QUANT CR FOR TRANSFORMATIVE BRIDGE ASSET MANAGEMENT

Quarterly Progress Report
For the period ending September, 2024

Submitted by:
PI- Bjorn Birgisson
Co-PI – Mi Chorzepa
Research Scientist – Sajib Saha
Research Scientist – Lynn Abdouni
Graduate Student – Adey Sowemimo

Affiliation: Civil Engineering,
School of Environmental, Civil, Agricultural, and Mechanical Engineering
University of Georgia
Athens, GA

Submitted to:
IBT/ABC-UTC
Florida International University
Miami, FL

1. Background and Introduction

The research team aims to develop an artificial intelligence (AI)-powered quantitative condition rating (QUANT CR) model which operates on a low-cost geographic information system (GIS) platform, aiding local and state bridge owners in maintenance, repair, and replacement (MRR) decisions while preserving the established inspection and condition rating practices.

The next generation asset management system leverages the knowledge gained from 50+ years of bridge inspection practices but is predictive, forward-looking, and transformative. QUANT CR embodies insights gained from the understanding of human behavior to better assist bridge owners in decision-making. Thus, we envision QUANT CR will be operated in parallel with the existing bridge condition ratings and provide simple decision aids for bridge owners.

We believe bridge condition ratings can be better predicted by modern machine learning methods, leveraging the historic data, evolving element condition ratings, and detailed defect items. Additionally, deep learning widely used for text recognition enables an analysis of inspectors' narratives describing bridge conditions. Lastly, computer vision and deep generative learning help bridge owners visualize the outcomes of their decisions - MRR actions/inactions, empowering bridge owners. QUANT CR will:

1) Reduce human errors and aid in training bridge inspectors;
2) Close the knowledge gap between predicted and actual bridge performance, noting that it only gets better with time/data;
3) Aid bridge owners in budgetary planning by providing access to performance prediction data and MRR options;
4) Enable the use of technologies such as a drone, autonomously assigning condition ratings and ultimately writing an inspection report that is better [regarding consistency] than one written by a human-writer.

Therefore, this technology is expected to improve bridge inspection outcomes, reduce costs, increase access to performance predictions, aid in MRR decisions, which are essential for asset management at local and state government levels. This innovation will particularly serve to aid rural areas with limited resources.

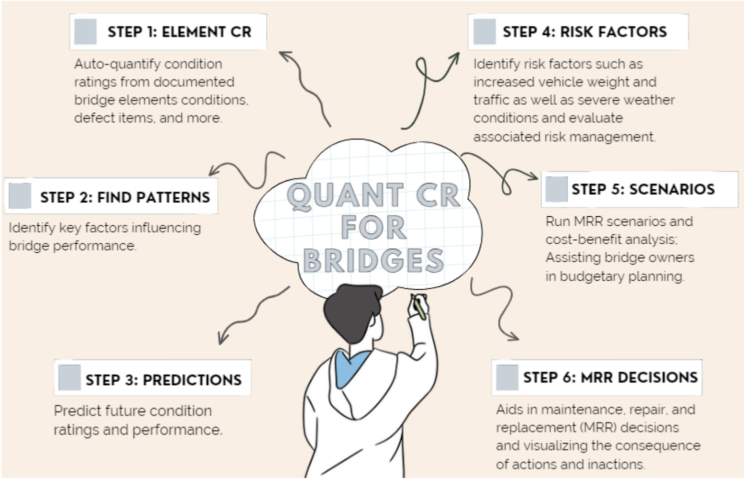

Figure 1. Steps involved in developing a Qaun CR model.

2. Problem Statement

Our bridge infrastructure is at a critical juncture, with over 42% of bridges exceeding 50 years of age and 7.5% classified as structurally deficient [1]. The call for an annual increase in bridge rehabilitation funding by 58% underscores the gravity of this issue [2]. The traditional methodologies of bridge condition assessments—relying heavily on visual inspections and on-site evaluations—are increasingly insufficient due to their resource-intensive nature and can be more efficient and successful, especially when managing disruptive events such as natural disasters. Increasing incidence of extreme weather events, rising sea levels, and climate change present new challenges that current bridge asset owners face in terms of managing their assets. The emergence of automated and heavy trucking poses additional challenges to bridge infrastructure, necessitating a re-evaluation of bridge load permits and condition assessments that account for changes in traffic patterns and vehicle technologies. There is a pressing need to transition from reactive to proactive bridge asset management strategies, which necessitates the development of innovative tools that leverage the vast historical data repositories, such as the National Bridge Inventory (NBI), and integrate them into more detailed bridge element data using modern technologies including AI, machine learning, and geospatial analysis frameworks.

