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A Risk-Informed Decision-Making Framework for Coastal Railroad System Subjected to Storm Hazards



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Executive Summary

A team of researchers from Michigan Technological University's Department of Civil, Environmental, and Geospatial Engineering, in collaboration with Argonne National Laboratory, conducted this study from May 2022 to July 2025. The researchers aimed to identify and mitigate risks of tropical storms affecting railroad infrastructure along the Gulf of America. The study focused on two of the most critical tracks owned and operated by CSX Transportation and CN Railway in the Northern Gulf of America (NGOA). The CSX's line is approximately 184 miles between Mobile, Alabama, and New Orleans, Louisiana; CN's track is about 27 miles, stretching from New Orleans, Louisiana, to Manchac, Louisiana. The findings of this research can help decision makers devise mitigation and retrofit strategies to minimize the risk of storm surge and waves to coastal railroads.

The research developed a comprehensive risk-based framework to estimate the impact of storm-induced surge and wave hazards on coastal railroads along the NGOA coastline. The model used a large synthetic storm dataset that overcomes the limitations of historical data and accurately and efficiently accounts for uncertainties in the frequency and intensity of future storms. The research team integrated a physics-based high-fidelity hydrodynamic model to simulate the storm surge and waves generated by tropical storms. The simulations include projected future storms and datum adjustments for the year 2050. The research team then integrated the probabilistic hazard model with a statistical model that assesses the failure probability of railroad track components to determine the probability of failure of tracks and bridges. The analysis focused on critical failure scenarios, including the washout of tracks due to ballast and embankment scour and the uplift of ballasted bridge decks. The failure probabilities were used within a statistical analysis to determine the expected life of tracks and bridges and to devise mitigation strategies that can increase the expected life of coastal tracks and bridges.

1. Introduction

The research team at Michigan Technological University's Department of Civil, Environmental, and Geospatial Engineering and Argonne National Laboratory leveraged their diverse backgrounds in storm hazard modeling, vulnerability assessment for natural hazards, and railroad operations to conduct a study from May 2022 to July 2025 to develop a risk-informed decision-making framework for coastal railroad systems subjected to storm hazard. The team developed a framework to analyze vulnerabilities and to increase performance levels for coastal railroads with respect to severe storm conditions. The risk analysis was conducted on segments of coastal railroad owned by CSX Transportation (CSX) from Mobile, Alabama, to New Orleans, Louisiana, and CN from New Orleans to Manchac, Louisiana.

1.1 Background

As train dynamics place restrictions on steep gradients and rapid grade changes, railway corridors are often placed in locations with modest grades and grade changes, such as riverbanks and coastal areas. While these locations provide smooth gradients, they also make corridors prone to storm-induced interruptions and damages (Tsubaki, Bricker, et al. 2016). Figure 1 shows examples of such incidents, which can include the inundation of track structure that causes operational restrictions, damage to tracks due to scour in the embankment or ballast, and damage incurred in rail bridges due to erosion of abutments, scour in piers, or uplift of ballast decks. Due to delays in passenger and freight transport and repair costs, these incidents cause significant direct and indirect economic losses or even losses of human lives through track-deterioration-caused incidents.

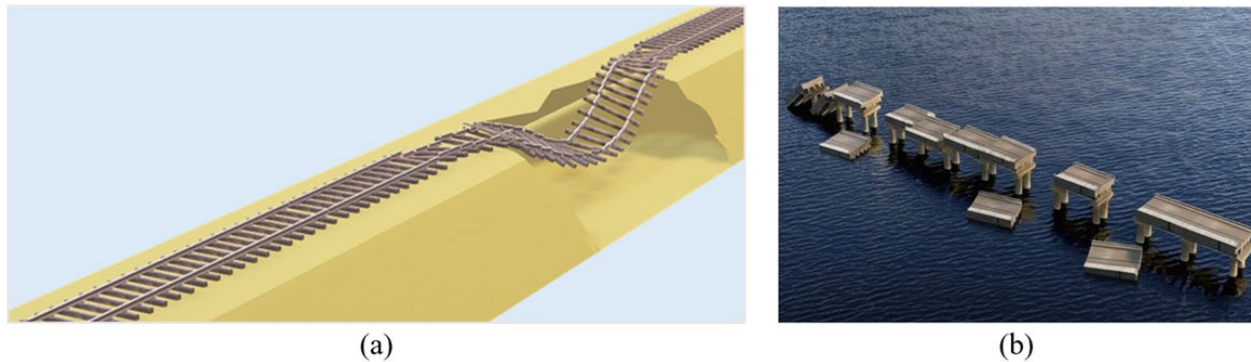


Figure 1. Failure of rail system after Hurricane Katrina, 2005: a) track washout and b) uplift of bridge decks

One of the coastal regions historically affected by storms is the Northern Gulf of America (NGOA). According to Trepanier et al. (Trepanier and Scheitlin 2014), between 1885 and 2010, more than 52 weather-related hazard events passed through the region. The NGOA coast has one of the largest rail systems in the country where all six major Class I railroads operate. The New Orleans railway hub serves as the interconnection between the Eastern and Western railroad systems (Grenzeback, Lukman et al. 2008). In New Orleans, CSX Transportation interchanges more than 1,000 railcars per day with the western railroads. Any disruption in this hub immediately disrupts the rail system in the United States writ large. For example, CSX Transportation was significantly affected by Hurricane Katrina (2005), where two-thirds of the tracks between Mobile and New Orleans and a large number of bridges between New Orleans

and Biloxi were damaged (Grenzeback, Lukman et al. 2008). To return the railroad to a safe operating condition, CSX Transportation restored five bridges and more than 40 miles of washed out tracks, imposing more than \$300 million in repair costs (Grenzeback, Lukman et al. 2008). In addition, the major rail hub in New Orleans was significantly damaged and needed considerable repair and reconstruction. Other rail companies also observed damage but not as significant as CSX Transportation. For example, Norfolk Southern's line into New Orleans experienced track washouts for approximately 5 miles of its tracks. There were also some damages in Union Pacific, BNSF Railways, Kansas City Southern, and Canadian National Railway (CN) (Grenzeback, Lukman et al. 2008).

Considering the importance of the rail system in freight and passenger transport and the direct and indirect costs that failure in rail system incurs, identifying vulnerabilities and devising mitigation solutions is paramount. In the upcoming decades, this vulnerability is expected to be further exacerbated in coastal regions due to the water datum adjustments and non-stationary storm effects that significantly increase the severity and frequency of future storms. For example, in the Louisiana coast, the water level datum is expected to rise by up to 84 inches by the year 2100 (2021), and along the Florida coast, the datum is projected to rise by up to 92 inches by the year 2120 (2019). This level of change could either completely inundate the current railroads or, when integrated with future storm events, incur significant damage to the coastal railroad system.

1.2 Objectives

The objective of this project was to develop a risk-informed decision-making framework to improve the current and future performance of the coastal railway system against storm hazards. The outcome of this work could be used by rail companies to identify vulnerable segments of the railroad system and to provide retrofit solutions to mitigate the vulnerabilities in the coastal rail system. CSX Transportation and CN are industry partners in the project and have provided the necessary data and input for the analysis.



Figure 2. Testbed railroad for the project spanning from Mobile to New Orleans (owned by CSX Transportation), and from New Orleans to Hammond (owned by CN)

1.3 Overall Approach

First, the team developed a probabilistic hazard model for storm surge and wave hazards along the NGOA coastline. This model utilized a large dataset of synthetic tropical cyclones to account for the uncertainties associated with storm intensity and frequency, including the effects of non-stationary storms. The team selected a representative subset of these storms using a maximum dissimilarity approach (MDA) (Costa, Bertolini, et al. 2020) to ensure computational efficiency while capturing hazard variability. The team then used the ADCIRC+SWAN (Guisado-Pintado 2020; Luettich and Westerink, 2023) to simulate storm surge and waves for the selected storms, incorporating projected water datum adjustments. The resulting storm intensities were integrated with fragility models for railroad tracks and bridges to assess the probability of failure for various components of the railway system. Finally, the team employed a Sequential Monte Carlo (SMC) simulation to generate temporal hazard scenarios for a specified future timespan and estimate the annual expected failures and life expectancies of the railway assets.

1.4 Scope

This research includes an analysis of approximately 184 miles of coastal rail system owned by CSX between New Orleans, Louisiana, and Mobile, Alabama, and about 27 miles of rail system owned by CN from New Orleans to Manchac, Louisiana. [Figure 2](#) shows the planned testbed for the project which includes including inland tracks and bridges along the 184 miles and 27 miles corridors. The study focused on specific failure modes for railroad infrastructure. For railroad tracks, the analysis considered ballast scour and embankment scour as the primary failure mechanisms. For railroad bridges, the research assessed the uplift of ballast decks.

Several potential failure modes are not included in this study. For railroad tracks, embankment seepage, rail buckling, and shear failure of rails or ties were not considered due to lack of availability of proper fragility models. Additionally, the scour of ballast in tracks on bridges was excluded due to inapplicability of existing fragility models. For bridge systems, the analysis did not include the erosion of abutments or scour in piers. Furthermore, fragility models for non-concrete (steel or timber) ballast-deck and all types of open-deck bridges were not available, so these bridges were excluded from the vulnerability assessment.

1.5 Organization of the Report

The report explains the models and tools the team used to determine failure probabilities and assess the viability of various mitigation actions for tracks and bridges. [Section 2](#) discusses the storm hazard modeling process, including the datasets, down-sampling method, and wave and surge simulations. [Section 3](#) describes the failure modes and associated fragility models. [Section 4](#) discusses the probabilistic vulnerability analysis framework for bridges and rail tracks. The results for annual expected failures and life expectancies are provided in subsections [4.2](#) and [4.3](#). [Section 5](#) is dedicated to proposed retrofit actions to enhance the lifespan and safety of the railway components. The retrofit options and results are detailed for rail bridges and inland tracks in this section. [Section 6](#) provides the conclusion and summary.

2. Hazard Modeling

The literature review offers a handful of studies that estimate the vulnerability of coastal infrastructure based on scenario-based hazard analysis (Doherty, Dora, et al. 2012; Adams and Heidarzadeh 2021; Darestani, Sanny, et al. 2021). However, a probabilistic approach that adequately covers the uncertainties associated with the intensity and frequency of storm hazards is absent in the literature. As historical storms are limited, they cannot be reliably used to account for all the uncertainties inherent in storm hazards. Moreover, performing a fully probabilistic storm surge and wave analysis requires computationally expensive and time-consuming hydrodynamic simulations (Dietrich, Zijlema, et al. 2011). To address these limitations, this study creates a fully probabilistic model for surge and wave hazards for the NGOA coastline, considering the effect of non-stationary storms. For this purpose, the team used a dataset that comprises 10,000 years of synthetic tropical cyclones (TC) (Bloemendaal, Haigh et al. 2020) as the benchmark for year 2018 to account for uncertainty in storm hazards within the area of interest. The team calls this dataset “STORM2018.” In addition, to account for non-stationary storms, the team used an enhanced version of the STORM dataset (Bloemendaal, de Moel et al. 2022), which resembles the non-stationary storms, considering RCP 8.5 (Tebaldi and Wehner 2018) for year 2050. The team refers to this dataset as “STORM2050.” The team developed the probabilistic hazard model from a statistically representative down-sampled subset of STORM2050 datasets to reduce computational costs. Furthermore, the team considered two water datum adjustment scenarios based on projections made for the year 2100.

2.1 Storm Hazard Characterization and Modeling

As noted earlier, a probabilistic hazard model is needed to estimate the vulnerability of railroad systems. The current literature offers historical storm data and models. For example, the HURDAT2 dataset (NOAA 2024) contains historical TC data for the North Atlantic Ocean including the Gulf of America’s coastline. Estimating the probability of failure of coastal railroads requires a large number of storm samples to account for spatial variability. However, only a limited number of historical storms have affected the NGOA coast. Besides, information is missing on historical storm tracks, including central pressure and radius to maximum wind which is crucial for obtaining the surge and wave values using hydrodynamic models. Therefore, historical storms cannot be used to reliably estimate the probability of failure of coastal railroads. Alternatively, recent studies utilized synthetic storm datasets, providing a large number of storms necessary for precise statistical analysis in coastal regions (Nederhoff, Hoek, et al. 2021; Balaguru, Xu, et al. 2023; Sohrabi, Darestani, et al. 2023). In this study, a synthetic dataset called “STORM2018,” (Bloemendaal, Haigh et al. 2020) consisting of 10,000 years of TC data for the North Atlantic Ocean, was used as the benchmark to develop a fully probabilistic storm hazard model for the NGOA region. The blue buffer zone in [Figure 3 \(a\)](#) shows the region of interest along the coast of Alabama, Mississippi, and Louisiana. A total of 2,345 storms with minimum and maximum 10-minute sustained wind speeds of 40.50 (mph) and 167.77 (mph), respectively, passed through the regions of interest. In addition, the team used the non-stationary STORM dataset (Bloemendaal, de Moel, et al. 2022) generated for year 2050, and named the dataset “STORM2050.” [Figure 3 \(b\)](#) shows the STORM2050 dataset, which includes 2,909 TC tracks (24 % more TC tracks) that pass through the region of interest. The STORM2050 dataset is composed of storms with minimum and maximum 10-minute sustained wind speeds of 40.26 mph and 171.34 mph, respectively.

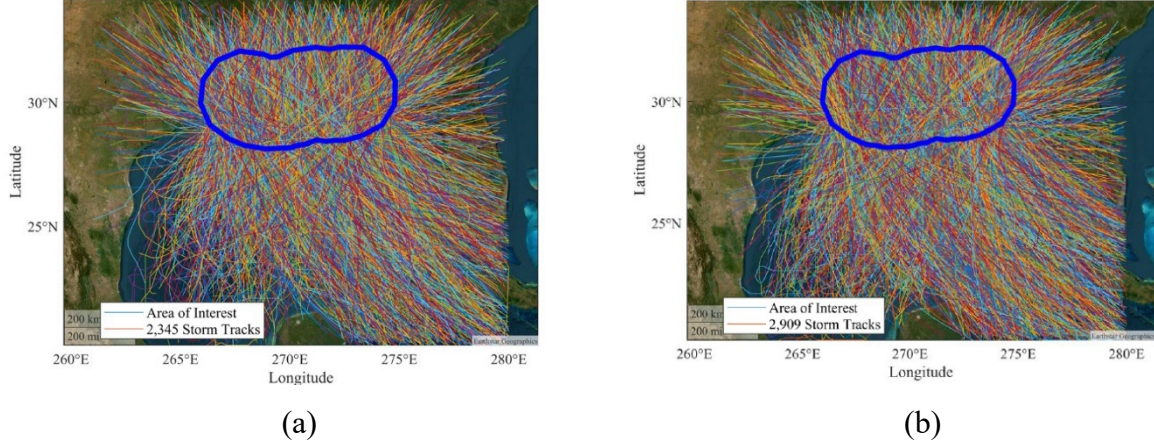


Figure 3. a) STORM dataset with 2,345 storm tracks; b) STORM non-stationary dataset with 2,909 storm tracks

In a previous study, Sohrabi, Darestani et al. (2025) evaluated the suitability of the STORM2018 dataset for the NGOA based on historical TCs from 1980 to 2018 (39 years) provided by HURricane DATaset (HURDAT2) (NOAA 2024). For consistency, between STORM2018 and STORM2050, the same 124.2-mile buffer zone was used, as the blue line indicates in Figure 3. Figure 4 (a) shows 45 historical TC tracks from 1980 to 2018 identified for the same buffer zone as Figure 3. Therefore, the return period of historical storm dataset is estimated as:

$$T_{\text{Historical}} = \frac{39 \text{ years}}{45 \text{ historical storms}} = 0.866 \text{ years} \quad (1)$$

The return period of STORM2018 dataset and STORM2050 dataset is also estimated as:

$$T_{2018} = \frac{10,000 \text{ years}}{2,345 \text{ synthetic storms}} = 4.264 \text{ years} \quad (2)$$

$$T_{2050} = \frac{10,000 \text{ years}}{2,909 \text{ synthetic storms}} = 3.437 \text{ years} \quad (3)$$

As seen from the equations above, the synthetic storms do not match historical storms in terms of return periods. This is expected as synthetic storms are commonly generated on a global scale, and they often underestimate historical records in terms of storm frequency. To remedy this issue, the synthetic storms must be adjusted to replicate historical records in terms of frequency. For this purpose, the team assigned a return period of 0.866 to STORM2018 dataset, and adjusted the return period for STORM2050 as follows:

$$T_{2050\text{-adjusted}} = T_{\text{Historical}} \times \frac{T_{2050}}{T_{2018}} = 0.866 \times \frac{3.437}{4.264} = 0.698 \text{ years} \quad (4)$$

Furthermore, the distribution of storms in terms of wind intensity was also adjusted to match historical records. In this process, the team first used the quantile mapping bias correction (QMBC) (Li, Wu, et al. 2023; Maciel-Tiburcio, Martínez-Alvarado, et al. 2025) to match the distribution of wind speed in the STORM2018 dataset to historical records. In the next step, the team used the difference between the cumulative density function (CDF) of wind intensity for STORM 2018 (red line in Figure 4.b) and STORM2050 (blue line in Figure 4.b) to determine the

adjusted STORM2050 model (green line in Figure 4.b) from adjusted STORM2018 model (black line in Figure 4.b).

