

A Remote Sensing Framework for Estimating Bridge Vulnerability to Floods in Data-Scarce Environments

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ABSTRACT

Traditional methods for modelling the infrastructure vulnerability to floods rely on detailed hydraulic and structural data, including historical flood intensity records and asset-specific attributes such as construction year. These requirements make such methods impractical in data-scarce regions, where infrastructure inventories and flood hazard-related records and/or modelling capabilities are limited or unavailable. To address this challenge, we propose a fully image-based (remote sensing) framework that leverages global, open-access satellite data to estimate whether bridges are compromised or not by flooding events. The framework consists of three key components: (1) extracting basic bridge characteristics visible in satellite imagery; (2) translating observable flood scars from this imagery into a proxy for flood intensity; (3) comparing pre- and post-event images to infer flood-related bridge compromise. We demonstrate and validate the framework using five flood events and 84 bridge structures (65 from data-rich contexts and 19 from data-scarce contexts) across six regions. We leverage the findings to develop an approximate flood vulnerability model linking the flood intensity proxy to bridge compromise probability. The results of the study indicate that remote sensing-based vulnerability assessment offers a scalable and practical alternative for system-level flood risk evaluation of bridge infrastructure in data-scarce environments, reducing reliance on traditional hydraulic-based models.

Keywords: Bridge vulnerability, Flood risk, Remote sensing, Data-scarce regions.

INTRODUCTION

More than 25% of global road and railway infrastructure is exposed to natural hazards, particularly flooding (Koks et al., 2019). Bridges, as critical components of transportation networks (Binesh et al., 2025), are notably vulnerable in the face of this exposure. For instance, (1) in the United States, floods account for approximately 49% of documented bridge failures (Xiong et al., 2023); (2) in Italy, 73% of recent reported bridge failures have been associated with floods (Scala et al., 2025); and (3) in Nigeria, floods were responsible for approximately 60% of bridge failures between 2010 and 2018 (Ede et al., 2019).

The vulnerability of bridges to flooding is typically quantified using fragility or vulnerability models, which relate hazard-intensity measures to the probability of damage or to some measure of loss. These models typically use flow velocity, discharge, or flood depth intensity measures, which must be derived either from field-observed data or hydrodynamic simulations (Watson et al., 2026). Alternative intensity measures such as scour depth (Argyroudis & Mitoulis, 2021), flood height normalised by structural height (Pucci et al., 2023), and stream power (Anderson et al., 2017) have been proposed to better capture damage-relevant processes, which also depend on detailed field-observed hydraulic, geomorphic, and structural data. Because of these demanding

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data requirements, conventional bridge vulnerability modelling approaches are difficult to leverage in data-scarce regions, such as those with ungauged streams (Larcher et al., 2024; Lidberg, 2025).

Remote sensing data (e.g., satellite imagery) provides a complementary way to characterise flood hazards across large spatial extents compared with intensive field measurements (Gorelick et al., 2017; Twele et al., 2016). Advances in satellite imagery, including Sentinel-1 Synthetic Aperture Radar (SAR) and Sentinel-2 multispectral data, have enabled consistent identification of flood extents and flow pathways, either in conjunction with hydrological modelling or as stand-alone observations. Remote sensing has been successfully used in diverse settings to characterise flooding, e.g., Egypt (Sadek et al., 2020), Europe (Bjelotomic Oršulic et al., 2025), China (Tan et al., 2022), and Salt Lake City, USA (Li & Bortolot, 2022). Multi-temporal satellite imagery integrated with GIS techniques (Deb & Ferreira, 2015; Hecher et al., 2012) and often complemented by normalised difference vegetation index (NDVI) based analyses (Li et al., 2021), enables the detection and quantification of channel geometric changes across diverse fluvial environments, which have well-established links to discharge increase in flood hazard (Frasson et al., 2019). Rathore et al. (2023) utilised satellite images to show a dramatic increase in the Rapti River's width, from 78 m to 946 m between 1980 and 2020, attributed to flood-driven erosional and depositional processes. [Click or tap here to enter text.](#)

