Assignment 4

Network Analysis

EPA133a Advanced Simulation

Group 16

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Outline

1. Introduction

Over the past decades, Bangladesh has experienced significant development, driven by international investment and exports from sectors such as fashion. However, these advancements are at risk of stagnation if the national infrastructure fails to adequately support the economy (Planning Commission & Asian Development Bank, 2021). Therefore, understanding the criticality and vulnerability of the current infrastructure is essential in order to prioritize maintenance investments and future development support.

With this in mind, the objective of this assignment is to support the World Bank's study on the criticality and vulnerability of roads N1, N2, and their main branches in Bangladesh.

This report is structured as follows. Chapter 2 introduces the key concepts of criticality and vulnerability in the context of transport infrastructure. Chapter 3 outlines the methods used in our study, including both the simulation-based analysis, which builds on our simulation model and integrates traffic and natural disaster data, and the network-based analysis, which uses empirical data to assess the importance and risk levels of roads and bridges. Chapter 4 presents the results from both analyses, while Chapter 5 offers the conclusion of the evaluation. Lastly, chapter 6 provides a reflection on the limitations of our work and suggests possible improvements.

2. Criticality and Vulnerability of Network Infrastructure

In this section we present the chosen definitions for the terms criticality and vulnerability. We use the overarching definition provided by the question task as a base. These are provided below as a reminder:

- *“Criticality relates to the amount of goods transported over the road, i.e., the economic importance of a road.”*
- *“Vulnerability relates to the probability that roads get impassable after natural disasters (cyclones, heavy rain, flooding, mudslides, earthquakes, etc.)”*

On the one hand, in the present assignment, we use a “probability-neutral” understanding of criticality. We will measure the importance of a component based on the impact of its disruption, regardless of how likely that disruption is to occur (Jafino et al., 2020 & De Oliveira, da Silva Portugal, and Junior, 2016). In our case, we consider that a bridge disruption is more critical if it provokes a higher accumulated retention of vehicles. In other words, we measure criticality based on delay time. It is worth noting that we make use of probability in the simulation model, however this one acts as an input, not an output. We do not drive conclusions based on the probability, but use it as one of the parameters for our experimental design. In the next section, this will be discussed in more detail, as well as the overall method.

On the other hand, we refer to vulnerability as “the road transportation system is a susceptibility to incidents that can result in considerable reductions in road network serviceability. These incidents may then be more or less predictable, caused voluntarily or involuntarily, by man or nature.” (Berdica, 2002). Overall, likeliness to disruption suggests vulnerability of the infrastructure to external factors. In our code, we use the bridge condition as well as climate and traffic conditions based on location as context setters.

First, we argue that a bridge condition directly influences its resilience to adverse events like floods. A bridge in optimal state is more likely to withstand heavy rains or floods that may otherwise break a structurally deteriorated one.

Secondly, the bridge's geographical location also plays a crucial role, as those situated in areas prone to extreme climate events are more susceptible to “black swan” occurrences, leading to devastating consequences in human safety and infrastructure stability. Thus, by incorporating both factors—infrastructure condition and environmental exposure—this approach captures a more comprehensive view of vulnerability, accounting for both the internal weaknesses of a structure and the external risks posed by its surroundings.

3. Method

This section explains how we studied the criticality and vulnerability of bridges in Bangladesh. We used two different methods: a simulation-based analysis and a network-based analysis. These methods give us different views on how important each bridge is and its susceptibility to potential damage. By using both, we attempt to give a more complete picture that can help policymakers make better decisions about where to invest in improving the country's road system.

3.1 Evaluation approach and metrics

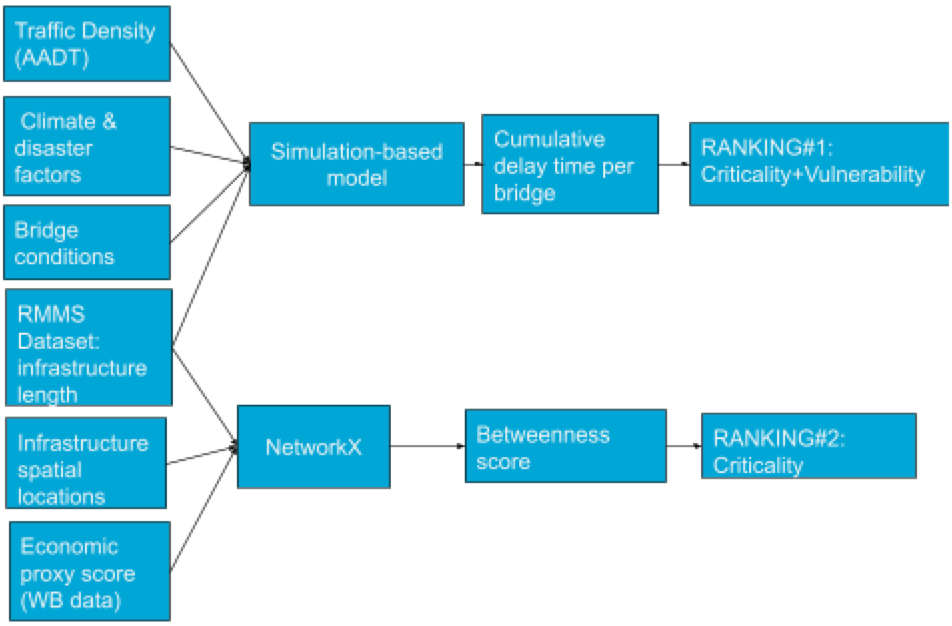

Figure 3.1.1: Overview of the two evaluation metrics

We use two metrics, average delay time and betweenness centrality of bridges, to assess the importance of bridge infrastructure in Bangladesh's road network. These metrics come from two different approaches: one based on a simulation of traffic model and the other based on a network analysis. We chose to use both methods because they offer different perspectives. Figure 3.1.1 presents the overall system from the input required on the left to the output of the analysis on the right.

The simulation-based metric studies how the road network is like under various scenarios by modeling how trucks move through the network in different broken bridge scenarios. The average delay time per bridge obtained from the simulation reflects how bridge failures impact actual travel experience. This method concerns both criticality and vulnerability aspects since the simulation model takes criticality-based and vulnerability-based data as the model input. On the one hand, the simulation-based model takes AADT data to estimate the traffic density, climate factors and bridge conditions—A, B, C, D—and the RMMS dataset. These inputs address both criticality and vulnerability:

Traffic density is used to determine generation frequency per source-sink pair.

- Climate factors illustrate the exposure of infrastructure to external hazards, aligning with our chosen definition of vulnerability.
- Bridge condition determines the duration (i.e., delay time) a bridge remains inoperable, directly related to criticality.
- As in the previous assignment, RMMS data is used to determine the shortest paths from source to sink using length as the weight in a NetworkX graph.

Overall, this metric combines both terms and gives an overall and simulation-driven perspective.

In contrast, the network-based metric uses structural information from the road network, together with empirical data, to calculate the betweenness centrality of each bridge. This helps identify which routes are most important for maintaining access and connectivity. Unlike the previous metric, this one relies solely on empirical data gathered through literature and databases, and does not involve simulation subject to stochasticity.

Here, we use the RMMS dataset and an economic proxy to define the weights in the NetworkX graph. The main output is betweenness centrality, which serves as the basis for a new ranking of the most critical bridges.