2.2 Storm Tracks Down Sampling

The synthetic storms are composed of thousands of storms tracks. Estimating surge and wave for these storm tracks requires computationally expensive hydrodynamic simulations such as ADCIRC+SWAN (Guisado-Pintado 2020; Luettich and Westerink 2023). The computational costs are significant, making the probabilistic storm analysis practically impossible. To remedy this issue, the synthetic storms must be down-sampled. In this down-sampling process, the selection of a subset of storm tracks that can accurately represent the original dataset is a crucial challenge. In the past few decades, several techniques have been developed for a robust hazard selection to capture the intensity and variability of storms. The simplest method is *random sampling*, where samples are selected randomly without considering the variability. For example, Sohrabi, Darestani, et al. (2023) and Sohrabi, Darestani, et al. (2025) addressed such challenge by dividing storm dataset into equally spaced intervals based on their maximum wind speeds, selecting one random storm track from each division. While such an approach is simple and significantly reduces the computational time, it cannot fully account for spatial and feature variability — especially for extreme events (Mohamad and Sapsis 2018).

K-means clustering is another commonly used technique that group storms into clusters based on feature similarity and selects representative tracks from each cluster. Although this method encompasses some degree of storm variability, it reveals several shortcomings. First, the specification of the number of clusters might introduce bias in the results. Second, K-means clustering algorithm suffer from dealing with outliers, including highly extreme storm events that can be left out in the process of selection while having crucial impact on the outcomes (Camargo, Robertson, et al. 2007).

The *hazard intensity thresholding method* selects storm tracks based on predefined criteria such as maximum wind speed thresholds. Although this approach is computationally efficient, it suffers from major limitations. First, it fails to encompass the spatial and temporal variability of storm characteristics, including the landfall location, and central pressure which significantly affects the surge and wave (Emanuel, Ravela et al. 2006). It only relies on historical intensity metrics such as maximum wind speed, which can cause underrepresentation of rare but high-impact storm events. In regions with a limited number of recorded storm events, it underestimates the frequency of such events.

On the other hand, alternative methods such as *joint probability method with optimal sampling and respond surface interpolation* minimize the number of simulations needed by leveraging a limited set of storm parameters (Toro, Resio, et al. 2010). However, these methods assume that the relationship between storms parameters and hazard outcome changes gradually. Therefore, they fail to consider the nonlinear interaction that influences surge and wave. To address the limitations, this report employs the maximum dissimilarity approach (MDA) (Snarey, Terrett, et al. 1997; Willett 1999) to select a subset of storm tracks across different track features to capture storm tracks' variability.

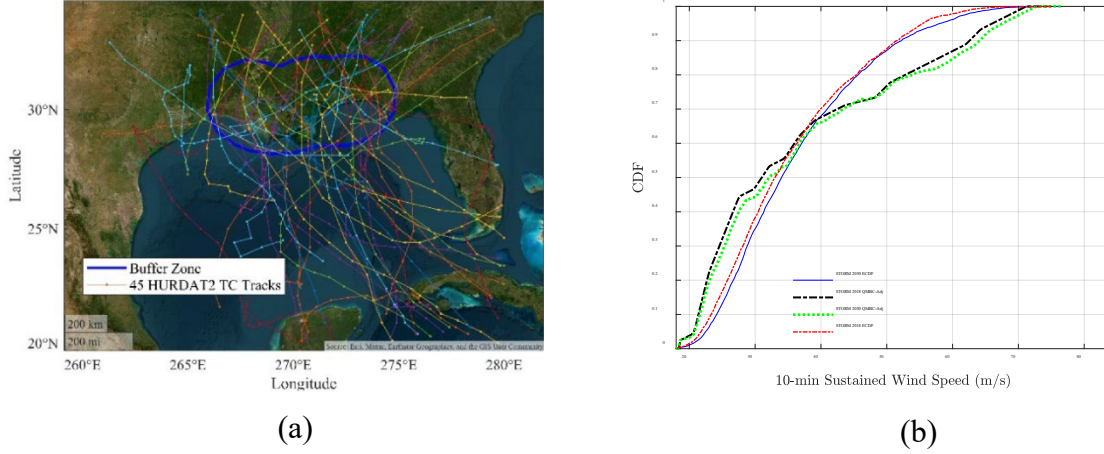


Figure 4. a) Historical storms passing through the buffer zone using HURDAT2 dataset (NOAA 2024); b) empirical CDF(ECDF) of STORM2018 and STORM2050 dataset

2.2.1 Maximum Dissimilarity Approach (MDA)

The team used an MDA (Snarey, Terrett, et al. 1997; Willett 1999) for the down-sampling a subset of storm tracks from an ensemble of 2,909 tracks obtained from STORM2050. MDA was used to maximize the diversity in the pool of selected storms by maximizing the dissimilarity among multiple features. The approach covers the variability in the features and incorporates outliers representation. The MDA involves feature selection, normalization, and track selection. In this study, the team selected a 200 km (124.2 mile) buffer zone, extending from Alabama to New Orleans to filter storms that could potentially impact the testbed coastal railroads (Figure 5). Furthermore, the team selected maximum wind speed, the radius to maximum wind, and the longitude and latitude of landfall as the features for storm selection within MDA. The features were normalized to [0,1] range, and then a weight of 1, 0.6, 1.2, 1.2 was assigned to maximum wind speed, radius to maximum wind speed, and the longitude and latitude of landfall, respectively. The dissimilarity between tracks was calculated using a weighted Manhattan distance as:

$$d(j, k) = \sum_{i=1}^n w_i |X_{j,i} - X_{k,i}| \quad (1)$$

where j and k are any two storm tracks in the dataset; i is the number of features in each storm track; w is the weight assigned to each feature; X is feature vector. The MDA algorithm begins by selecting the initial track based on an assumed maximum 10-minute sustained wind speed between 131.97 mph and 136.45 mph. This range was selected such that the initial storm was not too weak or too strong. To guarantee that the new selected track increases the maximal dissimilarity, the new tracks were selected iteratively, maximizing the minimum weighted distance to all previous storm tracks. The process continued until the desired number of storm tracks were selected. In this study, the team initially selected 400 storms, as shown in Figure 5. Later, the team conducted a convergence study to determine how many of the 400 storms were needed to get convergence on the failure probabilities.

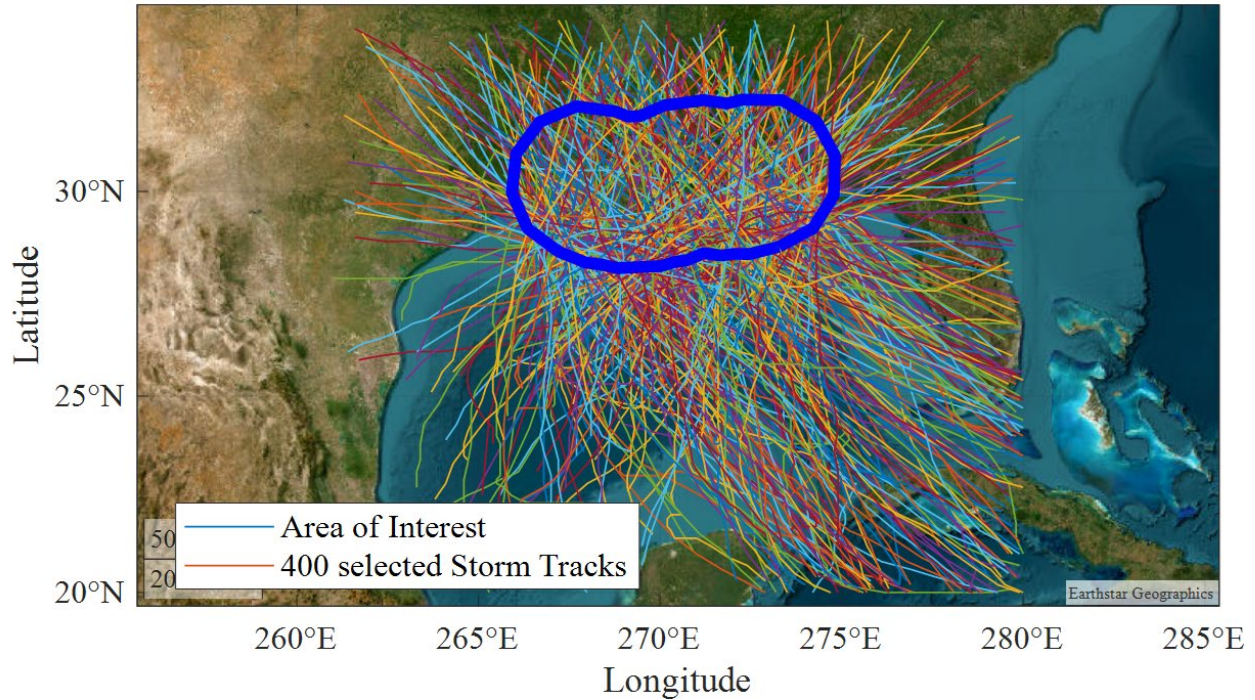


Figure 5. 400 selected synthetic storm tracks using MDA

2.3 ADCIRC+SWAN Model Setup and Validation

From the 400 down-selected storm tracks, the team determined the storms' intensity and trajectory. However, estimating coastal railroad vulnerabilities required estimates of surge and wave induced by the storms. This required using storm tracks as an input to hydrodynamic models and estimate surge and wave. This process involved transforming the storm information into a surface wind field model. The team adopted and used the CLE15 parametric vortex model (Chavas, Lin, et al. 2015) within ADCIRC v55 and SWAN v41.75 (Pringle, Wang, et al. 2021; Luetlich and Westerink 2023) to simulate storm surge and waves on a refined mesh with a minimum and maximum resolution of 50 m and 250 m, respectively, for the NGOA and its coast generated by OceanMesh2D toolbox (Roberts, Pringle, et al. 2019; Pringle, Wang, et al. 2021). Sohrabi, Darestani, et al. (2025) validated the accuracy of this ADCIRC+SWAN model. The team used historical observations of high water marks (HWMs) from USGS tide gauges (USGS 2021) to compare the storm surge predictions against observations from Hurricane Ida, 2021. In addition, the team compared significant wave heights at Luke Offshore Platform, south of Dauphin Island, Alabama (NOAA 2021) against Hurricane Ida. The comparison showed that the error between observed values and model prediction fell within an acceptable range, with a maximum error of 15.9% (Sohrabi et. al. 2025). The errors could be partially due to large-scale winds outside of the hurricane that were not modeled in the ADCIRC+SWAN model setup (Bilskie, Angel, et al. 2022). [Figure 6](#) presents the output of ADCIRC+SWAN Model simulations for one of the synthetic storms.

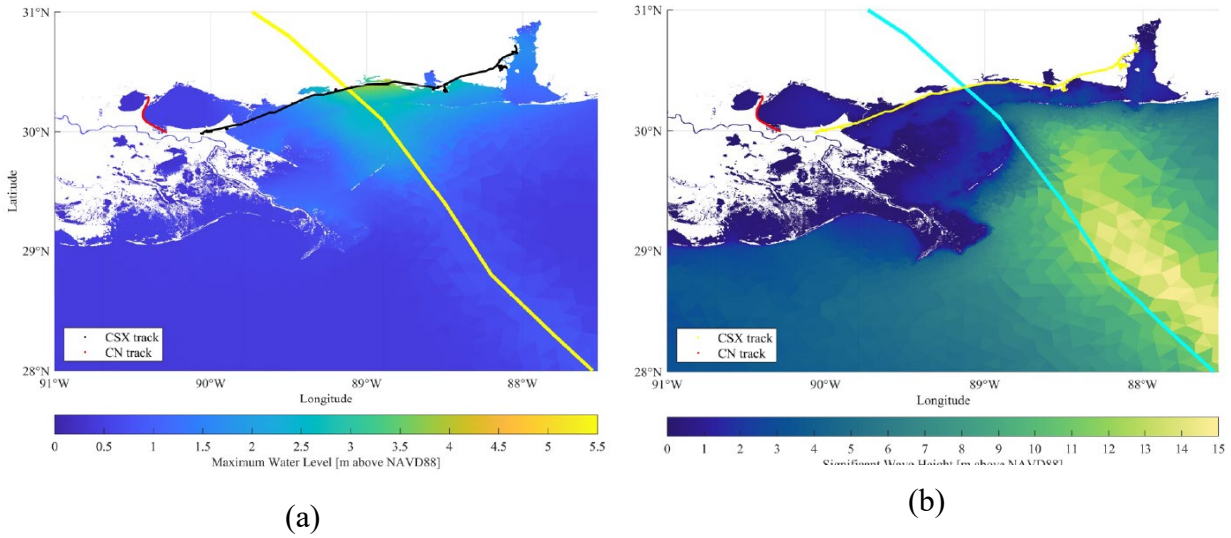


Figure 6. ADCIRC+SWAN output for a synthetic, non-stationary storm without water datum adjustment: a) maximum surge height; b) significant wave height

Furthermore, the water datum was expected to adjust significantly by year 2050. The national water datum explorer developed by the Interagency Task Force (2022) provides federally supported data visualizations on water datum levels. The datum adjustment scenarios and the associated supporting information come from the 2022 interagency datum adjustment technical report (Sweet, Craghan, et al. 2022). The updated 2022 report used the findings from the 2017 report as its starting point and updated the global mean datum scenarios and the associated projections to reflect recent advances in water datum level adjustment science. Datum level change was projected to reach 50 cm (1.64 ft) for the Bay Waveland Yacht Club, under the intermediate high scenario, as shown in Table 1 (Interagency Task Force, 2022). According to IPCC 6th assessment report there were five datum level scenarios representing the range of datum level projections up to year 2150. These scenarios considered a variety of processes that could influence datum level across a wide range of future warming conditions. They are defined by the target values of global mean datum level increase in year 2100.

Table 1. Datum adjustment for Bay Waveland Yacht Club, 2020–2050

Scenarios	Datum Adjustment (ft)
Low	1.18
Intermediate Low	1.31
Intermediate	1.44
Intermediate High	1.64
High	1.87

Furthermore, for the mid-century period relative to the year 2000, the datum change was estimated as 0.16 ft (NOAA 2024), as shown in Figure 7. Consequently, a datum adjustment of

1.8 ft was selected for the ACIRC+SWAN simulations. The surge and wave values are shown in [Figure 8](#) for one of the storm tracks considering the water level adjustments.