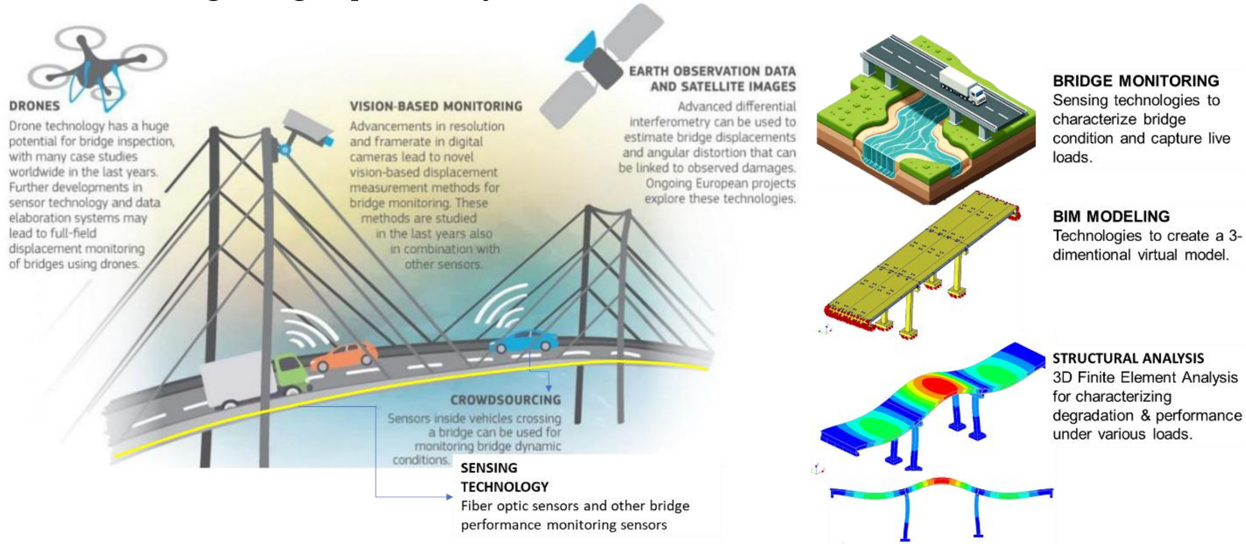

Figure 2. Emerging technologies [3] for bridge performance monitoring and management.

Currently, the AASHTOWare Bridge Management (BrM) is the main tool employed for bridge asset management at state-level; however, this platform is not accessible by local governments. The FHWA's Long-Term Bridge Performance (LTBP) Program's InfoBridge provides excellent resources for all owners but does not serve as an asset management tool. Unfortunately, existing bridge asset management practices fall short in several key areas: they do not sufficiently exploit emerging technologies such as AI to predict future bridge performance and service life based on past and emerging inspection results (refer to Figure 2); they lack comprehensive decision-making frameworks that incorporate a multitude of stressors and scenarios; and they are not adequately tailored to assist local and rural bridge owners with limited resources.

Furthermore, current tools do not fully account for interactions among bridge elements and various types of inter-dependencies that can lead to rapid degradation and cascading failures within the bridge networks, nor do they address the connectivity and sensitivity of the freight network to disruptions. The overarching problem, therefore, is the need for a bridge asset management system that is robust, predictive, and capable of integrating a multitude of data sources. Such a system must be economically viable, user-friendly, and adaptable to the rapidly changing landscape of transportation technology and environmental stressors (refer to Figure 3 for core elements).

