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16. Abstract Traditional bridge condition assessments often fail to capture structural interactions or assess freight network vulnerability to disruptions like bridge closures. This project presents QUANT CR, a data-driven AI model combining geographic information systems with graph-based network analysis. Advanced recurrent neural networks (LSTM and GRU) forecast individual bridge deck conditions using historical data, traffic volume, age, span length, and structural features. A graph-based representation of the freight network integrates geospatial and intersection data to evaluate structural and topological criticality. Applied to Georgia's bridges, this framework reveals key factors affecting performance and identifies network vulnerabilities that threaten freight mobility. QUANT CR supports risk-informed, predictive maintenance prioritization, advancing resilience in transportation infrastructure and complementing existing rating systems with user-friendly decision aids for bridge owners.			
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Quant CR for transformative bridge asset management

Final Report

December 2025

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Civil Engineering
The University of Georgia

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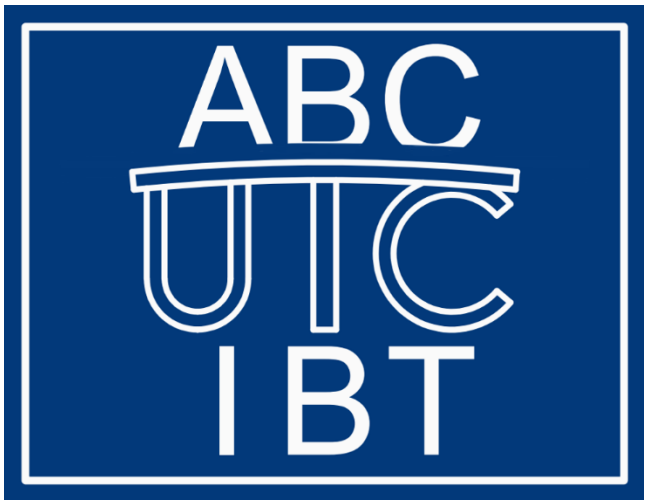

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CHAPTER 1. INTRODUCTION

1.1. Project Motivation

Bridge infrastructure plays a pivotal role in a nation's transportation system by connecting remote areas, reducing societal disparities, and driving economic progress. However, the aging and deterioration of bridge infrastructure are increasingly leading to safety hazards, compromised rideability, and higher user costs. In the United States (US), the situation has reached a critical point, with the average bridge age at 47 years and 6.8% classified as structurally deficient (ASCE 2025). As of 2023, the estimated cost to replace bridges in poor condition is $69.7 billion, while rehabilitation would require $47.4 billion, underscores the urgency of this issue (FHWA 2023). Additionally, the increasing frequency of extreme weather events and natural disasters such as floods, hurricanes, snowstorms, and blasts present new challenges for current bridge asset owners in managing their infrastructure. The rise of automated and heavy trucking further complicates matters, necessitating a re-evaluation of bridge load permits and condition assessments that account for shifts in traffic patterns and advancements in vehicle technologies.

In the United States, conventional bridge asset management primarily relies on visual inspections and on-site assessments to evaluate bridge condition. However, these practices fall short in several key areas (Gillins et al. 2016, Graybeal et al. 2002). Traditional methods lack the ability to predict future bridge performance and service life based on historical and emerging inspection data. Additionally, they fail to incorporate comprehensive decision-making processes that account for a range of stressors and potential scenarios. For instance, the AASHTOWare Bridge Management system does not capture the randomness of deterioration time intervals or rapid declines in condition (Politis et al. 2021).

Furthermore, current asset management tools do not adequately address the interdependencies among bridges, which could lead to cascading failures within the network. They also lack the capacity to evaluate the connectivity and sensitivity of the freight network to disruptions. To address these limitations, existing bridge asset management practices must exploit emerging technologies such as artificial intelligence (AI) to predict future bridge performance and service life based on past and emerging inspection results, as depicted in Figure 1.

The overarching challenge is the need to shift from reactive to predictive bridge performance monitoring strategies. These strategies should focus on maintaining bridge functionality over extended periods without major replacements, while enabling more efficient budgeting for maintenance, repair, and rehabilitation (MRR) activities. The ultimate aim of this project is to equip state and local governments with a tool that serves as an essential component of long-term bridge asset management, which not only safeguards against current vulnerabilities but also anticipates and mitigates future challenges.

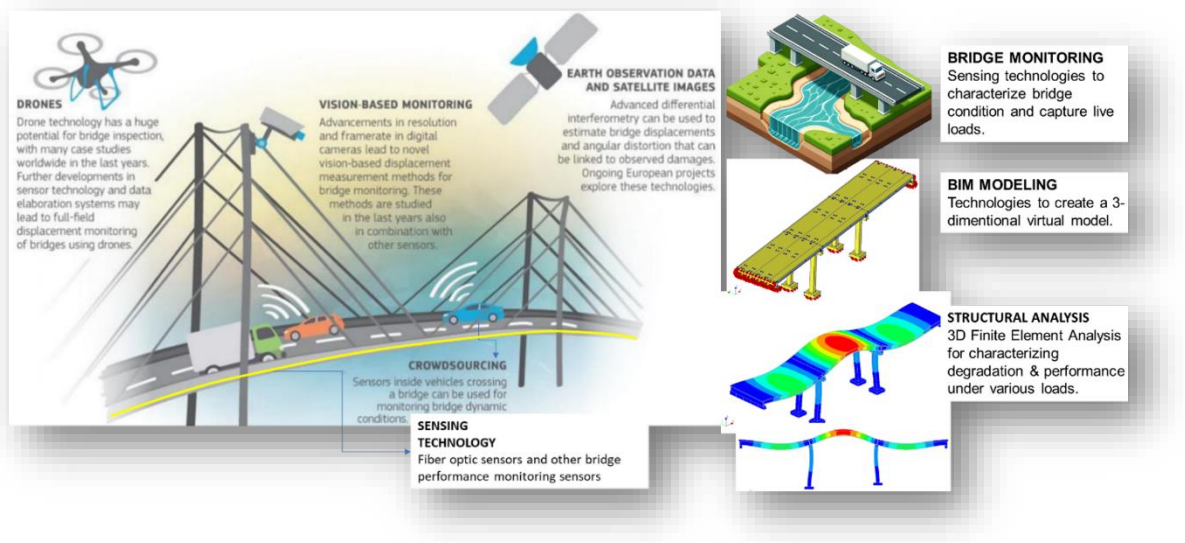


Figure 1. Emerging technologies for bridge performance monitoring and management (European Commission 2019).

1.2. Research, Objectives, and Tasks

Effective management of bridge infrastructure is essential to maintaining a safe, resilient, and efficient transportation system, especially for routes critical to national freight movement. As bridges continue to age and transportation demands evolve, traditional isolated bridge evaluation-based approaches are no longer sufficient. This project addressed these growing challenges by leveraging extensive historical bridge condition data and integrating it with modern technologies, including artificial intelligence, geographic information systems, and graph-based network modeling. The primary goal was to enable forward-looking insights into structural health and overall network connectivity, supporting proactive and risk-informed decisions for bridge maintenance, repair, and rehabilitation (MRR).

To accomplish this, a recurrent neural network model was developed that predicted future bridge deck condition ratings, helping identify deterioration before it becomes critical. These predictive results were then combined with a graph-based network model of the highway freight system to assess the structural and topological importance of individual bridges and determine their potential impact on freight connectivity. The analysis used diverse datasets that include bridge condition, structural performance, traffic volumes, and highway network characteristics.

The primary objectives of this research project were the following:

1. To develop a recurrent neural network forecasting model to predict changes in bridge deck condition ratings over time
2. To use these predictions to build a graph-based network model that evaluates the connectivity and vulnerability of the roadway and bridge system
3. To apply the combined modeling framework to Georgia's National Highway Freight Network and validate its ability to identify high-risk bridges, supporting the prioritization of maintenance and repair actions that improve network resilience

These objectives were accomplished through the following research tasks.

- Task 1 – Acquisition of bridge performance/condition data: The research team acquired the bridge performance, condition, structural, and traffic data for statewide bridge network assets from different sources and processed them into a geospatial data format. The National Bridge Inventory (NBI) and NBI Element datasets provided information on historical deck condition ratings, operational conditions, functional classifications, other inspection records, and element-level bridge condition deficiencies, respectively.
- Task 2 – Development of an AI-powered bridge condition rating prediction model: Based on the collected yearly datasets, a time-distributed recurrent neural network (RNN) model was developed in this task to process sequential data. To evaluate model efficiency, two different deep learning architectures—Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU)—were implemented, given their strengths in modeling sequential patterns and capturing long-term temporal dependencies.
- Task 3 – Enhance with a graph-based network model: The research team developed a graph-based networks of bridges and roadways within freight network based on the geospatial coordinate datasets and the degree of roadway intersections. In graph theory, a graph G consists of three primary components: a vertex (node) set V (G), an edge (link) set E(G), and a relation that associates each edge with two vertices. The developed graph-based network facilitated various topological vulnerability analysis for the bridges within the network.
- Task 4 – Case study and Verify model: To better illustrate the Quant CR model's time series predictions, pilot studies were conducted to compare the predicted versus actual deck condition ratings for sample bridges.
- Task 5 – Final Report: A final report is prepared meeting the RITA requirements for the ABC-UTC funded projects. The report contains a detailed description of the methodologies and results from the preceding tasks and recommendations for future work.

1.3. Research Advisory Panel (RAP)

The project work and the developed survey were done in collaboration with the Research Advisory Panel (RAP). The following people participated in the RAP:

- Bijan Khaleghi, Ph.D., P.E., S.E., Principal Structural Engineer, TranTech Engineering; Associate Research Professor and Director of Implementation, ABC-UTC at Florida International University.

1.4. Report Overview

This report provides a detailed overview of the development and application of a data-driven, AI-powered Quantitative Condition Rating (QUANT CR) model, which predicts bridge performance both temporally and spatially across a transportation network. It is organized into multiple chapters that collectively outline the research motivation, objectives, methodology, and findings. This chapter introduces the project background, key research objectives, and outlines the tasks undertaken. Chapter 2 reviews the existing literature on bridge asset management, artificial intelligence in infrastructure monitoring, and topological network modeling. Chapter 3 details the development of recurrent neural network (RNN) models, specifically Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU), to predict future bridge deck condition ratings. Chapter 4 presents the graph-based network modeling approach used to assess connectivity and vulnerability in Georgia's national highway freight network. Case studies are included in Chapter

5 to demonstrate the application and validation of the models. The final chapter provides conclusions and recommendations for future research and implementation.

CHAPTER 2. LITERATURE REVIEW

2.1. Current Bridge Asset Management Practices

Bridge asset management plays a vital role in ensuring the safety, longevity, and serviceability of bridges. Federal and state agencies in the United States rely on systematic frameworks to assess and maintain bridges, this includes condition evaluation, inspection standards, and life-cycle cost analysis (Abdallah et al. 2022, Ghafoori et al. 2024). The National Bridge Inspection Standards (NBIS), established by the Federal Highway Administration (FHWA) in 1971, mandate that publicly owned bridges be inspected at least once every two years, with results reported to the National Bridge Inventory (NBI) (Collins and Weidner 2023). These inspections are carried out using visual methods and, when necessary, non-destructive testing to assess structural components (Abdallah et al. 2022). Bridge components – decks, superstructure, and substructure - conditions are rated on a scale of 0 to 9, with lower scores indicating higher levels of deterioration. The ratings form the foundation of decision-making in bridge management systems (BMS), supporting maintenance prioritization, budgeting, and lifecycle planning. These systems incorporate data from inspections, bridge health indices, traffic volumes, and environmental conditions to evaluate performance and optimize maintenance strategies over the bridge service life (Wakchaure and Jha 2012).

However, manual inspections are conducted at infrequent intervals, increasing the likelihood that rapid deterioration may go undetected between inspection cycles. In addition, the data collected during inspections is typically stored in isolation, with little connection to real-time monitoring systems that could provide a more complete picture of a bridge performance (Ibrahim and Yunus 2019). Bridge maintenance remains largely reactive, addressing deterioration after it has occurred rather than anticipating it. This results in higher long-term costs and missed opportunities for early intervention (Essahli and Madanat 2012). As infrastructure demands grow and budgets tighten, there is increasing recognition that traditional BMS must evolve. Enhancements are needed in data integration, condition forecasting, and risk-informed planning to support more resilient and cost-effective infrastructure systems.

