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Doubling of flood-induced bridge asset failure loss in Mozambique under 2050 climate

Yaning Qiao[1,] Yaru Guo[1], Sebastian Rowan[2], Ricardo Medina[3], Xavier Espinet[4], Jonathan Cullen[5], Fanran Meng[6,*], Zhi Cao[7,**]

1. School of Mechanics and Civil Engineering, China University of Mining and Technology, Xuzhou, China
2. Department of Civil and Environmental Engineering, University of New Hampshire, Durham, New Hampshire, USA
3. Engineering Mechanics and Infrastructures, Simpson Gumpertz & Heger, Waltham, Massachusetts, USA
4. Office of the Chief Economist for Sustainable Development, The World Bank, Washington, D.C., USA
5. Department of Engineering, University of Cambridge, Cambridge, UK
6. Department of Chemical and Biological Engineering, Faculty of Engineering, University of Sheffield, Sheffield, UK
7. College of Environmental Science and Engineering, Nankai University, Tianjin, China

*f.meng@sheffield.ac.uk; ** zhicao@nankai.edu.cn

Abstract [200 words]

Mozambique, often impacted by severe flooding, faces challenges with its bridge networks, particularly due to climate change. Existing methods for evaluating flood-induced bridge asset failure loss lack a comprehensive national level risk assessment that includes a full spectrum of flood events and bridge-specific details. We introduce a new framework that quantifies flood-induced bridge failure loss nationally, incorporating climate change using an equivalent flood return period approach. This framework provides a continuous risk analysis, addressing the shortcomings of discrete flood return periods. Our analysis of 1,210 bridges in Mozambique indicates an annual expected values of bridge asset failure losses equivalent to 0.6% of its 2021

Gross Domestic Product (GDP), or 83 million dollars. Under a high emission scenario, this loss could increase to 162 million dollars by 2050. The findings highlight the vulnerability of Mozambique's bridges to floods with return periods of 500 to 1000 years, suggesting the need for revisions of bridge design codes. The framework's utility extends beyond Mozambique; Other Global South countries can apply it to assess their bridge asset failure risks and strategically enhance bridge resilience. This method improves infrastructure management by identifying high-risk areas and justifying resource allocation for adaptation, enabling proactive responses to flood-induced challenges and enhancing climate resilience.

1. Introduction

Mozambique faces one of the worst challenges due to severe cyclone-induced flooding in the world[1,2]. In 2015, the United Nations Sustainable Development Goals (Goal 13: Climate Action) emphasized the importance of combating climate change through national strategic planning and climate hazard risk assessment, particularly in the Global South countries[3]. Among all countries, Mozambique ranked 181 out of countries/regions in the Human Development Index in 2020[4]. The country's vulnerability to flooding is particularly concerning for its local bridges, many of which lack sufficient funds for climate adaptation, with Mozambique's National Road Administration (ANE) being a key stakeholder in addressing this issue. Flooding incidents are frequently reported along major rivers (e.g., Limpopo, the Zambezi, the Ruvuma, the Pungwe) and the coastal areas in Mozambique[5–8], where numerous bridges are located. Approximately 95% of Mozambique's registered bridges span over rivers or streams, rendering them susceptible to failure as climate change leads to more severe flooding[9,10]. Bridge failures disrupt connectivity for extended periods (e.g., even for some years after flooding), severely impeding traffic, hindering post-flooding rescue and threatening lives[11]. Therefore, urgent actions are required to identify critical bottlenecks in Mozambique's bridge network and enhance its flood resilience.

While there have been endeavors to quantify flood-induced bridge asset failure, damage, collapse, loss, and vulnerability at the project level (i.e., for specific bridges) over the past decades[12–17], few studies have assessed the risk of flood-induced bridge failure at the regional level[18]. National-level evaluations of flood-induced bridge loss are particularly scarce, reflecting ongoing challenges in scaling such analyses[19]. This difficulty arises primarily due to data paucity, as project-level analyses rely on technical information such as streamflow velocity, peak flow rates, water pressure, bridge pier strength, foundation shape, pile length, scour vulnerability index, and more[12–14]. However, collecting such comprehensive data for bridges at the national level is often impractical due to data collection difficulties, limited budgets, or issues with data transparency. Hence, there is an urgent need to establish a generalizable bridge asset failure loss model that strikes a balance between providing sufficient detail and minimizing data requirements to account for flooding impacts and future flood scenarios.

Specifically, we define bridge failure as an event that necessitates complete bridge replacement, thereby equating the bridge cost with the construction cost of a new bridge. Objective bridge asset failure risk is typically perceived by combining the probability of flood with the consequence of bridge asset failure in terms of economic losses[12–14,20,21]. Recent research has focused on using risk-based methods and economic metrics to assess the impact of climate change on transportation infrastructure[22–24]. As flood-induced risks can be quantified using expected values of economic losses, the total bridge asset failure loss should ideally encompass all flood scenarios with different return periods, their associated probabilities of failure, and the resulting direct economic consequences (such as repair and replacement) and indirect economic consequences (such as disruptions to transport networks, trade flows, and local economic activity). Unfortunately, existing literature often considers only certain return periods of flooding[12,14,20,25–27], leading to an underestimation of the total loss. Underestimating loss can give rise to flawed disaster reduction policies, resulting in insufficient attention being devoted to mitigation and/or prevention.

Here, we develop a generalizable risk evaluation framework that quantifies and compares the total failure loss of bridges at the national level, considering floods with continuous return periods. Our framework accounts for the total loss of flooding by conducting a definite integral of the risk evaluation model over the range of floods with the lowest and highest return periods (i.e., the integration domain). We apply this framework to an inventory of 1,210 registered bridges in Mozambique, considering baseline floods from 1979 to 1999 and projected 2050 flood scenarios. A medium emission scenario and a high emission scenario are considered for 2050 floods. Furthermore, we aim to identify critical factors that can contribute to the enhancement of flood resilience in bridge infrastructure.

Our risk evaluation model builds upon the current understanding of climate risks to infrastructure, specifically the probability and consequence of climate hazards on specific types of infrastructure[28]. This approach draws inspiration from the established practice of quantifying risk in performance-based seismic design[29], which focuses on assessing the potential failure of structures with quantification of probability and consequence of earthquakes. For our model, we extend this principle by creating a new framework that incorporates 1) a flood hazard function, 2) a bridge fragility function, 3) a bridge cost estimation function, and 4) an international construction cost index (ICCI) function.

This comprehensive framework enables the evaluation of the overall bridge asset failure loss due to flooding at the national level, specifically in resource-constrained Global South countries with limited data availability, particularly data for bridge costs. The framework requires minimal input data, primarily by replacing local bridge costs with estimation by multiplying the cost estimate function and the ICCI function. In contrast with other regional approaches (e.g. Liu et al.[24]), our unique framework obviates the need to collect comprehensive hydrological/hydrodynamic data (e.g. time series of maximum flow discharge, maximum flow depth, upstream flow depth, maximum upstream unit discharge, annual maximum flow, etc) on a regional/national level, which is commonly considered unrealistic.