As suggested by Jafino et al. (2020), using multiple metrics enhances the evaluation by enriching the analysis with diverse insights. By comparing the results from both approaches, we can gain a more comprehensive understanding of Bangladesh's road network—ultimately helping decision-makers to prioritize infrastructure investments based on both criticality and vulnerability.

3.2 Simulation-based Analysis

This analysis builds on the simulation model from the previous assignment, where we used NetworkX to calculate the shortest paths for trucks, making their movement more realistic in a complex road network. In this assignment, we extend that model to assess infrastructure criticality and vulnerability by integrating several real-world datasets from Bangladesh. These datasets help the model better reflect actual traffic conditions and infrastructure quality. This section explains conceptualization (what data we used and why we used it) and the implementation (how we used it).

3.2.1 Using traffic data to control truck generation and destination

Conceptualization

The traffic data used in this study is measured as Annual Average Daily Traffic (AADT), which estimates the average number of vehicles passing a road segment per day, in both directions, over a year. We obtained AADT values for Bangladesh from the RMMS database. Figure 3.2.1.1 shows the traffic levels along N1, N2, and their side roads, where it's clear that different parts of the network experience different levels of usage.

To reflect this variation in traffic, we used AADT values to determine the truck generation frequency at each SourceSink. We assumed that trucks are generated every 2 minutes at high-traffic sources and up to 10 minutes at low-traffic sources. We applied a min-max scaling approach to map the AADT values to truck generation intervals between 2 and 10 minutes. This ensures that busy roads generate more trucks, while quieter roads generate fewer, creating a more realistic simulation of traffic flow.

In addition to controlling generation frequency, we also used AADT to influence truck destination selection. By converting traffic volumes into sink selection probabilities, the model can assign destinations in a way that reflects real-world traffic patterns, resulting in a more data-driven and more realistic flow across the road network.

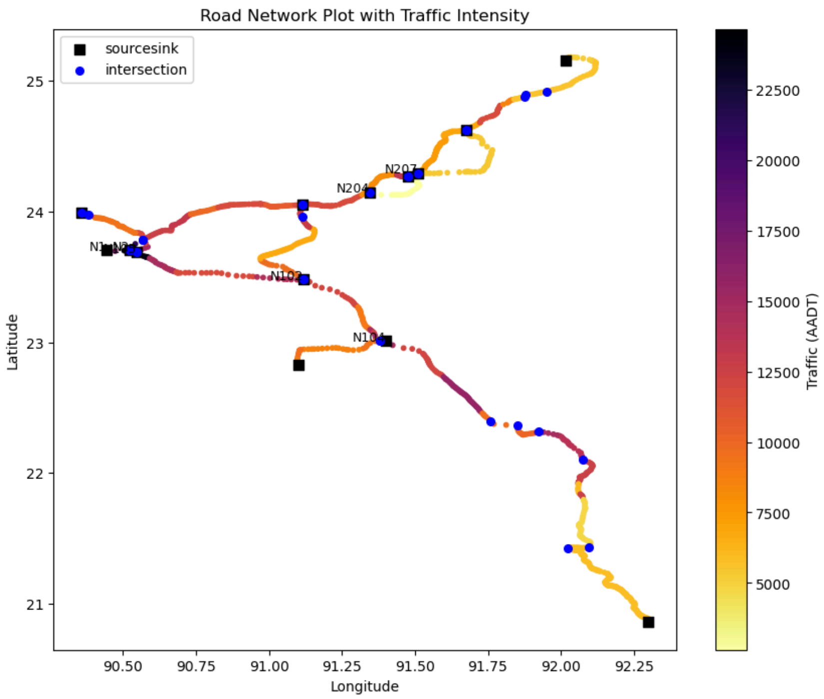

Figure 3.2.1.1: AADT of Bangladesh's road network

Implementation

We started by preparing the data using three Jupyter notebooks to clean, extract, and combine the road and traffic data needed for our model:

- **1_CleanDemoFile.ipynb:** This notebook keeps only the roads that are longer than 25 km and saves the cleaned data for the next steps.
- **2_ScrapeTrafficData.ipynb:** This notebook scrapes traffic data from the HTML files and saves it as CSV files so we can use it easily.
- **3_CombineDemoAndTrafficData.ipynb:** This notebook puts the road data (demo_100.csv) and traffic data (like N1_traffic.csv) together. It also calculates the necessary metrics used in the model:
    - truck_generation_frequency: how often trucks are created at each sourcesink
    - sink_selection_probability: how likely each sourcesink is chosen as a destination

    ○ heavy_truck_normalized: how much heavy truck traffic there is (used later in Section 3.2.2)

We also made some changes to the simulation model to incorporate the empirical data:

- **components.py:** We updated the SourceSink, Source, and Sink classes. The new SourceSink class works as both a start and end point for trucks. This is useful for places like sources or sinks. It takes in values like how often trucks should be created and how destinations are chosen.

- **model.py:** We modified the get_random_route() method in the BangladeshModel class. Now, it chooses routes for trucks based on the sink_selection_probability we calculated from the traffic data. This makes the model more realistic.

3.2.2 Using heavy truck traffic and natural disaster data to add complexity to bridge failure probability

Conceptualization

In addition to considering bridge structural conditions, this study aims to simulate a more realistic representation of the road network in Bangladesh by introducing additional complexity to the calculation of bridge failure probability: **probability modifiers**. In the previous assignment, failure probability was determined solely based on the bridge’s condition classification (A, B, C, or D), as shown in Table 3.2.2.1. Interpreting the condition categories, we create a constant bridge failure base probability, which is: {'A': 0.01, 'B': 0.05, 'C': 0.15, 'D': 0.30}. In this iteration, modifiers are introduced to add nuance, incorporating external stressors such as natural disasters and heavy traffic loads, allowing for a more context-sensitive simulation.

Table 3.2.2.1: Bridge Condition Category by the Ministry of Road Transport and Bridges Roads and Highway Departments of Bangladesh

Condition Category	Damage Degree	Urgency of Repair
A	0~20	No need of repair
B	20~60	Depending on situation
C	60~80	In its early stage
D	80~100	Emergency

Bridge failures in Bangladesh predominantly occur due to two significant factors: overloading by heavy trucks and damage from flood-induced erosion. Many of the country's older or temporary bridges are structurally insufficient to handle excessive loads, yet they frequently bear the weight of overloaded sand, stone, or rod-laden trucks, resulting in frequent collapses (The Daily Star, 2019; Dhaka Tribune, 2023). Simultaneously, Bangladesh's vulnerability to seasonal monsoon floods and riverbank erosion further exacerbates bridge degradation (University of Asia Pacific, 2001; The Daily Star, 2021). These issues happen during extreme weather events, where water pressure damages bridge foundations. Therefore, in modelling bridge failures, it is both practical and data-driven to base simulations on two dominant measures of vulnerability: **flood erosion** and **heavy truck overloading.**

To perform this simulation, heavy trucks traffic data from the RMMS database and floor risk category data from the Bangladesh Hazards database by the United Nations Office for the Coordination of Humanitarian Affairs (OCHA) are used as proxies to generate parametric values. Following the same approach as in the previous assignment, these values are applied as probability modifiers to simulate broken bridges in each run. The descriptions of each flood category can be seen in Table 3.2.2.2. Figure 3.2.2.1 shows the normalized distribution of heavy truck traffic along the N1, N2 and their adjacent roads. In contrast, Figure 3.2.2.2 shows the locations of LRPs across different districts, overlaid with their corresponding flood risk categories.