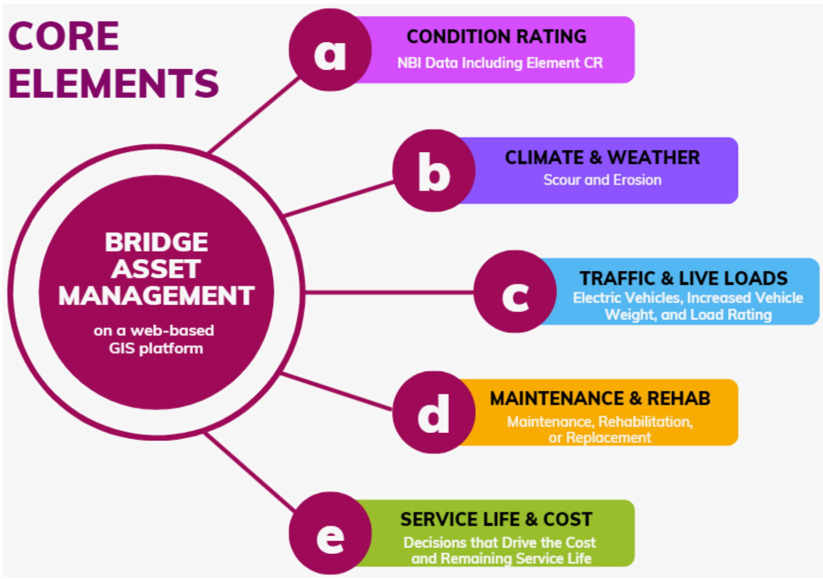

Figure 3. Core Elements for Bridge Asset Management.

The ultimate aim of this project is to equip state and local governments with a tool necessary for long-term bridge asset management, which not only safeguards against current vulnerabilities but also anticipates and mitigates future challenges. To do so, we need a powerful, yet low-cost and easy-to-implement, system that can help local and state bridge owners visualize and understand consequences resulting from their MRR actions or decisions.

Quantitatively computed rating is widely used for equity valuation and management in the financial markets; yet, bridge assets are not valued and quantitatively predicted despite of the significant value they hold.

3. Objectives and Research Approach

This project aims to empower local and state bridge owners to make informed decisions on MRR, optimizing budget plans across various scenarios. Thus, the research approach centers on developing an AI-powered quantitative condition rating (QUANT CR) system and decision analysis tool for bridges, which leverages historical data, including the extensive records of the National Bridge Inventory (NBI)'s element data, Long-Term Bridge Performance Program, bridge MRR scenarios, inspectors' narratives, and ultimately risk management including environmental, traffic, vehicle, and other relevant data to predict long-term bridge performance.

A web-based Geographic Information System (GIS) platform will store and visually represent bridge network assets, providing uniform access to all databases. A hierarchical approach to quantify bridge condition ratings and assigning them to the network analysis tool will improve long-term bridge performance predictions. Deep learning algorithms will analyze historical data and detailed bridge condition narratives to improve the bridge performance predictions at element level. Incorporating the element-level inspection results and detailed defect items is a key task for building a Quant CR model. Text recognition techniques will further interpret inspectors' descriptive reports, transforming qualitative comments into actionable quantitative data.

4. Description of Research Project Tasks

The following task is completed during the reporting period.

Task 2 –Development of a bridge condition rating prediction model

The architectures of both the LSTM and GRU models are used to capture the temporal dependencies in the bridge condition rating or performance data, as it is a time series problem.