The flood hazard function serves to characterize the probability associated with varying magnitudes of floods, offering insights into the likelihood of different flood scenarios. By combining the bridge fragility function with the flood hazard function using Bayes' theorem, we can compute the probability of bridge failure based on prior knowledge of flood magnitude.

In addition, the ICCI function is used to generalize the local construction costs for different types of bridges by relating to costs observed in the United States (U.S.)[30]. Furthermore, we conduct sensitivity analyses on our risk evaluation model, systematically varying the inputs to identify critical factors that significantly influence the outcomes.

By employing this rigorous framework, we address two crucial research gaps: (1) a generalizable model that integrates hazard, fragility, bridge replacement costs, and ICCI, thereby enabling the quantification of national level bridge asset failure loss caused by flooding, while considering the effects of climate change; and (2) a practical approach to assessing the bridge asset failure loss due to flood in resource-constrained Global South countries with limited data availability. This study focuses on the quantification of the direct physical failure loss of bridge assets, excluding indirect loss (e.g. loss of time and life).

2. Methods

2.1 Risk definition and quantification

In this study, risk is defined as the potential for flood-induced failure of bridge assets, quantified as the expected value of direct economic losses resulting from flood-induced bridge collapse. Hence, bridge failure refers to the collapse of a bridge with zero remaining value in this study. The underlying cause of this risk arises from floods occurring under both baseline and 2050 climate conditions:

- To quantify the risk, we first employ the hazard function, which represents the annual probability of a flood with a specific return period affecting a certain bridge. To account for the continuous range of return periods between the minimum and maximum values analyzed, we utilize an integral function (see Section 2.2).

- The failure probability of a particular bridge type is quantified using the fragility function, which denotes the likelihood of bridge failure given a flood event with a specified return period (see Section 2.3).
- To assess the direct economic loss of bridge failure, we consider the associated bridge replacement costs (see Section 2.4). As the responsibility for risk management lies with national transportation authorities, who act as the bridge owners, the bridge replacement costs serve as a representation of the agency costs incurred when a bridge fails and becomes non-functional. To quantify these replacement costs, we first employ a bridge costing function derived from data obtained from the U.S. Then, we use ICCI to adjust the bridge replacement costs in the analyzed country based on the ratio of its Gross Domestic Product (GDP)[31,32]. The ICCI alleviates the strong dependence on bridge asset cost data, making the framework more generic and widely applicable.

To determine the overall risk, we aggregate the risks associated with all bridges wintin the portfolio (Equation 1). Consequently, the risk evaluation model for flood-induced bridge failure at the national level is obtained by combining four components: (1) hazard function, (2) fragility function, (2) cost function, and (4) ICCI.

$$Risk_{total} = \sum_{\mathrm{n}=1}^{N}\left[\left(\int_{R_{min}}^{R_{max}} P_n(R) f(F|R) dR\right) * Cost_n\right] * ICCI_{GDP,m} \tag{1}$$

where $Risk_{total}$ denotes the annual total risk of bridge failures in a specific region; $P_n(R)$

denotes the flood hazard function of the n^{th} bridge (N bridges in a nation), where R is the return period of a flood ($P_n(R) = \frac{1}{R}$); the integral domain is between the maximum flood return period R_{max} and the minimum flood return period R_{min} in consideration; $f(F|R)$ denotes the bridge fragility function, which represents the conditional probability of bridge failure (n^{th} bridge) under flood; dR is an increase in return period; $Cost_n$ denotes economic loss function, meaning the economic losses of the n^{th} bridge failure; $ICCI_{GDP,m}$ denotes the international construction cost index function, which transfers construction costs to a specific region/nation related to GDP.

Equation 1 presents a typical risk analysis approach, integrating the hazard probability, fragility, and economic loss. It is also used to perform national-scale upscaling for all investigated bridges. In particular, $ICCI_{GDP,m}$ is added to the equation to account for the economic value of assets in assessed countries compared with a reference country. This factor overcomes the shortcoming that bridge asset cost information is unavailable in the assessed country.

To strengthen the analysis, the robustness of the GDP-cost correlation should be tested against the influence of local cost factors (labor, materials, transport) specific to various bridge types and regional contexts. While these local cost drivers are critical for project-specific estimates, they were beyond the scope of this study, which focuses on establishing a foundational, system-level correlation for national risk assessment.

2.2 Hazard function

The hazard function is a continuous curve that captures the relationship between flood depth and the likelihood of occurrence at each bridge, expressed as the inverse of the return period (Equation 2). These functions are derived from high-resolution fluvial flood maps provided by the World Bank, with a spatial resolution of 3 arc seconds (approximately 90 m)[33]. We superimpose the flood maps onto the available bridge location data in Mozambique to obtain the flood hazard function for each bridge. The bridge data were provided by ANE, containing Mozambique's national bridge inventory including information on bridge characteristics (length, width, types, number of spans), and geospatial coordinates. The flood maps provided by the World Bank encompass a range of return periods, including 5, 10, 20, 50, 75, 100, 200, 250, 500, and 1,000 years. Leveraging these maps, we employ interpolation techniques to determine the hazard functions specific to each bridge location. Doing this enables us to capture the variations in flood depth and occurrence likelihood at different return periods across the national bridge asset.

$$P_n(R) = \frac{1}{ERP_{n,R}} = \frac{1}{a_n * e\hat{}(b_n * FD_{n,R})} \qquad (2)$$

where $P_n(R)$ denotes the annual exceedance probability of a certain flood (reciprocal of the return period); $ERP_{n,R}$ denotes the equivalent return period, which is equivalent to the impact of the flood in 2050 to the baseline climate; a_n and b_n denote the two regression factors for the n^{th} bridge; $FD_{n,R}$ denotes the flood depth of the flood characterized by return period R for the n^{th} bridge.

We observe that floods with the same return period in 2050 will exhibit greater flood depths due to climate change[22]. To account for changing flood probabilities under future climate conditions, we developed the Equivalent Return Period (ERP) method. For example, a flood projected to have a 200-year return period in 2050 may correspond to a 432-year event under the baseline climate. The ERP represents the adjusted return period that reflects this shift. By integrating ERP into the hazard function, the model can be consistently applied across both baseline and future climate scenarios, enabling a more robust assessment of flood risk. Notably, the ERP for baseline events remains equal to their original return periods.

To determine the regression coefficients for the hazard function, we conduct a calibration process using reference data points obtained from the flood depth and return periods of the 5 to 1,000-year flood map layers under the baseline climate for each bridge location. The least squares method is employed to optimize the fit of the regression, yielding two regression coefficients, which are specific to the hazard function of each bridge. The regression analysis exhibits high degrees of fit, indicating a robust relationship between flood depth, return periods, and the corresponding hazard function coefficients. The relation revealed by Equation 2 may be impacted by topography or watershed characteristics, and the impact can be captured by different regression coefficients of Equation 2 at each bridge location.