Satellite imagery has also been used to detect infrastructure damage after hazard events, particularly in the case of buildings (Al Shafian & Hu, 2024). Approaches for extracting damage information from satellite imagery include manual interpretation (Cervone & Manca, 2011), advanced object-oriented methods that integrate LiDAR-derived height data (Niloofar Khodaverdi et al., 2019; Pham et al., 2014), as well as those involving the application of deep learning and AI (Al Shafian & Hu, 2024; Belenguer-Plomer et al., 2025; Destefanis et al., 2025). Additionally, the quality of satellite imagery damage assessments has been improved in combination with social media data (Cervone et al., 2016) and structural damage metadata (Kuo & Lin, 2025). In the case of bridges, remote damage sensing has primarily centred on the use of structural health monitoring through Interferometric SAR (Casas et al., 2024) to determine deformation risks (Miano et al., 2024).

This study investigates how remote sensing-derived flood hazard and infrastructure damage information can help address the applicability limitations of conventional bridge vulnerability modelling approaches. We propose and explore a framework for relating remotely observed flood hazard characteristics and bridge damage information. The results of this inquiry are used to develop an approximate bridge vulnerability model suitable for data-scarce regions (e.g., areas without hydrological records and/or detailed structural inventories).

METHODOLOGY

The proposed framework involves: (1) extracting basic bridge characteristics visible in satellite imagery; (2) translating observable flood scars from satellite imagery into a proxy for flood intensity; and (3) comparing pre- and post-event images to infer flood-related impacts in terms of bridge damage (compromise). The applicability of the framework to data-scarce regions is demonstrated by extracting a test dataset according to the three previously defined steps (i.e., exclusively from imagery). An initial validation of the framework is conducted using a benchmark dataset, in which damage information is instead extracted from pre-recorded (ground truth) data. The validation process involves a hypothesis test to confirm a systematic association between the selected flood intensity proxy and bridge compromise status. The test and

benchmark datasets are then leveraged to develop an approximate bridge vulnerability model based on remotely observable flood hazard and bridge damage information.

Satellite imagery

Google Earth Pro is used as the sole satellite imagery source for this study. This choice is driven by its consistently high spatial resolution (≤ 0.5 m), global coverage, and integrated measurement tools. Pre-event imagery corresponds to a time period approximately 0 to 5 years before each flood event of interest. The 0-to-5-year time window represents a practical balance between image availability and the recognition that channel morphology may evolve at different rates depending on local hydraulic, sedimentary, and geomorphic processes. Post- (or even possibly within-) event imagery is selected as close as possible to the reported flood date (i.e., within a 12-month time window) to reduce the impact of subsequent hydrological disturbances based on regional seasonal patterns. Within this window, the clearest available optical scenes are prioritised to ensure reliable identification of flood extents and observable morphological changes.

Extracting bridge characteristics from imagery

The extracted bridge characteristic is the opening length (L_0), defined as the total structural opening between abutments or wingwalls (depending on bridge archetype). L_0 is measured directly from the pre-event imagery, using the ruler tool of Google Earth Pro (see Figure 1a).