2.2. Use of Artificial Intelligence and Machine Learning in Predicting Bridge Condition

Effective bridge asset management is critical for maintaining structural performance, minimizing service disruptions, and guiding cost-efficient maintenance decisions. Traditional approaches that rely on scheduled inspections, historical records, and engineering judgment often struggle to capture the complex progression of deterioration across bridge components and their interactions over time (Ghafoori et al. 2024, Karaaslan et al. 2021). These methods also fall short in addressing broader network-level risks posed by freight growth, climate events, and emerging technologies such as connected and automated trucks. To address these limitations, there is increasing interest in predictive tools that provide predictive insights into future condition trends of bridges.

Artificial intelligence (AI) and machine learning (ML) are playing an important role in this shift. These technologies can analyze large volumes of inspection data, traffic counts, and environmental variables to detect deterioration and improvement patterns, forecast future conditions, and support decision-making in bridge management systems (Karaaslan et al. 2021, Sowemimo et al. 2024). Among these approaches, supervised learning methods have shown strong potential in modeling deterioration, especially for bridge decks which are directly exposed to traffic loads and environmental stressors. Studies have applied deep learning models such as artificial neural networks (Huang 2010), CNN-LSTM hybrids (Karaaslan et al. 2021), and feedforward networks

(Liu and Zhang 2020) to predict the condition of bridge components using National Bridge Inventory data. Common model inputs include structural attributes; bridge age, deck geometry, material type, and span length, operational metrics like average daily truck traffic (ADTT), and performance indicators such as deck health index (HI) (Sowemimo et al. 2024).

Time series learning models, particularly recurrent neural networks and their variants like Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU), have gained recognition for condition prediction tasks due to their ability to model temporal dependencies in inspection data (Sowemimo et al. 2024). These models are well-suited for learning gradual deterioration trends and have achieved strong performance when trained on multi-year bridge data. Despite these advances, several challenges remain. Generalizing models across different bridge regions is difficult when training data is limited to a single region. Efforts to address these challenges include the use of class weighting, data resampling techniques, and explainable machine learning methods such as SHAP values and LIME to understand which features drive predictions.

A recent work by Sowemimo et al. (2024) contributes to this effort by applying long short term memory and gated recurrent unit models with time-distributed output layers to forecast deck condition ratings using multi-year data from Georgia. The models were trained on multi-year sequences of bridge-level features and evaluated using both overall accuracy and class-level performance metrics. Both models achieved strong performance across several evaluation metrics, with particular attention paid to capturing rare condition states. The findings support the value of sequence learning in bridge condition forecasting and demonstrate how such models can inform both project-level maintenance and broader system planning efforts.

2.3. Application of Topological Network Modeling Approach

Topological network modeling approaches have been widely used to describe the behavior of transportation systems (Mattsson and Jenelius 2015, King et al. 2016, Zhou and Wang 2017, Abdulla et al. 2021). This is mainly due to their requirement for significantly fewer data and less computational time compared to physics-based methods. Use of network theory simplifies the assessment of infrastructure criticality through mathematical descriptions of linkages between network components (LaRocca et al. 2015). Given the planar nature of transportation networks, such as highways and bridges, graph-theory-based modeling offers an intuitive approach for identifying critical segments (Tamvakis and Xenidis 2013). In this context, a road network can be reduced to a mathematical matrix, where the vertices (or nodes) represent road intersections, and the edges denote the road sections connecting these nodes. Most graph-theory-based methods employed network centrality measures to identify critical or vulnerable locations in the network (Porta et al. 2006, Erath et al. 2009, Leu et al. 2010). Global efficiency is another important measure that was used to describe the response of complex networks to external factors (Crucitti et al. 2003). Additionally, metrics like node connectivity and betweenness centrality have been utilized to identify vulnerable areas in graph-based transportation networks (Boeing 2020, Gauthier et al. 2018, Furno et al. 2021). Schneider et al. proposed an index to measure the robustness of graph networks, which has successfully been applied to two real network systems (Schneider et al. 2011, Abdulla et al. 2020). Recent advancements in computing and the availability of large data sets have led to the development of a deep learning architecture known as Graph Neural Networks (GNN), which are designed to leverage graph structures and operate efficiently within topological networks (Jana et al. 2023; Wettewa et al. 2024). Liu and Meidani recently developed a GNN-based surrogate model for the seismic reliability analysis of highway bridge systems (Liu and Meidani 2024).

CHAPTER 3. DEVELOPMENT OF RNN BASED BRIDGE CONDITION RATING PREDICTION MODEL

3.1. RNN Model Architecture

Bridge deck condition ratings range from 0 to 9, where 0 indicates a failed deck and 9 signifies excellent condition. Each value in this range represents a discrete, categorical label. As such, the forecasting task was framed as a multi-class classification problem. Two deep learning models were developed using recurrent neural network (RNN) architectures shown in Figure 1, Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU), to predict deck condition ratings. Both architectures were selected for their strength in modeling sequential data and learning long-term temporal dependencies (Karaaslan et al. 2021, Sowemimo et al. 2024). This is particularly important in bridge deck deterioration predictions, where condition changes are gradual and influenced by historical patterns and interventions over time. Each model was trained on bridge-specific sequences, where the input data consisted of nine years of historical inspection and operational features. The goal was to predict the deck condition rating each year (0 to 9) as a class label in a state inventory, allowing the models to learn deterioration patterns and detect signs of maintenance or rehabilitation.

3.1.1. Model Structure and Configuration

Both the LSTM and GRU models were designed as a stacked architecture with four recurrent layers, each with 50 hidden units as shown in Figure 2. All layers were configured with the return_sequences parameter set to True, ensuring that the temporal structure was preserved throughout the network without temporal compression. This allowed each layer to pass the full sequence of outputs to the next, rather than collapsing the sequence. To regularize the models and reduce overfitting during training, dropout layers with a rate of 20% were applied after the second and fourth layers. The final layer in both models was a fully connected dense layer with 10 output units and a softmax activation function, producing class probabilities for each timestep in the sequence. This configuration allowed the model to generate a probability distribution over the 10 deck rating classes for every year in the sequence. The hyperparameter values for both models, including the number of layers, hidden units, dropout rate, batch size, and early stopping were selected through empirical tuning using validation set performance to guide model design.

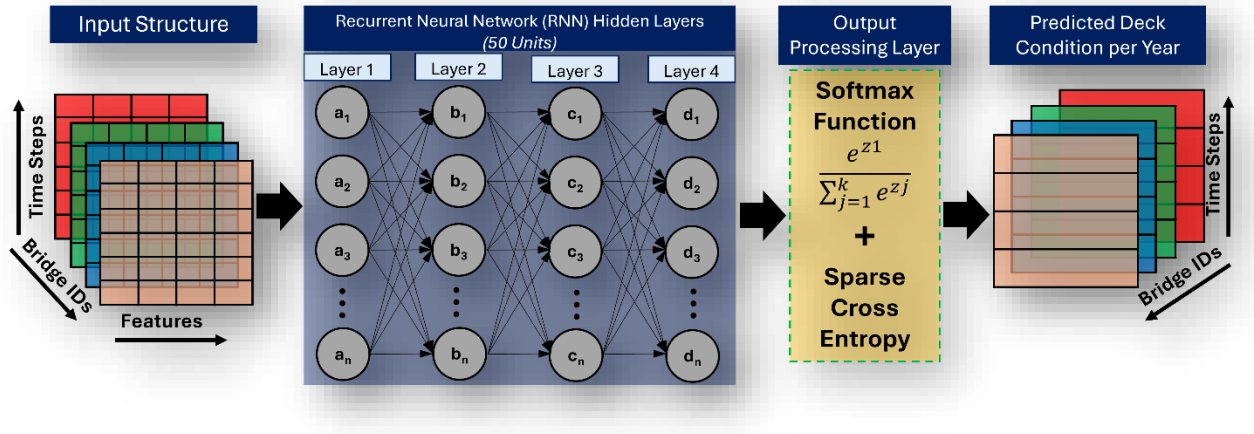


Figure 2. RNN Model Architecture for Bridge Deck Condition Prediction. The Model Outputs Predicted Deck Condition Classes for Each Future Time Steps.

The hyperparameters were iteratively refined to achieve a balance between model capacity and training stability.

While both models share the same input, output, and training configuration, they differ in their internal structure. The LSTM model uses three separate gates, input, forget, and output gates, to control the flow of information and maintain long-term dependencies. In contrast, the GRU model uses a more streamlined gating mechanism, combining the input and forget gates into a single update gate and employing a reset gate for memory control. Despite architectural differences in internal gating mechanisms, both models are capable of capturing long-range temporal dependencies and are well-suited for learning from sequential infrastructure data.

3.1.2. Activation, Loss Function, and Optimizer]

Both models used the tanh activation function within their recurrent layers. This nonlinearity maps input values to a range between -1 and 1, enabling the models to maintain gradient stability and learn expressive internal representations of temporal patterns in bridge condition data. At the output, a fully connected dense layer with softmax activation, which is standard for multi-class classification tasks to quantify the probability of each class was used to produce a probability distribution over the 10 deck condition rating classes (0 to 9) for each timestep. The models were trained using the sparse categorical cross-entropy loss function. This loss penalizes confident incorrect predictions more heavily, helping the models learn accurate class boundaries in the output space. To optimize the training process, the Adam optimizer was employed.

3.2. Data Source and Preprocessing

The data used for bridge deck condition prediction in this study was sourced from inspection records maintained by the Federal Highway Administration (FHWA) National Bridge Inventory (NBI) and National Bridge Inventory Bridge Elements (NBIE) database, specifically for the state of Georgia, covering the years 2016 through 2024. To support predictive modeling, each bridge's historical data was transformed into sequential records spanning nine consecutive years. Only bridges with complete data across this period were retained. Feature selection was guided by previous literature (Sowemimo et al. 2024), engineering judgment, and iterative refinement. The selected features included the previous year's deck condition rating, deck health index (HI); calculated using nonlinear coefficients applied to the percentage of deck area in each condition state, average daily truck traffic (ADTT), bridge age, maximum span length, and number of spans in the main unit. Figure 3 presents the distributions of selected input features used in the RNN model, providing additional context regarding their variability across the dataset. These selected features capture key structural and operational characteristics known to influence deck deterioration. In future work, incorporating additional attributes such as bridge typology (e.g., superstructure type, material) may further enhance predictive accuracy. All features except the target variable (deck condition rating) were normalized using min–max scaling to ensure uniform magnitudes across variables. The processed sequences were reshaped into a three-dimensional format (bridge ids, timesteps, features), preserving temporal order. For example, an input shape of (5811, 9, 6) indicates 5811 bridge sequences, each with 9 years of data and 6 features per timestep. A supervised learning structure was adopted, where each year's deck condition rating was predicted based on the inputs from lagged features from year (t – 1) ensuring temporal consistency. This processed dataset served as input for both LSTM and GRU models.