2.3 Fragility function

The fragility function plays a crucial role in predicting the likelihood of bridge failure based on a given flood return period (i.e., ERP). In alignment with the hazard function, which is related to the flood return period, the fragility function incorporates flood depth as a parameter to estimate the probability of bridge failure, employing a conditional probability of failure approach[23]. As an Africa/Mozambique specific model does not exist, we employ the widely used U.S. Federal Emergency Management Agency (FEMA) Hazus model[34]. This feasible and simplistic model considers factors including flood return period, scour potential, and span type (continuous or single span), offering a comprehensive assessment of bridge fragility. It distinguishes itself from previous studies that rely on parameters such as peak flow and flow discharge to establish a link between flood hazard and bridge fragility[23,24,35]. The Hazus model is graphically expressed in Figure 1.

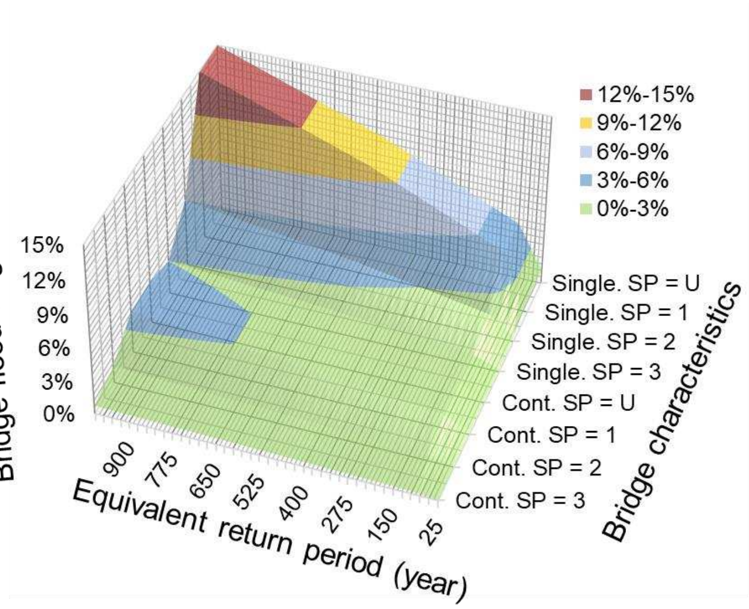


Figure 1 | FEMA's Hazus model of bridge flood fragility. Note: Cont. SP = continuous span, scour potential; Single. SP = single span, scour potential

This study iteratively generates fragility functions for each bridge, according to the equivalent return periods, bridge span type (continuous span or single span), and scour potential. This suggests the Hazus model does not associate fragility with bridge structure or material.

2.4 Quantifying economic losses

The quantification of economic losses resulting from flood-induced bridge failure considers the direct costs associated with bridge replacement. We adopt a simplified yet practical framework that incorporates key parameters, such as the length of the bridge and the width of the bridge, as described in Equation 3[36]. The regression coefficients are determined through a rigorous regression analysis using bridge replacement cost data from the U.S., as cost information/models are not available for the investigated Mozambique bridges. For all bridges, the coefficients are solved by regression analysis using data from the U.S., and the historical replacement costs are appropriately discounted to their present values in 2021[37,38]. To ensure the reliability of the regression analysis, we employ various diagnostic techniques, including collinearity diagnostics, residual diagnostics, and Cook's Distance, thereby enhancing the accuracy of the regression results. For culverts, we adopt a British model to conduct a similar analysis[39], thereby capturing the specific characteristics of these structures. Statistical analysis of the coefficient of determination (R^2) for each of the 12 types of bridge regression models reveals a mean R^2 value of 0.6 with a standard deviation of 0.22. The R squares indicate a satisfactory fit of the data in the calibrated models, providing confidence in the accuracy of the economic loss estimations.

$$Cost_n = 10^{\alpha_0} \times (L_n)^{\alpha_1} \times (W_n)^{\alpha_2} \quad (3)$$

where $Cost_n$ denotes the replacement cost of the n^{th} bridge; L_n denotes the length of the n^{th} bridge; W_n denotes the width of the n^{th} bridge; α_0, α_1, α_2 denotes regression factors for the n^{th} bridge.

To establish a correlation between the bridge replacement costs obtained from the U.S. data and the specific context of Mozambique, we develop a linear regression model (Equation 4):

$$ICCI_{GDP,m} = a * GDP_m + b \tag{4}$$

Where $ICCI_{GDP,m}$ denotes the international construction cost index of a country; GDP_m denotes the GDP of a country; a and b represent the regression coefficients.

To calibrate the model, we utilize a European dataset comprising the Construction Cost Index (CCI) values for 40 European countries[40], yielding a good fit with GDP per capita (R^2 value of 0.816). The resulting calibrated model serves as a practical tool for estimating bridge replacement costs in Mozambique by scaling U.S. cost data according to national economic conditions, using GDP per capita as a proxy.

2.5 Sensitivity analysis

Sensitivity analyses play a crucial role in discerning the pivotal factors that impact the risk evaluation model. In this study, we randomly select a bridge for each of the 12 bridge types and conduct an in-depth sensitivity assessment to identify the model inputs that most influence the calculated bridge risk. These inputs encompassed essential parameters such as bridge length, width, span number, and the depth of floods ranging from 5 to 1000-year events. To gauge the effect of these inputs on the model's output, we systematically increase each input by 10% while keeping others constant, following a One-At-A-Time (OAAT) approach. This meticulous process allows us to observe and analyze the resulting changes in the model's output, providing valuable insights into the critical factors that significantly influence the overall risk assessment.

2.6 Case study

We randomly selected the bridge with ID BR064307:0021.92, located in the Zambia delta, as an example to calculate the flood-induced bridge asset failure loss, to provide a detailed demonstration of the research methodology of this study. The bridge is single span steel Bailey bridge with a length of 10 m and a width of 4 m, which served as inputs for the model. In our analysis of some other bridges, the choice of different bridges does not affect the chosen method.

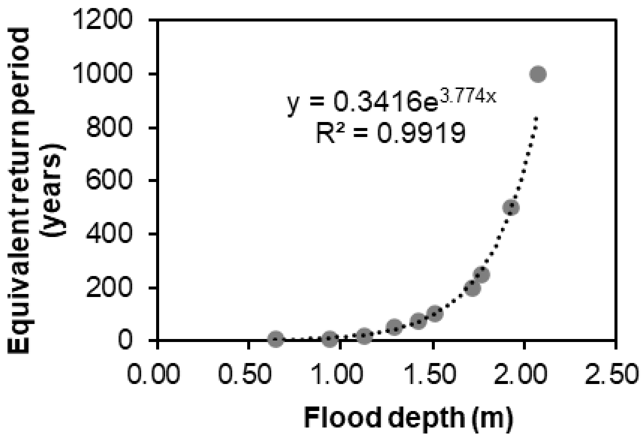


Figure 2 | Regression analysis for the flood depth and return period of the investigated bridge under the baseline climate.