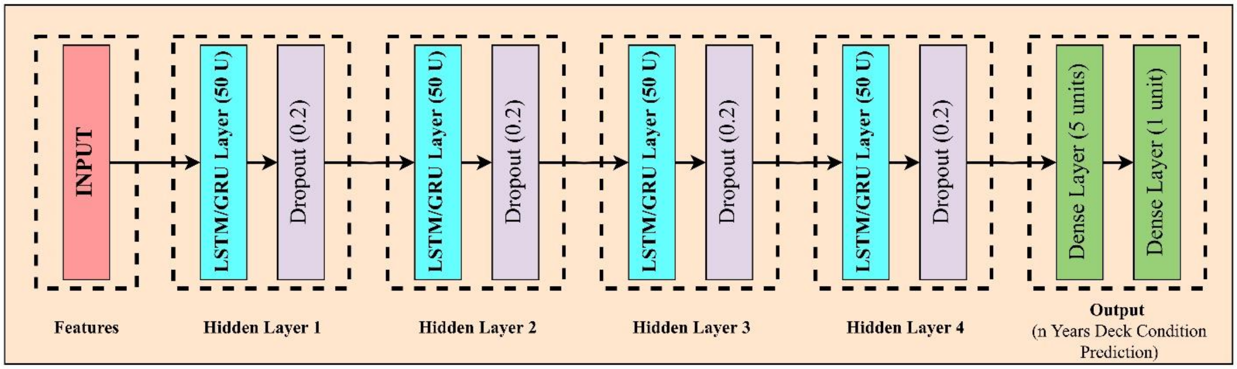

Figure 1. Architecture of RNN Models

LSTM: The LSTM model is made up of four layers of LSTMs, each with 50 units. These layers were chosen because they have the capability to retain information over long sequences, which is very important for times-series data like bridge condition ratings. The activation function used in the LSTM layers is the default hyperbolic tangent (tanh), which is a good function for this application because it helps maintain a balanced range for the data. Also, the model uses dropout layers to prevent the problem of overfitting. The dropout rate is set at 0.2. The Dense layer is configured to have 5 units, which processes the LSTM layer output and serves as a link to the final output layer. The output layer makes predictions for the deck condition rating across all 9 years, thus making the model suitable for sequential forecasting.

GRU: The GRU model follows a similar architecture to the LSTM model but replaces the LSTM layers with GRU layers. GRU layers were chosen for their simpler structure compared to LSTMs, allowing for faster training while still capturing the temporal dependencies in the data. Like the LSTM model, dropout layers with a 0.2 rate were applied after each GRU layer to prevent overfitting. The final Dense layer also generates predictions for 9 years of deck condition ratings.

Both models use the 'adam' optimizer and 'mean squared error' (MSE) as the loss function, optimized for regression tasks.

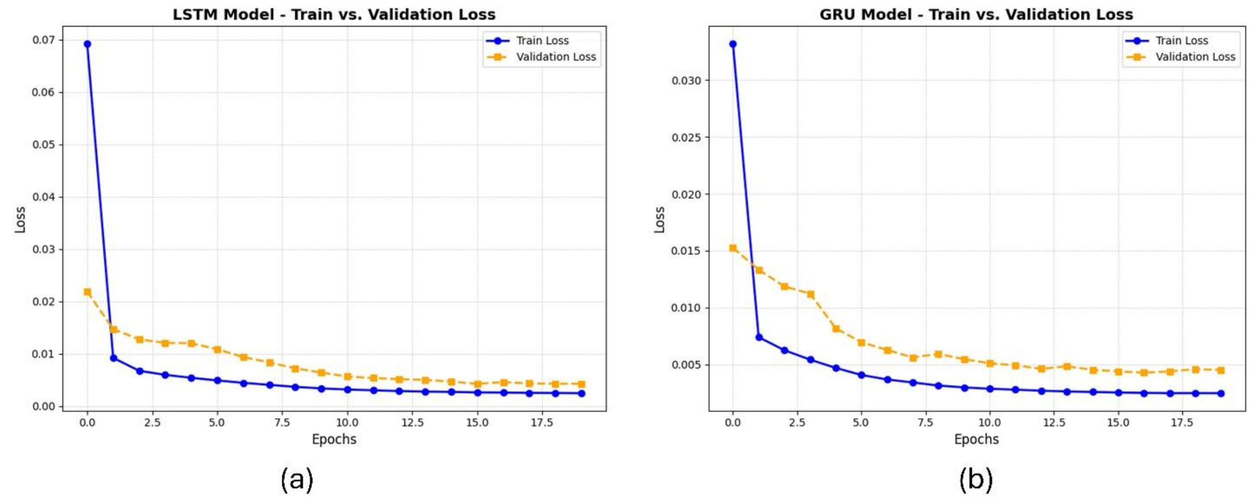

Figure 2. Train vs. Validation Loss Comparison for (a) LSTM Model (b) GRU Model

Figure 2(a) illustrates the training and validation loss curves for the LSTM model over 20 epochs. The training loss decreases rapidly in the initial epochs and progressively converges toward zero, indicating that the model is effectively learning from the training data. Similarly, the validation loss shows a sharp decline in the early epochs, before gradually stabilizing around 0.01. This steady reduction and stabilization in validation loss suggest that the model generalizes well to unseen data without significant overfitting. The small gap between the training and validation curves further confirms the model's strong generalization capabilities, as it indicates the absence of overfitting. After about 10 epochs, both curves stabilize, showing that the model has sufficiently learned patterns from the data while maintaining good performance on the validation set.