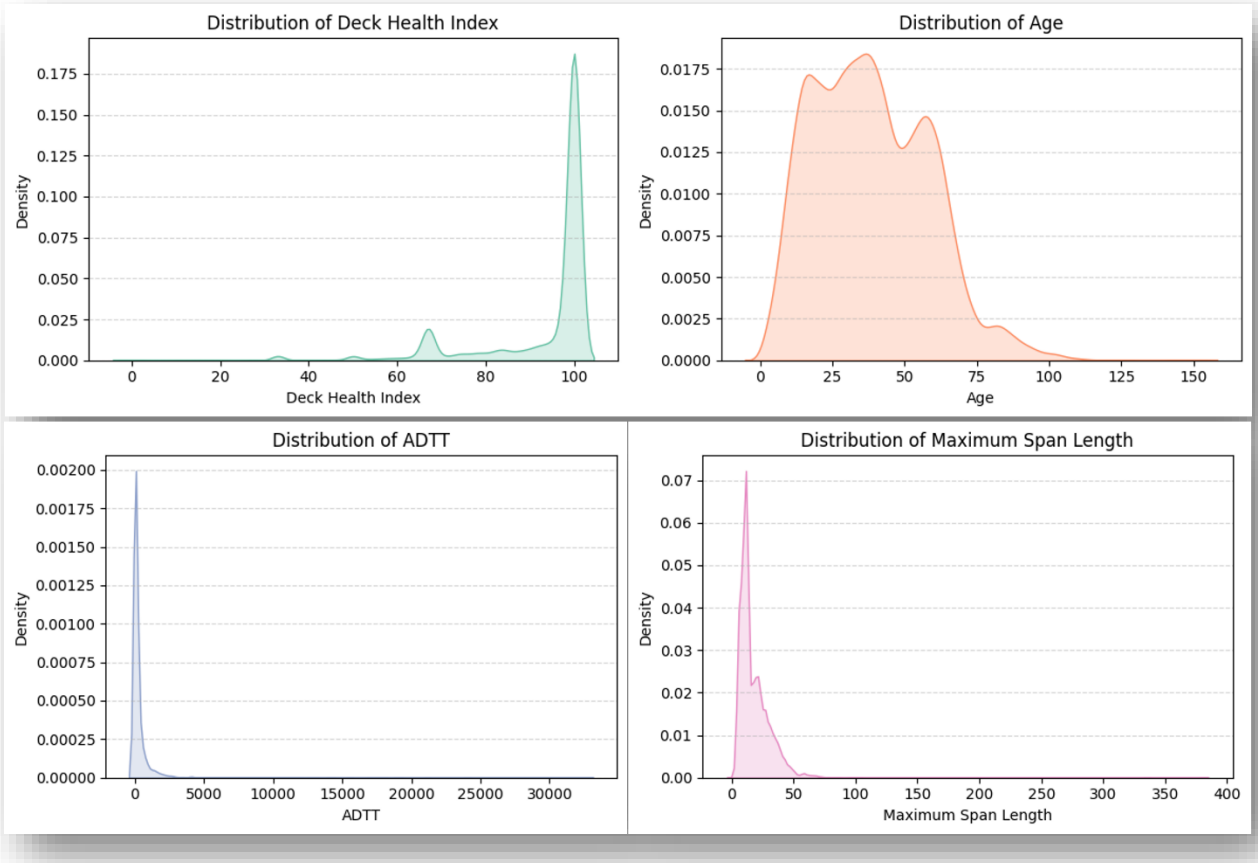


Figure 3. Distributions of Selected Input Features Used in the RNN Models for Bridge Deck Condition Prediction.

3.2.1. Class Imbalance and Weighting Strategy

Bridge deck condition ratings in Georgia inspection data are heavily imbalanced, with the majority of records concentrated in the fair to very good rating range (Classes 5 - 8), while extremely low or high ratings are rare (Classes 0, 1, 2, 3, 4, and 9). This imbalance was evident across the dataset, as shown in Figure 4, and posed a significant risk of making the models bias toward majority classes.

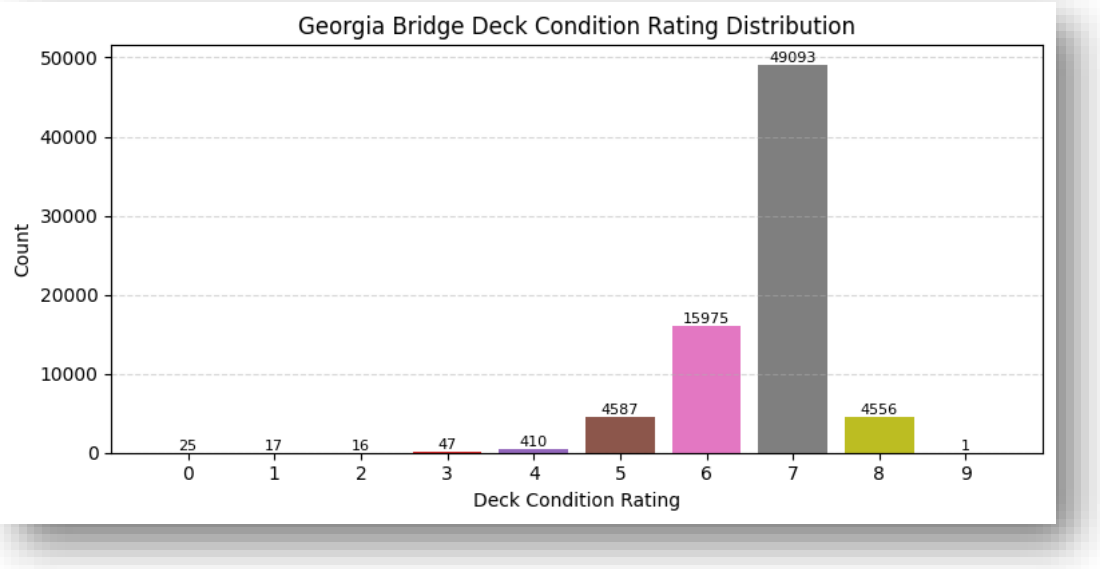


Figure 4. Georgia Deck Condition Rating Class Distribution.

Although there are various ways to address this, a class weighting strategy is implemented in this study to rebalance the learning signal during training. Class weights were initially calculated based on the inverse of class frequencies, assigning higher weights to underrepresented classes. However, this produced a wide range of raw values, with some extreme weights that could destabilize gradient updates and lead to poor convergence.

To improve robustness, the raw weights were smoothed using a logarithmic transformation and clipped to a defined range. Specifically, each weight was adjusted using *log(weight + 1)* to suppress outliers, then clipped between a minimum of 1.0 and a maximum of 7.0. This ensured that minority classes received higher but controlled emphasis, while dominant classes retained lower weights. Class weights were calculated based on the class distribution within the training set as shown in Table 1. The use of logarithmic smoothing and clipping intentionally compressed large raw imbalance ratios to maintain gradient stability during training. In particular, for high-frequency classes (5 - 8), applying small differences in weights was not expected to materially improve learning, given the large volume of training samples available. Clipping their weights to 1.0 ensured stable convergence and avoided over emphasizing minor differences between already well-represented classes. The logarithmic transformation approach was intentionally designed to improve learning for underrepresented classes while preserving training robustness. The final adjusted class weights applied during training are shown in Table 1.

Table 1. Adjusted Weights Applied to Each Class in the Training Set

Class	Description	Weight
0	Failed Condition	6.37
1	Imminent Failure Condition	5.73
2	Critical Condition	6.00
3	Serious Condition	5.35
4	Poor Condition	2.97
5	Fair Condition	1.00
6	Satisfactory Condition	1.00
7	Good Condition	1.00
8	Very Good Condition	1.00
9	Excellent Condition	7.00

3.3. Model Training and Validation

The dataset was divided into training (70%), validation (15%), and test (15%) sets using a bridge-level split to avoid data leakage across time. Unique bridge identifiers were first extracted, and then randomly assigned to one of the three subsets, ensuring that all nine years of data for each bridge remained within a single partition. This approach preserved the temporal continuity and structural context of each bridge throughout model development and evaluation. Model training was conducted using the full sequence data without shuffling, preserving the order of temporal features for each bridge.

3.3.1. Long Short Term Memory (LSTM) Model

The LSTM model was trained over 105 epochs using a batch size of 32. Early stopping was employed to monitor validation loss and halt training once convergence was observed. Class weights were applied as sample weights to guide the model toward learning underrepresented deck condition classes more effectively. The training history for the LSTM model shown in Figure 5 displays the training and validation loss curves and also presents the corresponding accuracy trends. The model showed steady improvement in both loss and accuracy over the first 40 – 50 epochs, after which it began to converge. The training loss decreased from 1.25 to approximately 0.39, while the validation loss followed a similar trend, stabilizing between 0.38 and 0.41. Simultaneously, training accuracy improved from 65.4% to around 87.4%, with validation accuracy peaking at approximately 87.2% before leveling off. This behavior indicates that the model generalized well to validation data, with no signs of significant overfitting.

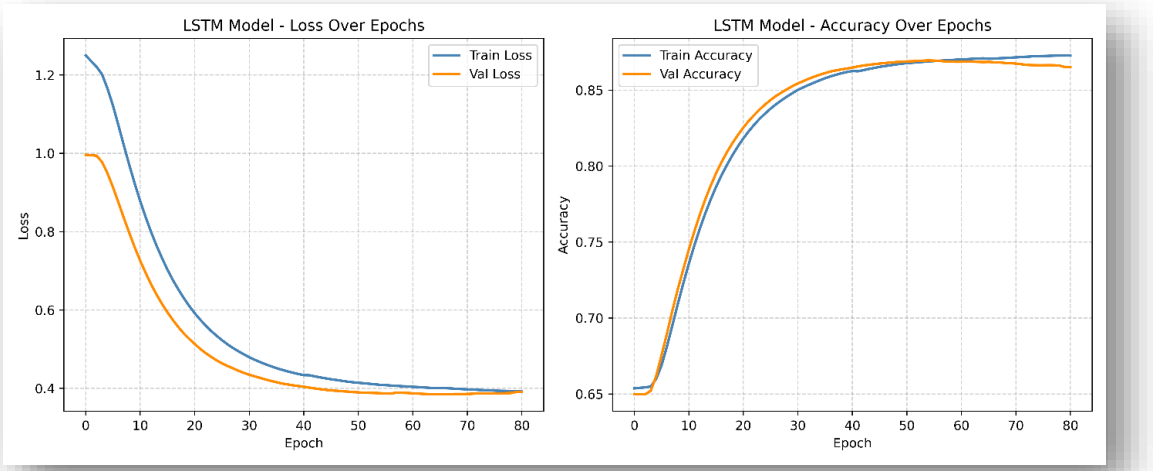


Figure 5. (a) Smoothed Training and Validation Loss Over Epochs for the LSTM Model. (b) Smoothed Training and Validation Accuracy over Epochs.

The validation accuracy remained consistently aligned with the training accuracy, and fluctuations toward the later epochs remained within acceptable margins. To improve visual interpretation, the curves were smoothed using exponential moving averaging with a decay factor of 0.9.

3.3.2. Gated Recurrent Unit (GRU) Model

The GRU model was trained using the same configuration as the LSTM, including class weights, batch size, and early stopping. Training was performed over 105 epochs with a batch size of 32 and without shuffling to preserve temporal structure. Early stopping monitored the training loss with a patience of 20 epochs. Figure 6 illustrates the training history of the GRU model and it shows the loss progression for both training and validation sets and also displays the corresponding accuracy trends. Like the LSTM, the GRU model exhibited rapid performance gains in the early epochs, with convergence occurring around epoch 40. The training loss reduced from an initial value of 1.19 to approximately 0.38, while the validation loss declined to a similar range, stabilizing between 0.38 and 0.40. Training accuracy improved from 64.9% to 87.6%, and validation accuracy reached a peak of 87.5%, maintaining close alignment throughout the later stages of training. These results indicate that the GRU model achieved a well-balanced fit without overfitting and performed comparably to the LSTM model.

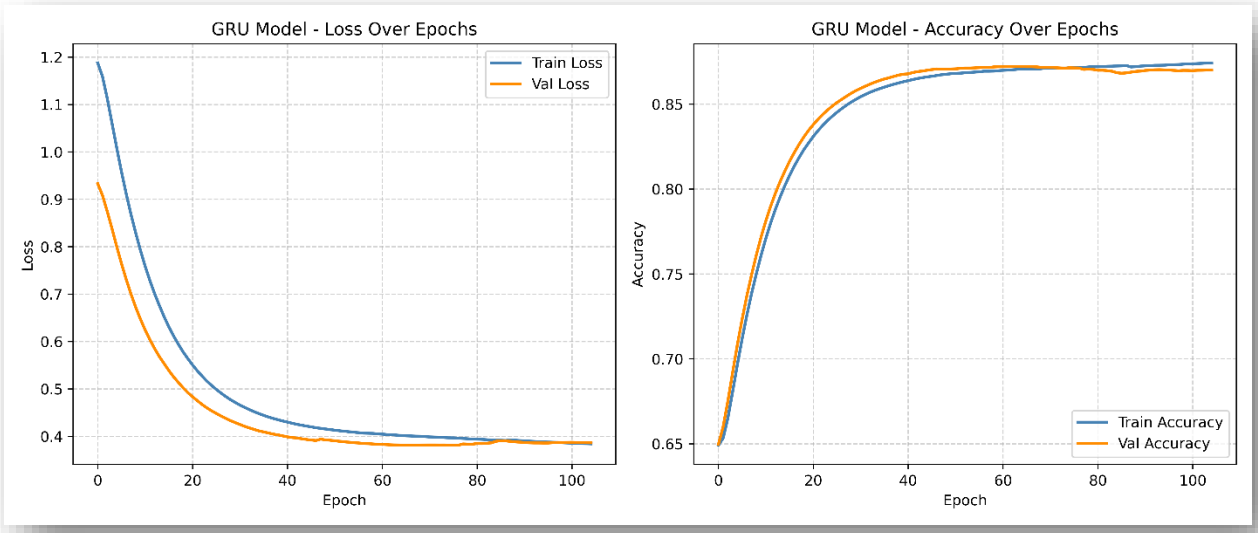


Figure 6. (a) Smoothed Training and validation loss over epochs for the GRU model. (b) Smoothed Training and Validation Accuracy Over Epochs.

