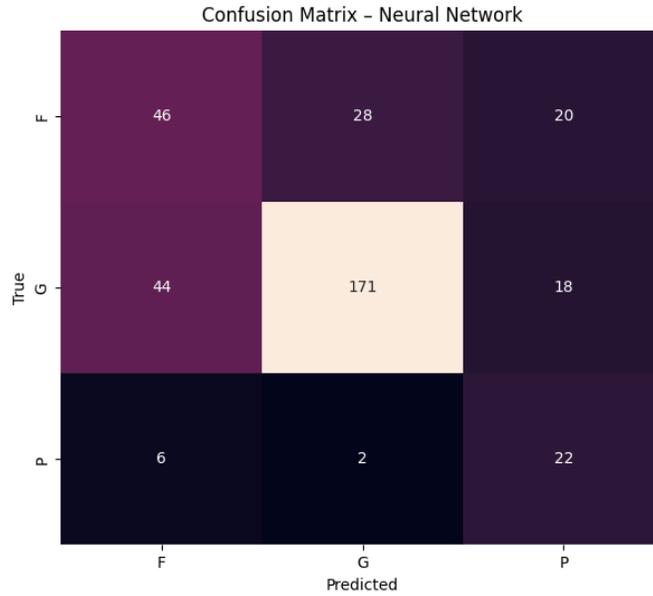


Figure 5.3. Confusion matrix for the 3-class neural network model (accuracy = 68%).

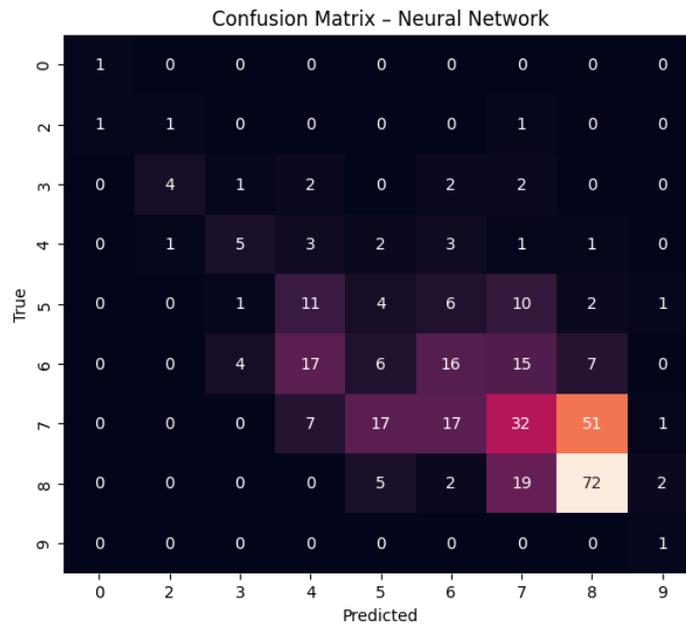


Figure 5.4. Confusion matrix for the 9-class neural network model (accuracy = 37%).

The machine-learning results were broadly consistent with the patterns identified in the statistical models. While the neural network offers less interpretability than regression models, its predictive performance and capacity to model complex relationships strengthen confidence in the overall findings.

5.5 Condition Evaluations Using Extended Environmental Input Data

A major component of this project involved evaluating how the models behave when supplied with extended environmental input data. This study demonstrates how incorporating a broader range of environmental inputs can influence expected condition distributions. This exploration helps assess model sensitivity and provides insight into long-term asset-management considerations.

Extended environmental inputs, derived from long-horizon datasets, were used to generate condition distribution outputs for two analysis years, 2050 and 2100.

5.5.1 Condition Distribution Under Scenario A (2050 Case)

Table 5.3 summarizes the estimated condition distribution under Scenario A using the multinomial logistic regression model and the neural network model. Across models, the condition distribution shifts from the baseline 2022 dataset, with a decline in the number of Good condition bridges and an increase in Fair and Poor condition classifications. This suggests that changes in environmental input values, whether historical or extended, can meaningfully influence expected deterioration outcomes.

Table 5.3. Condition distribution under Scenario A using logistic regression and neural networks.

Logistic Regression Model		
Condition	Year 2050	% Change from 2022
Good	1,302	-12.68%
Fair	712	+0.99%
Poor	361	+101.68%
Neural Network Model		
Condition	Year 2050	% Change from 2022
Good	1,258	-15.63%
Fair	770	+9.22%
Poor	347	+93.85%

Table 5.4. Condition distribution under Scenario B using logistic regression and neural networks.