Translating observable flood scars into a flood intensity proxy

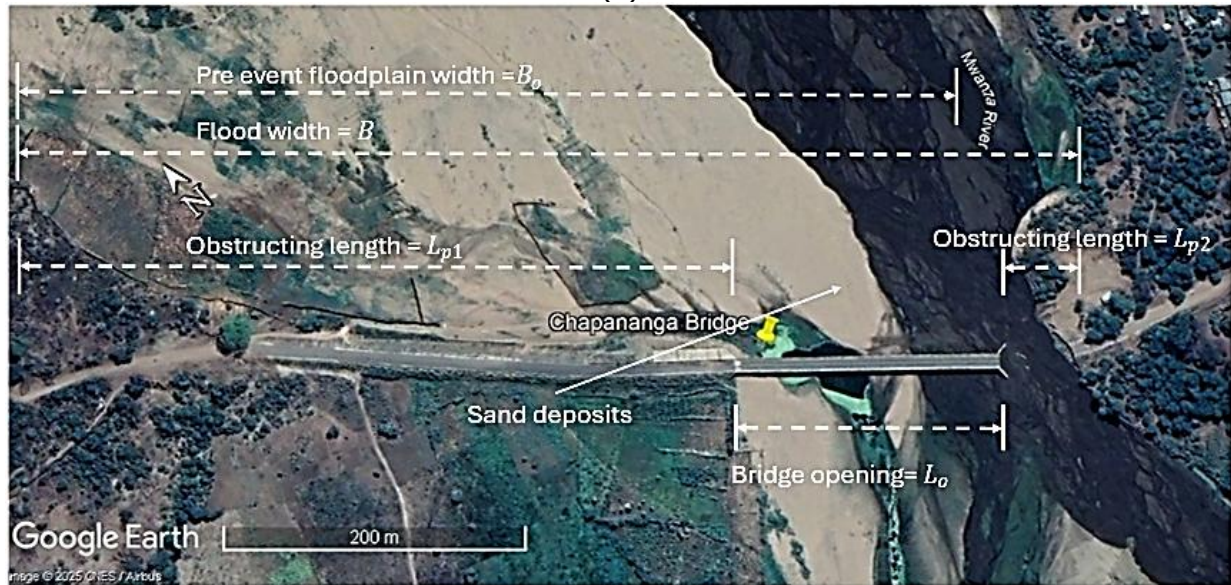
The proposed proxy for flood hazard intensity is a contraction ratio L_p/B , which is a dimensionless measure of floodplain obstruction. B is the active inundation width at the bridge crossing. L_p is the bridge encroachment length, representing the portion of the bridge and its approaches obstructing the active flood flow. The physical significance of L_p/B is supported by established bridge hydraulics and scour literature. Flow contraction at bridge crossings accelerates velocities and increases bed shear stresses, promoting contraction and abutment scour that undermine foundation stability (Ettema et al., 2010). Scour prediction frameworks such as HEC-18 (L.A. Arneson et al., 2012) explicitly account for geometric flow obstruction. Contraction and abutment scour equations, including those proposed by Froehlich and Hire (USACE HEC, 2025), incorporate parameters related to embankment length obstructing active flow and effective floodplain width. The National Cooperative Highway Research Program (NCHRP) 24-20 methodology (Ettema et al., 2010) introduces correction factors that scale scour depth as a function of L_p/B . Furthermore, L_p/B inherently accounts for variations in bridge sizes, supporting its global applicability.

To quantify this proxy, the width of the existing floodplain, B_o , is established from the pre-event imagery by examining visible geomorphic indicators of past flows, such as sand deposits (see Figure 1a). Additionally, the existing floodplain extents can be confirmed by viewing an approximate elevation profile using the path tool of Google Earth Pro. The active flood extent is delineated from the post-event imagery by identifying characteristic flood scars, including surface inundation, sediment deposition (Fernandez et al., 2025; Vázquez-Tarrío et al., 2024), debris accumulation (Erpicum et al., 2024), and flattened or damaged vegetation (Fawakherji et al., 2025). The inundated width B is measured perpendicular to the inferred flow direction using the ruler tool, assuming approach flow is approximately normal to the bridge opening, and at a location one to three times the bridge opening width upstream (see Figure 1b). This measurement window aligns with experimental and field evidence showing that flow contraction effects typically develop within this zone (Ettema et al., 2010). If the

bridge abutments are outside B_o , B corresponds to the full lateral extent of inundation observed during the event (see Figure 2b). Otherwise, B is equal to B_o plus the additional inundated area observed during the flood. L_p is quantified as $L_p = B - L_o = L_{p1} + L_{p2}$; see Figure 1b.



(a)



(b)

Figure 1. Floodplain and bridge opening measurements at Chapananga Bridge, Malawi, before and after Cyclone Ana (January 2022). (a) Pre-event imagery (November 2019) showing $B_o = 430$ m and $L_o = 184$ m. (b) Post-event imagery (September 2022) showing $B = 781$ m. A pronounced erosion scar is visible near the right abutment, indicating local scour and hydraulic realignment. $L_p = L_{p1} + L_{p2} = 597$ m. $L_p/B = 0.76$.



(a)



(b)

Figure 2: Floodplain and bridge opening measurements at Puketapu Bridge, New Zealand, before and after Cyclone Gabrielle in February 2023. (a) Pre-event imagery (December 2021) showing $B_0 = 116$ m and $L_0 = 126$ m. (b) Post-event imagery (April 2023) showing $B = 384$ m. The bridge was completely washed away. $L_p = L_{p1} + L_{p2} = 258$ m. $L_p/B = 0.67$.

