# Robustness of Urban Coastal Rail Network under Projected Future Floods

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Recent events suggest weather extremes are becoming more frequent and intense under a changing climate. The floods of the future, in all likelihood, will be more severe, causing substantial damage to human lives and critical lifeline systems such as urban transportation networks. With an aging infrastructure and rising climate risk, a research hypothesis to examine is how much of the increased climate risk will translate to critical lifeline systems downstream, especially in urban areas where exposure is the highest. In this work, we develop a resilience framework blending statistical analysis of weather extremes and network science-based modeling of impacted systems. Two major urban rail networks in the US - Boston and Washington DC - are considered case studies. This study aims to evaluate quantitatively how a future flooding scenario might impact the respective networks in terms of loss of functionality. The insights generated can help stakeholders in data-driven decision-making and adaptation strategies. Furthermore, the framework developed can be generalized to other types of weather extremes and critical networks for similar evaluation studies.

Key Words and Phrases: Extreme value theory, tidal flood, interconnected lifeline network, urban rail transportation system(URTS) network

## 1 INTRODUCTION

Floods are the most catastrophic natural disasters in many areas and nations, wreaking havoc on people's social and economic lives [16]. Floods can be caused by climatic phenomena such as extremely prolonged rainfall, a combination of high tides and raised sea levels, big waves linked with storm surges, changes in landuse and population, and land subsidence. Combination of river and tidal floods are common, particularly in the lowland (coastal urban) region [5]. As a result, the urban decision maker need information on river and tidal floods, such as geographical distribution, flood size and depth, and vital infrastructure damaged by flooding. A number of studies have been conducted on the flood hazard issue [8, 14, 18]. Nonetheless, decision-makers must consider the impact of future floods on current infrastructure to maintain resilience.

Lifeline Infrastructures provide facilities and services to people living in metropolitan settings [11]. The primary means by which the civilization maintains life and well-being are vast networks of energy, water, waste, transportation, landscapes, and communications. While society's need for infrastructure systems is widely understood, much focus should be placed on improving infrastructure systems' ability and resilience to provide the appropriate level of service. Urban rail transit systems, often known as metrorail or metro systems, are important transportation infrastructures that have attracted a rising number of passengers across the world by making urban mobility easier. City expansions, increasing urbanization, and economic prosperity have all benefited from urban rail transit networks. In turn, urbanization has accelerated the creation and expansion of metro systems, adding to their complexity. In a network-based architecture, every disruption of network components has a detrimental influence on overall system flow and network resilience [13]. Disruptions or even minor disturbances in a complex system might limit its functionality and put have a significant impact on commuter safety, as well as direct and indirect costs.

The structure of a metrorail system's network offers a foundation for assessing its functionality. A metrorail system has many of the same characteristics as a network [15]. It is made up of nodes (stations) and edges (links) which are the necessary elements for defining a system in a network form. The efficiency with which a network performs its functions is influenced by its structure. Many parts of the network's functional goals may be addressed by studying its structure, such as assessing significant nodes, recognizing the existence of nodes with high node degree, and analyzing the effects of network assaults or disruptions. High rainfall intensity combined with an inadequate urban drainage infrastructure causes local flood inundation and river flooding [10]. Meanwhile, tidal floods occur when high tides overwhelm coastal land [19]. Every year, the impact of tidal floods grows. This is due to the industrial developments replacing naturally flooded regions and replacement with impervious areas. These issues are also linked to the subsidence of lowland areas. This research focuses on the vulnerability and effect assessments of future floods, specifically the degrees of flexibility and capacity to maintain the survival of important functions even in the face of cascade failures, utilizing methods from network science. The primary idea we utilize to analyze the network robustness is vulnerability under different flooding situations.

Therefore, this research attempts to combine both climatic threats such as tidal floods and their influence on vital infrastructure like URTS networks in the Washington, DC metropolitan region and Boston area by: (a) analyzing tidal water level extremes over different future time periods (b) creating a flood vulnerability map to analyze fragile URTS stations c) looking at the effects of tidal flooding on existing URTS networks. Furthermore, by identifying fragility and tradeoffs of prioritizing in increasing resiliency measures using different scales in flood vulnerability assessments, this research will provide decision makers with a clear understanding of the impact of future floods on existing complex networked infrastructure.