Logistic Regression Model		
Condition	Year 2100	% Change from 2022
Good	0	-100.00%
Fair	1,591	+125.67%
Poor	784	+337.99%
Neural Network Model		
Condition	Year 2100	% Change from 2022
Good	0	-100.00%
Fair	2,342	+232.20%
Poor	33	-81.56%

5.5.2 Condition Distribution Under Scenario B (2100 Case)

Scenario B uses a broader and more extreme range of environmental input values, producing more pronounced shifts in condition distributions. Table 5.4 summarizes the estimated condition distribution under Scenario B using the multinomial logistic regression model and the neural network model. These results demonstrate the sensitivity of deterioration estimates to environmental variables. The large shift toward Fair and Poor categories reflects the fact that the model responds significantly to increased environmental stressors represented in these extended input datasets. Comparable patterns emerge in the 9-class model results (Figures 5.5 and 5.6), with both the logistic regression and neural network models exhibiting similar shifts in condition distributions under this scenario.

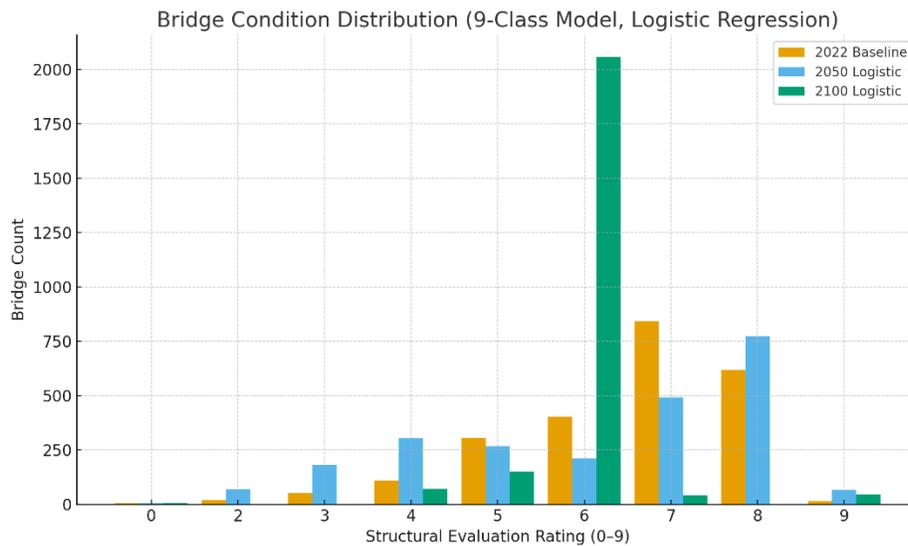


Figure 5.5 Bridge condition distributions (9-class model) estimated using logistic regression model.

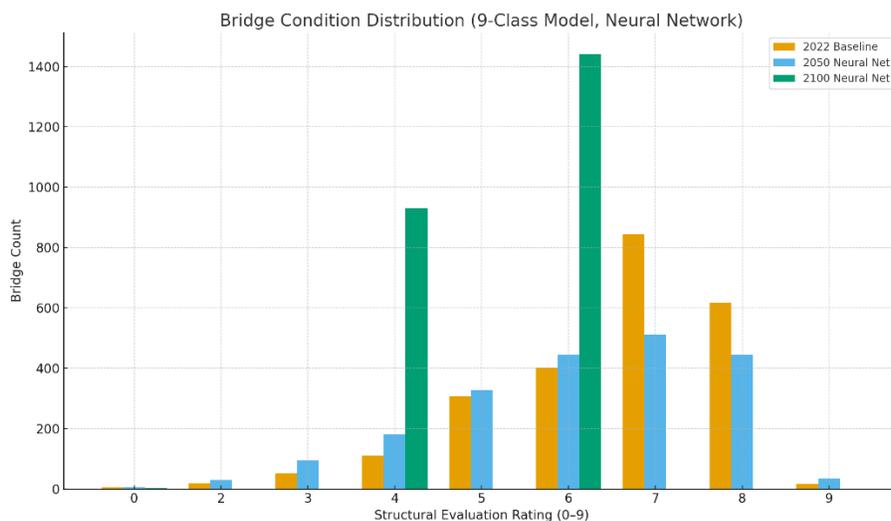


Figure 5.6 Bridge condition distributions (9-class model) estimated using neural network model.