Table 3.2.2.2: Flood risk category by The Bangladesh Agricultural Research Council

Flood Risk Category	Flood Description
0	**Not flood-prone**.
1	**Severe river flooding** involves extensive inundation of structures and roads near rivers. Such events often necessitate significant evacuations, leading to substantial property damage and potential loss of life (Queensland Government, n.d).
2	**Moderate river flooding** involves water levels exceeding the riverbanks and inundating structures and roads near the river. Evacuations might be necessary, and property damage is potential (Queensland Government, n.d).
3	**Low river flooding** refers to water levels that slightly exceed the riverbanks, causing minimal or no property damage but possibly some public threat or inconvenience (Queensland Government, n.d).
4	**Severe flash floods** are sudden, intense floods that occur within six hours of heavy rainfall or other causes. They are characterised by rapid water rise and high flow velocities, leading to significant damage to infrastructure and serious threats to life (National Severe Storms Laboratory, n.d.) (National Weather Service, n.d).
5	**Moderate Flash Flooding** involves rapid flooding with the potential to cause considerable damage and pose threats to safety (National Severe Storms Laboratory, n.d) (National Weather Service, n.d).
6	**Low Flash Flooding** refers to sudden floods that cause minimal property damage but may still pose some public threats or inconveniences, such as temporary road closures and localized disruptions (National Severe Storms Laboratory, n.d)(National Weather Service, n.d).
7	**Severe Tidal Surge** involves significant rises in sea level associated with storms, leading to extensive coastal flooding (National Severe Storms Laboratory, n.d).
8	**Moderate Tidal Surge** are characterised by a noticeable rise in sea level due to storm activity, causing coastal flooding (National Severe Storms Laboratory, n.d).

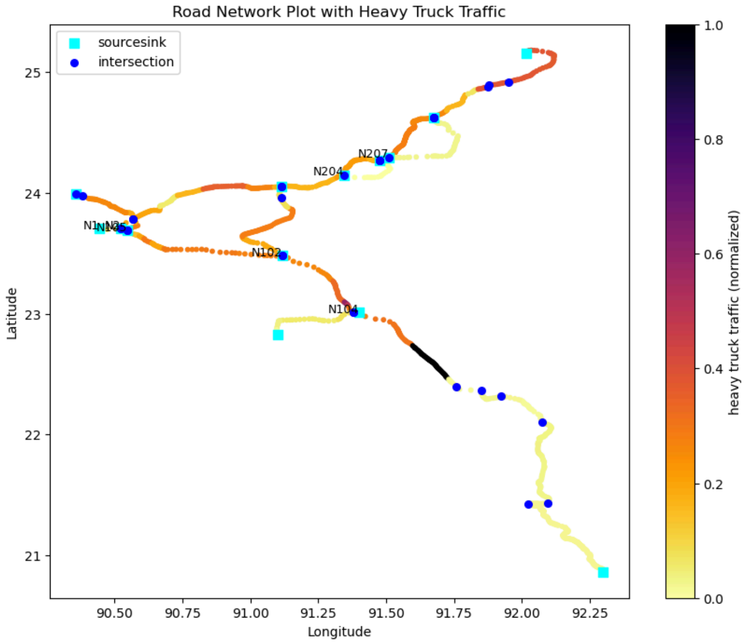

Figure 3.2.2.1: Heavy Truck traffic of Bangladesh's road network

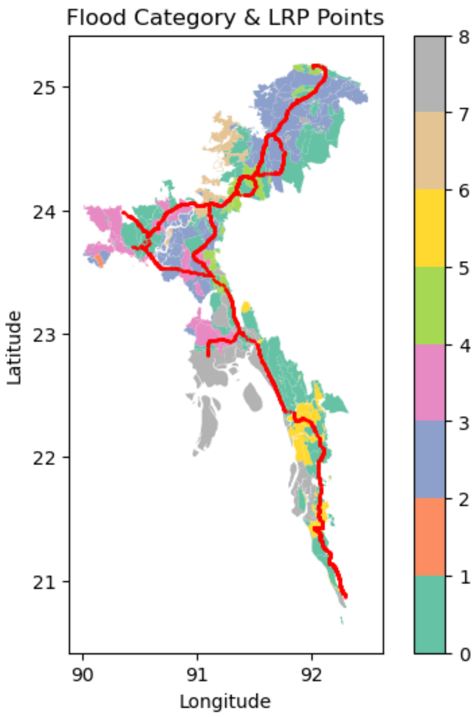

Figure 3.2.2.2: Districts with Flood Category (0-8) and LRP (red line)

The data is used to support the assumptions made when assigning probability values in the simulation. While these probability modifiers do not represent real-world failure rates, they serve as relative indicators of the likelihood of a bridge breaking under certain conditions. For example, if Bridge A is located in a district with flood risk category 0 (not flood-prone), it may be assigned a modifier value of 1. In contrast, Bridge B, situated in a flood risk category 7 district (severe tidal surge), is assigned a value of 3. This implies that, assuming both bridges have the same structural condition, Bridge B is considered three times more likely to fail during a flood compared to Bridge A.

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The same logic is applied when utilizing the heavy truck traffic data. By analyzing the quantile distribution of the traffic data, probability modifier values are assigned in proportion to the quantile ranges, higher traffic volumes correspond to higher quantile values, which in turn represent a greater likelihood of bridge failure due to overloading. Figure 3.2.2.3 shows the distribution of heavy truck traffic (note that it's not normally distributed).

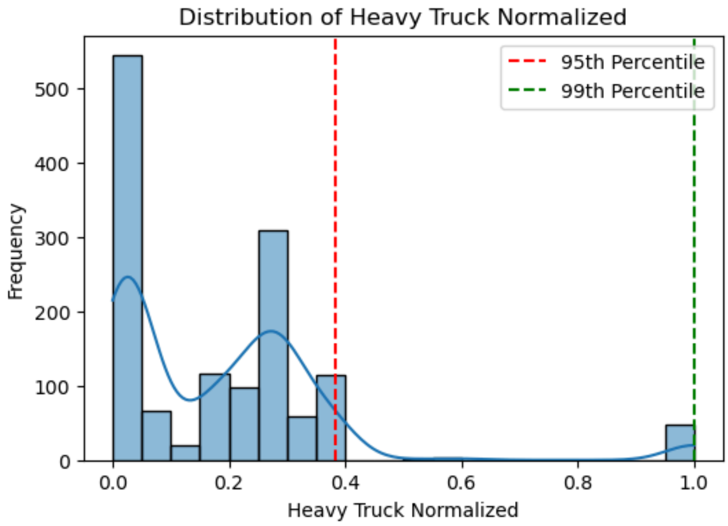

Figure 3.2.2.3: Heavy Truck Traffic Distribution

Similarly, delay times associated with bridge failures are estimated based on bridge length, under the rationale that longer bridges typically cause more severe disruptions when out of service. This logic is grounded in assumptions: small bridges or culverts usually result in minimal delays as surrounding informal routes may provide slow but functional detours. In contrast, medium-sized bridges—especially those located on national highways like N2—tend to cause moderate delays due to the limited number of viable alternate routes and higher traffic density. For large river bridges on major corridors such as N1, the impact is significantly greater, often requiring detours through distant crossings or temporary ferry operations, which increase travel time.