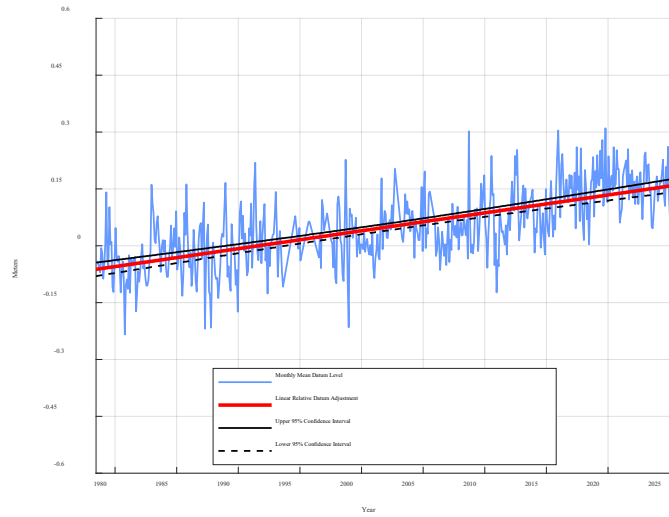


Figure 7. Datum adjustment for the mid-century period relative to the year 2000 for Bay Waveland Yacht Club (NOAA, 2024)

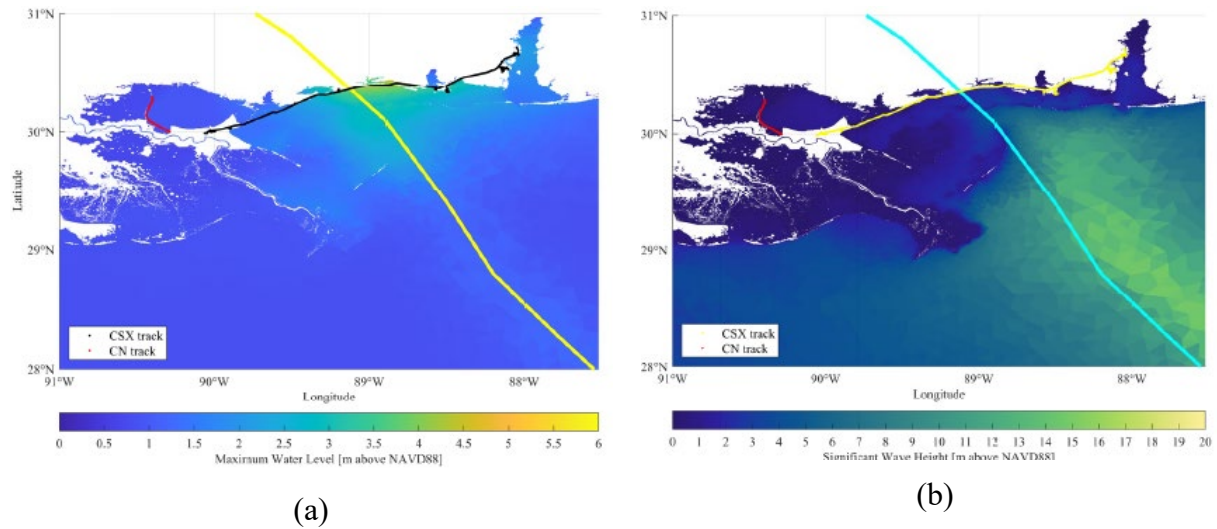


Figure 8. ADCIRC+SWAN output for synthetic non-stationary storm 15 with 55 cm (1.8 ft) datum adjustment: a) maximum surge height; b) significant wave height

3. Damage Assessment of Tracks and Bridges

To determine the vulnerability of railroad tracks and bridges, fragility models are needed. Fragility models estimate the failure probability of structural systems as a function of hazard intensity. Such models were integrated with the hazard model to estimate the probability of failure for tracks and bridges. In this study, a set of empirical and physics-based fragility models were adopted from the literature. In the following subsections, each of the adopted fragility models is explained.

3.1 Fragility of Inland Railroad Tracks

Figure 9 shows inland tracks which are commonly constructed over ballast and embankment layers. As seen in Figure 10, storm surge and wave can damage tracks through three different failure modes: a) ballast scour, b) embankment scour, and c) embankment seepage. However, because embankments used in tracks have a relatively low height, embankment seepage is not a predominant mechanism of failure for the majority of tracks (Tsubaki, Bricker, et al. 2016). Consequently, ballast and embankment scour will be regarded as the primary modes of failure for coastal tracks constructed over the ground. It should be noted that since the literature does not offer a fragility model for rails and track ties, their failure is not considered in this study.

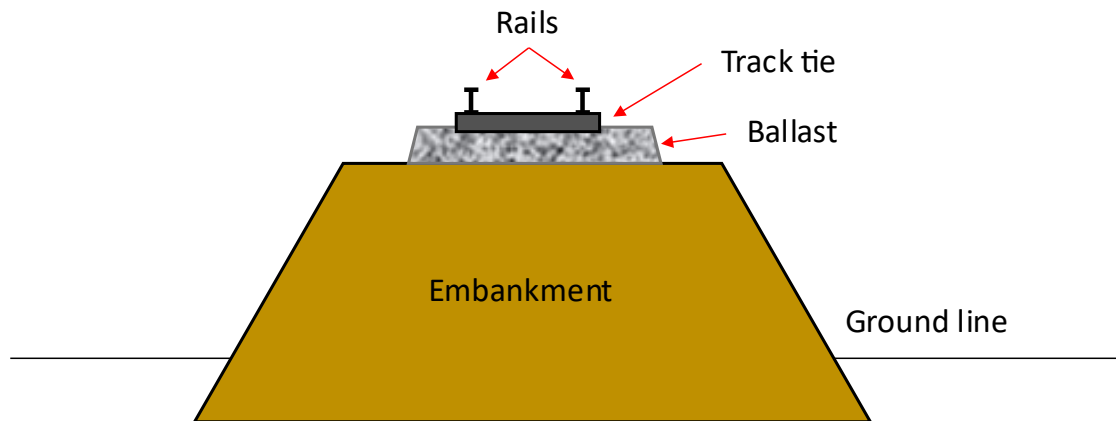


Figure 9. Tracks constructed over ballast and embankment layers

Due to the complex behavior of the granular materials used in the construction of ballast and embankment, physics-based fragility models are not available. Alternatively, the literature offers empirical fragility models for such structures. In this study, an empirical fragility was adopted to evaluate the vulnerability of rail embankments and ballasts (Tsubaki, Bricker, et al. 2016). This fragility model is available for various modes of failure such as ballast scour, embankment scour, and ballast and embankment scour combined. Fragility is presented as a function of the overtopping water depth. To account for both ballast and embankment scour, this study used the combined fragility model mentioned above (Tsubaki, Bricker, et al. 2016). The overtopping water depth was determined as the difference between the track elevation and the water level (the summation of surge and wave height) from ADCIRC+SWAN output.

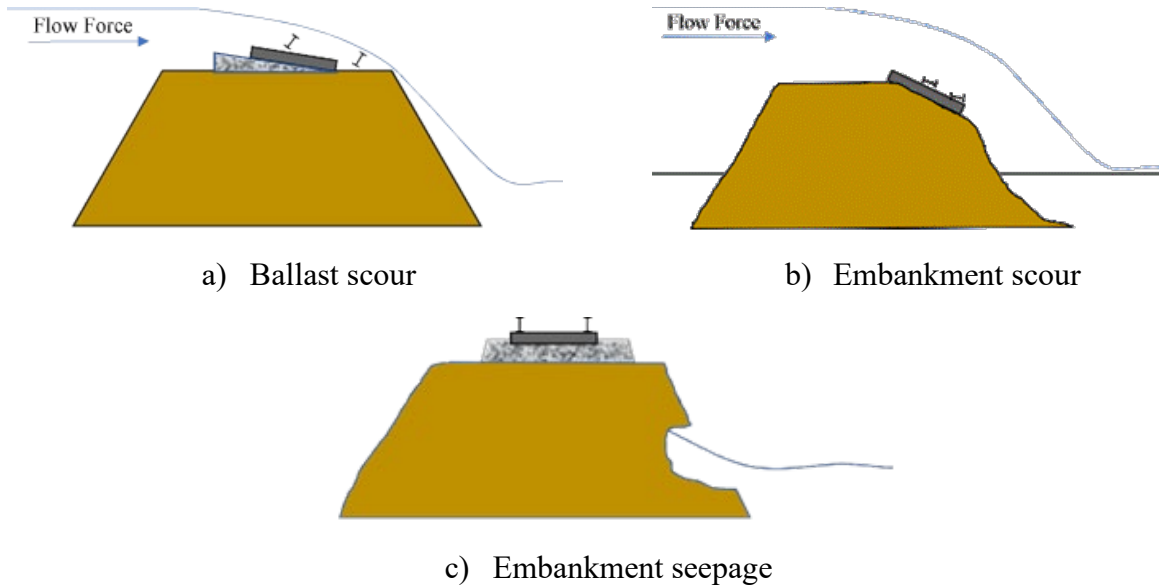


Figure 10. Track failure modes

3.2 Fragility of Railroad Bridges

Rail bridges are commonly categorized as either open deck or ballast deck. Figure 11 shows a schematic of a ballast-deck bridge (a) and an open-deck bridge (b). In an open-deck bridge, rails are connected to the bridge tie and girder. In a ballast deck, rails, and rail ties are constructed over a ballast that lies over a bridge superstructure. Historical storm events have demonstrated that these bridge systems are highly vulnerable to uplift forces caused by storm surge and waves. The uplift force can dislocate the bridge slab, damage the ties, and cause the tracks to fall over. Note that ballast scour in ballast-deck bridges can also cause operational hinderance and costs, but the fragility model for inland tracks is not applicable to them. This is because the stabilizing curbs in Figure 11 (a) provides additional protection against surge which make the failure mechanism different from failure modes shown in Figure 10.

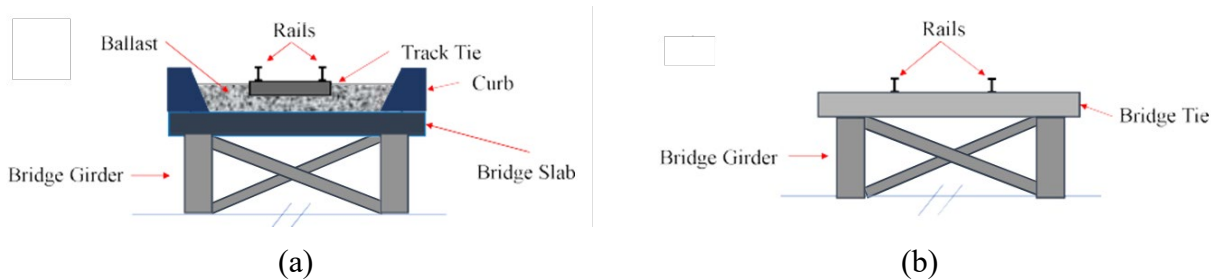


Figure 11. Different configurations of rail bridges: a) ballast deck and b) open deck

The literature offers a set of parameterized fragility models for highway bridges than can be adopted to assess ballast decks constructed over concrete superstructures (Balomenos, Kameshwar, et al. 2020). However, such fragility models are not applicable to bridges with superstructures made of non-concrete materials, including timber or steel. Additionally, there are no fragility models available for open-deck bridges. It should be noted that because open-deck bridges provide less surface area, the uplift force is smaller compared to ballast decks. At the

same time, the deck in open-deck bridges is directly fixed into the substructure, which makes it much less vulnerable to the uplift forces. Therefore, in this study, the research team assumed that open deck bridges were not vulnerable to uplift forces, and the results were only reported for concrete ballast-deck bridges. Additionally, other failure modes such as pier scouring due to storm surges were not considered in this study. This was due to lack of fragility models. Table 2 summarizes the failure modes considered in this study.

As noted above, for the ballast-deck bridges with a concrete superstructure, a set of physics-based fragility models for the uplift of the deck was used in this study (Balomenos, Kameshwar, et al. 2020). These fragility models estimated the likelihood of uplift for a bridge span as a function of surge and wave height, bridge elevation, geometric characteristics, and wave spatial variability. Wave spatial variability was a parameter that controls if a wave with a finite width struck the span fully or partially.

Moreover, information on deck constraining features such as shear blocks is not currently available. Existing fragility models also do not consider the impact of shear blocks. Due to this limitation, this study did not account for the impact of shear blocks in constraining railroad decks and reducing the probability of deck uplift. However, it is acknowledged that if any bridge contained shear blocks the probability of deck uplift was significantly lower.

Table 2. Common structural failure modes in tracks

Structural System	Failure Mode	Considered in this Study?
Bridge Systems	Uplift of decks (for concrete ballast-deck bridges only)	✓
	Erosion of abutments	✗
	Scour in piers	✗
	Scour in ballast	✗
Inland Tracks	Scour in embankment	✓
	Scour in ballast	✓
	Embankment seepage	✗
	Buckling of rails	✗
	Shear failure of rails	✗
	Shear failure of ties	✗
	Failure of fasteners	✗

As noted above, for the ballast-deck bridges with concrete superstructure, a set of physics-based fragility models developed by Balomenos, Kameshwar, et al. (2020) for the uplift of the deck was adopted in this study.

Note that the fragility models were originally developed for highway bridges and therefore need to be calibrated for much heavier railroad bridges — with usually narrower and deeper superstructures. This calibration was achieved through scaling down of hazard intensity measure, i.e., wave height and relative surge elevation, based on the ratio of weight per area of railroad bridges to standard highway bridges assessed by Balomenos, Kameshwar, et al. (2020). The scaled intensity measures were then introduced into the fragility model along with other required parameters to estimate the failure probability of railroad bridge spans. The logic behind this scaling is that the resistance of closed-deck bridges against uplift force is merely due to their heavy weight.

3.3 Vulnerability of Bridge Systems and Inland Tracks under a Storm Scenario

As discussed above, the adopted bridge fragility models for the unseating of bridge deck due to uplift force were developed for singular spans. To assess the failure probability of a bridge subjected to storm scenario, the team modeled the bridge as a series of dependent spans. To account for the spatial uncertainties regarding a wave striking a bridge, i.e., spatial variability, a Monte Carlo simulation with 10,000 realizations was adopted by uniformly sampling the wave crest center location and wave width. It was assumed that the wave width could range from the smallest bridge span length to the total bridge length. Accordingly, the spatial variability for each span was estimated for each realization by dividing the length of the span subjected to the wave by the total span length, resulting in value between 0 to 1.

Next, a Bernoulli trial was used in each Monte Carlo simulation to generate survival/failure scenarios for each span of a bridge. In this process, a span failure occurred if a uniformly sampled number between 0 to 1 exceeded the output of the fragility model given the calculated spatial variability and the scaled wave and surge heights reported at midspan. The surge and wave heights were the output of ADCIRC+SWAN model explained in Section 3.2. Ultimately, the failure probability of the bridge was estimated by counting the number of realizations in which at least one span failed and then divided it by the total number of realizations (10,000).

To perform the assessment above, an estimation on the span lengths was needed. Assuming spans were of equal length, the span length was derived by dividing the length of the bridge by the number of spans. The number of spans was counted based on the observations from Google Earth Pro (Google 2025). Moreover, the elevations of midspans required for calculating the relative surge heights were assigned based on the closest available rail-track elevation. It was also assumed that the structural specifications were uniform for the span, and the span slope was negligible and therefore set to zero.

Additionally, the vulnerability of inland railroad tracks was estimated by assessing the probabilities of scour in rail ballasts and embankments using the fragility model explained in Section 3.2. The fragility model developed for the scour in both ballast and embankment was employed in this study, as it provides the most reliable results among the three developed fragility functions for scour due to storm surges (Tsubaki, Bricker, et al. 2016).

3.4 Development of Decision-making Tool

Using the vulnerability models discussed above, railroads and other stakeholders can assess failure probabilistically given various storm scenarios. Based on the results obtained, they can take mitigatory actions under long-term planning where the effects of future water data adjustments and non-stationary storms are adequately considered. Accordingly, the team

developed separate Jupyter Notebooks for CN and CSX tracks to estimate life expectancies in an interactive and user-friendly tool that can be used for risk assessment and decision-making processes.