## 2 DATA AND STUDY AREA

In this study, tidal water level data is used to create flood map. Data is extracted from Center for Operational Oceanographic Products and Services, National Oceanic and Atmospheric Administration [17].

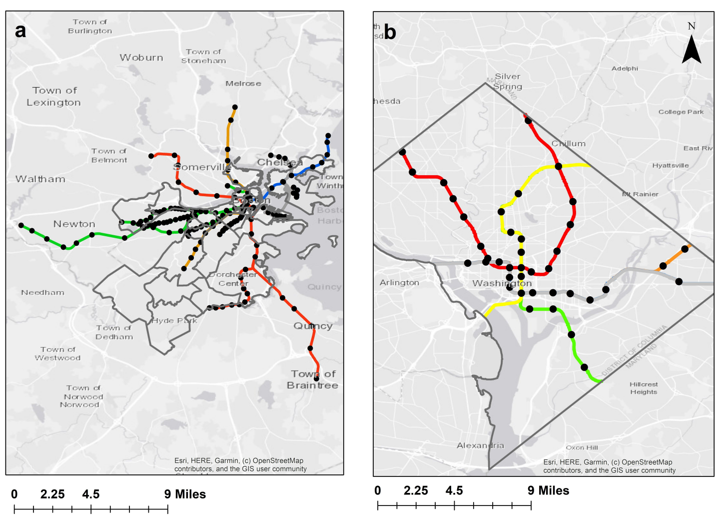


Fig. 1. Urban Coastal Rail Network a) Boston MBTA (https://www.mbta.com/maps) and b) Washington DC Metro Network system (https://www.wmata.com/schedules/maps/).

Recent NOAA study shows, most long-term trends point towards persistent sea level rise. Our focus for this work is two major urban areas of US, Washington DC and Boston. Both these cities have two urban rail transit system which are within top five busiest metro networks in USA [1]. NOAA's data is collected via an integrated system of real-time sensors based at major seaports, as well as temporary meters that collect observations for tidal current forecasting. The dataset contained monthly tidal water level in Boston and Washington DC from 1950 to 2022. Annual maximum water levels were calculated using monthly data to execute a extreme value analysis. Extreme Value Theory(EVT), one of the most used statistical approaches, was employed in this work to represent the maxima of a stochastic variable. This is frequently used to explain unusual phenomena, especially climatic events. EVT evaluates the tail of the examined parameter distribution, defining the extreme values. The Block Maxima or Peak Over Threshold (POT) methods are typically used to generate extreme results. When it comes to block maxima, it's commonly assumed that they follow an extreme value distribution quite closely [7]. This method splits the time horizon into blocks or periods and evaluates the maximum value of the variable throughout time, with these selected observations forming the extreme occurrences. The annual maximum tide water level was computed using NOAA data, and this data set contains extreme values. Following that, return levels for 100-year return periods were calculated. The flood map for Boston and Washington DC was created using 10 year and 100 year return levels derived from all of these return period values. The Figure-1 shows Boston MBTA and Washington DC Metro network with all the lines(edges) and stops(nodes).