5.6 Summary of Key Findings

Across all models and datasets, several high-level conclusions emerge:

1. Environmental variables exhibit significant associations with condition states across both statistical and ML models.
2. Precast concrete bridges show measurably different condition tendencies compared to cast-in-place structures, aligning with engineering expectations of material and joint behavior.
3. Extended environmental input analyses reveal meaningful shifts in condition distributions, offering insight into how deterioration forecasts may respond to broader environmental conditions.
4. Structural and operational attributes, including year built, design load, structure length, vertical clearance, and operating and inventory ratings, remain influential predictors of condition classification.
5. Bridge age continues to be a strong determinant of condition, aligning with established deterioration literature and reinforcing findings from the logistic regression.

These results provide a powerful foundation for the recommendations and practical applications discussed in Section 7.

6. Conclusions and recommendations:

This research set out to develop a comprehensive, environmentally informed approach to bridge condition evaluation, with special attention to the performance of PC bridges. By integrating structural, traffic, and environmental datasets into a unified analytical framework and applying both statistical and machine learning techniques, the study provides new insights into factors influencing bridge deterioration and advances the tools available for long-term infrastructure assessment and planning.

The project's contributions extend across multiple domains: methodological development, empirical findings, and state-of-practice implications. These contributions are summarized below.

6.1 Methodological Contributions

6.1.1 *Integrated Multi-Source Database*

The research produced a harmonized dataset that consolidates bridge structural characteristics, inspection records, traffic loading data, and detailed environmental observations. The integration of these diverse sources ensures that deterioration modeling reflects the multifaceted nature of bridge performance. The resulting structure-level dataset is ready for continued use, expansion, and adaptation by practitioners and researchers.

6.1.2 *Environmentally Informed Condition Estimation Model*

The project developed a condition-estimation framework that incorporates key environmental variables, specifically total precipitation and total snowfall, alongside structural and operational attributes. These environmental exposures contribute to deterioration mechanisms such as moisture ingress, freeze-related distress, and corrosion-related degradation. Integrating such

variables strengthens the linkage between observed condition outcomes and the environmental factors that influence material performance over time.

The combined use of multinomial logistic regression and neural networks provides complementary strengths: statistical interpretability from regression models and flexibility in capturing nonlinear relationships from machine-learning models. This hybrid modeling structure enhances diagnostic capability and improves the robustness of condition-classification performance.

6.1.3 Feature Engineering and AIC-Based Selection

The study employed rigorous feature engineering and model selection, resulting in a refined subset of predictors that contribute most meaningfully to deterioration classification. The transparent and systematic approach improves model clarity, reduces overfitting, and increases relevance for engineering interpretation.

6.1.4 Sensitivity to Extended Environmental Inputs

The model's application using extended environmental datasets demonstrates a procedure for incorporating long-term environmental information into deterioration analyses. These analyses show how deterioration forecasts respond when environmental inputs reflect broader patterns than those captured in historical records. This helps illustrate model sensitivity and provides pathways for evaluating long-term infrastructure planning scenarios.

6.2 Empirical Insights

6.2.1 Environmental Stressors Matter

Across multiple modeling techniques, the environmental variables included in the final feature set, total precipitation and total snowfall, showed clear relationships with bridge condition classifications. These exposures influenced shifts in expected condition states and consistently appeared as meaningful predictors in both statistical and machine-learning models. These findings reinforce that incorporating environmental information strengthens deterioration modeling and enhances the interpretability of condition outcomes.

6.2.2 Differences Between PC and CIP Bridges

The findings suggest that precast concrete bridges exhibit distinct deterioration tendencies when compared to CIP structures. PC bridges were somewhat less likely to fall in the Good category and more likely to fall in the Poor category. These differences may be explained by factors such as joint performance, moisture sensitivity at connections, and variations in thermal behavior across precast segments. Although the present analysis remains observational, the quantitative patterns highlight the need for continued attention to PC bridge performance and maintenance planning.

6.2.3 Robustness Across Modeling Techniques

Both the logistic regression and machine learning models produced consistent trends, reinforcing confidence in the results. Machine learning models detected nonlinearities and interactions not

fully captured by regression approaches, but overall insights were directionally aligned across methods.

6.2.4 Behavior Under Extended Environmental Conditions

Condition distributions shifted when models were evaluated under extended environmental inputs. These shifts, interpreted here as reflections of model sensitivity to environmental variation, demonstrate how environmental factors shape condition outcomes and suggest that long-term asset management strategies may benefit from analyses that incorporate broader environmental datasets.