Figure 2 shows the exponential relationship between the equivalent return period and flood depth for this bridge under the baseline climate. Due to adverse changes in the climate, the same return period of flooding means different for the baseline and future climate. For example, the magnitude (e.g. flood depth) of a 500-year flood under the future high scenario is greater than a 500-year flood under baseline climate, although both have an annual likelihood of exceedance of 0.2% (= 1/500). Hence, the ERP is chosen to represent the magnitude of flooding for comparing floods in different climate scenarios. In effect, the ERP is a translation of the future return period into the current climate by matching flood depth. The ERP of floods under baseline climate equals the original return period. For this bridge, the relationship between the ERP and flood depth for the investigated bridge can be expressed by the following formula (Equation 5):

$$ERP = 0.3416 \times e^{3.774 \times FD} \tag{5}$$

where ERP represents the flood equivalent return period function for the investigated bridge and FD represents the flood depth. In the calculation, the model coefficients 0.3416 and 3.3774 are unique for each bridge.

For example, a baseline flood of 1 m depth corresponds to approximately a 15-year flood for this bridge (according to Equation 5). Under the 2050 high emission scenario, a 15-year flood has a depth of 1.2 m. It corresponds to an ERP of 31.6 years (again according to Equation 5), which means this flood is a 31.6-year flood if under the baseline scenario. With this translation, we can obtain the ERP for the 2050 flood, and further, determine the fragility (bridge failure probability, see Figure 3).

The fragility function for each bridge is derived from a general fragility surface, as shown in Figure 1. Due to the unavailability of scour potential data, we assign the input "U" (unavailable) in the fragility function. This assumption introduces a conservative bias, typically resulting in a higher safety margin compared to the actual fragility of the bridge. When the span type is known, the fragility function becomes a piecewise function of the flood return period, expressed in terms of the Equivalent Return Period (ERP). This corresponds to the intersection of the fragility surface with the vertical plane defined by Cont. SP = U, as illustrated in Figure 1. The investigated bridge has the following fragility function (Equation 6):

$$f(F|R) = \begin{cases} 0.0005 \times ERP_{n,R}, & ERP_{n,R} \leq 100 \\ 0.0001 \times ERP_{n,R} + 0.0375, & 100 < ERP_{n,R} \leq 500 \\ 0.0001 \times ERP_{n,R} + 0.05, & ERP_{n,R} \geq 500 \end{cases} \tag{6}$$

where $ERP_{n,R}$ denotes the equivalent return period, which is equivalent to the impact of the flood R in 2050 to the baseline climate for the n^{th} bridge.

Based on Equations 5 and 6, the failure probabilities of the investigated bridge under different flood return periods for both the baseline and 2050 high and medium emission scenarios are calculated, as shown in Figure 3 below.

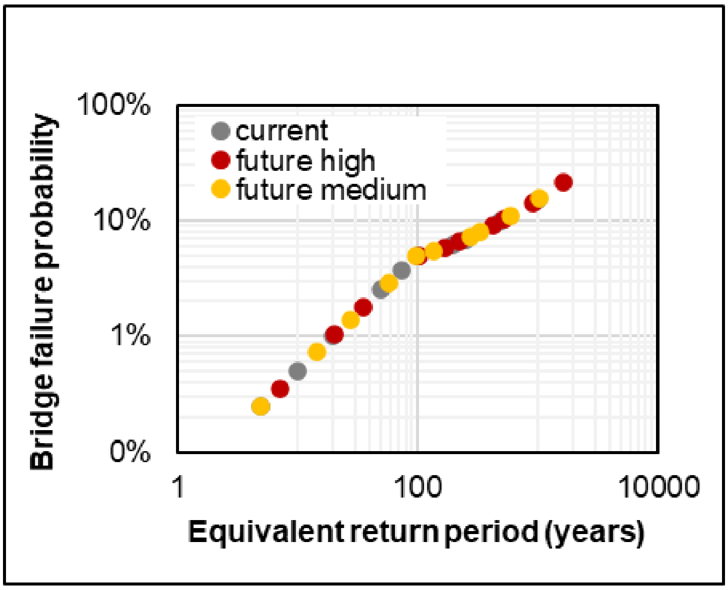


Figure 3 | Bridge failure probability caused by flood in different return periods.

In practice, the flood return periods often extend beyond the 10 types (horizontal axis, 10 plots for each climate scenario) considered in Figure 3. We calculate the failure probability for the investigated bridge across continuous return periods and then multiply it by the predicted bridge's cost to determine the flood-induced failure risk for the investigated bridge. In the end, the annual flood-induced bridge failure risks (i.e. mathematical expectation) are estimated to be 58 U.S. Dollars (USD), 72 USD, and 100 USD under the baseline climate, the 2050 medium emission scenario, and the 2050 high emission scenario, respectively.

3. Results

3.1 Flood depths are projected to increase across the country

Visualizing the country location (Figure 4a), bridge location and composition (Figure 4b), and fluvial flood data provided by the World Bank[33] (Figures 4c-e), we observe that the most severe flooding incidents are characterized by greater flood depths. These areas include the crossing point of the Zambezi and Shire Rivers in the central region of Mozambique (forming an X shape, in red color), the floodplain along the east coast, and the vicinity of the Limpopo River in the northern part of the country[33]. The average flood depth is found to increase further in the anticipated 2050 climates (Figure 4d and 4e). In the baseline climate, Gaza Province experiences the greatest average flood depth, ranging from approximately 0.24 to 0.27 meters, which is projected to increase by up to 10% in 2050 under the high emission scenario. Zambezia Province ranks second in terms of average flood depth, ranging from about 0.15 to 0.18 meters in the baseline climate, and is expected to rise to approximately 0.21 to 0.24 meters in 2050 under the high emission scenario. Niassa Province holds the third position in terms of average flood depth in Mozambique. Notably, the ranking of average flood depths across all provinces remains consistent in the anticipated 2050 climates.