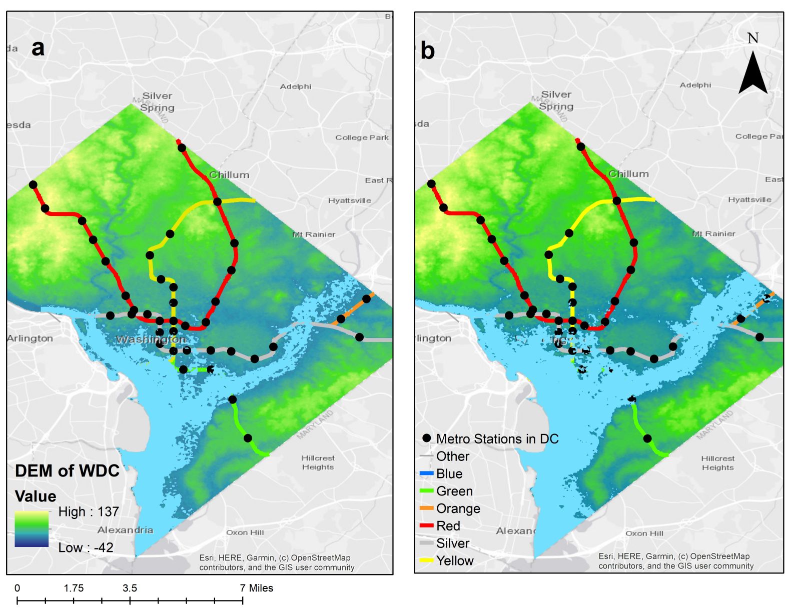


Fig. 2. Inundated regions in Washigton DC area due to tidal flooding for a) 10 year return level and b) 100 year return level. Blue areas have lower elevation and green area have higher elevation.

Digital elevation models (DEMs) are digital images that depict the height of the earth's surface. Each pixel contains an elevation value for the pixel's center point. The DEM data for both cities was collected from the Shuttle Radar Topography Mission (SRTM, courtesy of the U.S. Geological Survey) synthetic sperture radar data and has a spatial resolution of 30 meters. Return levels from EVT analysis was deployed on DEMS to visualize inundated places in both the cities. Figure-2 shows mostly areas close to the river and Virginia are tidal flood prone area. For a 100 year return value the flooded area increases near the river and in the east side. The elevations of URTS stations that were inundated were sorted, with the lowest elevation being the most vulnerable node. The nodes that were not inundated were grouped according to their distance from nearest river bank (closest one is more vulnerable). Flood-vulnerable nodes were detected using this method.

The network data for stops and linkages was gathered from the websites of the respective metro authorities. Then, using Python's Networkx [9] package, they were converted into the necessary format to construct a network. Even though Washington DC network is comparatively smaller in size than MBTA but it's one of the busiest URTS in USA. The average number of edges per node in the graph is called average degree. Given the structure of the nodes, one connection goes out and one goes in, URTS typically has an average degree of around 2. However, there are nodes in both of these networks that have greater connections. Because the MBTA Silver Line is not a rail system, it was not considered in this study. A summary of these two is shown in Table 1.

Table 1. Urban Rail Transportation Networks (URTS) Analyzed in the Study.

| **URTS Networks** | **Number of Nodes** | **Number of Edges** | **Average Degree** | **Largest Nodes Edges** |
|---|---|---|---|---|
| Washington DC Metro | 91 | 93 | 2.046 | 5 |
| Boston MBTA | 107 | 109 | 2.037 | 4 |

A substantial fraction of climatic extremes are precipitation-related extremes, which have huge implications on our civilization, ecology, and environment [12]. The World Climate Research Programme (WCRP) created the Coupled Model Inter-comparison Project (CMIP) to provide standardized climate simulation outputs for comparison among global circulation models (GCMs) from various modeling organizations throughout the world. The CMIP project has progressed to the sixth phase, and the CMIP6 models have been improved in terms of resolution and parameterization, and they now include more biogeochemical processes [6]. For the two cities, precipitation extremes from Canadian Centre for Climate Modeling and Analysis model Can-ESM have been analyzed for two different time periods, 1965-2014 and 2015- 2064. Analysis shows the return levels changes substantially in the upcoming year yielding 100 year return level to 20-40 year return level in the upcoming years. These extremes can get combined with coastal surge, tidal water level and other climate events putting the cities in greater risks [21]. The below Figure-3 shows how the extremes are projected to change in upcoming years.

## 3 RESULTS AND DISCUSSIONS

Data on annual tidal water levels in both cities from 1950 to 2022 indicates an upward trend. Figure-4 shows yearly water levels and extreme value distribution results. This is a probabilistic worst-case scenario for the two cities that occurs at the tails of the distribution.

10 year and 100 year return levels were obtained from the EVT analysis on tidal water level data. The return levels are summarized in table-2.