It can also be interpreted that flood risk category, bridge condition, and heavy truck traffic act as vulnerability measures—factors that influence the likelihood of failure—while bridge length serves as a measure of criticality, reflecting the scale of disruption once a failure occurs. In other words, the simulation integrates both vulnerability and criticality assessments to model the overall risk and impact of bridge failures across the network.

Since the objective of this model is not to precisely simulate driving times, but rather to identify relatively more critical and/or vulnerable bridges, these delay estimates serve their purpose adequately. The assumed values allow the simulation to reflect the relative impact of bridge failures, enabling informed comparisons and identifying high-risk segments (bridges) in the network.

Implementation

The data preparation process consists of three main tasks: **extracting heavy truck traffic data**, **extracting flood risk data**, and **introducing bridge failure probability modifiers to the model**. The traffic data is extracted using the same methodology as the AADT data, followed by normalization, values are scaled between 0 and 1. District-level geometry information—each associated with a corresponding flood risk category—is used for flood data. These geometries are then spatially aligned with the latitude and longitude of the LRPs, allowing the flood category to be assigned to each LRP based on the district within which it is located. However, due to slight coordinate mismatches between the district and LRP datasets, some LRP points do not fall within any district geometry. In such cases, missing values are filled with the flood category of the previous LRP in the dataset. Flood risk data extraction is carried out in **Explore flood risk.ipynb**.

The model is modified to introduce and implement probability modifiers:

- **components.py's** Bridge and Vehicle classes are updated. The Bridge class now has FLOODCAT and heavy_truck as its attributes; the values for delay_time are also slightly adjusted. The Vehicle class is modified to collect accumulated waiting time caused by broken bridges data into a dictionary, bridge_delays.
- **model.py** now takes flood and heavy_truck as arguments (boolean). We added methods to collect several data and to initially determine the broken bridges at the start of each replication, determine_broken_bridges(), which consists of the new flood_risk_modifers and heavy_truck_modifiers. When the flood or heavy_truck is True, then the corresponding modifier is multiplied by the base probability (the condition probability), resulting in a new bridge failure probability. The following are the modifiers:
    a. flood_risk_modifiers = {0: 1, 1: 1.7, 2: 1.3, 3: 1.1, 4: 1.8, 5: 1.4, 6: 1.2, 7: 3.0, 8: 2.5 }
    b. heavy_truck_modifiers = {(0, 0.02): 1.0, (0.021, 0.17): 1.05, (0.171, 0.28): 1.2, (0.281, 0.49): 1.4, (0.50, 1.0): 1.8}
- **model_run.py** is where the base probability for each condition can be set.

3.2.3. Experiment Setup

Three scenarios are executed within the simulation: (1) flooding, (2) overloading, and (0) no broken bridges (baseline). Each scenario is run for 100 replications using the same set of random seeds to ensure that results are comparable across scenarios. For each run, the average driving time is recorded, along with a dictionary of bridge IDs and their corresponding accumulated delay times.

Each simulation run spans 4,320 ticks, where 1 tick represents 1 minute, resulting in a total simulated time of 3 days. This duration is intentionally selected based on the longest source-to-sink route, which takes approximately 18 hours. By setting the simulation time to four times that duration, the model allows a sufficient buffer for observing network-level disruptions and rerouting effects under conditions of bridge failure.

3.3 Network-based Analysis

In addition to the previous metric, we designed a second one as an alternative way to measure criticality. The inputs of this metric are: the road configuration from the RMMS database - length of infrastructure, longitude and latitude) and an economical proxy. The purpose of this metric is to estimate the criticality of the infrastructure network taking into account its relevance of the location of the infrastructure for the national economy. Therefore, this metric follows an utilitarian approach, we consider that areas with higher economic activity are more critical. Additionally, and similarly to previous assignments, we include the infrastructure's length. We combine both the economic proxy and the length to determine our second ranking (see section 3.3.2) for algorithm implementation.

3.3.1 Empirical data used in network analysis: Population density as an economical proxy

Conceptualization

We assume that more densely populated areas have higher economic activity and, therefore, a more critical impact in case of disruption. While this proxy is a simplification, the results (explained in later sections) demonstrate that it is not an unreasonable assumption. Like many countries worldwide, Bangladesh is experiencing rapid urban development. This is attracting a large percentage of the population to major cities in search of better opportunities. According to the UN , Dhaka, Chittagong, and Khulna account for about 54% of the country's total urban population (UN-Habitat, n.d.). Rural areas tend to offer fewer career opportunities, and their role in the national economy is more limited. Nevertheless, it is important to highlight that areas led by the agricultural sector, although not generating as much revenue as manufacturing, are still indispensable as they meet fundamental societal needs. Therefore, while this assumption is acceptable, the results derived from it must be interpreted with caution.

Implementation

We started by preparing the data using one Jupyter notebooks to combine the road and traffic demo file we already created in previous steps, with economic data needed for network analysis:

- **4_CreateDemoFile_Network.ipynb:** This notebook combines the road demo file with economic data.

In this analysis, we use population density data from the 2011 World Bank dataset and corresponding shapefiles. Our aim is to create an index representing the economic activity of each union council through which roads N1 and N2 pass. Since we are studying a specific region—the areas where N1 and N2 are located—we first filtered the area of interest to include the following districts: Chittagong, Dhaka, Narayanganj, Feni, Comilla, Cox's Bazar, Brahmanbaria, Habiganj, Narsingdi, Moulvibazar, Sylhet, and Noakhali. Using district-level data would result in considerably fewer data points for comparison; therefore, we opted to study population density using the smallest administrative unit available: the union council (also called Level 4).

Next, we plotted a choropleth map, dividing the data into seven quantiles. Each union council geometry was assigned to one of these quantiles. Figure 3.3.1.1 illustrates this map. The

Level 4 administrative areas shaded in darker colors correspond to the most densely populated zones. A noticeable cluster of darker geometries can be observed in Dhaka and Chittagong, as expected.

It is worth noting that during data preparation, we discussed whether to use quantiles or the equal interval method. We concluded that quantiles were more appropriate, given the heterogeneity in population density across the area of interest.

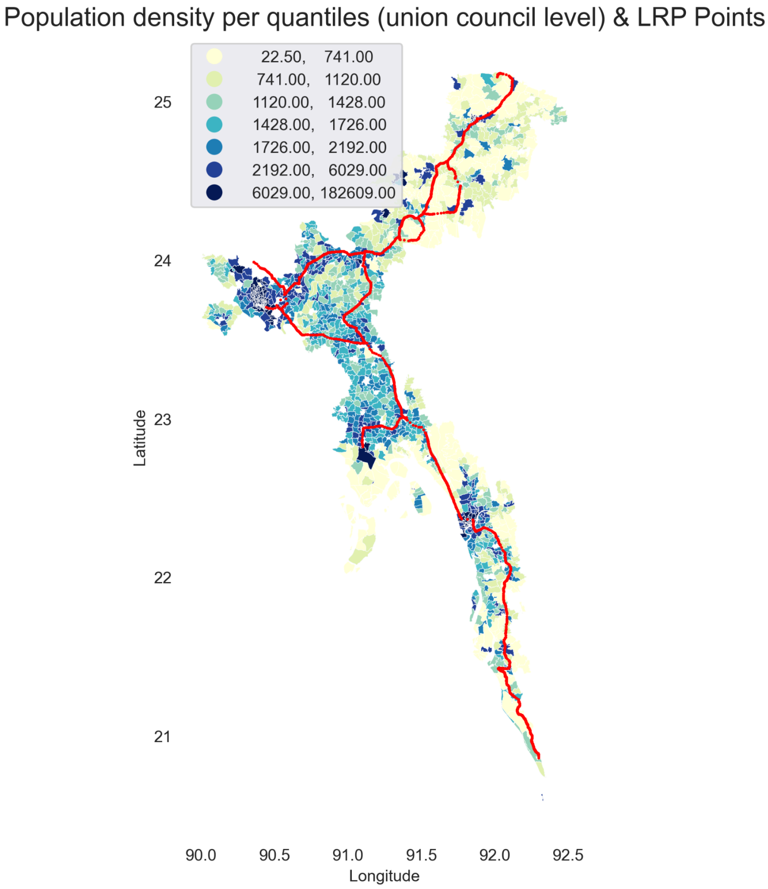

Figure 3.3.1.1: Choromap of the population density at union council level and N1 and N2's LRPs