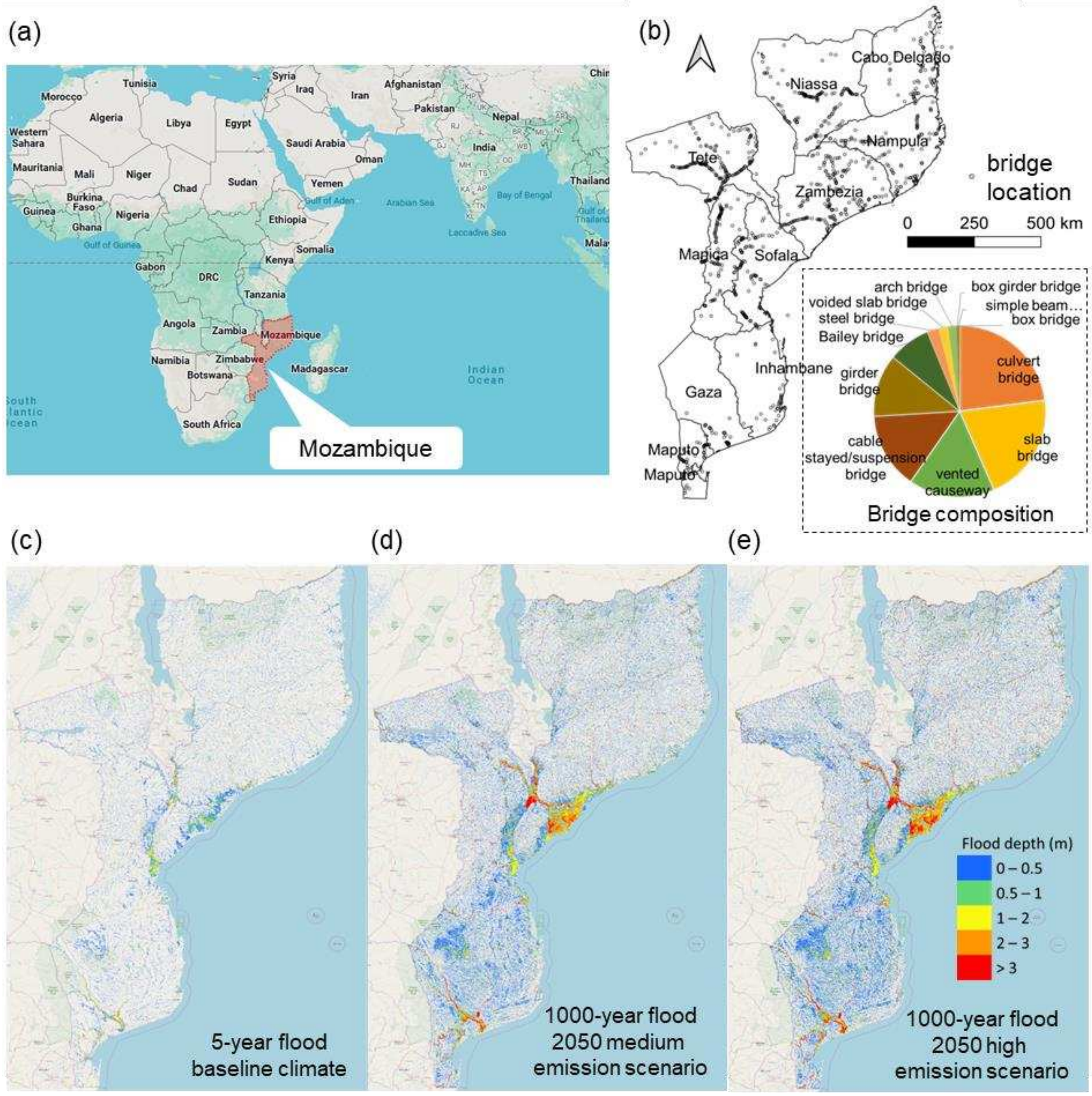


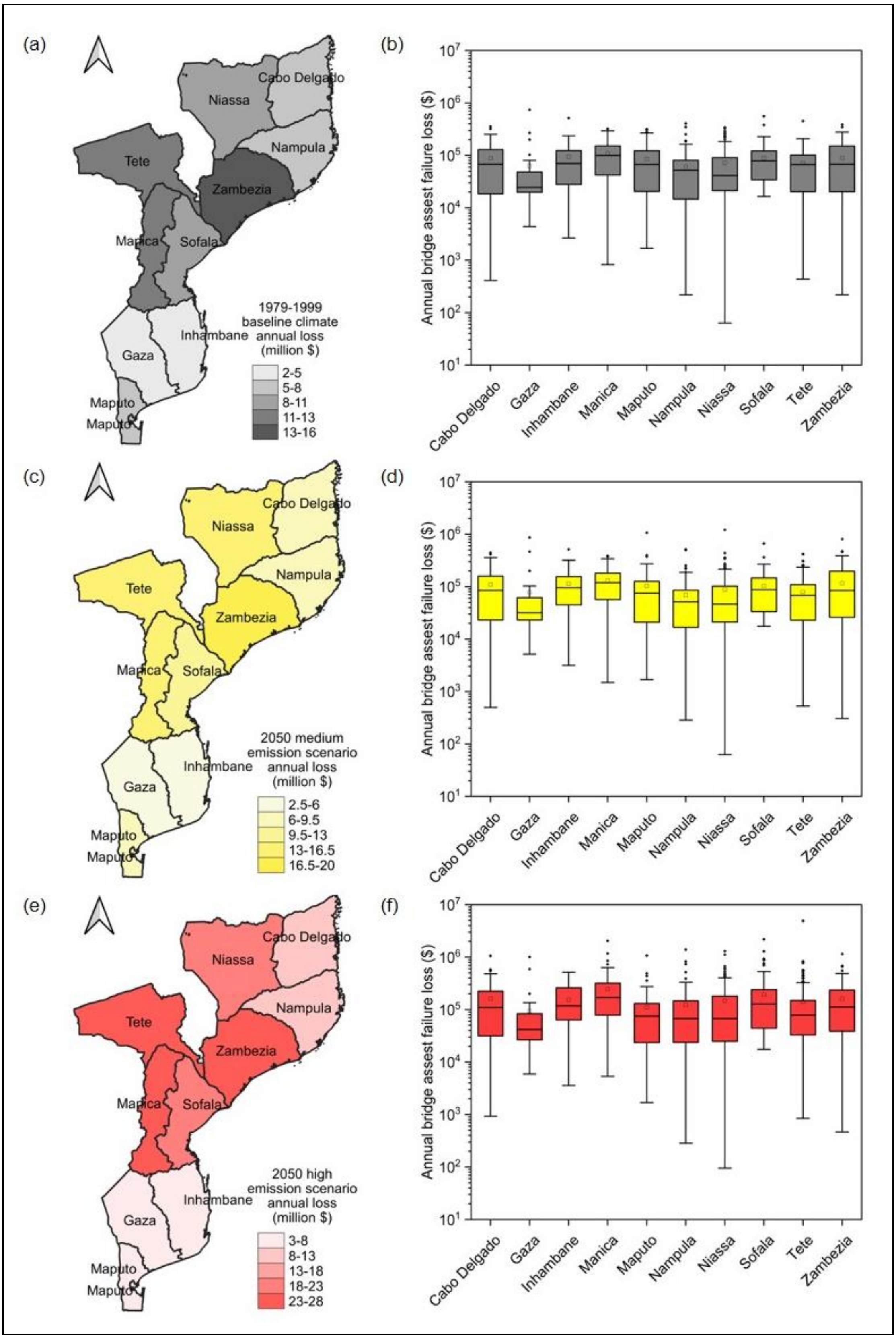
Figure 4 | Visualization of the World Bank's flood maps and the location of the studied bridges in Mozambique. (a) Location of Mozambique in Africa. (b) Locations of all studied bridges and their composition. (c) Flood map with a return period of 5 years under the baseline climate scenario. (d) Flood map with a return period of 1000 years under the 2050 medium emission scenario. (e) Flood map with a return period of 1000 years under the 2050 high emission scenario.