3.4. Model Performance

To assess model performance on the test dataset, multiple evaluation metrics were employed, capturing both overall classification performance and class-specific behavior. Given the imbalanced multi-class nature of the bridge deck condition prediction problem, a combination of five different metrics was used to get a good overview of how well the models performed, not just overall accuracy, but also how balanced the predictions were across all classes. The evaluation metrics include accuracy, precision, recall, F1-score, and the confusion matrix. Accuracy measures the overall proportion of correct predictions. Precision and recall assess the rate of false positives and false negatives, respectively, while the F1-score balances both. Confusion matrices visualize prediction distribution and highlight misclassification patterns.

The final performance of both LSTM and GRU models evaluated on an unseen test dataset comprising 15% of the initial data is detailed in Table 2. Test accuracy and loss were computed along with detailed classification metrics and confusion matrices to assess performance.

3.4.1. Predictive Performance Using Key Metrics

The LSTM model achieved an accuracy of 86.84% with a categorical cross-entropy loss of 0.38, while the GRU model reported a comparable accuracy of 86.79% and a slightly higher loss of 0.39. While both models performed similarly in terms of overall accuracy and weighted metrics, the LSTM model demonstrated stronger performance across underrepresented classes, as reflected in its higher macro-averaged precision, recall, and F1-score.

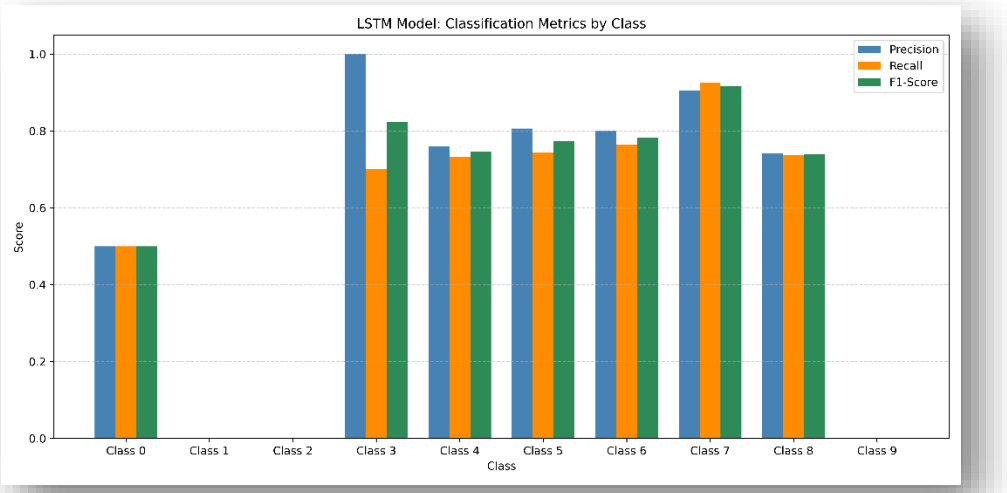
Table 2. Overall Performance of the Deck Prediction Models

Metrics	LSTM	GRU
Accuracy	86.84%	86.79%
Loss	0.38	0.39
Macro Precision	0.55	0.44
Macro Recall	0.51	0.40
Macro F1-Score	0.53	0.40
Weighted Precision	0.87	0.87
Weighted Recall	0.87	0.87

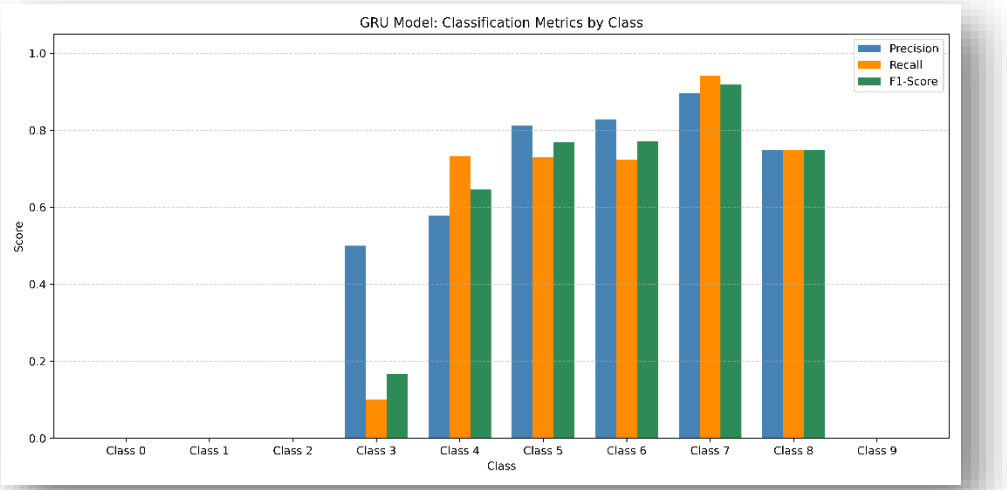
These macro-level scores are more sensitive to minority class behavior and thus suggest that the LSTM model provides more reliable performance on rare deck condition classes, a trend that is further examined in the class-specific performance below. In contrast, the weighted metrics, dominated by frequent classes such as 6, 7, and 8, were nearly identical for both models, confirming their comparable effectiveness on the most common bridge conditions.

3.4.2. Class-Specific Performance

Figure 7 illustrates precision, recall, and F1-scores across all deck condition classes. For the LSTM model in Figure 7(a), strong class-level performance was observed in the majority classes (Classes 5–8), with F1-scores above 0.74. The GRU model in Figure 7(b) also performed well in these dominant classes but exhibited reduced recall in some classes, especially Class 3 and Class 4. The LSTM model showed a slight edge in handling rare categories, reflected in more stable F1-scores. This class-level pattern aligns with the LSTM model's higher macro-averaged scores in Table 2, confirming its improved handling of minority classes.



(a)



(b)

Figure 7. (a) LSTM Model Precision, Recall, and F1-Score by Class. (b) GRU Model Precision, Recall, and F1-Score by Class.

The confusion matrices in Figure 8 provide additional insight into how each model distributed predictions across classes. For both models, most misclassifications occurred between adjacent deck condition classes, such as Class 6 and 7, or 7 and 8. The LSTM model demonstrated fewer off-diagonal errors and better separation across Class 5 to 8, particularly in minimizing misclassifications between Classes 6 and 7.

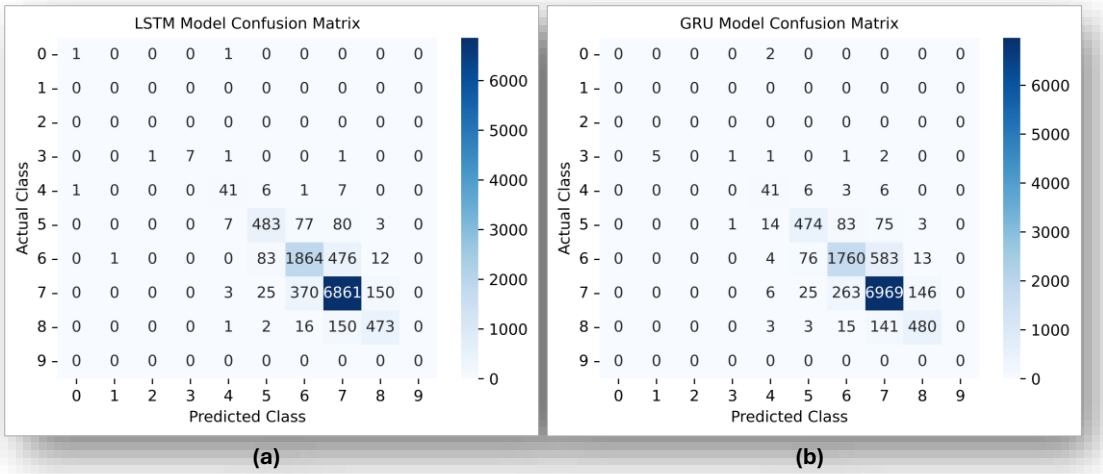
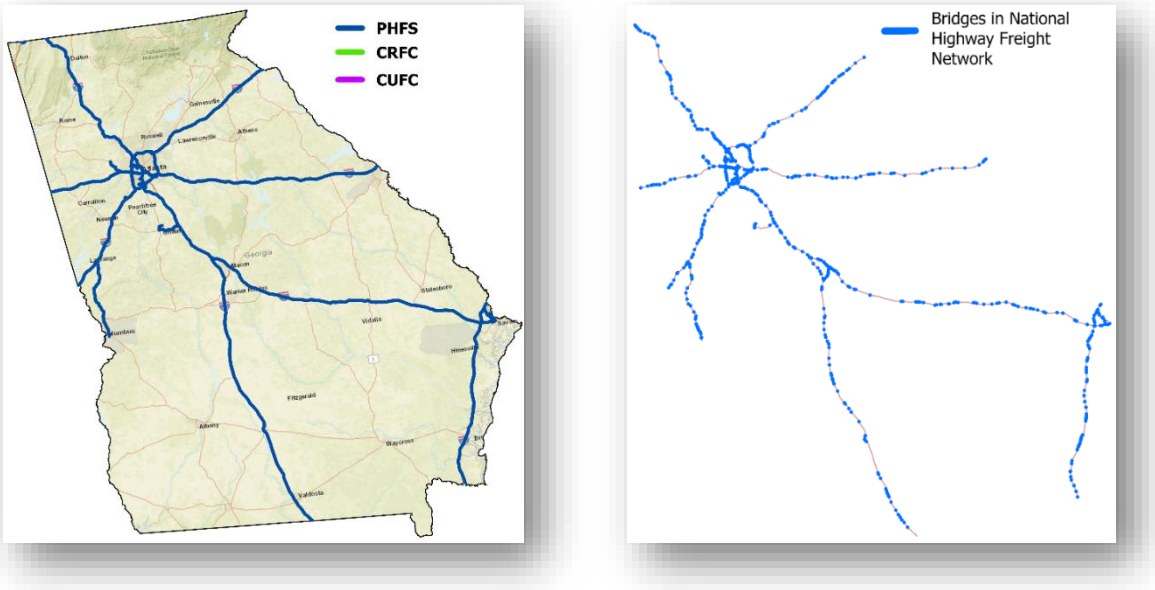


Figure 8. (a) LSTM Model Confusion Matrix. (b) GRU Model Confusion Matrix.

CHAPTER 4. DEVELOPMENT OF GRAPH-BASED NETWORK MODEL OF BRIDGES WITHIN NHFN

Given the inherently planar structure of highway systems, they can be naturally modeled using primal graphs. In graph theory, a highway network can be simplified into a mathematical matrix, $G = (V, E)$, where 'V' denotes the set of nodes and 'E' the set of edges connecting them. In a highway network system, nodes correspond to highway intersections, while edges represent the highway segments linking those intersections. Each edge can be expressed as $(u, v) \in E$ where 'u' and 'v' are the indices of the two connected nodes.

In this project, a graph-based network model has been developed to analyze the topological integrity of Georgia's highway-bridge system for a segment of the National Highway Freight Network (NHFN). Spanning approximately 1,753 miles, this network comprises key freight corridors that link major urban centers—Atlanta, Savannah, Augusta, Macon, and Columbus—and form the backbone of Georgia's logistics-oriented economy (GDOT 2024a, GDOT 2024b). Bridges on the NHFN are subjected to heavy traffic loads, particularly from commercial trucks and freight carriers, which increases the likelihood of wear and the risk of closures for maintenance and repair activities. As illustrated in Figure 9a, the NHFN in Georgia is composed of three primary components: the Primary Highway Freight System (PHFS), Critical Rural Freight Corridors (CRFC), and Critical Urban Freight Corridors (CUFC).