3.5 Datasets and Additional Assumptions

The fragility models required hazard intensity measurements and parameters relevant to the geometric and structural specifications. To estimate the fragility of embankments and ballast, the relative surge elevation, i.e., the elevation of water minus the elevation of the tracks' top, is the only required measurement. For bridge spans, however, in addition to the relative surge elevation measured at the bottom of the deck, the fragility models require wave height, wave spatial variability, type of superstructure, span length, slab thickness, girder area, girder weight, number of girders, and span slope. The hazard intensity measures, i.e., maximum surge elevation and maximum wave height, were generated using ADCIRC+SWAN for the 400 down-sampled storms explained in Section 3.

The calculation of the relative surge elevations needed a proper estimation of track elevations. CSX provided the locations and elevations of center track points at 50-ft distances for their track included in this study. Likewise, CN provided exact locations and elevations of bridge endpoints. The team used the locations and elevations from the railroads and natural ground slope to estimate the track elevations. It was assumed that the railroad followed the same elevation profile as the ground between any two bridges. The ground elevation was extracted by performing a spatial join analysis to join elevation data from the Louisiana Statewide Lidar Project (2023) to the points generated at 60-ft intervals along the CN line. Furthermore, a function was developed to shift (translate) and rotate the ground elevation profile to meet the track elevations, as provided by CN at the ends of each road segment. The team also checked for compliance between the road gradients (slopes) and the maximum allowable value, assumed to be 1.5%; therefore, elevations of the points causing higher gradients (slopes) were modified. [Figure 12](#) shows the resulting track elevations for a selected segment. For the CN bridges, it was assumed that the elevations changed linearly from one end to the other.

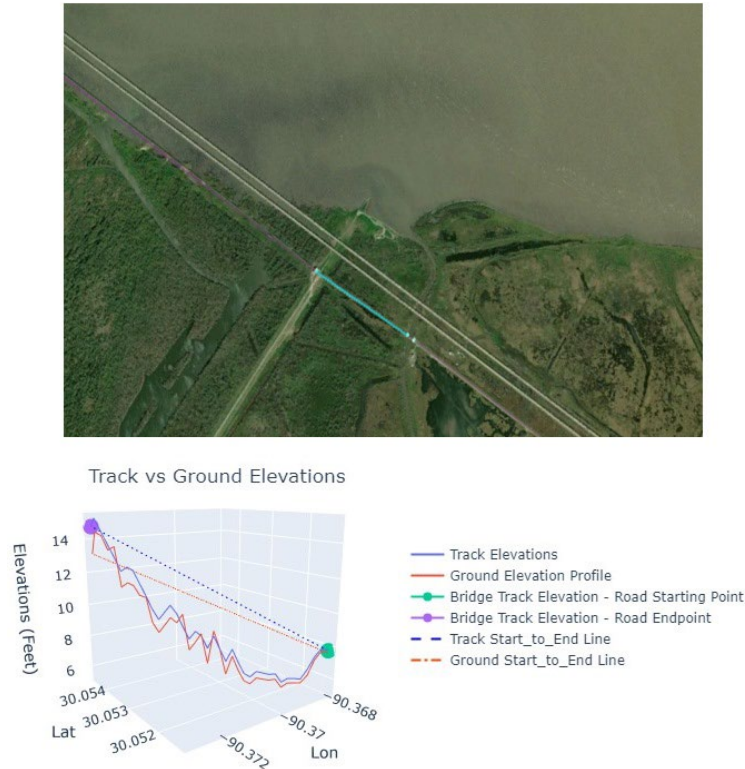


Figure 12. Location of the selected track segments and elevation variations

Measurements related to the physical attributes of the bridges were estimated based on Google Earth Pro (Google 2025) information, in addition to photos provided by CSX. Some bridges, such as vehicular overpasses and small bridges over drainage canals, were deemed inapplicable and removed. Some long bridges comprised of different structural systems were broken into individual bridges. The whole process resulted in a total of 66 bridges on CSX’s line and 19 on CN’s line. Of CSX’s 66 bridges, 57 are ballast deck, while 9 are open deck. Only 20 CSX ballast-deck bridges have a concrete superstructure such as slab, box beam, or slab and girder. For CN’s line, 5 of 19 bridges are open deck, and 14 have concrete superstructures. Note that ballast-deck bridges constructed by other materials, for example timber and steel and open-deck bridges, were not included in the assessments. The associated probabilities of failure were set as “N/A” due to the absence of a proper fragility model. Lastly, for the remaining concrete ballast-deck bridges, it was assumed that there was a 25-cm (10 in) ballast layer and a 20-cm (8 in) tie over the superstructure. These were required for the weight-based scaling of hazard intensity measures, as noted in Section 3.2.

4. Probabilistic Reliability Analysis

Probabilistic hazard assessment traditionally uses annual exceedance curves (Sohrabi, Darestani, et al. 2025). However, this approach underestimates the risk, as it does not account for the possibility of multiple storms occurring in a single year. To address this issue, temporal hazard scenarios were generated by resampling from synthetic storms while considering the impact of water datum adjustment and non-stationary storms on the frequency and intensity of the storms. These scenarios informed the frequency of expected storms on an annual basis and their severity in terms of surge and wave intensity. Each hazard scenario predicted storm events over a 32-year period from 2018 to 2050. In this analysis, assuming that storm events followed a Poisson point process (Slimacek and Lindqvist 2016; Darestani, Sanny, et al. 2021), the time between consecutive storms, Δt , follows an exponential distribution with the following cumulative distribution formula (CDF):

$$F(\Delta t; T_t) = 1 - e^{-\frac{\Delta t}{T_t}} \quad (2)$$

Where T_t is the return period of storms at time t . To estimate the return period at a time t , the research team performed a linear interpolation between the return periods of events in years 2018 and 2050. Return periods were set as 0.866 and 0.698 for the years 2018 and year 2050, respectively (explained in Section 3). This approach effectively accounts for the increasing trend in the frequency of storms, as shown in Figure 13.

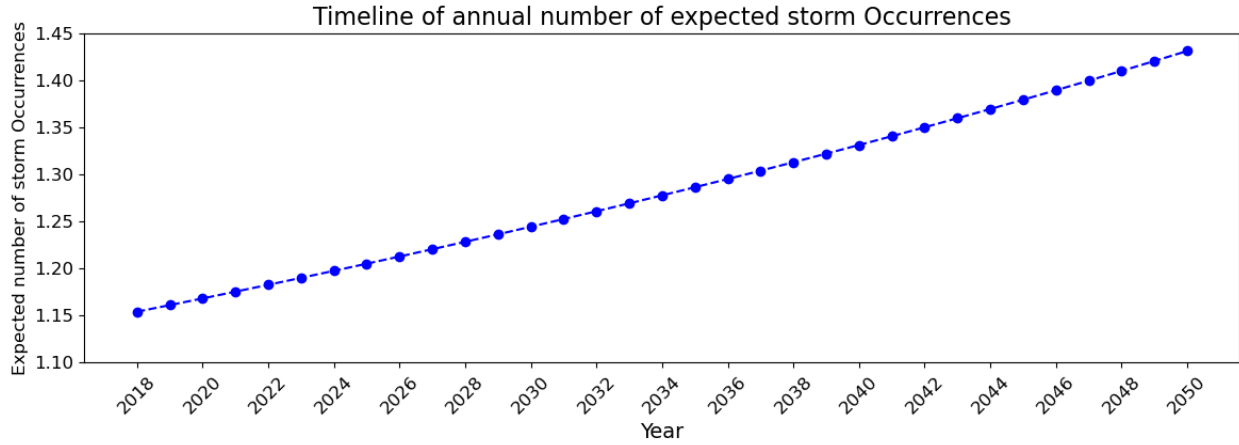


Figure 13. Expected number of storms through the coming years

Moreover, a linear interpolation, as shown in Figure 14, was performed to estimate the temporal change in CDF, i.e., the distribution of storms' maximum wind speeds. The interpolation addresses the increase in the intensity of the future storms. Subsequently, wind speeds were sampled from the interpolated CDFs for each storm event. Figure 15 shows the sampling method. First, a random value between 0 and 1 was generated, and then the corresponding wind speed was estimated by inverting the CDF to find the corresponding wind from the generated random number. Finally, the storm tracks were sampled by identifying the storm IDs in the downsampled dataset with a maximum wind speed closest to the sampled maximum wind speed (Figure 15). The small blue bars in Figure 15 mark the time of storm occurrences. Maximum wind speeds for events with values higher than 50 m/s are shown.

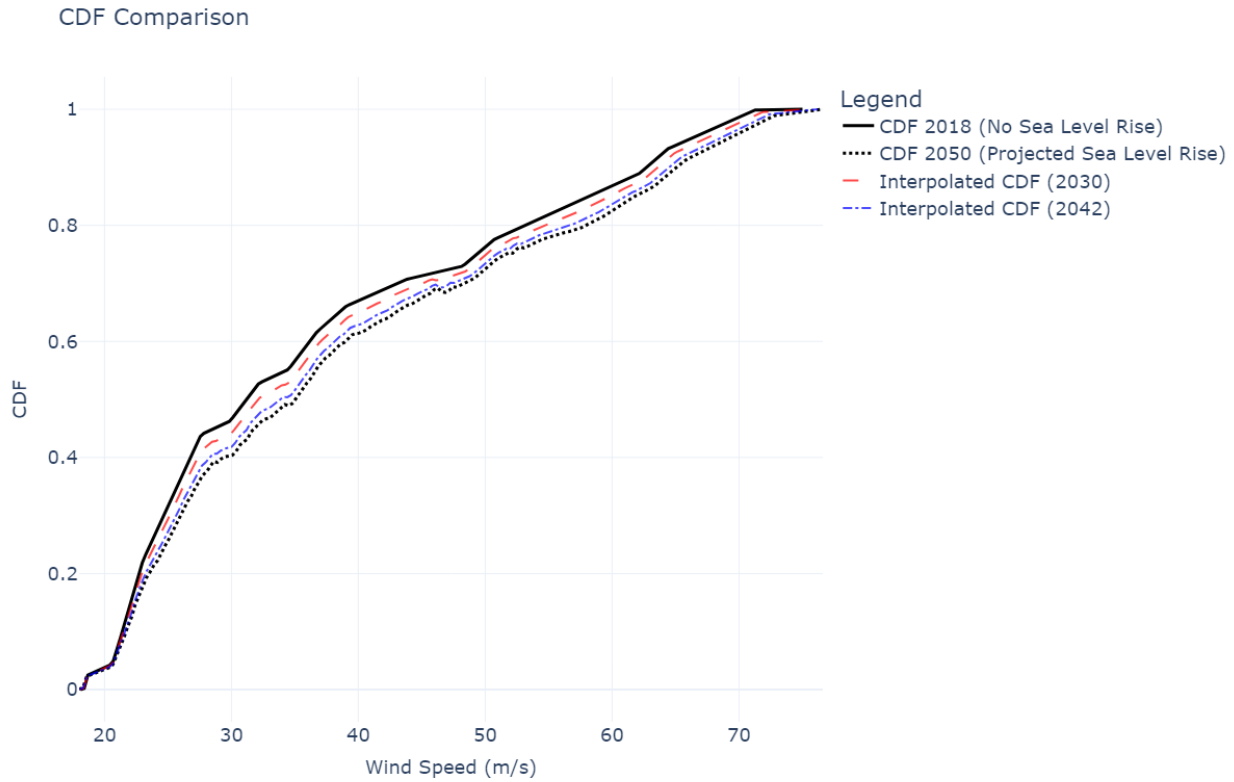


Figure 14. Interpolated CDFs for two time samples, years 2030 and 2048

By assigning storm tracks to each event, the surge and wave intensities at locations of railway components could be estimated using ADCIRC+SWAN outputs for each event. These readings were integrated with the fragility function to determine probabilities of failure. Moreover, the water datum adjustment for future weather conditions must be considered. To do so, the team conducted two sets of ADCIRC+SWAN simulations for the 400 down-sampled storms from STORM2050: one with water datum adjustment of 0.49 ft (15 cm) for year 2018 (datum adjustment from 1990 to 2018), and one with datum adjustment of 1.8 ft (55 cm) for the year 2050 (datum adjustment from 1990 to 2050). Subsequently, given the ID and time of occurrence for each storm event, the surge and wave intensities were linearly interpolated.

To account for uncertainties in the frequency and severity of storms, the research team adopted a sequential Monte Carlo (SMC) approach. A large sequence of possible hazard scenarios were generated to effectively account for uncertainties within and across years. The SMC process generated a large sample of simulations for the sequence of storm occurrences and used Bernoulli trials to generate failure/survival events for each storm event (Saperstein 1973, Bernier, Gidaris et al. 2019). Figure 16 illustrates this process. For instance, in scenario m and year n, a total of three storms were sampled, and two of these storms caused a failure in a rail track. The failures for inland track and bridges were evaluated by using the fragility and vulnerability models presented in Section 3 through sampling Bernoulli trials. Lastly, for each component of the rail track, annual expected failures (AEF) could be estimated by averaging the results obtained from SMC simulations.

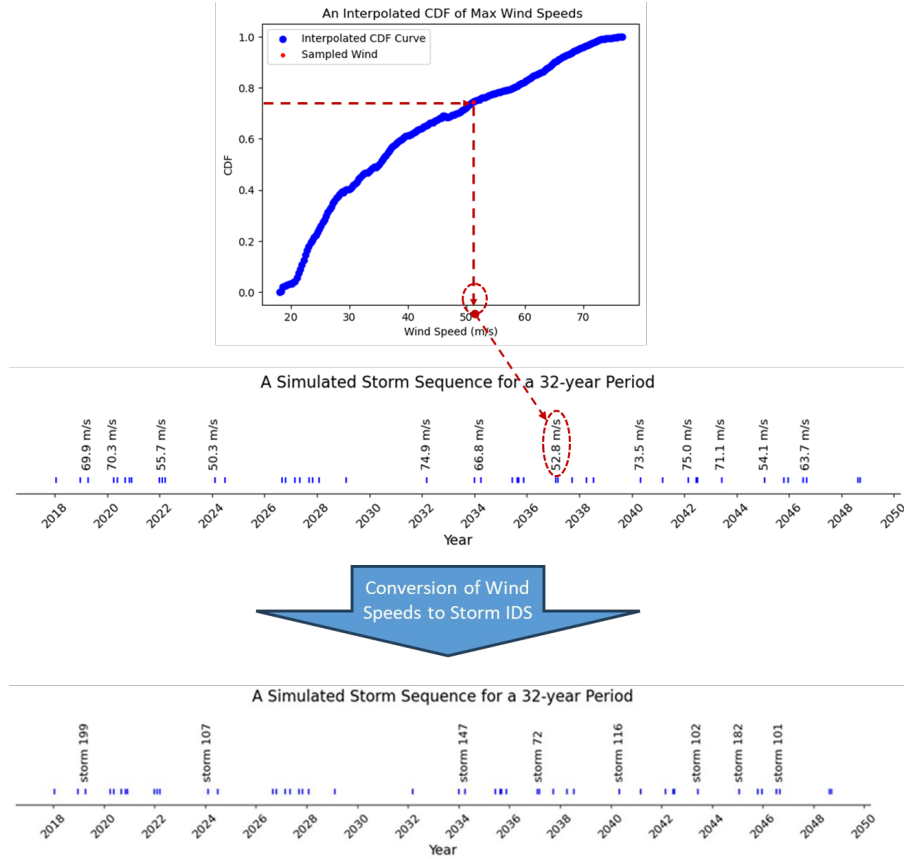


Figure 15. Storms' max wind speed sampling process for a simulated event sequence and conversion to storm IDs

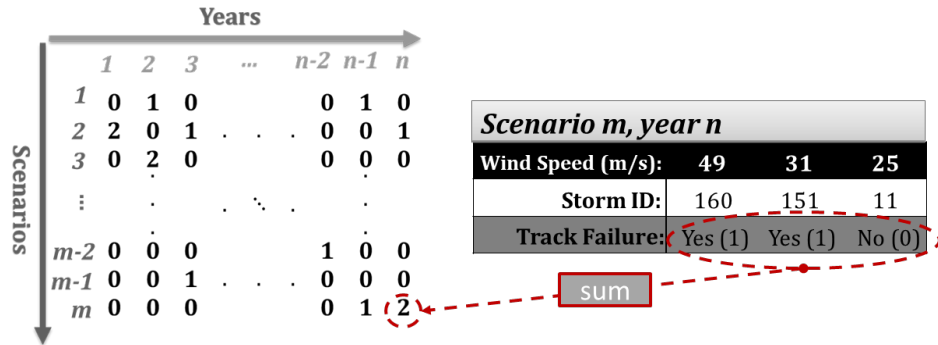


Figure 16. An example of a sequential Monte Carlo simulation

In addition, the researchers calculated the life expectancy of bridges and inland tracks. In this study, life expectancy, λ , is estimated as:

$$\lambda(\text{years}) = \frac{1}{AEF} \quad (3)$$

where AEF is the Annual Expected Failures. For instance, a λ of 10 years indicates that, when analyzed over an extended period, the system failed on average once every 10 years. This does not imply a failure will occur precisely every 10 years but rather over an extended period; the average interval between failures is 10 years. Presenting results in terms of life expectancy is more informative for rail companies and authorities, aiding them with decision-making processes.