Inferring bridge damage from pre- and post-event imagery

An affected bridge is classified as compromised if the post-event imagery shows new evidence of functional or structural impairment, compared to the pre-event imagery. Examples of this evidence are debris accumulation within the bridge opening, severe scour at abutments or piers, erosion or washout of approach roads resulting in loss of access, partial structural failure, or complete washout (see Figures 1b and 2b). Otherwise, an affected bridge is classified as not compromised.

Datasets

Test dataset

The test dataset incorporates bridges in: (1) Tanzania, affected by Cyclone Hidaya (May 2024); and (2) Malawi, affected by Cyclone Ana (February 2022). In both cases, event-related engineering documentation and structured damage records are not available. Affected bridge locations for both events are manually identified as follows. First, flooded locations are determined using information from official reports and media coverage, then, at each location, pre- and post-event satellite imagery is consulted to examine the road network and identify bridges over streams that exhibited an observable response to the given flood event. The dataset includes 18 bridges (15 compromised, three not compromised) affected by the Cyclone Hidaya event. The furthest pre-event imagery analyzed for this event was from June 2019, and the furthest post-event imagery was from April 2025. The dataset also includes one bridge (classified as compromised) affected by the Cyclone Ana event. The pre-event imagery for this event was from November 2019, and the post-event imagery was from September 2022.

Benchmark dataset

The benchmark dataset incorporates bridges in: (1) Greece, affected by the Mediane Ianos flood (September 2020); (2) Germany, affected by the European flood (July 2021); and (3) New Zealand, affected by Cyclone Gabrielle (February 2023). It covers six bridges (four compromised, two not compromised) affected by the Mediane Ianos event, 16 bridges (15 compromised, one not compromised) affected by the European event, and 43 bridges (35 compromised, eight not compromised) affected by Cyclone Gabrielle.

B values for the Mediane Ianos flood are determined according to the proposed framework, using pre-flood imagery dating as far back as August 2020 and post-flood imagery up to January 2023. Affected bridges, L_o values, and bridge damage statuses are identified/determined from field-observed information by Loli et al., (2022). This information comprises an inventory of 117 bridges in the Karditsa Prefecture, Greece, compiled from a geospatial flood hazard and risk assessment and supplemented by details from post-event inspections of a representative subset of 16 bridges. These inspections documented damage ranging from minor distress to complete failure and were supported by photographic evidence. The benchmark dataset incorporates the bridges covered by Loli et al., (2022) that can be associated with a valid L_p/B value (i.e., are not located within engineered or channelized river systems- details to follow in Discussion and Conclusions - and where satellite imagery is not obstructed by cloud or snow cover) and for which bridge damage information is recorded. Bridges deemed to be in a medium or high damage state by Loli et al., (2022) are defined as compromised; all other bridges are defined as not compromised.

All data for bridges affected by the European floods are derived from Erpicum et al. (2024), which presents a dataset of documented post-flood floating debris accumulations at 71 bridges. The dataset was compiled using official authority reports, public databases, post-event photographs, and field inspections, and includes detailed information on bridge geometry, flood conditions, and debris characteristics. The

benchmark dataset incorporates the bridges covered by the Erpicum et al. (2024) dataset with recorded B values that are not located within engineered or channelized river systems and are not subjected to free-surface flow (where water is strictly limited to below the bridge deck). Bridges deemed to have experienced any amount of damage (from “weak” to “complete”) by Erpicum et al., (2024) are classified as compromised; undamaged bridges are defined as not compromised.

B and L_o values for the Cyclone Gabrielle event are determined according to the proposed framework, using pre-flood imagery dating as far back as August 2019 and post-flood imagery up to November 2023. Affected bridges and bridge damage statuses are identified/determined from the Gisborne District Council (*Bridge Repair Works | Gisborne District Council*, n.d.) and the Hastings District Council (*TE TŪHONOTANGA BRIDGING THE GAP*, n.d.). These platforms contain interactive GIS maps with photographs that document and monitor the restoration of bridges damaged by these floods in Gisborne (171 bridge assessments) and Hastings (11 bridge assessments) district councils, respectively. The benchmark dataset incorporates the bridges included in these maps that are associated with Cyclone Gabrielle, are not located within engineered or channelised river systems, and where visibility in satellite imagery is not obscured by dense vegetation cover or terrain shadowing. Bridges reported as damaged, partially failed, or washed out are classified as compromised; all other bridges are defined as not compromised.