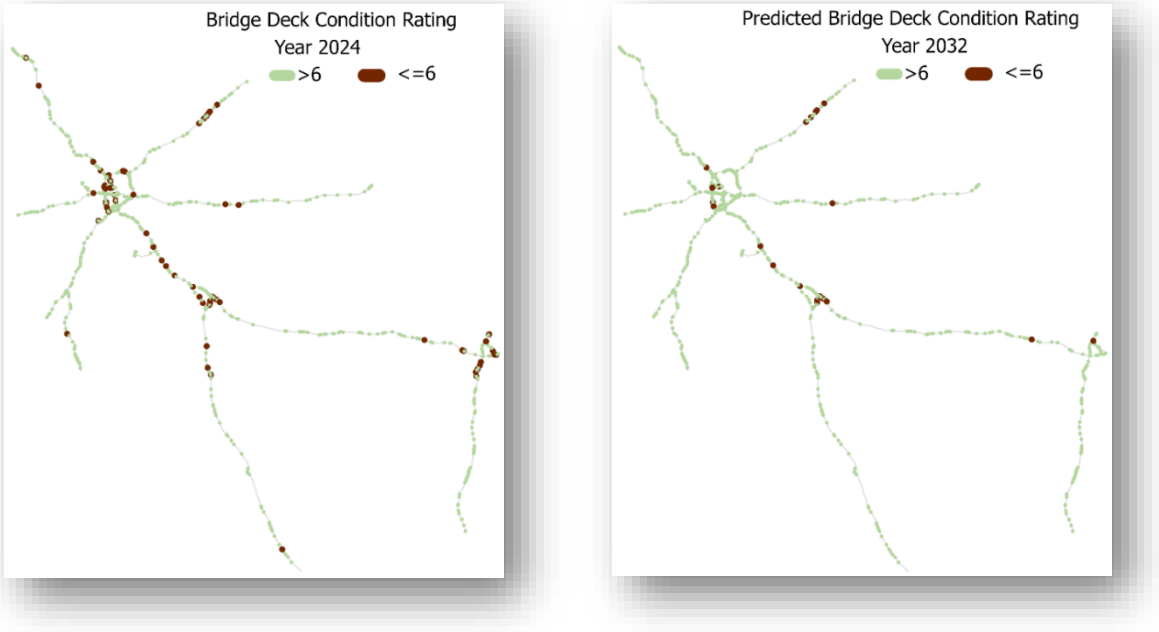
(a) **(b)**

Figure 9. National Highway Freight Network (NHFN) of Georgia: (a) Roadways and (b) 684 Bridges in NHFN

To construct the network model, Geographic Information System (GIS) shapefiles of the National Highway Freight Network (NHFN) were obtained from the Federal Highway Administration (FHWA) portal. Furthermore, the spatial distribution of bridges in Georgia was collected from the Georgia Department of Transportation's Bridge Information Management System (BIMS).

Among the 15,505 bridges statewide, 684 were found to be situated along the NHFN, as depicted in Figure 9b.

The Deck Condition Rating (DCR) is selected in this project as the basis for classifying and prioritizing bridges along Georgia's NHFN, as it effectively reflects the actual deterioration state of bridge decks and highlights those that require urgent intervention. DCR is a key performance metric for bridge structure, as bridge decks tend to deteriorate more rapidly than other structural elements (Assaad and El-adaway 2020). A maintenance threshold of DCR 6 is adopted in this project to demonstrate the application of the graph-based network analysis approach. While lower thresholds such as DCR 4 or 5 are often more indicative of serious distress, their use was not feasible here due to the overall high DCR values observed across the state's bridge inventory. In 2024, a total of 68 NHFN bridges in Georgia were identified with a DCR of 6 or below, as illustrated in Figure 10a. Predictions from the recurrent neural network (RNN) model project that this number will drop to 23 by the year 2032. This trend reflects anticipated improvements in rating resulting from ongoing maintenance and repair activities (Figure 10b). These lower-rated bridges are then used in a graph-based network analysis to assess how potential closures might affect freight mobility across the state, as detailed in the next section.



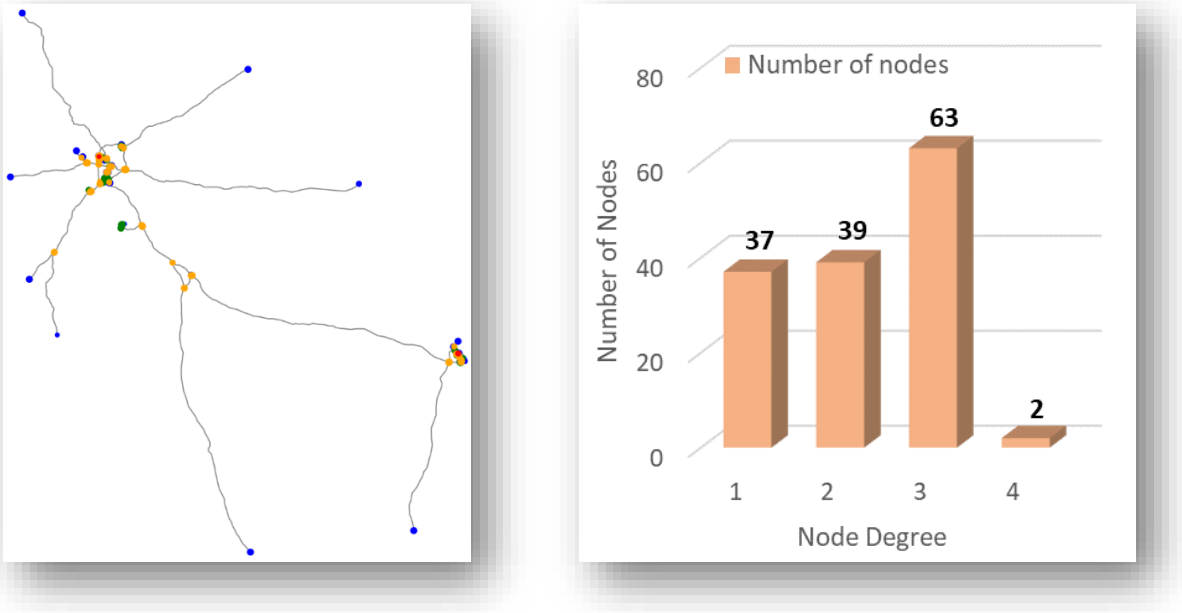
(a) **(b)**

Figure 10. (a) 68 Bridges with a Low Deck Condition Rating (≤ 6) in 2024; (b) 23 Bridges with a Low Deck Condition Rating (≤ 6) in 2032.

4.1. Characterization of Freight Network Connectivity Measure

The transformation of the NHFN shapefile into a network graph is carried out using the Python library 'NetworkX'. Figure 11a presents the resulting network structure by illustrating the distribution of node degrees—defined as the number of edges connected to it. The nodes in the NHFN are displayed using color codes, where blue, green, orange, and red indicate node degrees of 1, 2, 3, and 4, respectively. As depicted in Figure 11b, the complete freight network comprises

37 nodes with a degree of 1, 39 nodes with a degree of 2, 63 nodes with a degree of 3, and only 2 nodes with a degree of 4. Bridges within the NHFN are integrated into this graph-based network based on their geospatial coordinates. For the purpose of this project, it is assumed that bridges are the only component that can fail within the network. Consequently, a bridge closure is modeled as the removal of an edge (u,v{)} from the graph, representing a disruption in connectivity between two adjacent nodes.



(a) **(b)**

Figure 11. (a) Structure of the Graph Network for the NHFN in Georgia with a Distribution of Node Degrees; (b) Number of Nodes by Specific Degree

The graph-based network facilitates various analyses of the topological integrity of transportation networks using specific types of centrality measures for individual nodes or the entire network. A list of these identified measures is described below.

- Global Efficiency (*GE*)

Global efficiency refers to the effectiveness of information exchange within a network (Crucitti et al. 2003). If Z_{st} represents the length of the shortest path between nodes *s* and *t*, then the global efficiency of the network can be calculated using the following equation

$$GE = \frac{1}{N(N-1)} \sum_{s \neq t} \frac{1}{Z_{st}}$$

Where:

GE = global efficiency,

N = number of nodes,

Z_{st} = length of the shortest path between nodes *s* and *t*

Equation 1. Global Efficiency of a Network

The greater the global efficiency of the network, the more redundant it becomes, enhancing its resilience against disruptions.

- Average Distance (*AD*)

The average distance is a measure of the exchange of information within a network. If d_{st} represents the length of the shortest path between nodes *s* and *t*, the average distance of the network can be calculated as follows.

$$AD = \frac{1}{N(N-1)} \sum_{s \neq t} d_{st}$$

Where:

AD = average distance,

N = number of nodes,

d_{st} = length of the shortest path between nodes *s* and *t*

Equation 2. Average Distance Within a Network

- Percolation Limit (p_c)

The percolation limit of a network refers to the critical fraction of nodes that must be removed for the network to disintegrate or disconnect (Cohen et al. 2000). In this context, *p* represents the fraction of nodes (vertices) and their connections (edges) in a graph or network that are randomly removed. The threshold, p_c, is calculated, meaning that if *p* exceeds p_c, the network will break into smaller, disconnected components.

$$p_c = 1 - \frac{1}{\frac{\langle k_0^2 \rangle}{\langle k_0 \rangle} - 1}$$

Where:

$k_0 = \Sigma \delta_i / n$,

$k_0^2 = \Sigma \delta_i^2 / n$

n = number of nodes,

δ_i = degree of node *i* in the network

Equation 3. Percolation Limit of a Network

- Average Node Connectivity (*ANC*)

The average node connectivity (*ANC*) of a graph is defined as the average, over all pairs of vertices, of the maximum number of internally disjoint paths that connect these vertices.

$$ANC = \frac{1}{n}\sum_{i}^{n} NC$$

Equation 4. Average Node Connectivity of a Network

- Maximum Betweenness Centrality (*MBC*)

The minimum betweenness centrality (MBC) is a measure of centrality in a graph, based on the number of shortest paths that pass through a specific node.

$$MBC = argmax\, B\, C$$

Where:

BC = set of betweenness centrality of the nodes within the network,

argmax = a mathematical operator that returns the argument (i.e., the input value) at which the function reaches its maximum.

Equation 5. Minimum Betweenness Centrality of a Network

- Network Robustness Index (*R*)

Network robustness index, *R*, can be characterized by the integrated size of the largest connected component throughout the entire percolation process (Schneider et al. 2011). It is expressed as follows.

$$R = \frac{1}{N}\sum_{Q=1}^{N} s(Q)$$

Where:

N = total number of the nodes in the network,

s(*Q*) = fraction of nodes in the largest connected component after removing $Q=N(1-\varphi)$ nodes,

1/*N* = normalizing factor,

R = robustness index value that ranges from 1/*N* (in a star graph) to 0.5 (in a fully connected network),

φ = probability of a certain node to be functional at a given time (or under a given scenario). The

values for φ range from 0 to 1.

Equation 6. Robustness Index of a Network

In this project, the integrity of the road network is assessed using the connectivity measure defined as the ratio of the size of the giant connected component in the network after highly vulnerable nodes are removed and the original size of the network. This measure is chosen because it enables a comparison of connectivity under both disruptive and normal scenarios. Mathematically, the connectivity can be defined as presented in Equation 7, where *CON* is connectivity level in road network; S_{GC} is the size of the connected giant component after certain nodes are removed; and S_o is the original number of nodes in the uninterrupted network.

$$CON = \frac{S_{GC}}{S_O}$$

Equation 7. Connectivity of a Network

As illustrated in Figure 12, if the original intact network is comprised of 32 nodes and 33 functional edges, but five edges become nonfunctional due to a disruption, the network will break into five sub-networks. In this scenario, the largest sub-component will contain 18 nodes. Therefore, the relative size of the giant connected component (*GCC*) under this given disruption can be calculated as 18/32 = 0.5625.