Finally, these quantile values were added as a new column to the traffic dataset created in the previous method. Each LRP point has been assigned a value from 1 to 7, depending on the quantile it belongs to (see Figure 3.3.1.2). These integer values have been used as weights, together with length, in the next step of the analysis. Based on the length and population density columns, we created a new column that combines 50% weight from both the normalized length and population density.

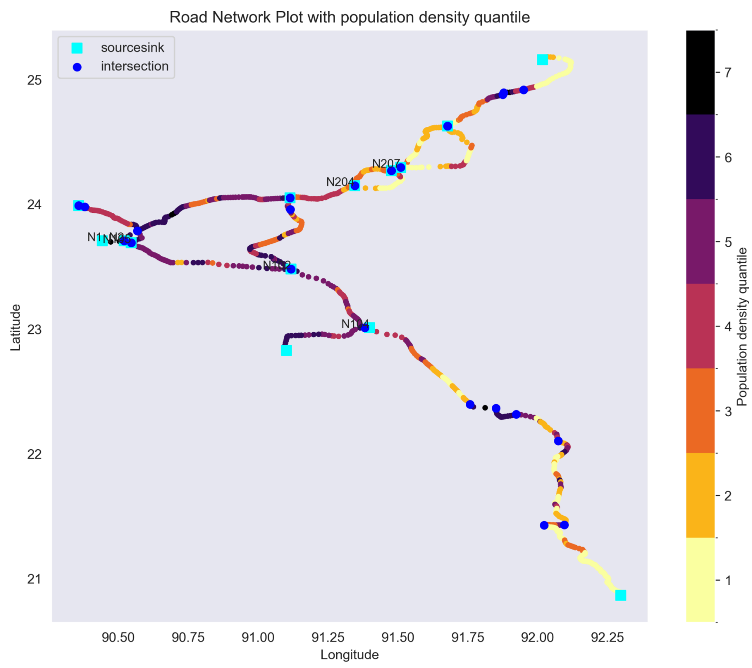

Figure 3.3.1.2: Population density index based on quantiles for N1 and N2's LRPs

3.3.2 Betweenness centrality calculation in network

Implementation

The next step is to calculate based on different weighting methods in NetworkX, by using the Jupyter notebook.

- **5_Network_bridge_rank:** This notebook contains the calculation of betweenness centrality based on three weighting methods.

To evaluate bridge criticality within the road network, we conducted a betweenness centrality analysis using NetworkX. Each road segment was modeled as a node, with edges linking adjacent segments. Centrality was first computed using road segment length as edge weight (see Figure 3.3.2.1), reflecting travel cost and physical connectivity. We then integrated population exposure by assigning quantile-based weights derived from local population density (see Figure 3.3.2.2). Finally, we constructed a combined weight by normalizing and averaging the length and population quantile values, producing a composite score that captures both structural and societal importance.

Figure 3.3.2.1: Network with 10 top bridges with length-based weights

Figure 3.3.2.2: Network with 10 top bridges with population-based weights

The resulting density plot (see Figure 3.3.2.3) compares centrality distributions across the three weighting methods. The population-based and combined approaches yield nearly identical distributions, highlighting the strong role of population exposure in shaping network importance. In contrast, the length-based method shows a distinct distribution, emphasizing physical structure alone. Based on these insights, we adopted the combined weighting method for final bridge ranking, as it offers a more overall assessment of network criticality by accounting for both infrastructure and human impact.

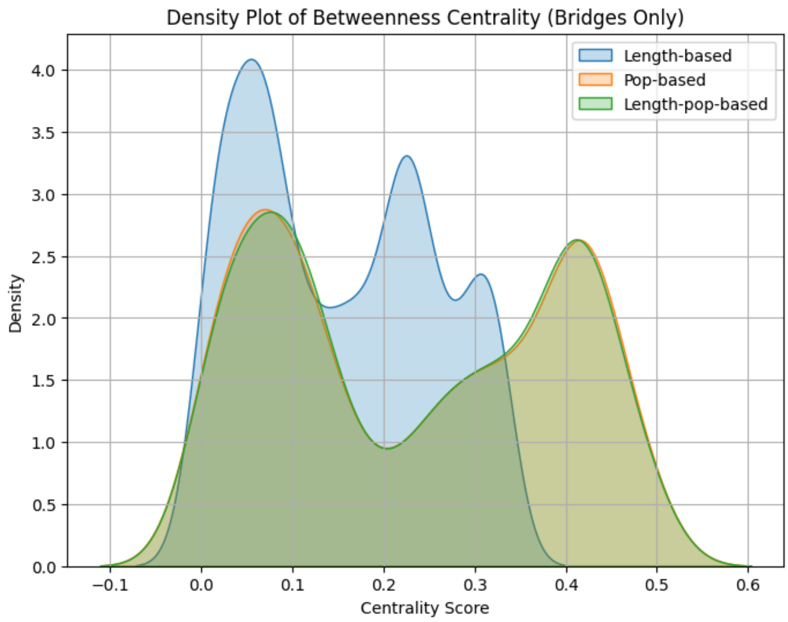

Figure 3.3.2.3: Density plot for three methods

4. Results and Discussion

In this section, we discuss the results of both the simulation and network approach to list the top ten bridges per scenario that resulted in the most critical and vulnerable and assess which bridges should be the target of the investments.

For the simulation-based approach, it is important to note that vulnerability and criticality are used combined. Referring to our definitions in section 2, a bridge is more critical if it provokes a higher accumulated retention of vehicles. In other words, the higher the delay, the more critical a bridge is. These **delays** are calculated based on two scenarios: **Flooding** or **Overcapacity of Heavy Trucks.** These two indicators refer to vulnerability, acting as probability modifiers. Depending on the experiment, the model will calculate the probability of a bridge failing by multiplying the probability modifier with the probability of a bridge failing based on its condition (A, B, C or D).

The accumulation of the delay time is used to evaluate each scenario by capturing the overall impact of a bridge over time. It considers how frequently the bridge is used, reflecting its total contribution to disruption during a given period or event. Each simulation run represents a somewhat realistic traffic pattern, allowing us to assess the cumulative burden caused by a broken bridge. This approach prioritizes understanding the long-term disruption rather than isolated incidents.

For the network-based approach, the importance of bridges is ranked using **betweenness centrality**, which identifies those that are most frequently situated on the shortest paths between key economic areas. This method focuses solely on the criticality aspect, assessing how essential each bridge is for maintaining overall network connectivity.