Hypothesis test

A hypothesis test is used on the benchmark dataset to investigate whether L_p/B is associated with bridge compromise. The null hypothesis (H_0) states that L_p/B cannot distinguish bridge condition, i.e., its values do not differ between compromised and non-compromised bridges. The alternative hypothesis (H_1) states that distributions of L_p/B associated with compromised bridges are shifted to the right of those associated with non-compromised bridges, such that the proxy can distinguish between bridge conditions. We use the Mann–Whitney U Test (Mann & Whitney, 1947), which evaluates differences in the ranked distributions between two independent samples that are not necessarily normally distributed and can handle the binary outcomes within our data.

The test reveals a statistically significant difference between the L_p/B values of compromised and non-compromised bridges ($U = 359$, $p = 0.00063$), with non-compromised bridges tending to exhibit lower L_p/B values than compromised bridges (see Figure 3). Given the group sizes ($n = 58$ compromised, $n = 7$ non-compromised), this U value is close to the maximum possible value of 406, indicating that in most pairwise comparisons, a compromised bridge has a higher L_p/B than a non-compromised bridge. This result provides promising evidence that L_p/B can be useful for distinguishing bridge damage as part of a flood bridge vulnerability assessment.

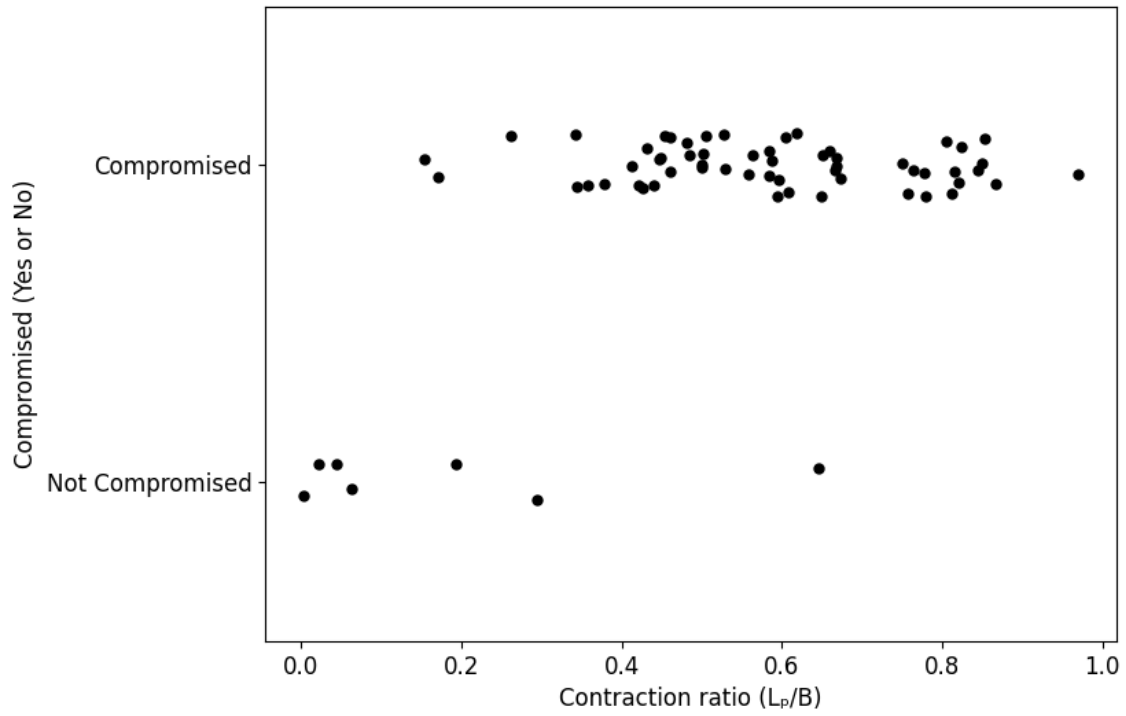


Figure 3: Bridge damage status versus L_p/B values of the benchmark dataset, used for the hypothesis test.