Boston's tidal water level is higher than DC's over the next 10 and 100 years, placing it at greater risk. Flood maps were developed using these return levels and a digital elevation model for both cities to undertake vulnerability evaluations on soft lifeline infrastructure systems like URTS. The resilience of a network given the failure of a portion of its nodes

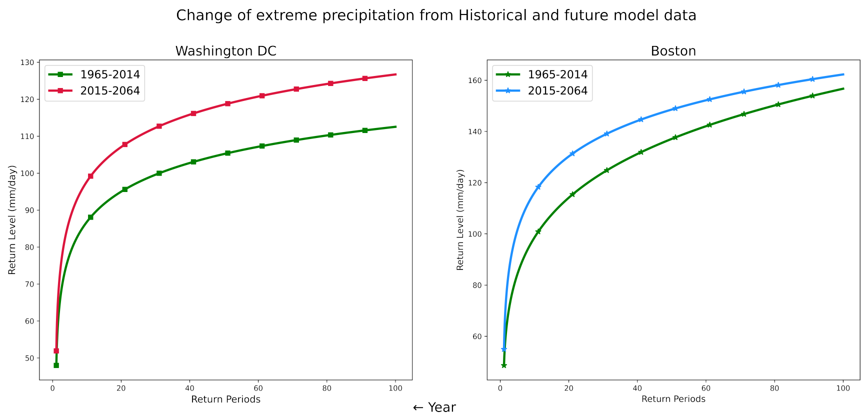


Fig. 3. Historical and model projected(Can-ESM) precipitation extremes for 100 years using extreme value analysis.Data obtained from CMIP6 archive. https://esgf-node.llnl.gov/projects/cmip6/

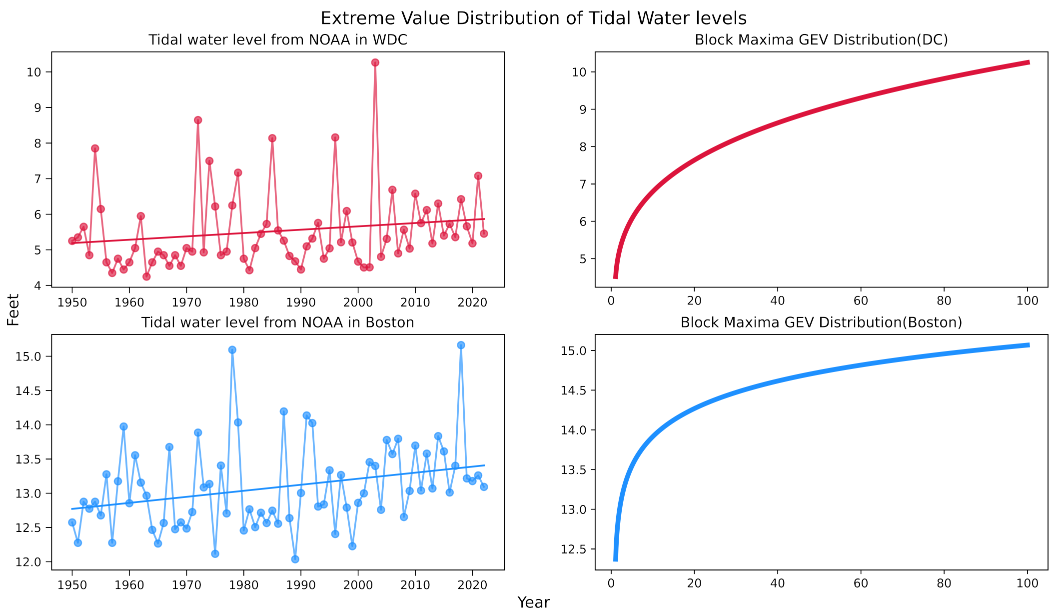


Fig. 4. Tidal water level data from NOAA showing an increasing trend over years with extreme value distribution over 100 year return periods.

Table 2. Return Levels of 10 Year and 100 Year using Block Maxima Method.

| URTS Networks | 10 Year Return Level (ft) | 100 Year Return Level (ft) |
|---|---|---|
| Washington DC Metro | 6.89 | 10.25 |
| Boston MBTA | 13.96 | 15.08 |

is one of the most commonly researched features in network science [2, 3, 20]. The giant connected component (GCC) is used as a proxy for network functionality, and resilience is measured by how much the GCC size changes before and after a failure. The resilience of the URTS networks is evaluated in terms of the relative size of the giant connected component (GCC) following successive node removal under various interruptions in this study. Nodes were sorted in more vulnerable to lower vulnerable form for both the URTS based on the elevation values of the stops and their distance from the flooded zone. The failure analysis was then carried out by removing nodes in sorted order keeping a trace of GCC. Most vulnerable nodes are considered having lowest elevation and close to rivers.