4.1 Scenarios

4.1.1 Simulation-based

As mentioned before, three scenarios are simulated to better capture the accumulation of delay times per bridge to improve the assessment of which bridges should be the target of the investments:

- **Scenario 0 - No broken bridge**: This is a base scenario in which bridges don`t break.
- **Scenario 1 - Flooding:** In this scenario, the probability of bridge failure is based on the flood category of the region in which the bridge is located. The categories of flooding are listed in Table 3.2.2.2.
- **Scenario 2 - Overcapacity of Heavy Trucks:** The probability is calculated based on the amount of heavy trucks that go through the bridges, increasing the chance of damage.

4.2 Results

4.2.1 Simulation-based

Figure 4.2.1.1 exhibits the distribution of the accumulation of average driving time per scenario. For scenarios 1 and 2, the average accumulation is higher—453.741 and 407.027 minutes, respectively–compared to the base scenario (203.537 minutes), meaning that delays were correctly implemented and that for both scenarios, the accumulation of average driving time is higher. Furthermore, it can be seen that bridges are causing disruptions in the roads, and it takes more time to go from point A to point B.

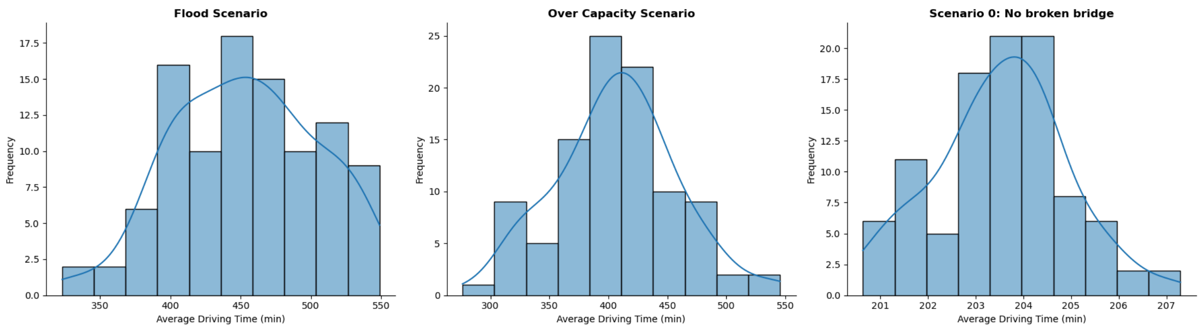

Figure 4.2.1.1: Distribution of Accumulation of Average Driving Time per Scenario

The bridges with the highest accumulated delay time per scenario are presented in Figure 4.2.1.2. Both scenarios show similar accumulation of delay times, being the highest approximately 3500 minutes (≈58 hours) and the lowest 1500 minutes (≈25 hours). It can be inferred that when assessing infrastructure investments, the impact of both over capacity of heavy trucks and flooding is extremely relevant, as these bridges could collapse the overall traffic and stop important economic activities.

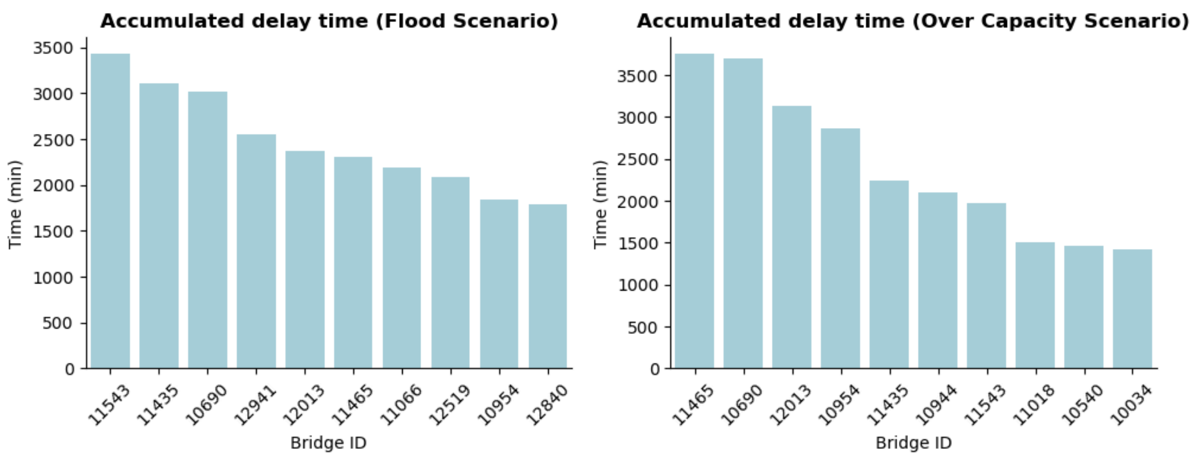

Figure 4.2.1.2: Bridges with the highest accumulated delay time per scenario

4.2.1.1 Model-base + Scenario 1: Flooding

Figure 4.2.1.2 presents the count of bridges per condition and flood index. Most of the bridges (+ 400) are condition A and are not prone to damage by flooding. This means these bridges are less critical and vulnerable, as they don`t need repair, will cause minimal delays in the average driving time and are protected from natural disasters due to their location. For this scenario, bridges with condition A would not be a good target of extensive investment, but can be subject of frequent maintenance check-ups to prevent future damages.

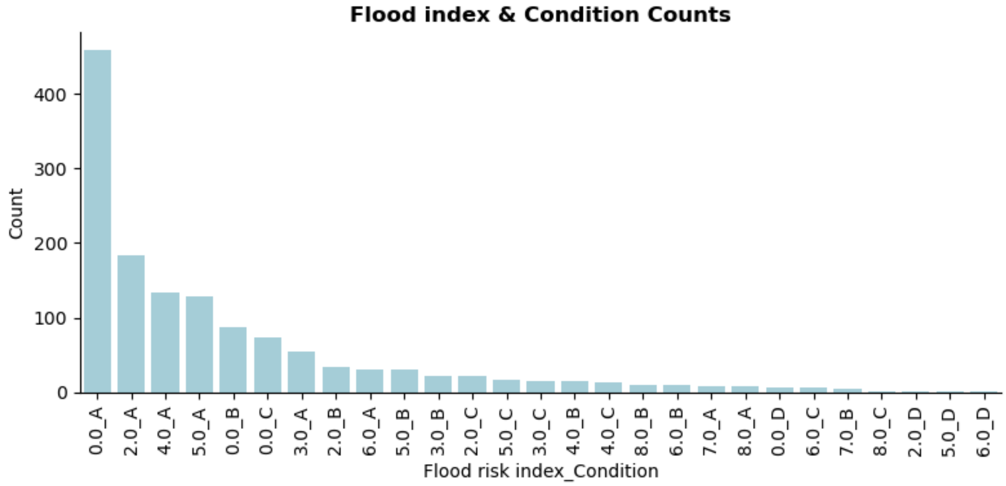

Figure 4.2.1.3: Count of Bridges per Condition and Flood Index

Table 4.2.1.1 showcases the top 10 bridges with the highest accumulated delay time in scenario 1. It is interesting to note that all of them have a condition C or D, meaning that they are already in the early stages of damage or its maintenance is being catalogued as an emergency. Furthermore, the length of the bridges weigh in this outcome, as 5 of them are more than 200 meters long. The remaining 5 ones are shorter, but are all category D. Low and Moderate river flooding—category 2 and 3—as well as low flash flooding -category 6- are the present categories of flooding. It is important to emphasize that 4 of the bridges are not prone to be affected by floods, which might point out that flooding impacts do not weigh as much as bridge condition and length when delaying traffic.