4.1 Results and Discussion for Bridges

The procedure was implemented using Python and documented in Jupyter Notebooks (Randles, Pasquetto, et al. 2017). [Figure 17](#) presents the analysis of life expectancies for the CN coastal bridges. The locations of the excluded bridges, marked as “N/A,” are also shown in the figures with blue solid circles. As noted earlier, for these bridges, the failure probabilities were not estimated as fragility models, for open-deck bridges and timber/steel ballast-deck bridges do not exist. The results show that the majority of bridges have a life expectancy of around 10 to 20 years. The most vulnerable bridge, located just outside New Orleans, has a life expectancy of about 12 years. Additional information on life expectancy is provided in [Table 3](#). The results indicate that about 47 percent of bridges have a life expectancy below 20 years, highlighting their vulnerability.

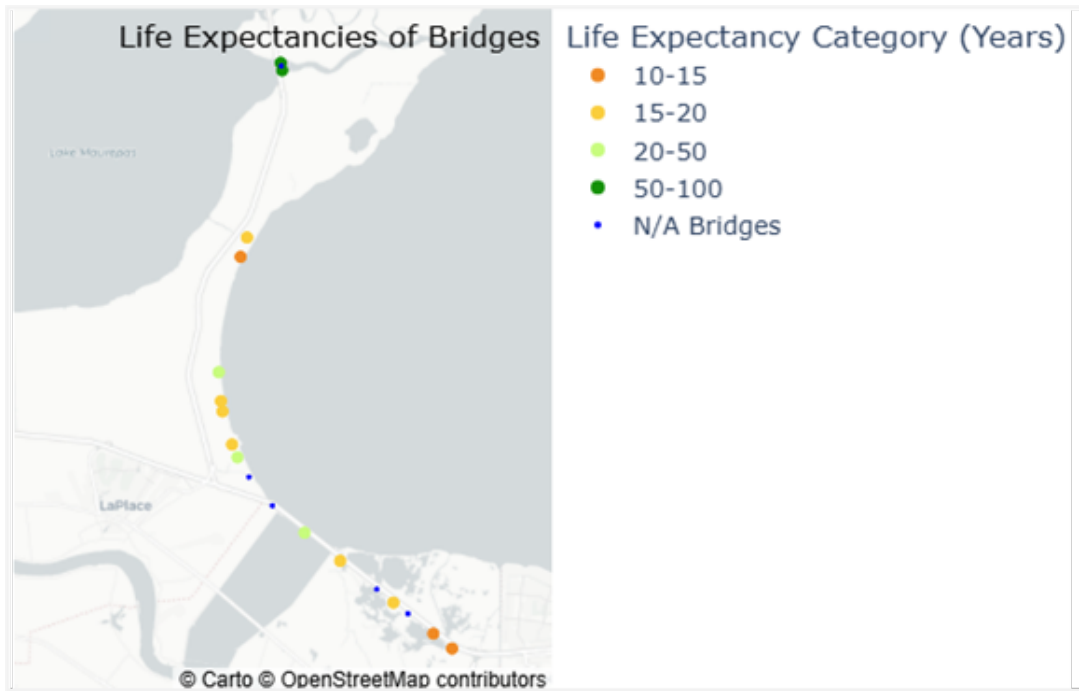


Figure 17. Life expectancies of CN bridges

Table 3. Frequency of CN bridges in each life expectancy category

Life Expectancy Range (Years)	0-5	5-10	10-15	15-20	20-50	50-100	>100	N/A Bridges
Number of Bridges	0	0	3	6	3	2	0	5
% of Bridges	0.0	0.0	15.8	31.6	15.8	10.5	0.0	26.3

Figure 18 shows the life expectancies of bridges along the CSX line under uplift forces. The high vulnerabilities shown by light red and solid orange circles in Figure 18 are localized just outside New Orleans, Louisiana, near Pearl River (Louisiana/Mississippi border). The bridges in this specific region have life expectancies between 5 and 15 years. Additional information on the vulnerability of CSX bridges is provided in Table 4. The results indicate that about 9 percent of CSX's bridges have a life expectancy below 20 years. This translates to 30% of concrete ballast-deck bridges on this line.



Figure 18. Life expectancies of CSX bridges

Table 4. The frequency of CSX bridges in each life expectancy category

Life Expectancy Range (Years)	0-5	5-10	10-15	15-20	20-50	50-100	>100	N/A Bridges
Number of Bridges	0	1	2	3	5	6	3	46
% of Bridges	0.0	1.5	3.0	4.5	7.6	9.1	4.5	69.7

The research team also looked at the CSX and CN lines as a whole and categorized concrete ballast-deck bridges into four subsets based on the following intervals for life expectancies (in years): low-vulnerability ($\lambda > 50$), medium-vulnerability ($20 \leq \lambda < 50$), high vulnerability ($10 \leq \lambda < 20$), and extreme vulnerability ($\lambda < 10$). Table 5 shows the percentages of bridges falling into each category. The results show that more than one-third of bridges are in the high vulnerability category, while one bridge is in the extreme vulnerability category. Note that the uplift of bridge decks was the only mode of bridge failure considered in this study. The research team excluded any non-concrete ballast-deck bridge from the evaluations due to lack of fragility models. In addition, as open-deck bridges appeared to be strong against uplift forces from storm surge and waves, it was expected that such bridges are not significantly vulnerable to storm surge and waves.

Table 5. Categorization of concrete ballast-deck bridges based on the levels of vulnerability

Vulnerability level	Low	Medium	High	Extreme
Num. of Bridges	11	8	14	1
% of Bridges	32.4	23.5	41.2	2.9

Figure 19 shows the life expectancy distributions for the study region when CN and CSX bridges were combined into a single dataset. The results indicate that about 18 percent of rail bridges have a life expectancy of less than 15 years. It is noteworthy that the losses corresponding to the failure of bridges were considerably higher than the failure of tracks, as bridges are extremely expensive structures to build, repair, and maintain. Overall, these alarming statistics call for targeted maintenance strategies and risk mitigation actions, especially for highly and extremely vulnerable components of the railroad system.

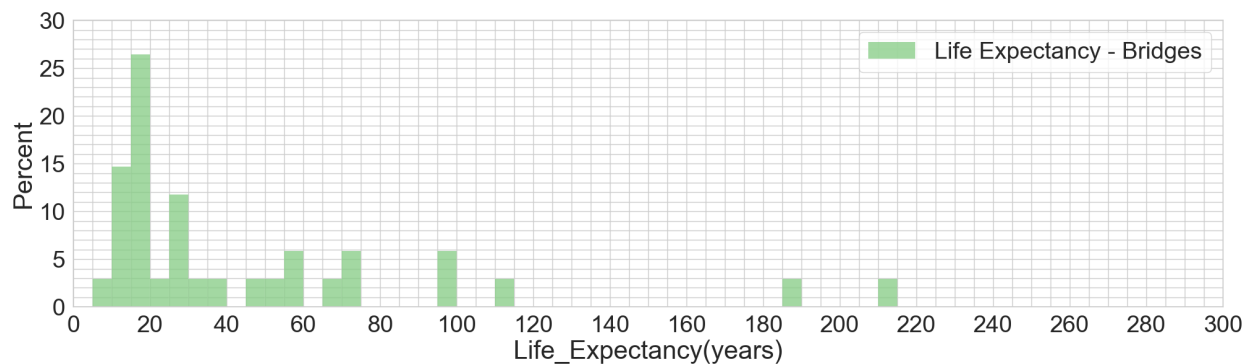


Figure 19. Distribution for life expectancies of selected bridges for both CSX and CN lines presented in Figure 2

4.2 Results and Discussion for Inland Tracks

The researchers determined the vulnerability of inland railroad tracks by implementing the SMC procedure explained above. Figure 20 shows the life expectancies associated with scour in either ballast or embankment along CN's line from New Orleans toward Hammond. The majority of segments show high vulnerabilities in their ballast and embankments. The life expectancies are generally less than 10 years — and go as low as 2 years in some locations. Table 6 provides additional information on life expectancies as a function of the length of tracks. The results indicate that around 6.8 miles out of the total 27 miles have a life expectancy of less than 5 years, and around 17 miles have a life expectancy of less than 10 years.



Figure 20. Life expectancies of CN tracks

Table 6. Miles of CN inland tracks in each life expectancy category

Life Expectancy Range (Years)	0-5	5-10	10-15	15-20	20-50	50-100	>100
Miles of Inland Railroad	6.81	10.52	3.11	1.14	1.73	0.34	0.36
% of Inland Railroad	28.4	43.8	12.9	4.8	7.2	1.4	1.5

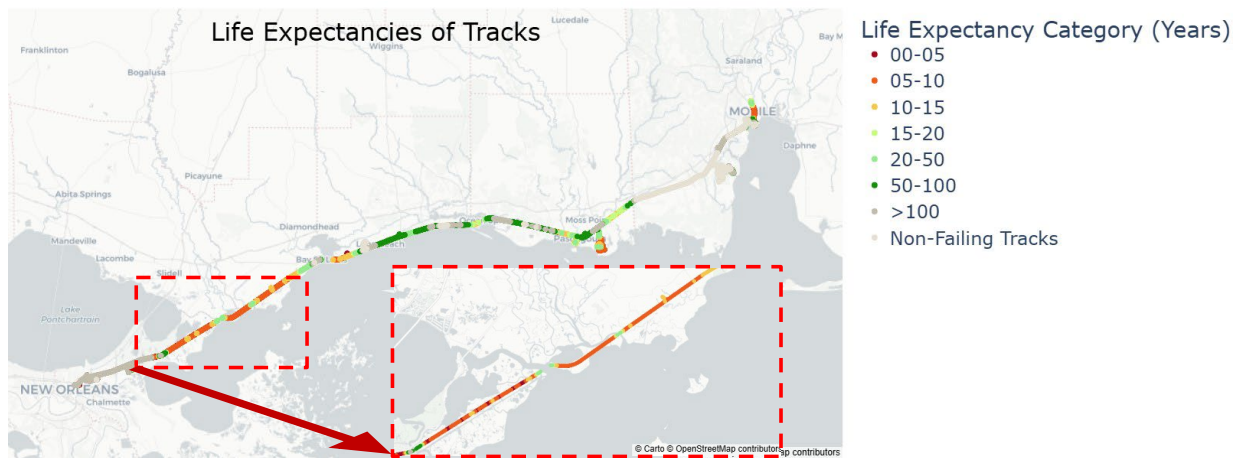


Figure 21. Life expectancies of CSX tracks

The research team also investigated the vulnerability of CSX tracks from New Orleans to Mobile; [Figure 21](#) shows the results of the probabilistic analysis the team conducted. The life expectancies reveal very high vulnerabilities (life expectancy less than 10 years) in some segments, including the area between just outside of New Orleans and the Mississippi/Louisiana border. The life expectancy in these locations can go as low as 1 year. These locations are highly susceptible to scouring in ballast and embankments during hurricanes.

[Table 7](#) shows life expectancy in each range for the length and portion of CSX inland tracks. On average, about 37 percent (66 miles) of CSX tracks were estimated to fail in less than 50 years with a significant portion (8.2 miles) showing life expectancies between 0 and 5 years.

Table 7. Miles of CSX inland tracks in each life expectancy category

Life Expectancy Range (Years)	0-5	5-10	10-15	15-20	20-50	50-100	>100
Miles of Inland Railroad	8.2	26.8	13.2	5.9	12.0	22.0	89.8
% of Inland Railroad	4.60	15.10	7.40	3.30	6.70	12.40	50.40

Similar to bridges, the research team combined the results of the CN and CSX lines and categorized the inland railroad segments into low-vulnerability ($\lambda > 50$), medium-vulnerability ($20 \leq \lambda < 50$), high vulnerability ($10 \leq \lambda < 20$), and extreme vulnerability ($\lambda < 10$). To accomplish this, the team divided the 200 miles of coastal railroads mentioned above into 202 segments, each approximately 1 mile in length, as shown in [Figure 22](#).

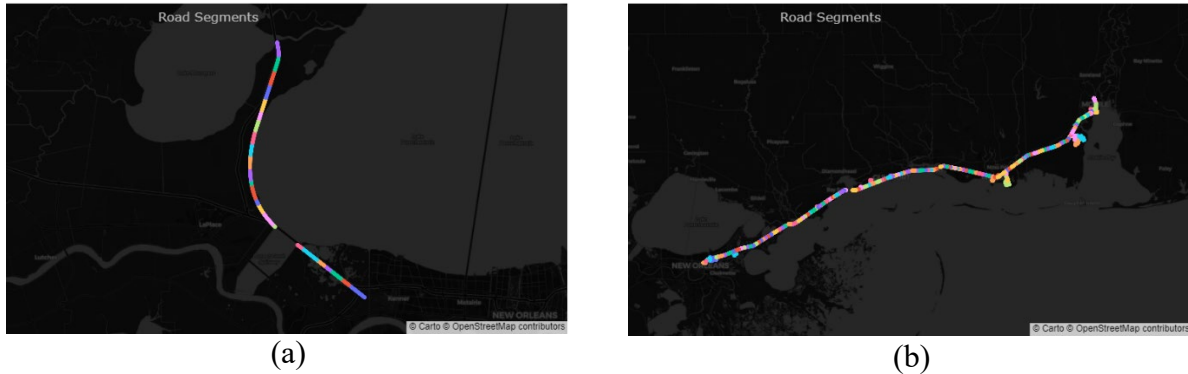


Figure 22. Division of inland railroads into 1-mile segments: a) 24 segments for CN line and b) 178 segments for CSX line

For each segment, the researchers evaluated the life expectancy of tracks at about every 60 ft, and the sub-segment with the lowest life expectancy was set as the performance metric of the entire segment. The percentages of track segments falling into each category are presented in [Table 8](#). Nearly 37 percent, approximately 74 miles of track segments, are in the extreme vulnerability category, while 9 percent, or about 19 miles of track segments are in the high vulnerability category. As coastal rail networks do not offer redundancy, any failure can cripple the transportation of goods and people and therefore can incur a significant economic loss.

Table 8. Categorization of railroad components based on the levels of vulnerability

Vulnerability level	Low	Medium	High	Extreme
Num. of segments	87	22	19	74
% of segments	43.1	10.9	9.4	36.6

[Figure 23](#) shows the distribution of life expectancies estimated for inland track segments. The majority of the segments, about 56 percent, have life expectancies less than 40 years. Notably, 20 percent, 37 percent, and 46 percent of the segments have a life expectancy of 5, 10, and 20 years, respectively. These failures, due to limited redundancy of the railroad systems, will incur frequent transportation disruptions and considerable economic losses. Therefore, the analysis shows that tracks on the coast of Gulf of America are highly vulnerable to storm-induced surge and wave loads.