6.3 Implications for Bridge Management and Planning

Several practical implications arise from the research:

1. Environmental considerations should be integrated more explicitly into deterioration modeling used for management decisions. Traditional models may omit influential stressors, potentially leading to underestimation or mischaracterization of risk.
2. PC bridges warrant targeted monitoring and preventive strategies, given the observed statistical propensities toward poorer condition categories. Inspection guidance, maintenance schedules, and rehabilitation planning may be better optimized when explicitly accounting for material- and system-specific vulnerabilities.
3. Use of extended environmental datasets provides a pathway for long-term planning. Analyzing model behavior under broader environmental ranges helps asset managers identify structures likely to be sensitive to environmental variability or long-horizon stress conditions.
4. The modeling framework is portable. Although developed for Illinois, the methodology, data processing workflow, variable engineering, model structure, and evaluation procedure, can be adapted readily to other states or regions with comparable data availability.

6.4 Limitations and Opportunities for Future Work

While this research makes critical contributions, certain limitations remain and point to valuable avenues for future work.

6.4.1 Data Availability and Resolution

Environmental data were available from only four NOAA stations in the state, and bridge-to-station mapping introduces spatial averaging. Improved spatial granularity or elevation-specific modeling could sharpen environmental exposure measurement and reduce aggregation bias.

6.4.2 Model Extensions

Expanding the model to include:

- element-level deterioration modeling,
- temporal deterioration trajectories, or
- stochastic or Bayesian formulations

could increase its relevance for lifecycle analysis and reliability-based asset management.

6.4.3 Integration with Cost and Maintenance Planning Tools

Translating condition probabilities into lifecycle cost implications would strengthen the utility of the model for DOT decision-making. Incorporating maintenance actions, deterioration transition probabilities, or optimization routines would enable full decision-support modeling.

6.5 Overall Conclusion

This project advances bridge deterioration modeling by integrating environmental conditions into a multi-source, data-driven analytical framework and by providing new quantitative insights into the performance of PC bridges. The findings reflect the importance of environmental stressors in shaping condition outcomes, highlight distinctions between PC and CIP structures, and demonstrate the value of incorporating extended environmental information into long-horizon evaluations.

The resulting methodology supports TRANS-IPIC's mission by informing maintenance strategies, enhancing durability assessment, and contributing to long-term planning for critical transportation infrastructure.

7. Practical application/impact on transportation infrastructure:

The research conducted in this project provides a suite of practical tools, insights, and datasets that can support transportation agencies as they develop strategies to preserve the durability and extend the service life of bridge infrastructure. By integrating environmental, structural, and traffic information into a unified estimation framework, the project delivers capabilities that can enhance inspection planning, maintenance prioritization, and long-range asset management. The following subsections summarize the major practical contributions and impacts of the work.

7.1 Advancing Bridge Condition Assessment Practices

A critical outcome of this project is the environmentally informed condition estimation model, which demonstrates that incorporating environmental variables alongside structural and traffic factors yields richer and more informative assessments than models that rely exclusively on historical inspection data. This advancement directly supports the needs of state transportation agencies seeking to better anticipate deterioration trajectories, allocate resources efficiently, and target structural types that exhibit higher sensitivity to particular stressors.

The modeling framework remains fully compatible with existing asset-management systems. Because the model inputs consist of commonly available NBI, traffic, and weather station data, state DOTs can integrate these analyses into their existing workflows with modest adjustments. The approach also improves transparency by offering interpretable coefficients from regression models and complementary performance metrics from machine learning models.

7.2 Informing Maintenance and Rehabilitation Prioritization

One of the core practical benefits of the modeling framework lies in its ability to support prioritization decisions. The findings from Sections 5.1-5.4 highlight several structural, operational, and environmental predictors, such as year built, design load, structure length, vertical clearance, operating and inventory ratings, and precipitation- and snowfall-related variables, that are associated with poorer condition classifications. Transportation agencies can use these results to:

- Identify bridges that may be more susceptible to deterioration under greater environmental exposure or limited operational capacity.
- Allocate inspection resources proactively to bridges that exhibit higher sensitivity to these predictors.
- Evaluate whether certain groups of bridges, defined by structural configuration or operational characteristics, warrant earlier maintenance interventions.
- Integrate the model outputs with cost or risk-based prioritization frameworks to inform maintenance sequencing and resource allocation.

This approach supports data-informed prioritization by highlighting the factors most strongly linked to deteriorated condition states and by enabling agencies to explore how alternative input conditions affect expected outcomes.