Table 4.2.1.1: Top 10 Bridges with the highest accumulated delay time in Scenario 1

Rank	Bridge ID	Accumulated Delay Time (minutes)	Bridge characteristics		
			Bridge Length (meter)	Bridge condition	Flood Risk Category
1	11543	3436.767	203.75	C	6
2	11435	3112.313	241.61	C	3
3	10690	3020.272	300.0	C	0
4	12941	2557.549	12.7	D	2
5	12013	2366.032	282.35	C	2

Rank	Bridge ID	Accumulated Delay Time (minutes)	Bridge characteristics		
			Bridge Length (meter)	Bridge condition	Flood Risk Category
6	11465	2309.333	428.91	C	3
7	11066	2189.997	12.3	D	0
8	12519	2082.692	48.4	D	6
9	10954	1845.588	61.3	D	0
10	12840	1785.279	13.5	D	0

4.2.1.2 Model-base + Scenario 2: Heavy Truck Over Capacity

The top 10 bridges with the highest accumulated delay time in Scenario 2. As in scenario 1, bridges in this table have a condition C or D and 5 of them are longer than 200 meters. The similarity in both scenarios regarding condition and length overemphasize the importance of these two factors when analyzing the delay times caused by the bridges. The ranked 1 bridge has the highest heavy truck traffic value and it is also the longest bridge. It is interesting to highlight the fact that heavy truck traffic metric goes hand in hand with bridge length and condition, as it will have more effect on the longest or the most damaged bridges.

Table 4.2.1.2: Top 10 Bridges with the highest accumulated delay time in Scenario 2

Rank	Bridge ID	Accumulated Delay Time (minutes)	Bridge characteristics		
			Bridge Length (meter)	Bridge condition	Heavy Truck Traffic (normalized)
1	11465	3760.213	428.91	C	0.358
2	10690	3698.221	300.0	C	0.029
3	12013	3139.347	282.35	C	0.264
4	10954	2857.416	61.3	D	0.020
5	11435	2240.057	241.61	C	0.358
6	10944	2097.870	11.2	D	0.020
7	11543	1969.426	203.75	C	0.168
8	11018	1511.776	15.4	D	0.032
9	10540	1459.127	50.4	C	0.019
10	10034	1418.574	159.52	C	0.143

4.2.1.1 Discussion

The simulation results from both the flooding and overloading scenarios identified the 10 most critical bridges in terms of accumulated delay time caused when a bridge fails. This metric reflects not just the bridge's likelihood of failure (vulnerable), but also the scale of disruption its failure causes in the network (critical). Notably, all bridges fall under either C or D condition.

Bridge 11465 ranks first in the overloading scenario and sixth in the flooding scenario. Its considerable length (428.91 meters) and condition (C) make it both highly vulnerable to truck overload and flood (low risk of river flooding) and highly disruptive if it fails. Bridges 10690 and 12013 also appear in the top rankings for both scenarios, further reinforcing that long bridges in fair condition (C) consistently pose high risk.

Interestingly, a number of short bridges, Bridge 12941 (12.7m), 11066 (12.3m), 10944 (11.2m), and 11018 (15.4m), also appear in the top 10 due to their poor condition (D). This suggests that even small bridges can generate large delays. This emphasizes how criticality, location-wise, can outweigh vulnerability (low risk of flood and overload) in some cases, especially when detours are limited or congested—should be investigated further.

These findings support the modeling logic used in the simulation, where bridge condition, flood risk category, and heavy truck traffic volume act as vulnerability indicators, while bridge length functions as a measure of criticality. The simulation thus reflects the dual impact of how likely a bridge is to fail and how severe the consequences would be if it does. The data shows that some bridges rank high due to high vulnerability, some due to high criticality, and some due to both—justifying the integrated approach used in the simulation.

From a planning perspective, the results help prioritize which bridges may need more urgent reinforcement, or alternative routing strategies. Bridges like 11465, 10690, 12013, 10954, 11543, and 11435 emerge as top candidates for priority maintenance due to their consistently high impact across multiple hazard types—appear in both rankings. Meanwhile, bridges like 12941, despite being short, reveal network fragility in areas with moderate river flooding and may not have alternate routes. These insights can inform risk-based investment decisions, emphasizing the importance of not only structural upgrades but also network-level planning.

4.2.2 Network-based

In Table 4.2.2.1, we can observe that all of the top-ranked bridges are situated along the N1 road, a major national route in Bangladesh. Their IDs are sequential, ranging from 10160 to 10178, and their latitude and longitude coordinates are closely spaced, indicating that they are clustered within a specific segment of the road. This suggests a critical corridor where multiple bridges serve the same continuous, high-demand route. The population density values, reaching up to 5,434 people per square kilometer, reinforce the idea that these bridges are vital for economic and social connectivity in densely populated urban areas. Therefore, based on this static metric, which considers both network structure and socio-economic factors, the bridges listed along the N1 road (see Figure 4.2.2.1) should be prioritized for resilience planning.

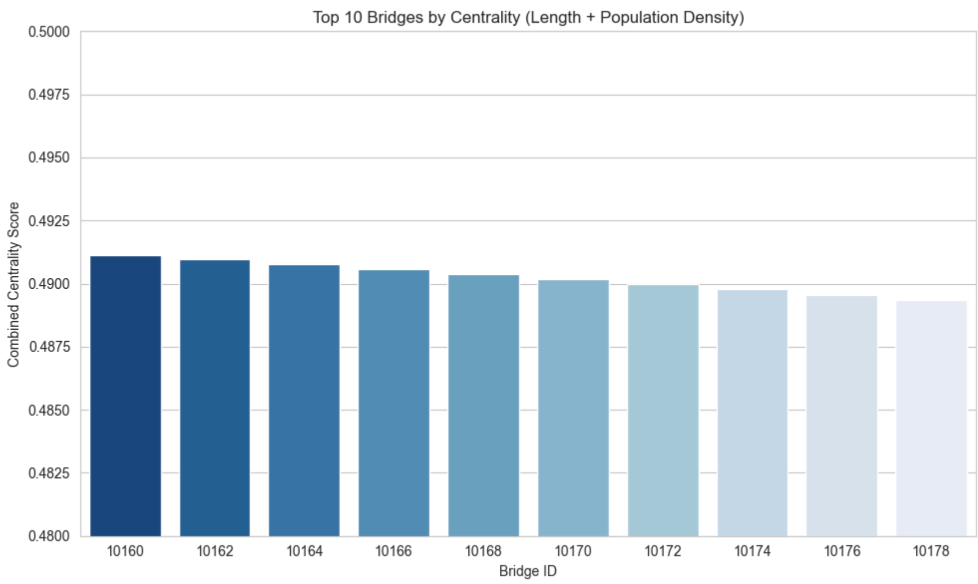

Figure 4.2.2.1 Top 10 bridges with network-based metrics

Table 4.2.2.1: Top 10 bridge information with network-based metrics

Rank	Bridge ID	Betweenness Centrality	Bridge characteristics		
			Road	**Population density (people per sq. km.)**	**Length (m)**
1	10160	0.49115	N1	5434	1.4
2	10162	0.49095	N1	5434	2.9
3	10164	0.49076	N1	1971	23.4
4	10166	0.49057	N1	1971	35.97
5	10168	0.49037	N1	1971	27.35
6	10170	0.49017	N1	1971	27.9
7	10172	0.48997	N1	2140	30.48
8	10174	0.48977	N1	1253	22.8
9	10176	0.48956	N1	1874	14.3
10	10178	0.48935	N1	1874	24

5. Conclusion

Based on the results gathered from experiments shown in section 4, the simulation-based and network-based approaches, a **hybrid prioritization strategy** is recommended to assess the investment of transport infrastructure in Bangladesh. This proposal acknowledges that each approach provides valuable but distinct insights into the vulnerability and criticality of bridge infrastructure.