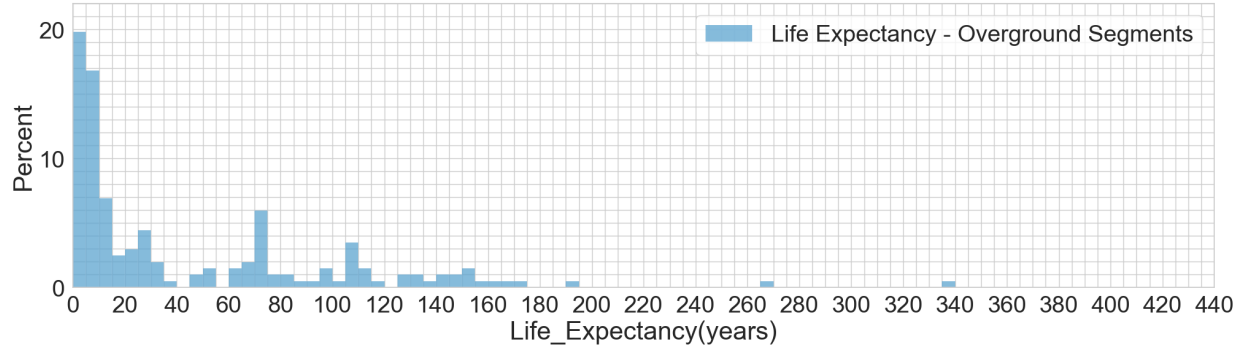


Figure 23. Distribution for life expectancies of selected inland track segments induced by scour in ballast and embankment under tropical cyclones

4.3 Convergence Study

This section summarizes the convergence study performed to ensure confidence in the results presented above. For a full convergence, the team ensured that both the number of down-sampled storms and number of SMC scenarios were sufficient. Therefore, a 2-dimensional search was conducted to find minimum values for these parameters to satisfy convergence. The annual repair cost of bridges and tracks was used as the convergence criteria. Therefore, the annual repair costs for different cases of down- sampled storms were estimated and compared. The annual repair cost, C^1 , is calculated as follows:

$$C^1 = \sum_{i=1} F_{b_i}^1 \cdot l_{b_i} \cdot c_b + \sum_{j=1} F_{t_j}^1 \cdot l_{t_j} \cdot c_t \quad (4)$$

where $F_{b_i}^1$ and l_{b_i} are respectively annually expected failures and length of bridge i , c_b is the cost of bridge repair per mile, $F_{t_i}^1$ and l_{t_i} are respectively annually expected failures and length of inland rail track segment i , and c_t is the cost of rail track repair per mile. The costs of bridge and rail track repairment per mile were assumed to be \$50 and \$2 million per mile in this study (Compass International 2023; Rail-Track.com 2023; U.S. Department of Transportation – Federal Highway Administration 2024). The study showed that 1600 SMC scenarios were sufficient for the convergence by controlling the cost difference between two consecutive search steps to be under 5 percent. Table 9 and Table 10 show that 1,600 SMC scenarios and 200 down-sampled storms are sufficient to provide the desired confidence in the results for both CN's and CSX tracks.

Table 9. Convergence results for CN line per 1,600 SMC scenarios

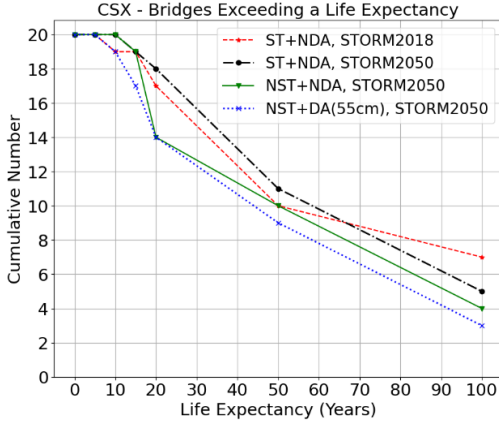
Number of Down-Sampled Storms	50	100	150	200
Annual Repair Cost (Million Dollars)	36.9	26.6	23.8	23.7
% of Point-To-Point Change	0.0	-27.9	-10.5	-0.4
% of Change Relative to 50 Storms	0.0	-27.9	-35.5	-35.7

Table 10. Convergence results for CSX line per 1,600 SMC scenarios

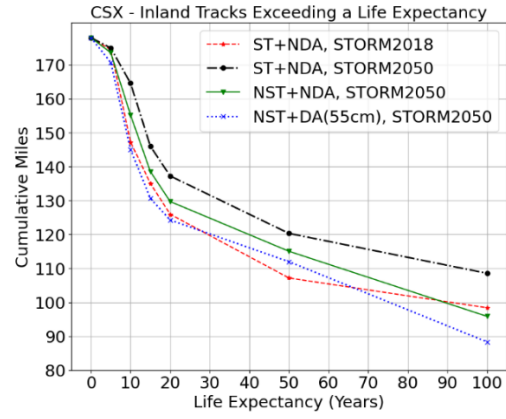
Number of Down-Sampled Storms	50	100	150	200
Annual Repair Cost (Million Dollars)	80.9	49.7	44.7	43.1
% of Point-To-Point Change	0	-38.6	-10.1	-3.45
% of Change Relative to 50 Storms	0	-38.6	-44.7	-46.7

4.4 Impacts of Datum Adjustments and Non-stationary Storms

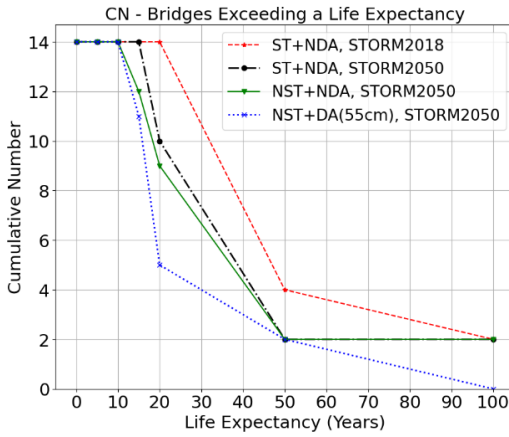
Figure 24 illustrates the comparative analysis the research team conducted to investigate the significance of water datum projections and non-stationary trends for storm events. The graphs show the cumulative number of bridges (a, c) and miles of inland tracks (b, d) exceeding a given life expectancy under scenarios considering stationary (ST) and non-stationary (NST) storms, with and without a 55 cm datum adjustment (DA). The graphs reveal interesting insights into both modeling uncertainties and projected weather patterns. First, the team performed SMC and generated samples for time of occurrences of storms. This sampling was random for the time period between 2018 and 2050. There are two synthetic datasets available: a) STORM2018, based on historical data up to year 2018, and b) STORM2050, based on projections for future storms. To investigate the impact of selection of storms from either dataset, the team first performed an analysis by using only one of the two synthetic datasets separately. The results showed significant differences in the outcomes, as shown in Figure 24. This was an interesting observation, as the team set the frequency and severity of storms exactly the same in the two models. The team hypothesized that this discrepancy was due to the inherent differences in the two datasets, such as differences in the landfall, radius to maximum winds, and the path that storm tracks take. This issue is difficult, as it requires generating two synthetic datasets that exactly match each other. Doing so is beyond the scope of this work. To remedy this issue, the team decided to use only storms from the STORM2050 dataset. It is critical to point out that the team used the return periods and CDF based on STORM2018 and STORM 2050. The only adjustment here was that when selecting the 200 storms, the team selected them exclusively from the STORM2050 dataset to accurately estimate the effect of non-stationary storms and water datum adjustments.



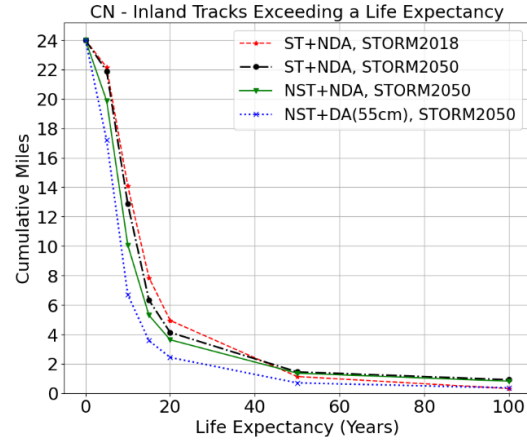
(a)



(b)



(c)



(d)

Figure 24. Projected life expectancy of CSX and CN lines under various storm modeling assumptions

When selecting storms from STORM2050 dataset as the baseline, a consistent trend was observed for both rail bridges and inland track segments. The trends show that adding non-stationarity effect (NST-NDA, green line) and datum adjustment (NST-DA, blue line) significantly lowers the survival curves for the railway components. In other words, both non-stationary storms and datum adjustments significantly reduced the life expectancy of bridges.

5. Long-Term Retrofit Actions to Enhance Track and Bridge Reliability

The research team applied several mitigation strategies to the rail tracks and bridges to enhance the reliability of the coastal railroads against the projected storm hazards. For inland tracks, they explored two primary strategies: a) elevating the tracks, and b) relocating vulnerable tracks away from shorelines. Both strategies aim at reducing inundation depths, potentially decreasing the vulnerabilities. Additionally, for ballast-deck bridges, the research team explored elevating the bridges to increase the clearance level from the ground or water surface, which can decrease the relative surge and wave height with respect to bridge deck elevation — and subsequently decrease the probability of failure. These targeted strategies, in the short term, can assist railroad owners and authorities in planning for a more robust and resilient railway infrastructure to ensure safe and reliable transportation in the face of tropical storms. It should be noted that all analyses were conducted with the consideration of future datum adjustments and non-stationary storms.

Note that the research team was well aware that some levels of elevation, such as an 18-foot rise, require extensive geometric modifications to the infrastructure, posing significant challenges due to right-of-way constraints, highway intersections, and environmental sensitivities. However, the team included these potentially impractical mitigation strategies to identify the highest level of elevation at which the risk from storm surge and waves is nearly eliminated.

5.1 Mitigatory Interventions and Results for Bridges

As noted earlier, to reduce vulnerabilities, both CSX and CN bridges are elevated. [Figures 25–27](#) show the impact of mitigation interventions for CN bridges on the life expectancies when bridges are elevated by 6, 12, and 18 ft, respectively. When compared with [Figure 17](#) (which shows the performance of the system without any mitigation intervention), elevating CN bridges by 6 feet shifts the minimum life expectancies from less than 15 years to over 50 years. Furthermore, the life expectancy of 12 bridges will increase to above 100 years, indicating a notable improvement in life expectancy.

Furthermore, a 12-foot increase in bridge elevation ([Figure 26](#)) extends the life expectancies for all CN bridges to above 100 years, demonstrating a substantial enhancement in life expectancy. [Figure 27](#) presents the impact on life expectancy of the bridge when elevated by 18 ft. This seems unnecessary, as all bridges (when elevated by 12 ft) are already expected to survive for a long time when exposed to the uplift force induced by tropical storms.

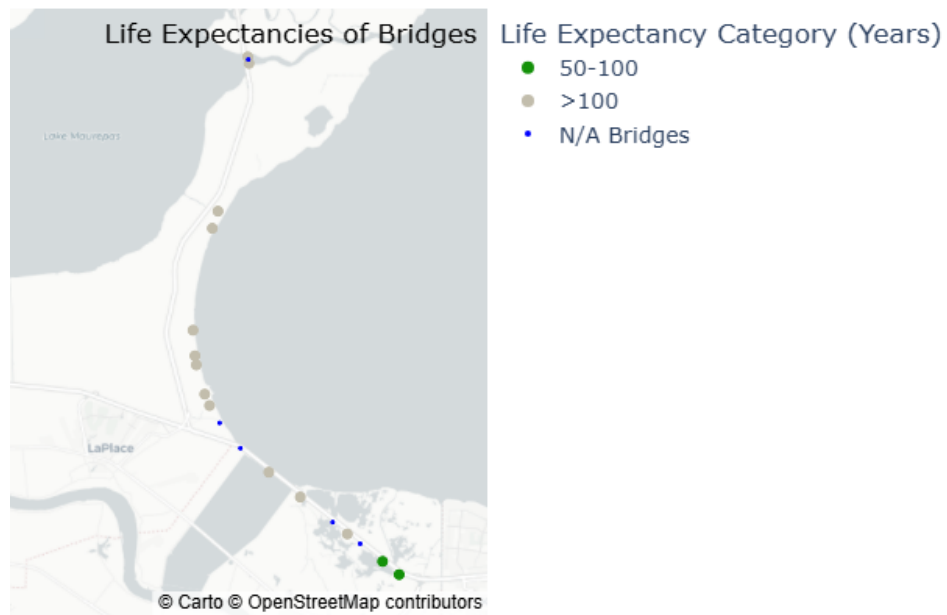


Figure 25. Effects of elevating CN bridges by 6 ft on vulnerabilities

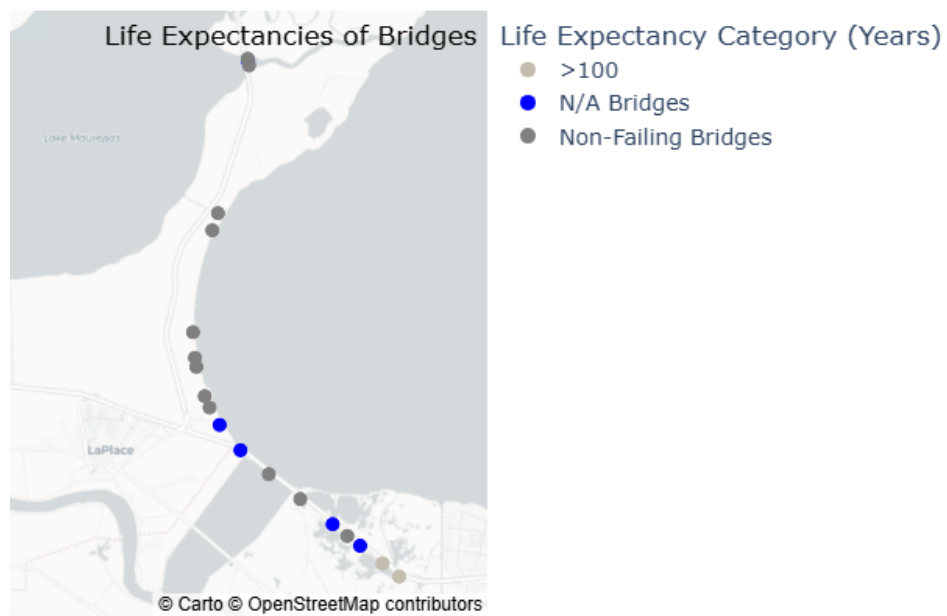


Figure 26. Effects of elevating CN bridges by 12 ft on vulnerabilities

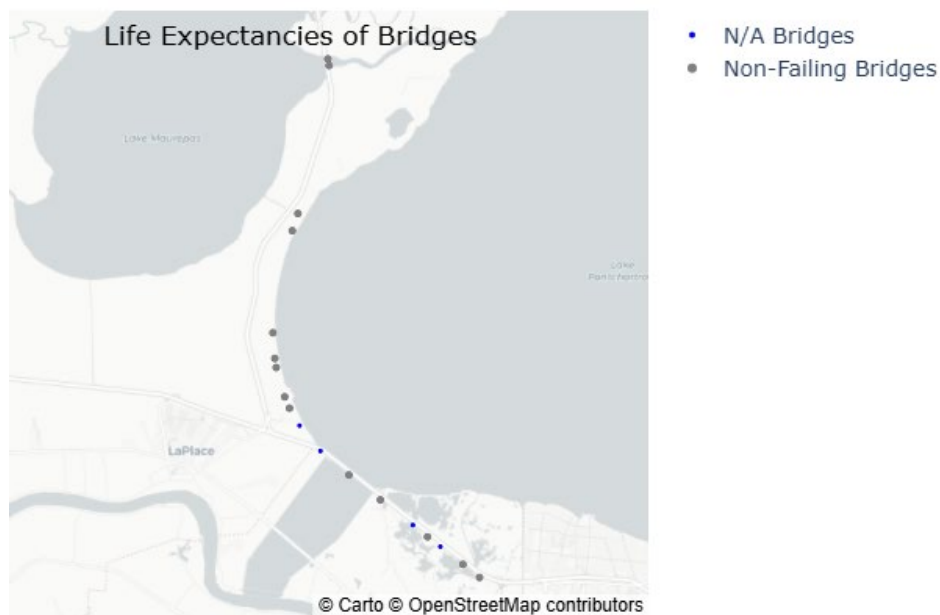


Figure 27. Effects of elevating CN bridges by 18 ft on vulnerabilities

Table 11 summarizes the observations above. Decision-makers can then choose the level of the mitigation based on the desired level of performance.