Table 3. vulnerable stations in the URTS networks.

| **Washington DC Metro Node/Station** | **Boston Metro Node/Station** |
|---|---|
| Arlington Cemetery Metro Station | Aquarium |
| Cleveland Park Metro Station | Airport |
| L'Enfant Plaza Metro Station | Assembly Square |
| Waterfront | North Station |
| Crystal City Metro Station | Kenmore |

As we are looking through giant connected component lens for the connectivity performance of the metro, individual stations lying at the end of a specific metro line might have less impact on the connectivity loss, but that station might have substantial impact of it's own on ridership.

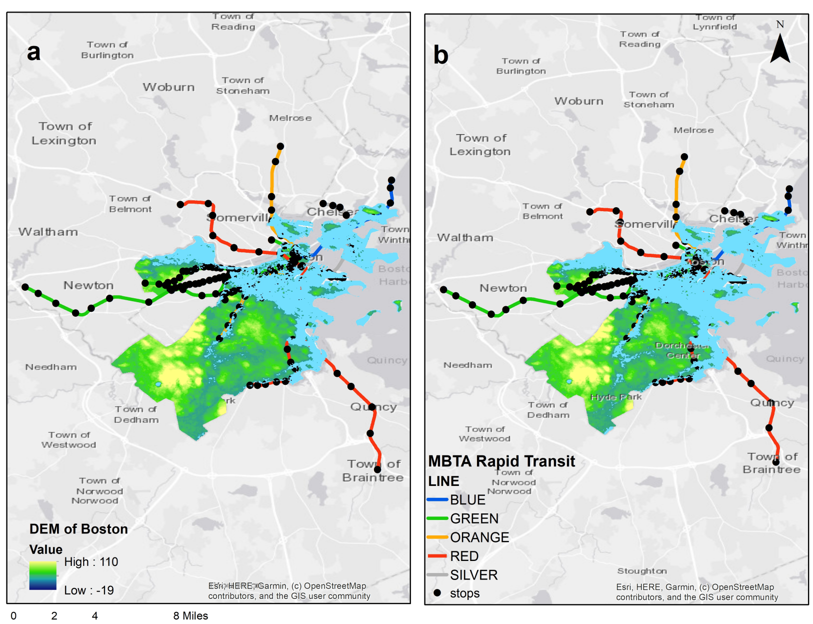


Fig. 5. Inundated regions in Boston area due to tidal flooding for a) 10 year return level and b) 100 year return level.

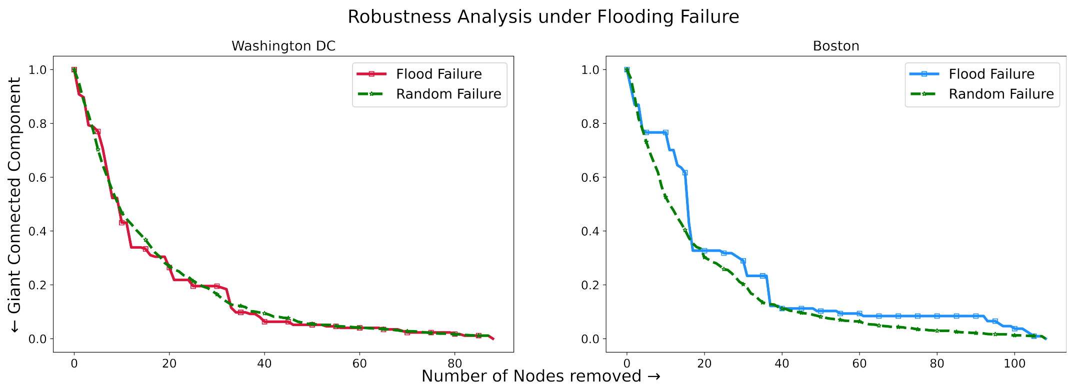


Fig. 6. Robustness of the two urban rail transportation networks (URTS) under flooding failure. The y-axis refers to the relative size of the giant- connected component (GCC) as the network fails and x-axis includes the number of nodes (stations) failed till that point. The performance of each URTS is compared with average random failure profile. Robustness is defined as the area under the curve (AUC), i.e., a lesser AUC (faster degradation) reflects lower robustness