The simulation-based model identifies bridges that generate significant delays under stress scenarios—exposition to flooding or heavy truck overcapacity. Notably, the bridges, 11465, 10690, 12013, 10954, 11543, and 11435, appear on both simulated scenarios, signaling their dual importance in terms of traffic disruption when it comes to exposure to natural disasters and heavy truck traffic. These bridges should be top candidates for urgent reinforcement, targeted maintenance, or even structural upgrades**,** particularly due to their length and conditions. Furthermore, the model approach also reveals that shorter bridges in poor condition (condition D)—such as 10944, 11018, and 12941—can have a disproportionate impact on overall mobility, hence should also be taken into account as targets of investment.

The network-based approach further points to the **N1 road** as vital for Bangladesh economical activities. The high-betweenness bridges presented in the analysis bridging densely populated areas. These bridges should be frequently monitored to ensure smooth movement of goods, hence a portion of the investment should also be allocated to them.

In conclusion, investment should prioritize bridges that are in poor condition and critically positioned—particularly those of considerable length and poor condition—as these have the greatest potential to disrupt mobility. Additionally, regular maintenance and monitoring should be ensured along the N1 corridor, given its strategic importance for national connectivity and economic activity. By integrating simulation-based risk assessment with network-criticality analysis, this study provides a nuanced and practical framework for identifying the most vulnerable and impactful bridges within the N1 and N2 network. Such a hybrid modeling approach can support more targeted and cost-effective infrastructure planning, ultimately contributing to a more resilient transportation network across Bangladesh.

Based on the results of the analysis, two policy recommendations are assessed:

- **Prioritize Rehabilitation of Long and Deteriorated Bridges**
  Allocate resources to rehabilitate and upgrade bridges that are both structurally deficient (C and D condition) and longer in length, as they pose a higher risk of mobility disruption, particularly during flooding and overloading events.

- **Establish Routine Monitoring for Critical Routes**
  Implement a monitoring and maintenance program focused on majorly connected corridors such as the N1, ensuring the reliability of economically vital transport routes and preventing unexpected disruptions.

6. Reflections

An Utilitarian Approach

Throughout this analysis, we have exclusively used a utilitarian approach. In the first metric—the simulation-based one—we focused solely on heavy trucks, prioritizing the movement of goods. In the second metric—the network-based one—we used population density as our economic proxy. This means that several social considerations have been overlooked in our evaluation. For instance, the connection of smaller villages to the main road has not been classified as critical. In our current metrics, a village with low goods transport and connected to the infrastructure by only one bridge is not considered critical. However, if that bridge were to fail, the consequences for the inhabitants would be considerable. In this sense, we have adopted a macro-level perspective.

Simplifications and assumptions

First, in the simulation-based analysis, the flood scenario assumes that all bridges along the N1, N2, and their adjacent road networks are simultaneously exposed to flooding. Similarly, in the overload scenario, all bridges are considered equally at risk due to heavy truck traffic occurring at the same time. In reality, such uniform exposure is unlikely; flood intensity and traffic patterns vary both spatially and temporally. Incorporating weather patterns, real-time flood extents, and traffic dynamics through time-series data would enhance the accuracy and realism of the model.

Second, a constant speed of 48 km/h is used for these vehicles, based on the official 50 km/h speed limit for goods-laden trucks in Bangladesh (The Daily Star, 2023). However, this simplification may not reflect variations in speed due to congestion, road conditions, or vehicle type.

Third, the model is currently limited to the N1 and N2 segments, which, although critical, do not represent the entire national road network. Including other national, regional, and local roads in future simulations would provide a more comprehensive picture of network vulnerability and criticality.

Lastly, as stated earlier, the network-based analysis relies on population density as an economic proxy. While this assumption has proven to be reasonable, it remains limiting. Moreover, the available data is from 2011. It is likely that these figures have changed over the years, although the trend towards greater urban development at the expense of rural population is expected to have continued.

Future research

In future work, it would be interesting to follow an egalitarian approach. Doing so would likely lead to radically different conclusions. Additionally, increasing the number of replications would enrich the results. We consider that one hundred replications illustrate the overall picture reasonably well; nevertheless, in order to confidently identify the top ten critical bridges using an ABM model, stochasticity should be further addressed with more replications.

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Acknowledgement

The use of AI

Use of AI in Code Development: In this assignment, AI tools such as GitHub Copilot and ChatGPT were used to improve code quality and generate ideas for implementation. These tools assist in structuring code, suggesting optimizations, and debugging issues. However, AI's role was strictly supportive—we conducted final decisions, implementations, and refinements to ensure accuracy and adherence to project requirements.

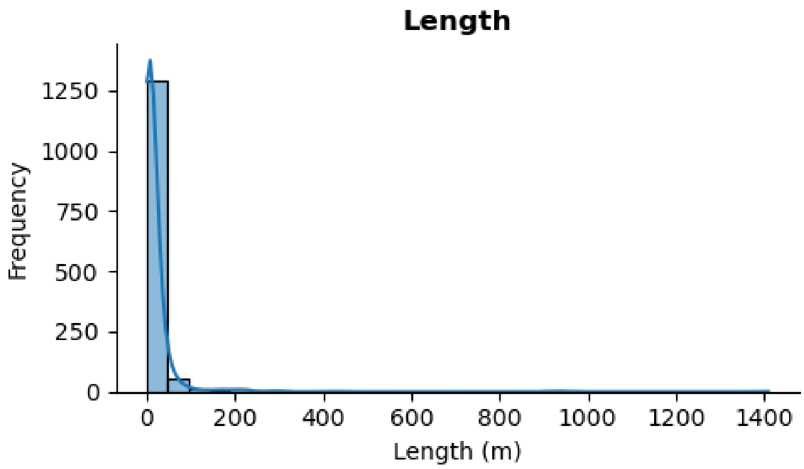
Use of AI in Writing and Editing: ChatGPT and Grammarly were used for text improvement, helping refine clarity, coherence, and grammatical correctness. It assisted in brainstorming alternative phrasings and ensuring correct writing standards. However, all AI-generated suggestions were critically reviewed, modified when necessary, and integrated into our work only after careful validation. This approach ensured that AI served as a tool rather than a replacement for our original analysis and insights.

Contribution of each member

Member	Contribution
Rachel Delvin Sutiono	- Simulation-based analysis - Report
Celia Martínez Sillero	- Network-based analysis - Report
Daniela Ríos Mora	- Simulation-based analysis - Report
Thunchanok Phutthaphaiboon	- Simulation-based analysis - Report
Yao Wang	- Network-based analysis - Report

Appendix

A. **Bridge length distribution**



B. **Bridge heavy truck traffic distribution**