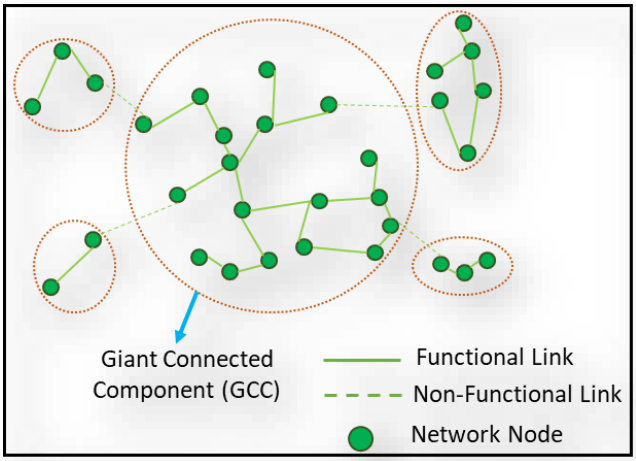


Figure 12. (a) Giant Connected Component (GCC) of a Network

This report assesses the connectivity of the NHFN under different levels of random bridge closures, targeting bridges with low deck condition ratings (≤ 6). A detailed description of the

graph theory-based network model and the methodology for assessing connectivity and system vulnerability was presented in a recently published study (Saha et al 2025). The connectivity profiles of the NHFN for the years 2024 and 2032 are depicted in Figure 13a and 13b, respectively. These figures demonstrate the impact of removing bridges with low deck condition ratings on the connectivity of the network by randomly eliminating a percentage of bridges and recalculating connectivity with each removal. This process simulates the potential effects on the freight network due to bridge closures for repair or maintenance. In order to reduce the possible impact of random sampling, 50 simulations are conducted at each step, with bridge removals occurring in 2% increments. The average ratio of the size of the giant components to the size of the original intact network is then calculated for each step. As shown in Figure 13c, the highway network in 2032 exhibits improved connectivity, indicating greater resilience to bridge closures involving low deck condition ratings compared to the 2024 network. For instance, when 40% of low-rated bridges are closed, the connectivity of the 2032 freight network is reduced to 65% of its original size, whereas in 2024, connectivity drops to approximately 46%.

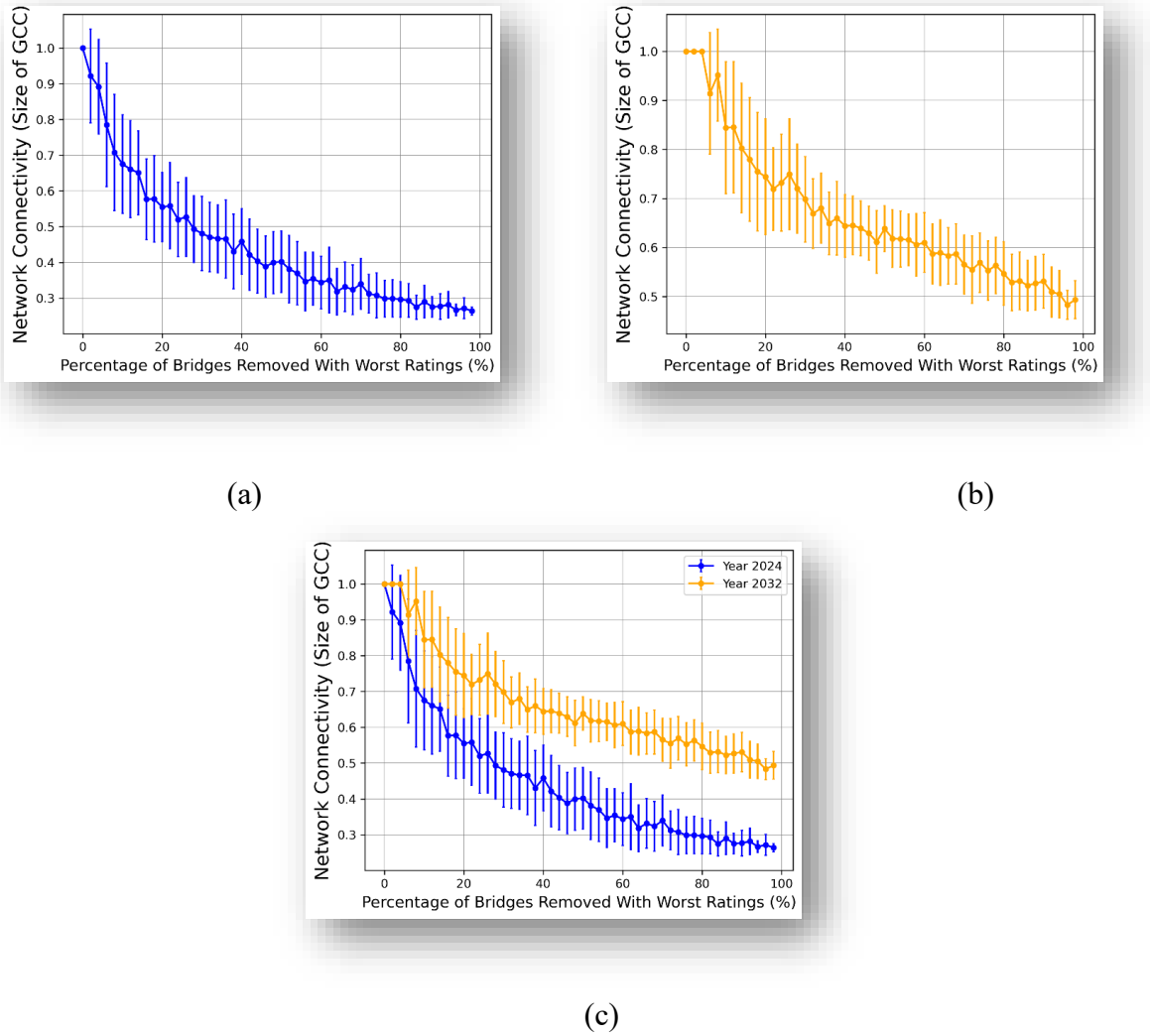


Figure 13. (a) Connectivity of the Road Network in (a) 2024; (b) 2032 (After Removing Edges, Including Bridges, with a Deck Condition Rating of 6 or less) (c) Comparison of Network Connectivity Between 2024 and 2032.

4.2. Identification of Bridges that Pose a High Risk to the Overall Freight Network

Following the analysis performed in the previous sections, highly critical bridges have been identified based on two independent factors: low deck condition rating, and high network connectivity. Six bridges have been found to maintain a low deck condition rating (6) from 2024 to 2032, at the same time their removal would lead to a significant reduction in network connectivity. Table 3 list the network connectivity measures after the removal of each bridge separately, along with the current (Year 2024) and predicted future (Year 2032) deck condition ratings. Figure 14 illustrates the geographical locations of the critical bridges, highlighted in brown, within the NHFN. The findings suggest that, when allocating limited budget resources for bridge repairs, it is advantageous to prioritize based on the predicted future deck condition and the specific bridge's overall impact on freight network connectivity.

Table 3. Measure of Network Connectivity and Deck Condition Rating for Identified Critical Bridges

Bridge ID	Network Connectivity after Closing	Deck Condition Rating (Year-2024)	Deck Condition Rating (Year-2032)
1	0.6705	6	6
2	0.7216	6	6
3	0.7216	6	6
4	0.7216	6	6
5	0.7216	6	6
6	0.75	6	6

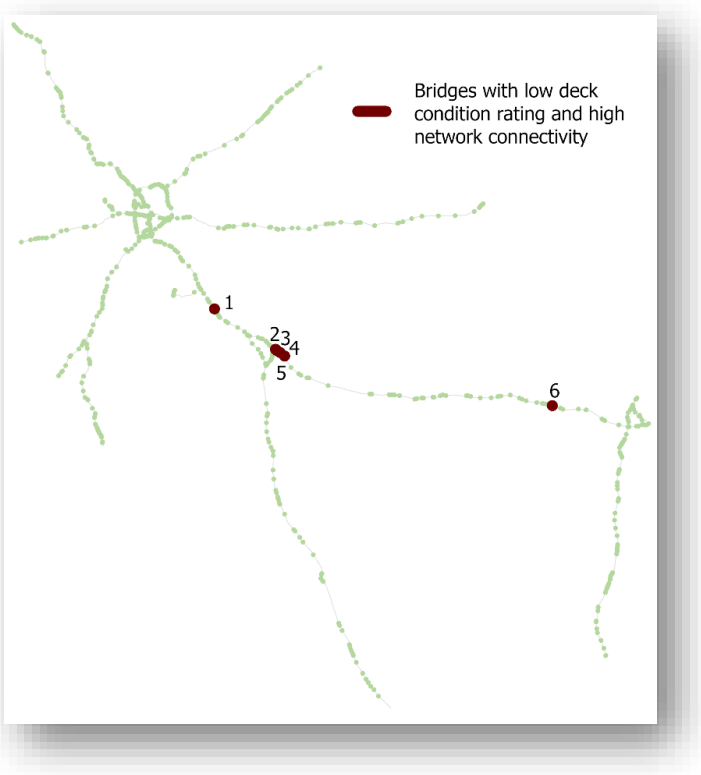


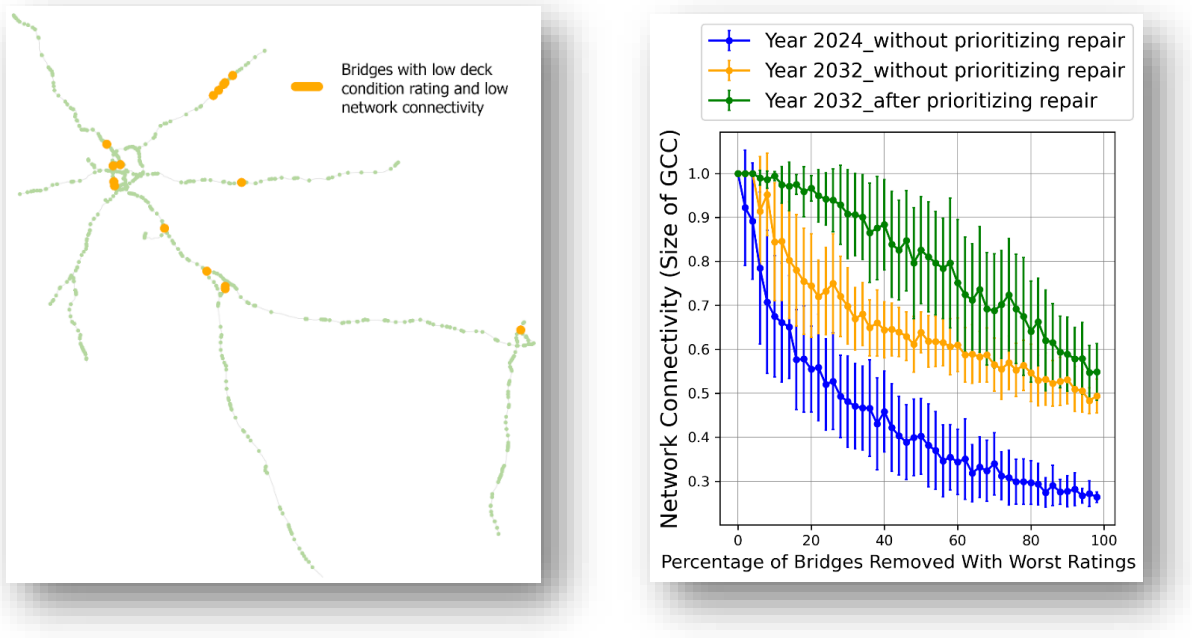
Figure 14. Bridges with Low Deck Condition Ratings that Play a Major Role in Network Connectivity.

4.3. Improved Robustness of the Freight Network after Prioritizing Bridge Repair Actions

To assess the robustness of the freight network following prioritized bridge repairs, a simulation was carried out to represent the network's condition in the year 2032. This evaluation focused on the 17 remaining bridges predicted to have low deck condition ratings (DCR $\leq$ 6) after targeted repair actions were undertaken on six critical bridges identified in the previous section. The spatial locations of these 17 bridges are depicted in Figure 15a.

Figure 15b presents a comparative analysis of network connectivity across three scenarios: (1) the NHFN in 2024 without any repair prioritization, including 68 low DCR bridges; (2) the projected NHFN in 2032 without prioritization, including 23 low DCR bridges; and (3) the NHFN in 2032 following prioritized repairs, reduced to 17 low DCR bridges. The findings reveal that repairing the six most critical bridges will significantly enhance network connectivity by 2032, thereby improving resilience against potential disruptions from bridge closures. For example, the 2032 network will maintain over 86% connectivity even when up to 40% of the remaining low-rated bridges are closed, compared to just 65% without any repair prioritization.

These outcomes underscore the effectiveness of integrating predictive condition rating modeling with graph-based network criticality analysis to guide maintenance prioritization. This integrative approach enables informed, cost-effective allocation of limited budget resources to enhance the long-term stability and performance of the freight network.