Table 11. Comparison of mitigation strategies for CN bridges

Life Expectancy Range (Years)	Number of Vulnerable CN Bridges			
	Current Status	6 ft elevation	12 ft elevation	18 ft elevation
0-5	0	0	0	0
5-10	0	0	0	0
10-15	3	0	0	0
15-20	6	0	0	0
20-50	3	0	0	0
50-100	2	2	0	0
>100	0	12	14	14

Figures 28–30 show the impact of bridge elevation on CSX bridges. When compared to Figure 18, where no mitigation intervention was applied, if bridges are elevated by 6 feet, the minimum life expectancy increases from less than 10 to over 20 years. Furthermore, a 12-ft increase in the elevation increases the minimum life expectancy to above 50 years.



Figure 28. Effects of elevating CSX bridges by 6 ft on vulnerabilities



Figure 29. Effects of elevating CSX bridges by 12 ft on vulnerabilities

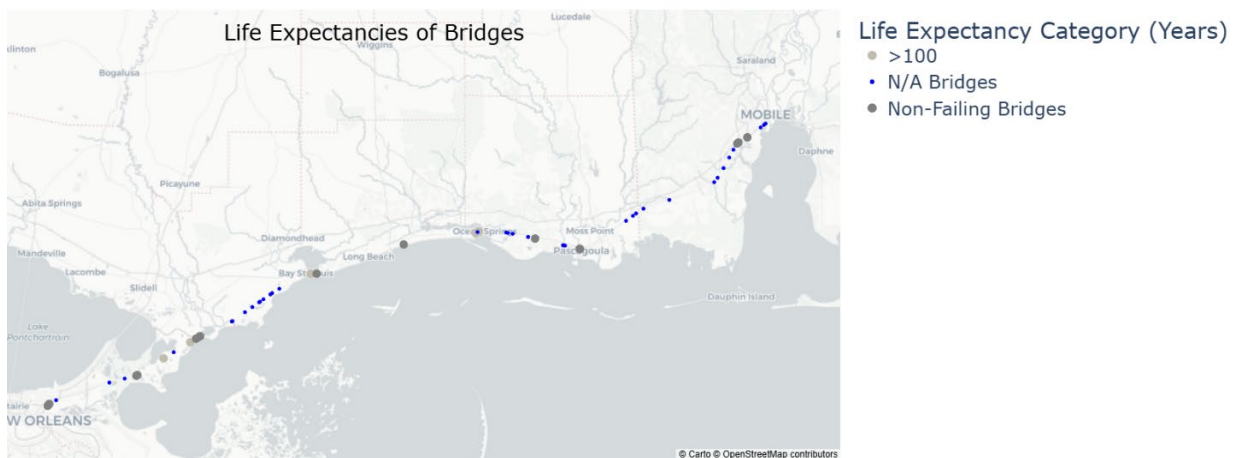


Figure 30. Effects of elevating CSX bridges by 18 ft on vulnerabilities

Table 12 presents the summary of the above observations. Elevating the bridges by 18 feet leads to the most pronounced improvement, ensuring all bridges survive at least 100 years, on average, under storm surge and waves. All bridges either do not fail or last at least 100 years under this scenario. It should be noted that elevating tracks and bridges by 18 feet may not be practically possible and may require building elevated corridors. A life cycle cost analysis is needed to estimate if this mitigation strategy is financially viable and effective. Doing such is beyond the scope of this report.

Table 12. Comparison of different mitigation strategies for CSX bridges

Life Expectancy Range (Years)	Number of Vulnerable CSX Bridges			
	Current Status	6ft elevation	12ft elevation	18ft elevation
0-5	0	0	0	0
5-10	1	0	0	0
10-15	1	0	0	0
15-20	4	0	0	0
20-50	4	5	0	0
50-100	6	3	1	0
>100	4	12	19	20

5.2 Mitigatory Interventions and Results for Inland Tracks

Elevating tracks is the first mitigation intervention the researchers examined. Figure 22 shows the track segments examined to be either individually or all together elevated to decrease the vulnerabilities. For this report, all inland tracks are elevated by 6, 12, and 18 feet.

Figures 31–33 show the life expectancy effect of elevating inland CN tracks. Compared to Figure 20, when elevated by 6 ft, the minimum life expectancy increases to at least 5 years, while elevating tracks by 12 ft increases the minimum life expectancy to at least 20 years. Elevating tracks by 12 ft appears to be very effective, as it increases the life expectancy for most of the rail tracks to above 100 years. Similar to the CN bridges, further elevation to 18 ft seems unnecessary.

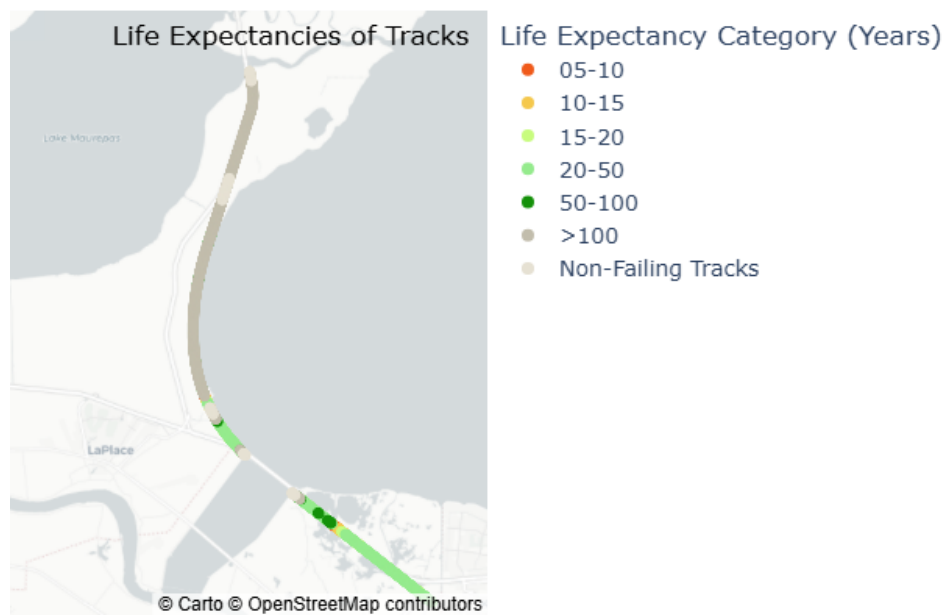


Figure 31. Effects of elevating CN inland tracks by 6 ft on vulnerabilities

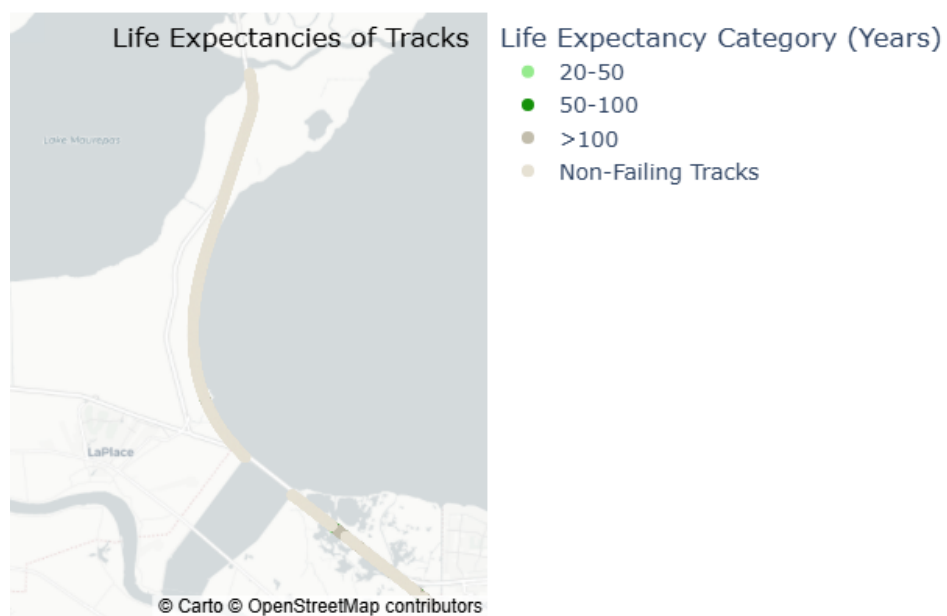


Figure 32. Effects of elevating CN inland tracks by 12 ft on vulnerabilities



Figure 33. Effects of elevating CN inland tracks by 18 ft on vulnerabilities

Figures 34–37 present the second strategy of shifting tracks away from shoreline. This strategy was executed in three levels by shifting the tracks 500, 1000, and 1500 ft inland. The effect of shifting the tracks are also shown in Figures 34–37. The results show that shifting tracks does not provide a substantial improvement in life expectancies. This is mostly due to the topography of the region, as a large portion of the tracks are constructed in swampy areas where the ground elevation is almost at the datum level. Shifting the tracks, thus, appears to be not very effective.

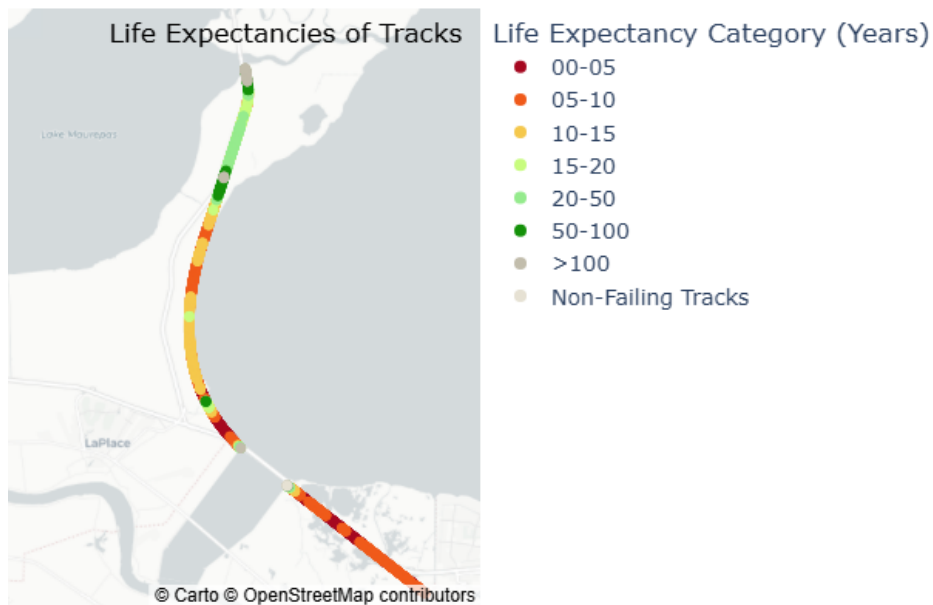


Figure 34. Effects of shifting CN inland tracks away from the shore by 500 ft

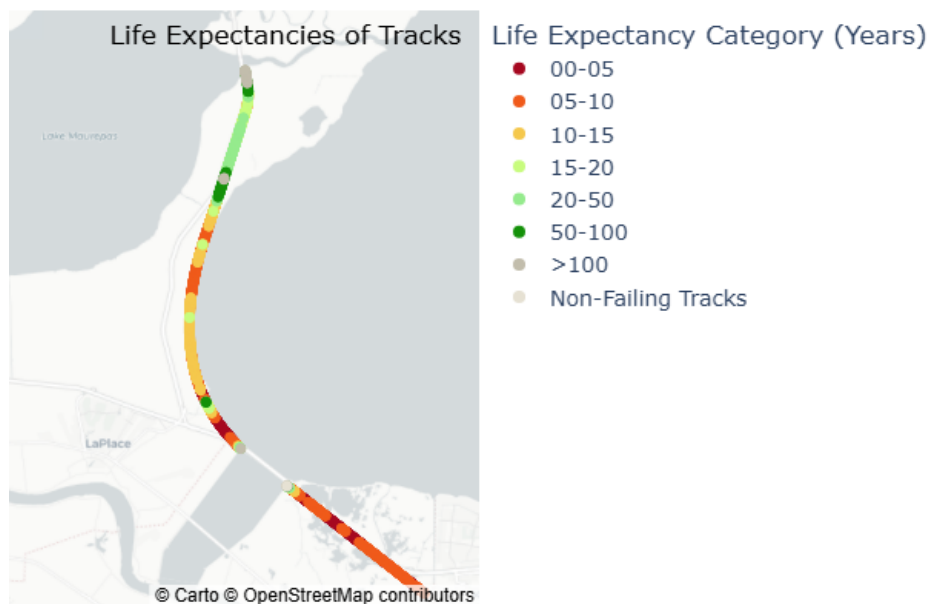


Figure 35. Effects of shifting CN inland tracks away from the shore by 1000 ft

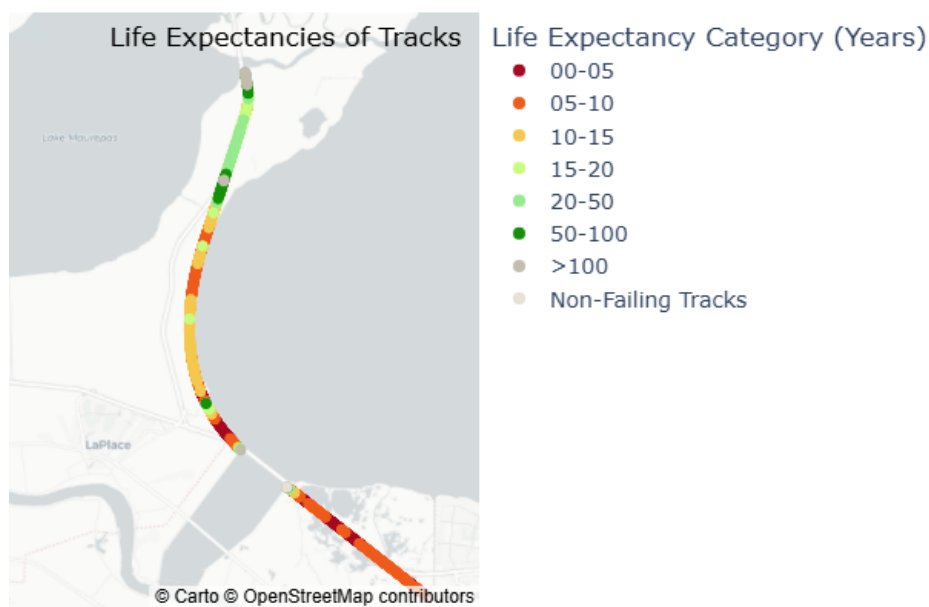


Figure 36. Effects of shifting CN inland tracks away from the shore by 1500 ft

Table 13 provides a comprehensive comparison between different strategies for mitigating vulnerabilities in CN inland tracks, providing the life expectancies with respect to track mileage. Among all mitigation interventions, the results show that if rail tracks are elevated by 12 ft, the vulnerabilities are mostly mitigated, where only 0.5 miles will have a life expectancy less than 100 years, while the rest of the tracks exceeds this value.

Table 13. Comparison of different mitigation strategies for CN tracks.

Life Expectancy Range (Years)	Miles of Vulnerability for CN Inland Tracks						
	Current Status	6 ft elevation	12 ft elevation	18 ft elevation	500 ft inland shift	1000 ft inland shift	1500 ft inland shift
0-5	6.8	0.0	0.0	0.0	5.0	5.0	4.9
5-10	10.5	0.3	0.0	0.0	8.7	8.7	8.4
10-15	3.1	0.5	0.0	0.0	4.9	4.8	5.1
15-20	1.1	1.0	0.0	0.0	1.7	1.9	1.7
20-50	1.7	7.2	0.2	0.0	2.2	2.2	2.3
50-100	0.3	0.8	0.3	0.0	1.0	1.0	1.1
>100	0.4	14.1	23.5	24.0	0.4	0.4	0.5

Figures 37–39 present the life expectancy effect of elevating CSX’s inland tracks, about 178 miles long. Elevating the tracks by 6 feet increases life expectancies; however, Figure 37 shows a few tracks which still expected to have a life expectancy of less than 15 years. Figure 38 shows the impact of elevating the tracks by 12 feet, which increases the minimum life expectancy to above 20 years. When tracks are elevated by 18 feet, all tracks become either non-vulnerable or show life expectancies beyond 100 years (gray lines in Figure 39). Note that seepage in the tracks is also a concern and can also cause damage. The models did not account for seepage because fragility models are not available for that failure mode. Also note that elevating tracks will not protect them against seepage damage. Therefore, the team cannot simply increase the elevation and assume all tracks will be safe against all possible failure modes.