3.2 Flood-induced bridge failure risk will double by 2050

Our analysis reveals that the annual risk of bridge asset failure caused by floods in Mozambique amounts to approximately 83 million USD under the baseline climate conditions of 1979 to 1999. The risk, representing the expected values of economic losses, is equivalent to 0.6% of Mozambique's GDP in 2021 (14.02 billion USD)[41]. Looking ahead to the anticipated flood scenarios in 2050, the annual flood-induced bridge failure risk is projected to range between 100 and 162 million USD (equivalent to 0.7% to 1.2% of the 2021 GDP) under the medium and high emission scenarios. Compared with the baseline climate scenario, the flood-induced bridge failure risk is expected to increase by 14% in 2050 under the medium emission scenario, while it would unexpectedly double under the high emission scenario. In the calculation, we intentionally did not account for inflation by using a discount rate for the 2050 future losses. This is to establish a relatively "fair" comparison, as the loss will become negligible if discounted from 2050 to 2021. However, using the inflation approach will, obviously, underestimate the damage loss future flooding will impose on bridges.

3.3 Flood-induced bridge failure risk varies across space

We find that Zambezia Province exhibits the highest cumulative flood-induced bridge asset failure loss across all assessed climate scenarios (Figures 5a-f). The annual total loss in Zambezia amounts to 15.6 million USD, 20.3 million USD, and 28.2 million USD for the baseline climate scenario, 2050 medium, and high emission scenarios, respectively. These figures indicate a substantial increase of 30.1% to 80.8% failure loss in 2050 climates compared to the baseline climate. To visualize the distribution of annual flood-induced failure loss for individual bridges in each province, we present box and whisker plots sorted by province (Figures 5b, 5d, and 5f). Examining the mean values and variations of the loss (represented by the horizontal lines within the boxes), we observe that under the baseline climate, the annual average loss estimation for a random bridge in different provinces typically ranges between 10,000 USD and 100,000 USD. However, under the 2050 high emission scenario, the mean loss value exceeds 100,000 USD in five provinces, namely Manica, Sofala, Inhambane, Zambezia, and Cabo Delgado. It is important to note that although Gaza Province experiences greater average flood depths, the total loss in this province is not significant due to lower bridge density (as depicted in Figure 4b).



369 **Figure 5 | Flood-induced bridge failure risk at the provincial level.** (a) and (b) Baseline
370 climate scenario. (c) and (d) 2050 medium emission scenario. (e) and (f) 2050 high emission

scenario.

Taking a district-level perspective, our findings indicate that climate change will result in the expansion of high-loss districts, characterized by annual total loss ranging from 1 million USD to 10 million USD (Figure 6). Under the baseline climate scenario, there are 21 such high-loss districts. However, this number is projected to increase to 44 under the 2050 high-emission scenario, representing a substantial 110% increase. The data presented in Figure 5 and Figure 6 provide a comprehensive understanding of the flood-induced bridge asset failure loss faced by different districts in Mozambique. Such information serves as a foundation for making well-informed decisions and allocating resources strategically to enhance bridge resilience and minimize the economic disruptions of future flood events.

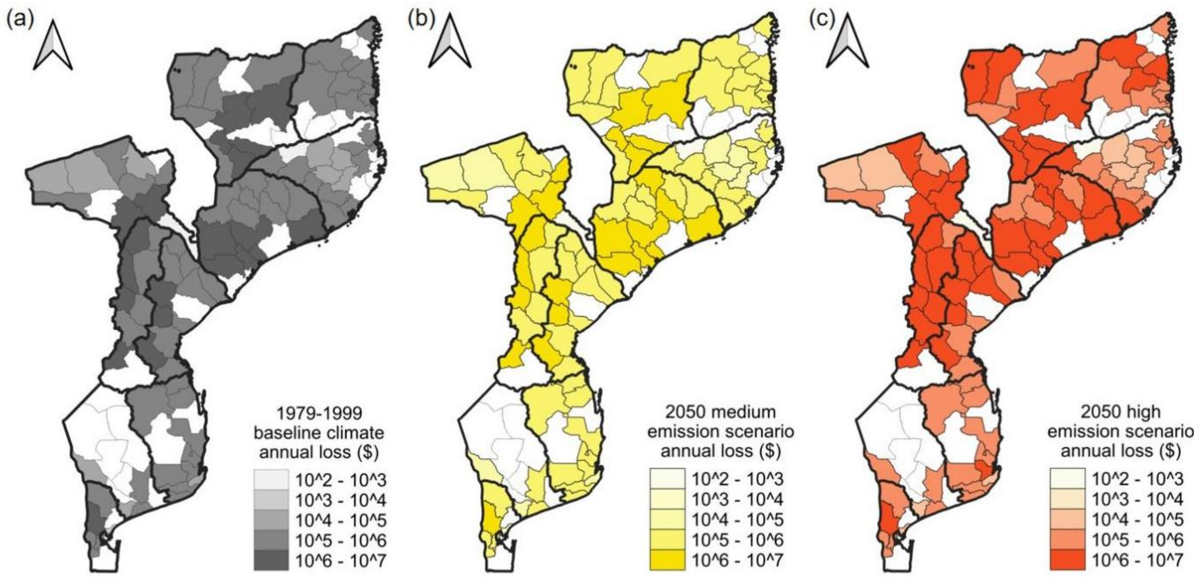


Figure 6 | Flood-induced bridge failure risk at the district level. (a) Baseline climate scenario. (b) 2050 medium emission scenario. (c) 2050 high emission scenario.

3.4 Critical factors for enhancing bridge flood resilience

The study's reliance on regression models and proxies necessitates sensitivity analyses to quantify uncertainty. Through sensitivity analyses, we identify the key factors that significantly influence the risk evaluation model for different types of bridges in Mozambique (Figures 7a-l), including arch bridges, Bailey bridges, simple beam bridges, box bridges, box girder bridges, cable stayed/suspension bridge, culvert bridge, girder bridge, slab bridge, steel bridge, vented causeway, and voided slab bridge. The classification is categorized according to Mozambique's bridge asset database. Specifically, we assess the sensitivity of the bridge failure loss of each type of bridge to different inputs using the OAAT approach. Figure 7 shows the relative sensitivity of bridge (types a to l) failure loss to inputs (attributes I to XIII).