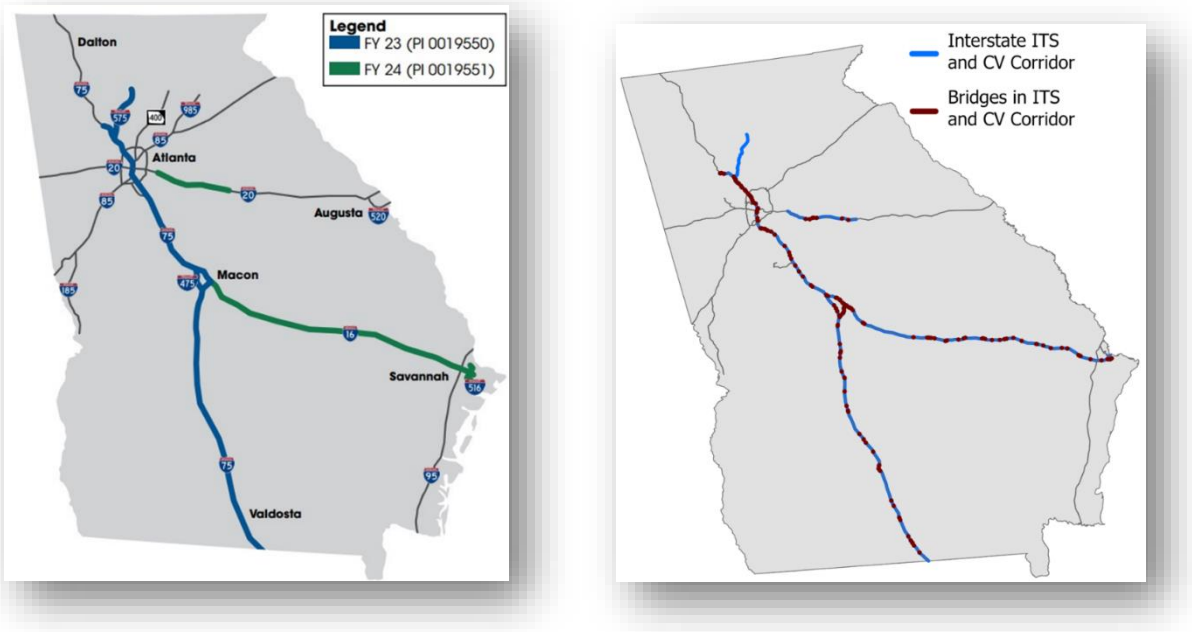


(a) (b)

Figure 15. (a) Bridges with Low Deck Condition Ratings as well as Low Network Connectivity; (b) Comparison of Network Connectivity Before and After Prioritizing Bridge Repair Activities.

4.4. Future Application of Graph-Based Network Modeling Approach

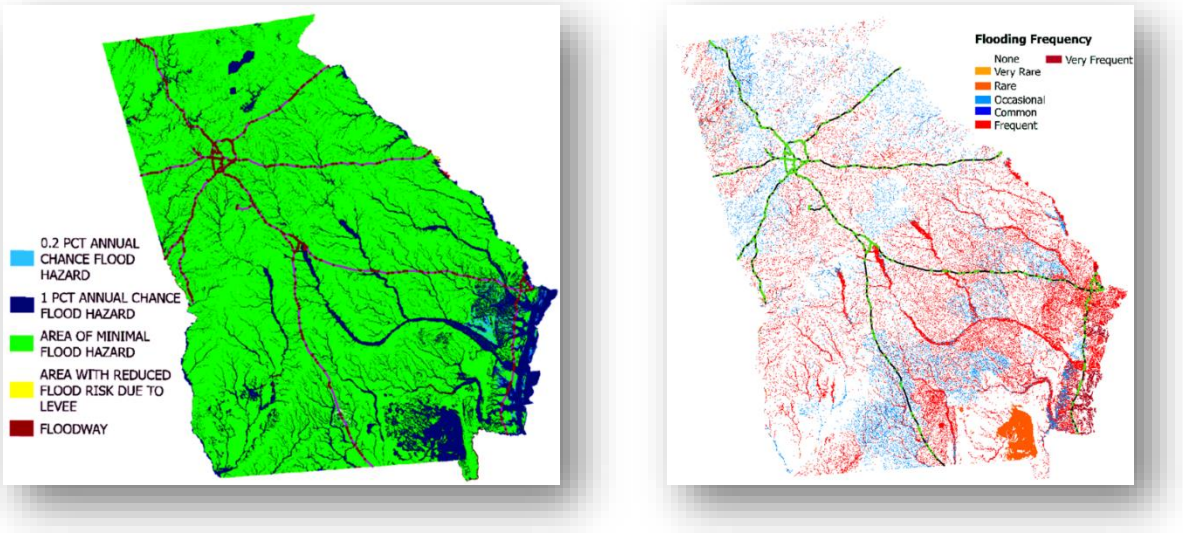
This graph-based network modeling approach can also be applied to identify high-risk bridges within road networks, under various disruptions such as flooding and the introduction of automated vehicles. In Georgia, the Interstate Intelligent Transportation System (ITS) and Connected Vehicle (CV) Implementation projects aim to implement a future connected/autonomous vehicle system along Interstate-75, stretching from the Florida/Georgia border to State Route (SR) 92 north of Atlanta, as well as along I-475 and I-575 (GDOT 2023). Figure 16a illustrates the 539 miles of project corridor along the interstate. There are 178 bridges located along this corridor, as shown in Figure 16b. The implementation of connected vehicles will expose these bridges to heavy truck traffic, increasing the risk of potential disruptions. Therefore, the proposed integrated modeling approach can be utilized for predicting the structural condition of these bridges and assessing the impact of potential closures on network integrity.



(a) (b)

Figure 16. (a) The Interstate Intelligent Transportation System (ITS) and Connected Vehicle (CV) Implementation Project Corridor in Georgia; (b) Bridges along the Project Corridor.

Similarly, bridges have unique structural characteristics that contribute to their susceptibility to flooding. The flood hazard map and flood frequency class map of Georgia, shown in Figure 17a and 17b, display the probabilities of bridge closures in different flood zones. The network modeling approach can be applied to assess the impact of flooding events on road network connectivity and can provide valuable insights for guiding bridge asset management decisions.



(a) (b)

Figure 17. (a) Flood Hazard Area Map of Georgia; (b) Geospatial Distribution of Bridges Correspond to Flood Frequency Class Zone.

CHAPTER 5. CASE STUDY: PERFORMANCE PREDICTION FOR SELECTED BRIDGES

To better illustrate the model's time series predictions, Figure 18 presents the predicted versus actual deck condition ratings for a sample bridge. The models were evaluated on their ability to accurately predict the full sequence from 2017 through 2024, using the initial 2016 data point as the starting input. Both the LSTM and GRU models successfully captured the overall condition stability observed in the sequence, accurately predicting class 6 across most years. This aligns with the overall performance observed in the evaluation metrics presented above, where both models demonstrated strong accuracy and well-balanced precision-recall characteristics. The GRU model showed a bit more movement in its predictions, temporarily shifting up to class 7 in the middle years before settling back down, while the LSTM maintained a more uniform trajectory. These differences reflect the internal dynamics of each architecture, GRU's compact gating mechanism tends to respond more directly to input variations, while LSTM's layered gating structure emphasizes maintaining the longer-term trend. Overall, both models demonstrated effective time series predictions and produced outputs that closely align with the actual behavior of the bridge deck condition ratings over time.

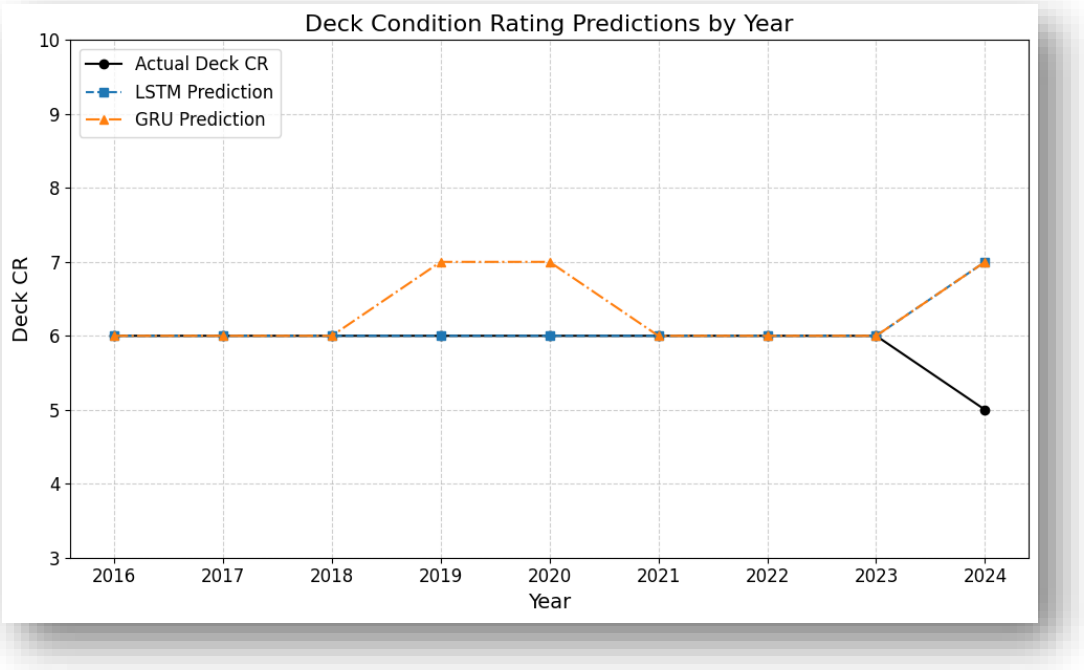


Figure 18. Actual vs. Predicted Deck Condition Ratings for a Sample Bridge.

To evaluate the long-term use of the trained model, predictions were extended beyond the historical test range to forecast bridge deck condition ratings from 2025 through 2032. The LSTM model, which showed marginally better generalization across classes during model evaluation, was selected for these future forecasts. Figure 19a presents the model's predictions for another selected bridge in Georgia. The bridge maintained a steady rating of 7 from 2020 to 2024, with minimal variation. The model projects a temporary decline to rating 6 in 2025 and 2026, followed by a return to rating 7, which remains stable through 2032. By learning from several years of uniform

historical data, the model anticipates a minor deterioration event, possibly routine deterioration, and then reverts to the longer-term trend it has observed.

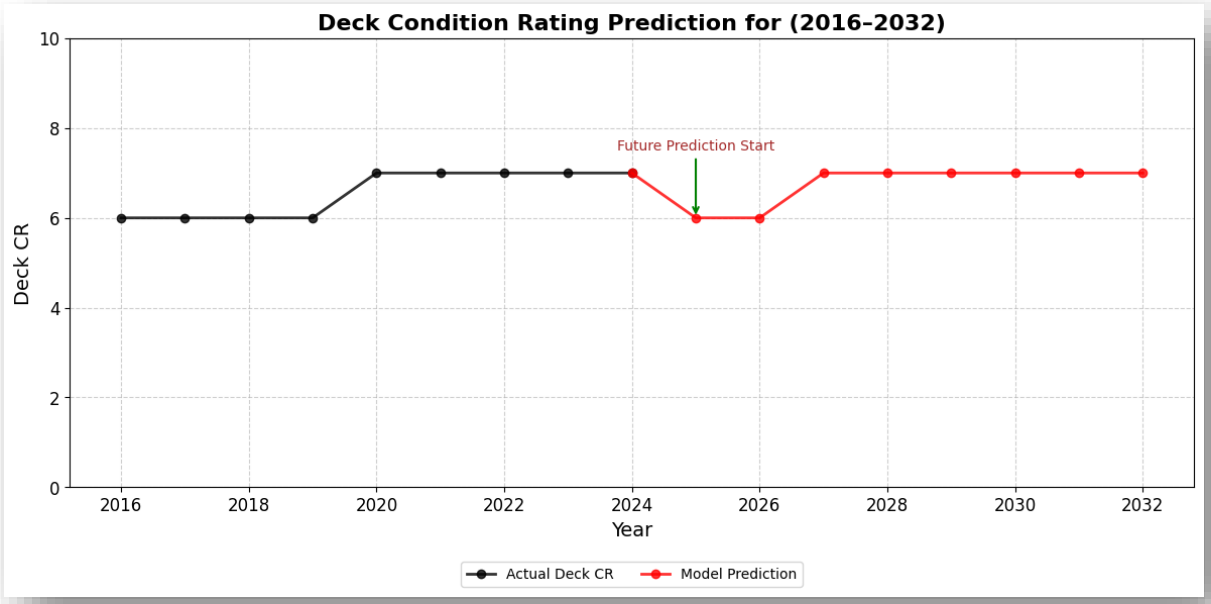
However, because many Georgia bridges exhibited stable or improving deck condition trends, the RNN model's ability to learn from and predict progressive deterioration could not be adequately tested using Georgia data alone.