Figure-6 illustrates that eliminating 10 nodes from the Washington DC metro reduces connection by around 50%, whereas losing 10 nodes from the Boston metro reduces connectivity by approximately 25%. The cause for the loss of connection is determined by the location and relevance of the nodes that have been deleted. Because the GCC is a performance indicator in this analysis, nodes with fewer linked nodes will have a less influence on the GCC. However, the nodes that are removed may have a higher socioeconomic influence on commuting.

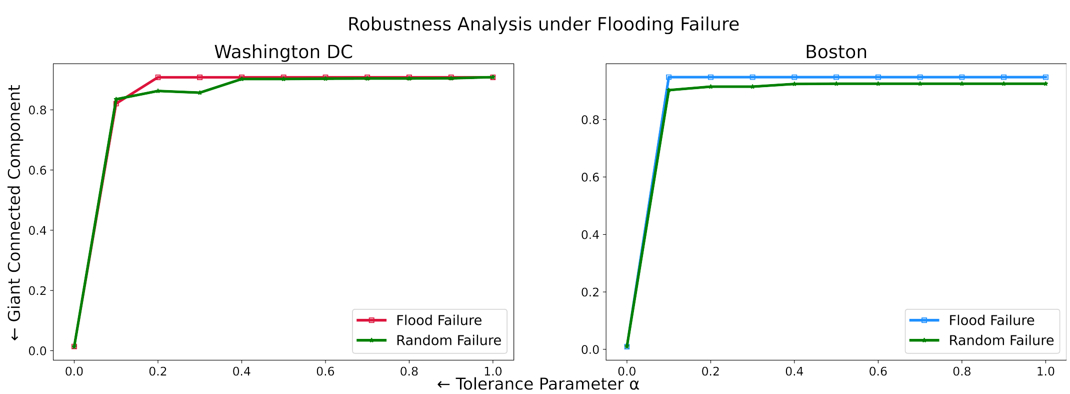


Fig. 7. Robustness of the two urban rail transportation networks (URTS) under removal of one node due to flood. The y-axis refers to the relative size of the giant-connected component (GCC) as the network fails and x-axis covers the tolerance parameter $\alpha$ (range 0-1).The performance of each URTS is compared with average random failure profile. A higher remaining GCC for the same value of $\alpha$ points to higher robustness

After that chances of cascading failure by removal of one node was investigated. To start with, only one node is withdrawn from the network, and the node is chosen based on the risk of tidal flooding. After then, that node's load is dispersed among its neighbors.Load of each node has been considered proportional to betweenness centrality of individual nodes [4]. GCC remains constant if the node can withstand the overload. If a node becomes overcrowded or cannot resist the load from nearby nodes, it will be removed from the network immediately. If a station's updated load exceeds its capacity limit, the station will fail, causing a large portion, if not the whole URTS, to fail. The tolerance parameter, which is comparable to the network's safety factor, is represented as a function of network robustness in terms of GCC. The Figure-7 shows for high tolerance parameter value there is not much chance of cascading failure in both the networks however if the extra load bearing capacity approaches close to 0.2, Washington DC metro network may become susceptible to cascading failure losing functionality of the whole network.

## 4 CONCLUSION

In this work, we have developed a climate resilience framework for urban lifeline systems such as interconnected transportation networks. Using future projections (2015-2064) from the Can-ESM global climate model, we observe that 100-year precipitation return levels for Washington, DC, and Boston are expected to increase by approximately 25% and 10%. In other words, more intense precipitation events will, in all likelihood, translate to higher floods in the future. Based on this insight, we develop probabilistic flood maps for the two cities (Boston and Washington DC) using the future return levels and digital elevation models (DEMs) to estimate the increased risk on the rail networks in the respective cities. We demonstrate how disparate tools can be brought together for quantifiable climate adaptation, from statistical risk analysis to network science-based system modeling. Lastly, the proposed framework is generalizable to other types of lifeline networks (e.g., power grids) and climate hazards of the future.

## 5 ACKNOWLEDGEMENT

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