Figure 2(b) shows the training and validation loss curves for the GRU model over 20 epochs. The training loss decreases steadily, converging close to zero, while the validation loss drops sharply in the first few epochs and stabilizes around 0.005. The minimal gap between the two curves indicates that the GRU model generalizes well and avoids overfitting. Both losses stabilize around epoch 10, suggesting effective model convergence. The slight fluctuations in validation loss between epochs 7 and 15 further confirm the model's ability to capture sequential patterns while maintaining generalization to unseen data.

The UGA team will continue refining the condition prediction models in the next reporting period.

Task 3 – Graph-based network models

The research team has developed a graph-based network of bridges and roadways within Georgia's National Truck Network, integrating them based on the geospatial coordinate datasets. A total of 2,146 bridge sections were identified passing through the truck network of Georgia, as shown in Figure 3. The developed graph-based network facilitates various topological vulnerability analysis for the bridges in Georgia. 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. In this analysis, bridge endpoints and roadway intersections serve as nodes (V) and while the roads themselves serve as edges (E).

Figure 3(a) illustrates the network's connectivity and structure under existing conditions by showing the distribution of node degrees, where a node's degree is the number of edges connected to it. Nodes are color-coded, with blue, green, orange, and red representing nodes with degrees of 1, 2, 3, and 4, respectively. Figure 3(b) shows a modified version of the network, excluding nodes with a degree of 2 to assess the impact on network efficiency from the omission of specific intersection points.

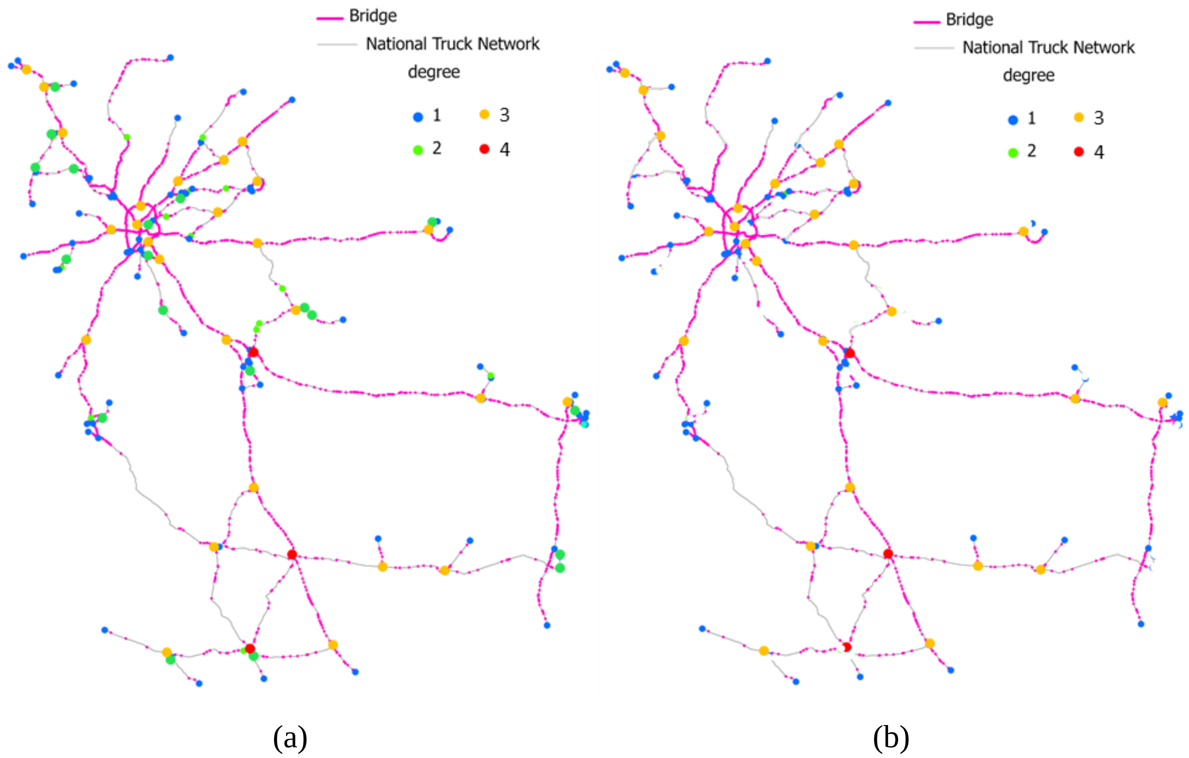

Figure 3. Connectivity of bridges and roadways within the National Truck Network of Georgia (a) before (b) after node removal (degree =2)

Figure 4 illustrates the efficiency of the network by progressively removing edges and calculating the global efficiency - defined as the average of the inverse shortest path lengths between all pairs of nodes - after each removal step.