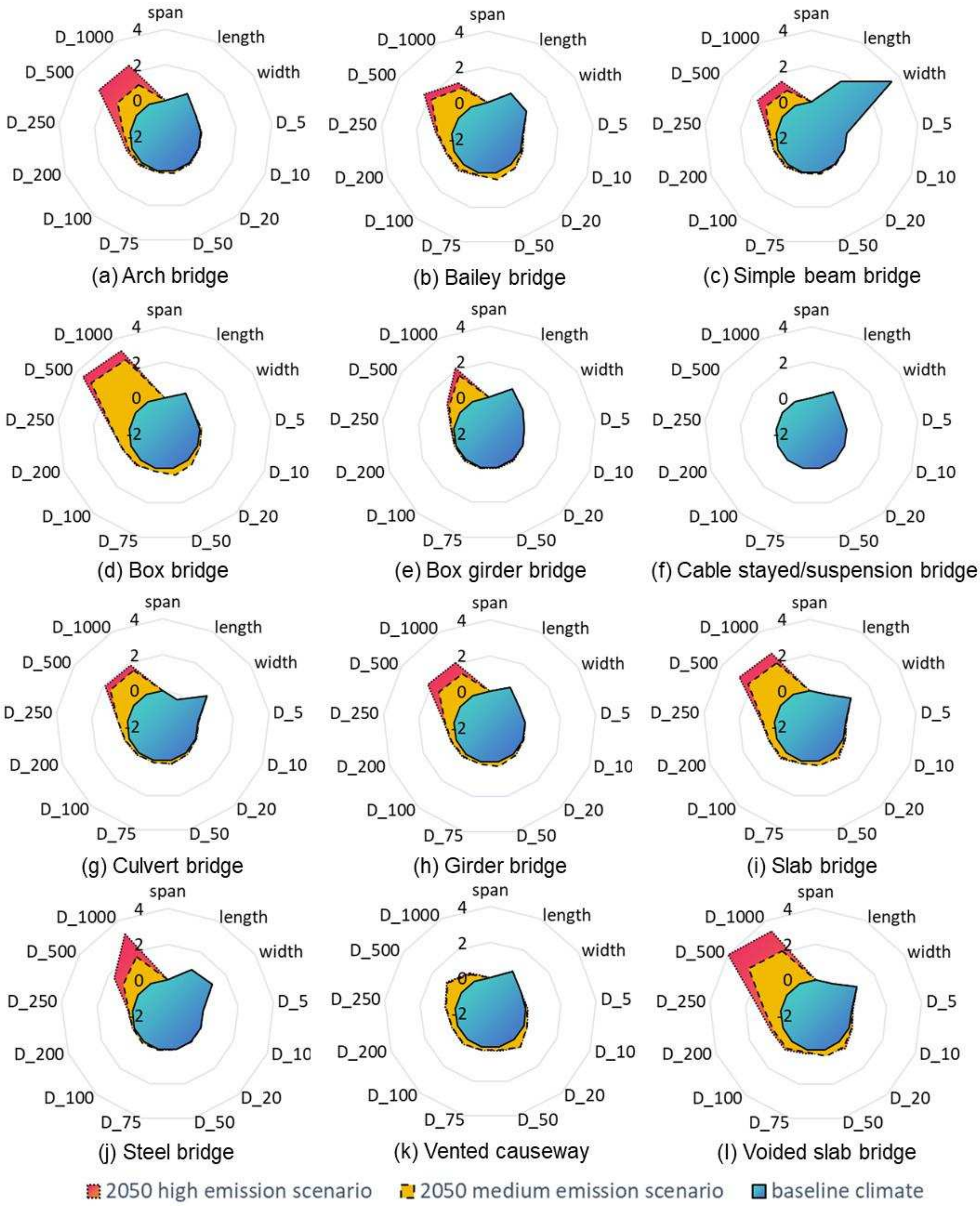


Figure 7 | Critical factors affecting bridge failure risks. (a) Arch bridge. (b) Bailey bridge. (c) Simple beam bridge. (d) Box bridge. (e) Box girder bridge. (f) Cable stayed/suspension bridge. (g) Culvert bridge. (h) Girder bridge. (i) Slab bridge. (j) Steel bridge. (k) Vented causeway. (I) Voided slab bridge; Attributes I-XIII stand for: I) span number, II) bridge length, III) bridge width, IV) D_5: flood depth of 5-year return period, V) D_10: flood depth of 10-year return period, VI) D_20: flood depth of a 20 year return period, VII) D_50: flood depth of a 50 year return period, VIII) D_75: flood depth of a 75-year return period, IX) D_100: flood depth of a 100-year return period, X) D_200: flood depth of a 200-year return period, XI) D_250: flood depth of a 250-year return period, XII) D_500: flood depth of a 500 year return period, XIII) D_1000: flood depth of a 1000-year return period. Scores 0.0-4.0 represent relative sensitivity.

Our findings reveal that for arch bridges, box bridges, and voided slab bridges, their failure loss is highly sensitive to flood depths associated with 500-year and 1000-year floods. These bridge types in Mozambique are significantly impacted by larger-magnitude floods. Cable-stayed/suspension bridges, box girder bridges, and vented causeways exhibit lower sensitivity to flooding, suggesting they are more resilient to flooding. Consequently, these types of bridges demonstrate greater resilience in the face of flood events. These critical factors provide valuable insights for enhancing the flood resilience of different bridge types, allowing for targeted mitigation and adaptation strategies to be implemented. By understanding the specific vulnerabilities and strengths of each bridge type, authorities can prioritize efficient measures to bolster their resistance to flood hazards, ultimately contributing to a more resilient bridge network in Mozambique.

4. Discussion on limitations

The estimation of flood-induced bridge asset failure loss is subject to various uncertainties that can impact the accuracy of the results. These uncertainties arise from factors such as flood prediction, fragility function, cost function, and data quality[42,43]. In particular, the prediction of climate or flood events is prone to uncertainties[42], as the ability of flood models to accurately represent real-world flood situations is still a subject of debate[44,45]. Moreover, the future trajectory of climate change itself is highly uncertain, influenced by unpredictable greenhouse gas emissions moving forward[46]. To address these uncertainties, the incorporation of probabilistic approaches to quantify the likelihood of occurrence for different emission scenarios can enhance the evaluation of total loss, once such data become available. Rather than presenting the results by medium and high emission scenarios (Figures 4 to 7), we can eliminate the uncertainty of choosing different emission scenarios then. In addition, the future advancement of hazard, fragility, and cost models holds the potential to improve the accuracy of the risk evaluation.

It is important to acknowledge certain assumptions and simplifications made in this study, which may lead to an underestimation of the total flood-induced bridge asset failure loss. First, the Hazus flooding model employed in this study only considers bridge failure caused by scour[32], overlooking other potential failure modes such as uplift and debris strikes, which have been reported as causes of bridge failure[44,47,48]. From visual evidence (i.e. bridge failure photos provided by ANE), scour is a popular bridge failure mode locally. Second, while the quantification of asset loss serves as a significant consequence of bridge failure, it is essential to recognize that bridge failures can also result in other direct or indirect loss e.g. maintenance, user delays and even loss of life[49–52]. Their costs are not covered in the scope of this study. Therefore, the annual flood-induced failure loss in Mozambique is likely to exceed our conservatively estimated figures of 0.6% of GDP in 2021 and a twofold increase by 2050.