Figure 37. Effects of elevating CSX inland tracks by 6 ft on vulnerabilities



Figure 38. Effects of elevating CSX inland tracks by 12 ft on vulnerabilities



Figure 39. Effects of elevating CSX inland tracks by 18 ft on vulnerabilities

For the CSX line, the shifting strategy could not be applied to the entire track due to geographical constraints, particularly where water was present on both sides (see Figure 40). The shift was implemented from a few miles beyond the Mississippi/Louisiana border to Mobile, Alabama. The results of shifting inland are shown in Figures 41–43. Shifting CSX tracks away from the shore by 500 feet seemed to decrease vulnerabilities by extending the life expectancies over 100 years in many shifted locations; Figure 41 shows an increase in gray spots, indicative of increased life expectancy. However, further shifts did not seem to significantly change the status of vulnerabilities.

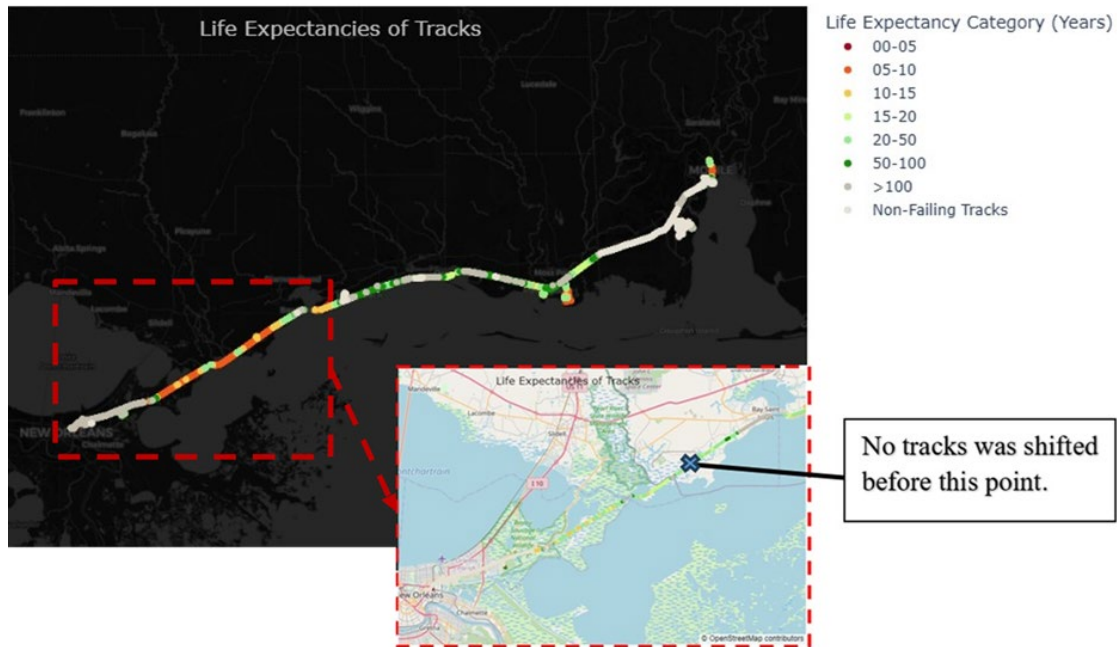


Figure 40. Constraints in shifting part of CSX tracks away from shore due to surrounding water bodies and swampy wetlands

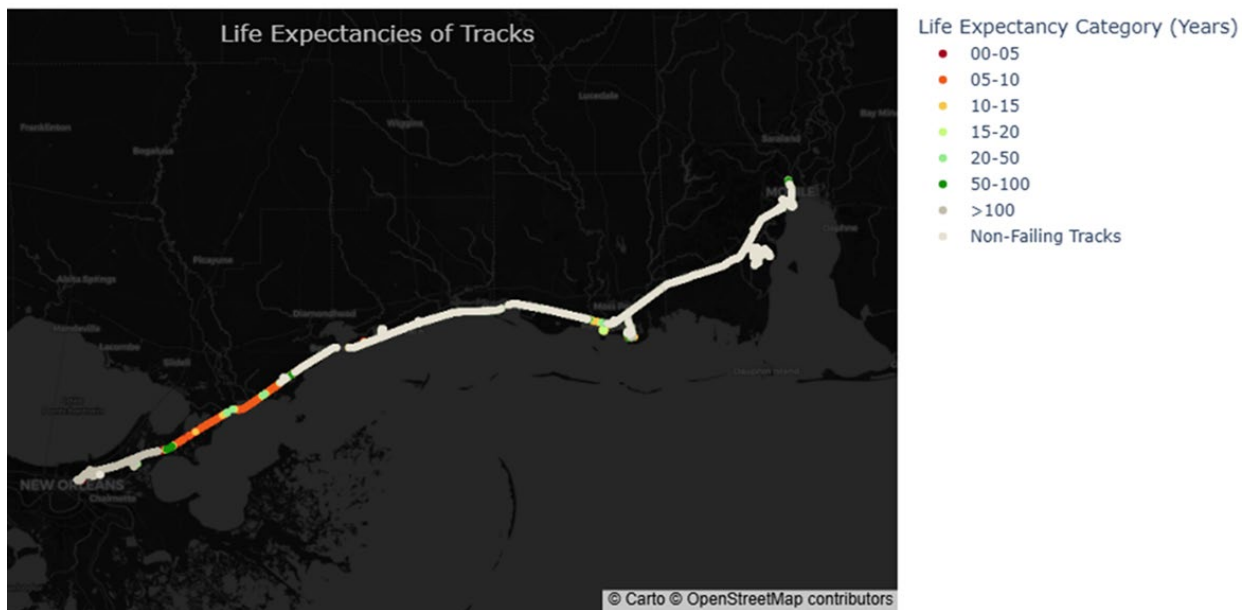


Figure 41. Effects of shifting CSX's inland tracks away from the shore by 500 ft

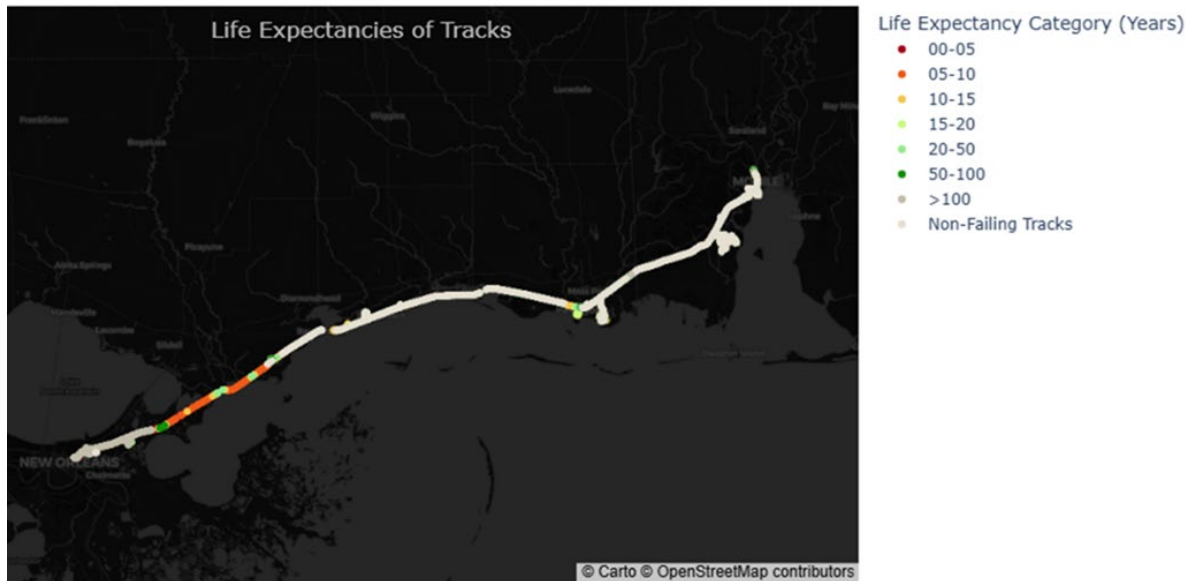


Figure 42. Effects of shifting CSX’s inland tracks away from the shore by 1000 ft

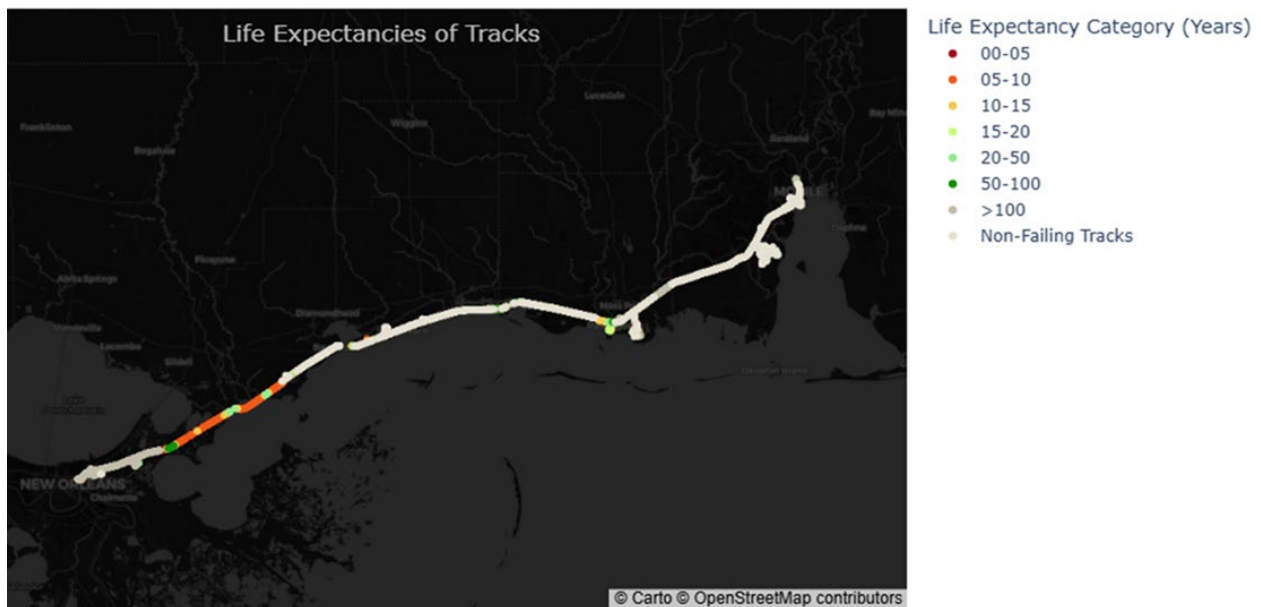


Figure 43. Effects of shifting CSX inland tracks away from the shore by 1500 ft

Table 14 shows a more detailed comparison between different mitigation interventions. Elevating the tracks appeared to be significantly more effective in reducing vulnerabilities compared to inland shifting strategies. Additionally, elevating tracks by 12 feet extended the life expectancies of 91 percent of rail tracks to beyond 100 years. Moreover, the 500-ft shift away from shore proved sufficient to significantly reduce vulnerability in the shifted railroad segments. However, most of the high and very high vulnerabilities were within the unshifted

segments shown in [Figure 40](#). Therefore, for CSX, this strategy is effective in protecting a portion of the track, and its overall impact is limited due to geographical constraints.

Table 14. Comparison of mitigation strategies for CSX tracks

Life Expectancy Range (Years)	Miles of Vulnerability for CSX Inland Tracks						
	Current Status	6 ft elevation	12 ft elevation	18 ft elevation	500 ft inland shift	1000 ft inland shift	1500 ft inland shift
0-5	8.2	0.0	0.0	0.0	8.9	8.7	8.5
5-10	26.8	0.0	0.0	0.0	18.3	17.9	17.7
10-15	13.2	1.2	0.0	0.0	8.9	9.1	8.5
15-20	5.9	10.8	0.0	0.0	4.8	5.1	5.5
20-50	12.0	20.6	0.8	0.0	10.4	10.2	9.5
50-100	22.0	15.7	14.9	0.0	16.9	15.8	16.0
>100	89.8	129.7	162.3	178.0	105.2	111.2	112.3

6. Conclusion and Summary

Researchers from Michigan Tech and Argonne National Laboratory developed a probabilistic framework to assess the reliability of Gulf Coast railroad infrastructure and to devise mitigation strategies for decision-making purposes. First, a shift was made from traditional scenario-based analysis to a fully stochastic storm hazard model. The process successfully tackled the issue of insufficient historical events and high computational costs by down-sampling a sufficient number of hurricanes from a subset of a 10,000-year synthetic storm dataset. The research team then integrated storm models with fragility models for tracks and bridges through a sequential Monte Carlo simulation to estimate the life expectancies for the railroad components. The framework successfully addressed the occurrences of multiple tropical storm events while considering the projected water datum adjustment and increasing frequency and intensity of future storms. A comparative analysis also revealed that factors such as the effect of non-stationary storms and water datum adjustments significantly reduce the operational life of railway components.

The researchers also evaluated the reliability of bridges against uplift forces. Additionally, the vulnerability of the tracks was assessed based on the likelihood of the ballast or embankment scour. The results indicated that for testbed railroads (CN and CSX), roughly 18% of concrete ballast-deck bridges and 44% of inland rails were expected to fail in less than 15 years. Overall, for the bridges, the vulnerabilities are less significant than inland tracks. Bridges carry significant costs associated with their repair and replacement, requiring higher safety factors when they are designed and constructed. The results of this study can help railroad owners and authorities allocate resources for mitigation and retrofit processes.

The research team applied several mitigation strategies to the tracks and bridges and explored elevating bridge decks. Bridges were elevated by 6, 12, and 18 feet, with improvements in life expectancy observed at each level. Elevating rail tracks was the first strategy explored for inland rail tracks. To analyze the effect of track elevation as a mitigation strategy, researchers elevated tracks by 6, 12, and 18 feet, and found significant improvements in reliability against storm surges at each level. Shifting tracks away from shore was the second strategy. For CSX, it was effective in protecting a portion of the track. However, for CN's tracks, shifting showed minimal impact due to the swampy nature of the surrounding areas.

Decision-makers in the railroad industry can use this study to select the appropriate level of mitigation based on the desired performance objectives. However, this process can be challenging without taking financial and operational considerations into account; extreme raises of 12 or 18 feet would require extensive geometric adjustment to the current state of the railroad infrastructure. This would pose implementation challenges, including acquiring right-of-ways and environmental considerations. Additionally, some of the proposed mitigation strategies, if practically feasible, may be costly, underscoring the importance of evaluating costs versus benefits. Therefore, conducting a lifecycle cost analysis could be a crucial element in determining the viability of these mitigation strategies.

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8. Abbreviations and Acronyms

ACRONYM	DEFINITION
ADCIRC+SWAN	ADvanced CIRCulation and Simulating Waves Nearshore
AEF	Annually expected failures
CN	Canadian National
CSX	CSX Transportation
CDF	Cumulative distribution function
DA	Datum adjustment
ECDF	Empirical CDF
HWM	High water mark
HURDAT2	HURricane DATaset
MDA	Maximum dissimilarity approach
MFRI	Mean failure recurrence interval
NOAA	National Oceanic and Atmospheric Administration
NST	Non-stationary (storms)
NGOA	Northern Gulf of America
SMC	Sequential Monte Carlo
ST	Stationary (storms)
TC	Tropical cyclones