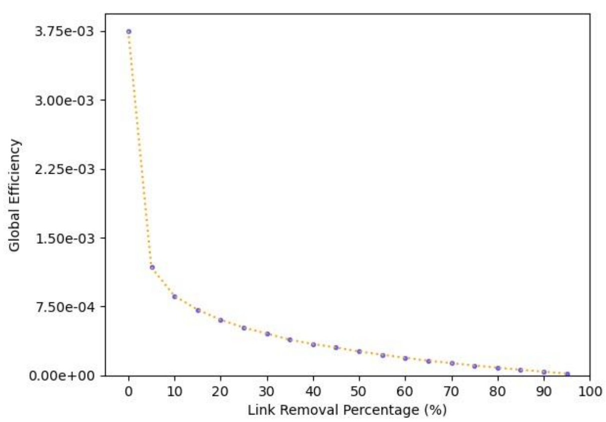

Figure 4. Effect of random edge removal on global efficiency of the network

5. Expected Results and Specific Deliverables

This project will create a QUANT CR system that employs artificial intelligence including advanced machine learning algorithms, in order to quantitatively predict condition ratings of bridges, autonomously suggest MRR actions, and ultimately enable writing inspection reports for the next period. The web-based GIS system can run various what-if MRR scenarios and help bridge owners visualize the results. The research team will submit a Technical Report summarizing the methodologies employed to develop a QUANT CR system and data sources.

Description of specific deliverables from this reporting period:

A graph network has been developed for Task 3, and the bridge condition rating prediction modeling framework (a many-to-many, multivariate, time-distributed RNN) has been further refined using LSTM and GRU models for Task 2.

6. Schedule

Progress of tasks in this project is shown in the table below.

Item	% Completed
Percentage of Completion of this project to Date	50

Table 1 - Gantt chart depicting the timeline.

Months	1-3	4-6	7-9	10-12	13-15	16-18
Task 1						
Task 2						
Task 3						
Task 4						

Notes:

Completed

Task 1 – Acquisition of bridge performance/condition data into geospatial format

Task 2 – Development of a bridge condition rating prediction model

Task 3 – Enhance with a graph-based network model

Task 4 – Verify model and explore benefits from employing other technologies

7. References

1. ASCE (2021) A Comprehensive Assessment of America's Infrastructure (Reston, WV: American Society of Civil Engineers (ASCE))

2. U.S. Department of Transportation, (2020) Federal Highway Administration, "Status of the Nation's Highways, Bridges, and Transit Conditions and Performance Report," Chapter 7 – Capital Investment Scenarios – Highways, 23rd Edition.

3. https://joint-research-centre.ec.europa.eu/jrc-news-and-updates/keeping-european-bridges-safe-2019-04-05_en

4. Bui, Q. D., Luu, C., Mai, S. H., Ha, H. T., Ta, H. T., & Pham, B. T. (2022). Flood risk mapping and analysis using an integrated framework of machine learning models and analytic hierarchy process. Risk Analysis. doi:10.1111/risa.14018
5. Xiong, J., Li, J., Cheng, W., Wang, N., & Guo, L. (2019). A GIS-Based Support Vector Machine Model for Flash Flood Vulnerability Assessment and Mapping in China. Isprs International Journal of Geo-Information, 8(7), 297. doi:10.3390/ijgi8070297
6. Feloni, E., Mousadis, I., & Baltas, E. (2020). Flood vulnerability assessment using a GIS-based multi-criteria approach—The case of Attica region. Journal of Flood Risk Management, 13(S1). doi:10.1111/jfr3.12563
7. Vignesh, K. S., Anandakumar, I., Ranjan, R., & Borah, D. (2021). Flood vulnerability assessment using an integrated approach of multi-criteria decision-making model and geospatial techniques. Modeling Earth Systems and Environment, 7(2), 767-781. doi:10.1007/s40808-020-00997-2
8. Newman, M. E. J. (2010). Networks: An Introduction. Oxford University Press, Oxford.