However, the current method's presumption of equating total replacement cost with fragility-induced failure overlooks functional deterioration and partial damage. Employing a more sophisticated approach, for instance, incorporating damage states with associated cost ratios, would thus substantially improve the model's realism and generalizability. Nevertheless, this would require more data, such as bridge age and time series of condition indicators.

In addition, future studies should pursue active validation efforts to assess the accuracy and robustness of the results as relevant data become available. For the fragility function, it may mean validating the Hazus model using relevant Bayesian methods e.g. decision tree learning or random forest. Hazus-based fragility functions, if not calibrated to local conditions, may be significantly affected by differences in material quality and construction methods between the United States and Mozambique. For the cost function, this can involve fitting cost models using accurate cost information or using transparent bills of quantities.

5. Conclusions

Infrastructure plays a crucial role in driving national economic development, and the failure of bridge assets can have a profound impact on a country's socioeconomic progress. With climate change projections indicating a substantial worsening of conditions in the midcentury, it becomes imperative to develop a comprehensive and internationally recognized approach to assessing the impact of floods on infrastructure failure. By doing so, we can proactively plan and implement climate adaptation strategies well in advance. A risk-based assessment methodology not only enables us to prioritize the allocation of adaptation budget effectively but also supports decision-making processes in the face of uncertainties.

Our findings reveal the significant loss posed by floods to bridge failures at the national level in Mozambique, with an annual impact equivalent to 0.6% of the country's 2021 GDP, amounting to approximately 83 million USD. Furthermore, our analysis indicates that the risks associated with bridge failures are projected to double by 2050 under the high emission scenario due to the impacts of climate change. At the provincial level, Zambezia Province emerges as the most vulnerable to both historical and future loss, experiencing the highest potential for bridge failures. Interestingly, our risk mapping aligns with another study that examines the displacement of people caused by flooding at the provincial level in Mozambique[53]. This correlation suggests that the severity of floods has a substantial influence on both the number of displaced individuals and the vulnerability of bridges to failure. It is worth noting that our flood depth data exhibit similarities to the results obtained by the study, known as ROSA[53]. These findings indicate a strong relationship between flood severity, bridge risks, and population displacement in Mozambique.

As the first attempt to quantify the loss of flood-induced bridge failures at the national level, our study sheds light on several key factors contributing to the significant loss observed in Mozambique. These factors can help elucidate the underlying causes of this national level loss and highlight the uniqueness of our approach compared to previous research efforts:

- First, floods pose a substantial risk to bridges, and Mozambique experiences a high frequency and intensity of such events. In the U.S., it is estimated that 53% of bridge failures are attributed to flooding[54]. Considering that construction standards and quality control in the U.S. are likely more stringent, it is plausible that the proportion of bridge failures caused by flooding in Mozambique may be even greater.
- Second, prior studies have typically focused on quantifying loss/risk associated with specific magnitudes of floods, such as 100, 200, or 500-year events[16,21,22,25,42,43]. Our approach discovered the importance of evaluating risks across a broader range of flood magnitudes by adopting a wider integration domain. This finding is crucial because targeting risk evaluation solely at specific flood magnitudes neglects the potential risks posed by other floods, as evidenced by our sensitivity analyses. These analyses reveal that the floods targeted in previous studies may not necessarily contribute the greatest proportion of loss when compared to other flood events. However, examining the loss compounded by a full spectrum of flood events is challenging. Therefore, to conduct national level studies, it is essential to strike a balance between incorporating technical details and ensuring the applicability and feasibility of the risk evaluation models.
- Last, while numerous studies have attempted to assess the impact of floods on a regional scale, a significant proportion of these studies have overlooked the intricate technical aspects of bridges or the underlying hazards they face[22,26,55]. Our model quantifies flood-induced bridge failure risk at the national level using a minimal yet essential set of inputs: flood maps (depth, frequency, and geospatial coordinates) to generate hazard function;

ERP, bridge span type (continuous span or single span, determined by span number), and scour potential to estimate fragility; and bridge characteristics (length, width, type, and ICCI) to calculate costs. Importantly, the model does not rely on bridge cost data, making it applicable in contexts where data availability is limited. While the case study focuses on Mozambique, the framework is designed to be transferable and can be applied in other Global South countries with similar data constraints.

Our analysis underscores the substantial loss posed by floods to bridge infrastructure in Mozambique, with the projected climate conditions in 2050 exacerbating these losses twofold. The implications of our analysis extend beyond Mozambique, as numerous Global South countries face urgent needs to assess their loss associated with flood-induced damage to their civil infrastructure in the context of climate adaptation[1,2].

Our generalizable bridge asset failure risk evaluation model offers a valuable framework that can be applied to other Global South countries (e.g. Chad, South Sudan, The Republic of the Congo, etc) grappling with the significant challenges posed by flood-induced bridge failures. Our approach is inherently adaptable and applicable across different climate zones (e.g., mountainous or flat areas) and to all common bridge types (e.g., arch bridge, Bailey bridge, simple beam bridge, box bridge, cable stayed/suspension bridge, culvert, girder bridge, slab bridge, or steel bridge). Its core components, the generalized hazard function, the fragility function, and the ICCI function, are not constrained by specific geographies or structural forms.

By adopting our approach, these countries can gain critical insights into their national level infrastructure management, enabling them to identify highly risky bridges, vulnerable districts, and susceptible provinces. Moreover, our framework can serve as a robust tool for justifying the allocation of future adaptation budgets and facilitating targeted investments to enhance the resilience of bridges against the destructive forces of flooding. By replicating this study in other contexts, policymakers and infrastructure managers can make well-informed decisions to safeguard a nation's critical transportation networks. The ability to locate and prioritize high-loss areas will enable strategic interventions, ensuring that resources are directed where they are most needed. Ultimately, this comprehensive risk evaluation approach empowers countries to proactively address the challenges of climate change and enhance the resilience of their critical infrastructure, thereby minimizing the economic and social disruptions caused by flood-induced bridge failures.

Although as a generalizable model, our approach faces limitations. For example, the HAZUS model considers only scour, omitting other failure modes such as debris impact. The cost function equates any damage with total replacement, overlooking partial damage states. Broader socioeconomic losses from traffic delays or fatalities are excluded, likely causing an underestimation of total cost. These key limitations need to be addressed in future work.

Data availability

Data for quantifying the risks associated with all bridges are available from the corresponding authors upon reasonable request.

Code availability

Codes for reproducing the analysis are available from the corresponding authors upon reasonable request.

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