To fairly evaluate the model's ability to predict declining condition scenarios, bridge data from Iowa were incorporated. Iowa was selected because its deck condition ratings exhibit more consistent downward trends over time, providing a balanced assessment of the RNN model's predictive performance under deterioration-dominant conditions.

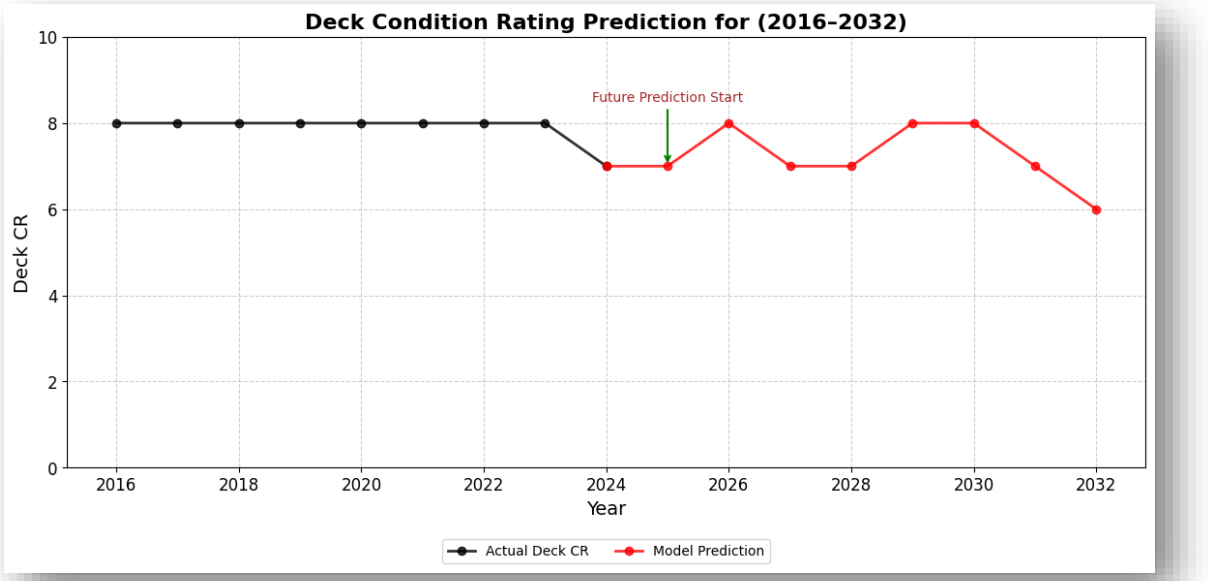
The Iowa bridge illustrated in Figure 19b exhibits a different performance trajectory. The historical data shows a flat trajectory at class 8 (or condition rating 8) for several years, but the condition drops to class 7 in 2024. The model predicts the class will remain at 7 in 2025, show a brief recovery in 2026, and subsequently oscillate between classes 6 and 8 before gradually declining to class 6 by 2032. This behavior reflects how the model, trained on Iowa-specific data, interprets the 2024 downward shift as an early indicator of long-term deterioration. Since the Iowa dataset includes a more balanced distribution of condition ratings, especially in the mid-range (classes 4 to 6), the model has seen more diverse deterioration paths compared to the Georgia case. As a result, the model is better equipped to anticipate gradual deterioration, even in its early stages. Instead of defaulting to stability, it projects a slow but consistent decline, consistent with patterns learned from similar bridges in Iowa's inventory. This underscores the importance of region-specific training data in capturing localized deterioration trends and enhancing predictive sensitivity.

At the network level, Figure 20a and b present future deck condition forecasts for a subset of bridges in Georgia and Iowa inventories, respectively. The Georgia predictions illustrated in Figure 20a present an outlook with minimal change, as most bridges maintain condition ratings between classes 6 and 8 through 2032. This reflects the distribution of the training data, which was heavily concentrated in the mid-to-high condition range. The model appears to extend this historical trend, with few bridges showing significant deterioration or improvement.

In contrast, the Iowa projection shown in Figure 20b reveals a broader range of predicted outcomes. A higher number of bridges are forecasted to fall below class 6 over the eight-year period, with some exhibiting non-linear transitions—dropping to lower classes before leveling off or slightly improving. These shifts reflect the more balanced class distribution in Iowa's dataset, which contains a higher proportion of bridges in classes 4 through 6 compared to Georgia. Since the Iowa model was trained using localized features and data, the observed variability aligns with realistic deterioration dynamics. The potential for improvement suggests that the model has learned associations between specific input features and rehabilitation events.

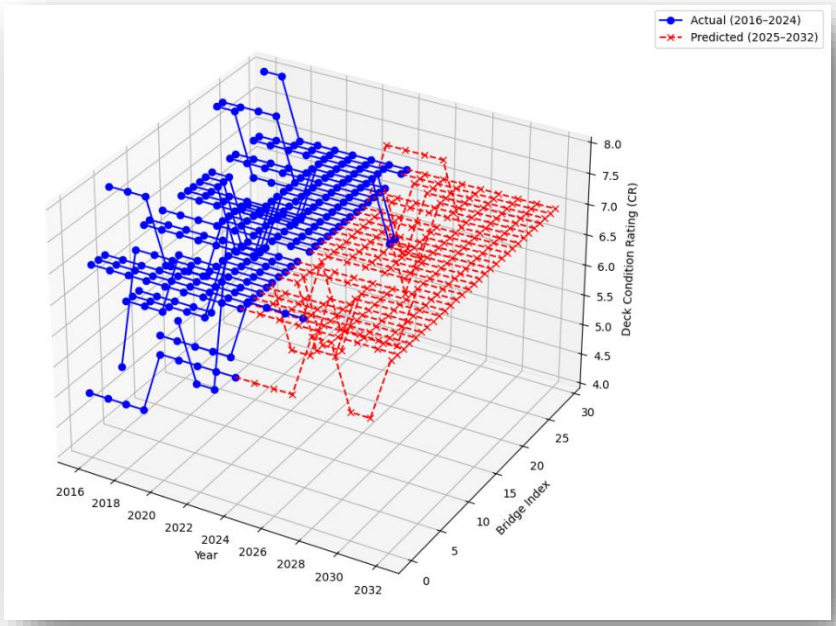


(a)

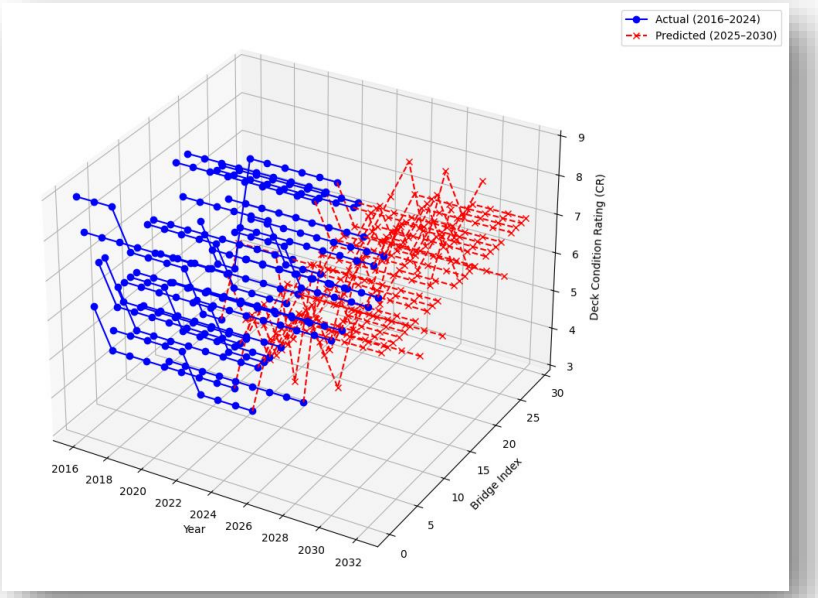


(b)

Figure 19. Bridge Deck Condition Predictions for Selected Bridges in (a) Georgia and (b) Iowa. The Black Line Represents Actual Deck Condition Ratings up to 2024; The Red Line Represents the Model's Forecast of Future Deck Condition Ratings From 2025 Onward.



(a)



(b)

Figure 20. Network-Level Deck Condition Ratings and Predictions for 30 Selected Bridges in (a) Georgia and (b) Iowa.

These results highlight the influence of training data characteristics on model behavior. A dataset with limited condition rating variation such as Georgia's tends to produce forecasts with minimal

change, reinforcing the dominant patterns. In contrast, a more diverse dataset, such as Iowa's, allows the model to capture a broader range of deterioration trajectories, including both steady declines and potential improvements resulting from maintenance or intervention. This underscores the importance of aligning model design with the operational context and the specific experiences of each state. If a model is to be deployed across multiple states or regions, targeted retraining will be necessary to maintain accuracy. The deterioration patterns of bridge decks are highly influenced by localized factors such as climatic conditions, traffic volume, maintenance practices, funding level, and policies. As such, the RNN models developed in this study are sensitive to regional variations. Therefore, deploying this predictive approach in different states or regions will require retraining using local features to ensure that the models accurately capture region-specific deterioration trends.

From a planning and budget allocation perspective, the ability to simulate future condition trajectories at both the bridge and network levels facilitates data-driven maintenance prioritization, resource allocation, and long-term capital investment strategies.

CHAPTER 6. CONCLUSIONS AND RECOMMENDATIONS

The Recurrent Neural Network (RNN) model developed in this project successfully predicts bridge deck condition ratings from 2025 to 2032, enabling the identification of bridges that require maintenance planning to prevent further deterioration. In Georgia, unlike in Iowa, the predicted results suggest an improving trend in bridge deck conditions over the coming years. Simulation results from the graph-based network model, which incorporates time series predictions for Georgia bridges generated by the RNN model, indicate that the National Highway Freight Network (NHFN) in 2032 will exhibit higher connectivity, demonstrating increased resilience to closures of bridges with low deck condition ratings compared to the network in 2024. The RNN-driven graph-based network model identifies critical bridges whose closure would significantly impact network performance, enabling targeted, mission-critical, and cost-effective maintenance prioritization. Finally, prioritized repairs of six critical bridges, based on condition predictions and connectivity impact, significantly improved the robustness of the NHFN by 2032.

With increasing disruptions to bridge infrastructure systems, growing demands for management, repair, and replacement (MRR), and ongoing budget constraints, the need for an efficient and scalable bridge asset management framework has become critical. This report introduces a novel AI-driven, graph-based modeling approach that evaluates both the structural deck condition and the topological criticality of bridges within the highway network. Based on the findings of the proposed RNN-based graph network model, the following conclusions are drawn:

- A novel RNN-driven, graph-based network modeling approach is proposed, which evaluates both the structural deck condition rating predictions and the topological criticality of bridges at the highway network level. Unlike traditional asset management practices, which primarily rely on visual and on-site inspections, this approach takes a forward-looking, interconnected view of bridge networks, where decision-making prioritizes both individual structural performance and network-level robustness.
- The Recurrent Neural Network (RNN)-based time series prediction model effectively predicts bridge deck condition ratings over time, revealing current maintenance strategies and identifying bridges that require maintenance planning to prevent further deterioration.
- The graph-based network model, incorporating RNN-based condition predictions, effectively identifies specific bridges that pose a high risk to freight network connectivity, supporting the prioritization of repair actions to maintain network resilience.

The findings of this project provide valuable insights for guiding asset management decisions, particularly in the context of allocating limited budget resources for bridge maintenance. Additionally, the integrated approach developed here can be applied to identify high-risk bridges within road networks, especially under various disruptions, such as flooding or the introduction of automated vehicles. Exploring these applications further represents a promising direction for future work.

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