7.3 Enhancing Understanding of Precast Concrete Bridge Performance

A specific contribution of this research is improved insight into the performance of PC bridges. The quantitative comparisons in Section 5 indicate that PC bridges display different condition patterns relative to CIP concrete bridges, even after controlling for key confounding variables. This finding has direct implications for TRANS-IPIC and its partners:

- Maintenance strategies can be calibrated to account for PC-specific behaviors, especially for older PC structures or those located in regions experiencing high environmental variability.
- Inspection protocols may be adapted to focus on joint behavior, segmental connections, or moisture-infiltration pathways associated with PC systems.
- Design considerations for future PC infrastructure may be informed by recognizing which environmental and operational stressors play the largest role in long-term condition outcomes.

By providing empirical evidence of how PC bridges compare with other structural types in the presence of environmental and traffic stresses, the project strengthens TRANS-IPIC's mission to extend the life of precast concrete transportation systems.

7.4 Supporting Long-Horizon Planning Using Extended Environmental Information

The analyses performed with extended environmental input datasets (Scenario A and Scenario B in Section 5.5) demonstrate how deterioration modeling frameworks can remain operationally useful when supplied with long-horizon environmental information. The results illustrate several practical benefits for state DOTs:

- Sensitivity evaluation: Agencies can assess how sensitive deterioration outcomes are to broader environmental patterns.
- Strategic planning: Insights about condition distributions under extended inputs can guide long-range maintenance and replacement planning.
- Resource allocation: By understanding how condition assessments shift under different environmental contexts, agencies can better prioritize investments for at-risk regions or structural types.
- Scenario comparison: The approach provides a template for evaluating a range of plausible long-term environmental patterns, without requiring probabilistic forecasting or attribution.

These benefits are especially relevant for states with large inventories of aging bridges and diverse environmental conditions, as the approach supports forward-looking asset management without reliance on assumptions beyond the scope of available engineering and environmental datasets.

7.5 Transferability of the Modeling Framework

The framework developed in this project is designed to be adaptable. Although Illinois served as the case study region, the methodology is broadly transferable to other states or regions because:

- NBI datasets are standardized nationwide.
- Traffic datasets can be aligned via route identifiers or geospatial matching.
- Environmental variables can be derived from local weather stations or regional environmental datasets.
- The variable engineering and model selection procedures remain valid regardless of location.
- Computational requirements are modest and compatible with DOT-level analytical resources.

This transferability supports technology dissemination, one of TRANS-IPIC's core objectives, and provides a scalable solution for states seeking to modernize their deterioration modeling workflows.

7.6 Contribution to Research and Workforce Development

The project also contributes to research development and technical capacity building in several ways:

- It introduces students and early-career researchers to advanced deterioration modeling concepts.
- It provides reproducible workflows for integrating environmental and structural data in bridge performance studies.
- It establishes a methodological foundation on which future TRANS-IPIC research, such as work on life-cycle cost analysis, reliability modeling, or data-driven design improvements, can build.

Through these pathways, the project strengthens the technical knowledge base relevant to PC infrastructure and supports development of the next generation of infrastructure resilience researchers and practitioners.

8. References:

- Agrawal, A. K., Kawaguchi, A., and Chen, Z. (2010). "Deterioration rates of typical bridge elements in New York." *Journal of Bridge Engineering*, 15(4), 419–429.
- Estes, A. C., and Frangopol, D. M. (2001). "Bridge lifetime system reliability under multiple limit states." *Journal of Structural Engineering*, 127(7), 750–759.
- Hastie, T., Tibshirani, R., and Friedman, J. (2009). *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*. Springer, New York.
- Liu, M., and El-Gohary, N. (2022). "Hybrid data-driven bridge deterioration modeling integrating structural and environmental factors." *Journal of Performance of Constructed Facilities*.
- Liu, M., and Zhang, Z. (2020). "Environmental impacts on bridge deterioration patterns: A data-driven approach." *Journal of Infrastructure Systems*.
- Liu, M., El-Gohary, N., and Elbeltagi, E. (2018). "Machine learning-based modeling of bridge deterioration considering environmental variables." *Journal of Computing in Civil Engineering*, 32(3), 04018018.
- Mishalani, R., and Madanat, S. (2002). "Computation of infrastructure transition probabilities using stochastic duration models." *Journal of Infrastructure Systems*, 8(4), 139–148.
- Morcoux, G. (2006). "Performance prediction of bridge deck systems using Markov chains." *Journal of Performance of Constructed Facilities*, 20(1), 26–33.
- Robelin, C.-A., and Madanat, S. (2007). "History-dependent bridge deck deterioration models." *Journal of Infrastructure Systems*, 13(3), 195–203.

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