Vulnerability model development

We develop an approximate bridge vulnerability model in the form of a fragility function that is fit according to a log-normal cumulative distribution function, following the approach of Baker et al. (2015). Note that the use of a logistic regression formulation (e.g. Balomenos et al., 2020) yields very similar results. We first fit a fragility function with the benchmark dataset (Figure 4), evaluating its performance with the test dataset using the ROC–AUC and Brier score (Gneiting & Raftery, 2007). The ROC–AUC quantifies the discriminatory capability of the model, indicating how effectively it distinguishes between compromised and non-compromised bridges across the full range of predicted probabilities, independent of any classification threshold. The Brier score evaluates probabilistic accuracy and calibration by measuring the agreement between predicted probabilities and observed outcomes. The function yields an ROC–AUC value of 0.967 and a Brier score of 0.143, indicating excellent discriminatory capability and close agreement between predicted and observed outcomes. Based on this strong predictive performance, the fragility function is subsequently re-fit using both datasets (Figure 5).

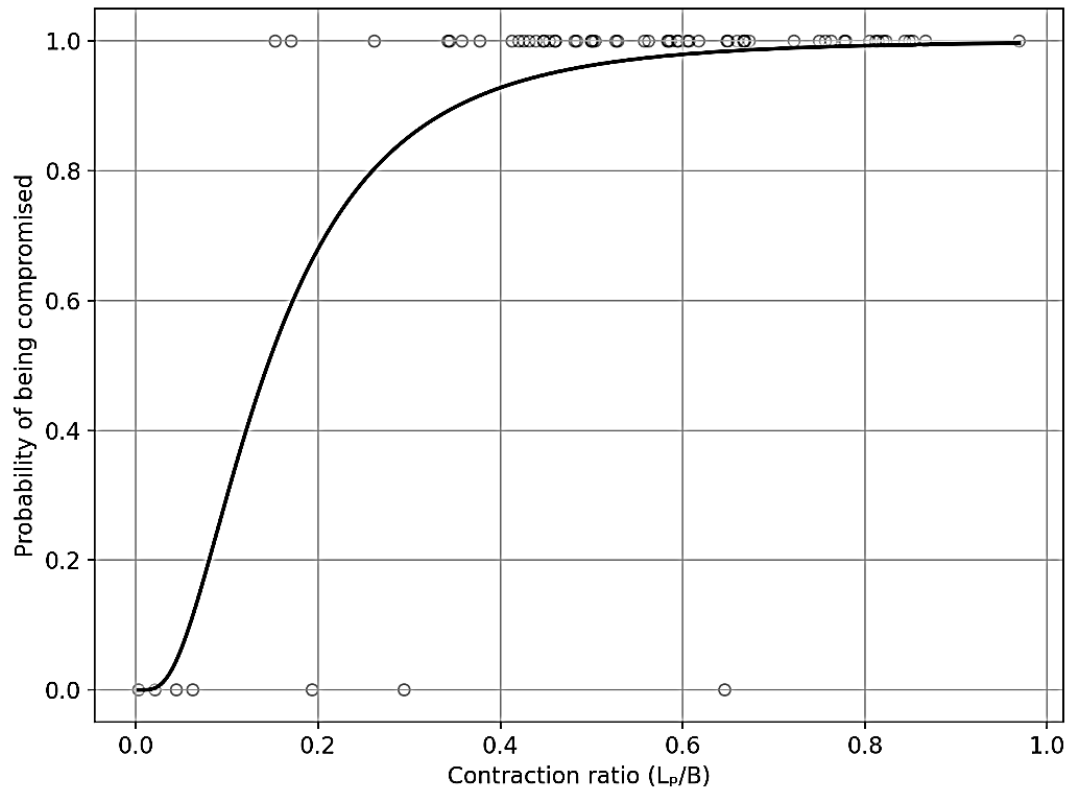


Figure 4: Fragility curve fit using the benchmark dataset (shown as individual data points). Corresponding median and dispersion values are 0.14 and 0.69, respectively.

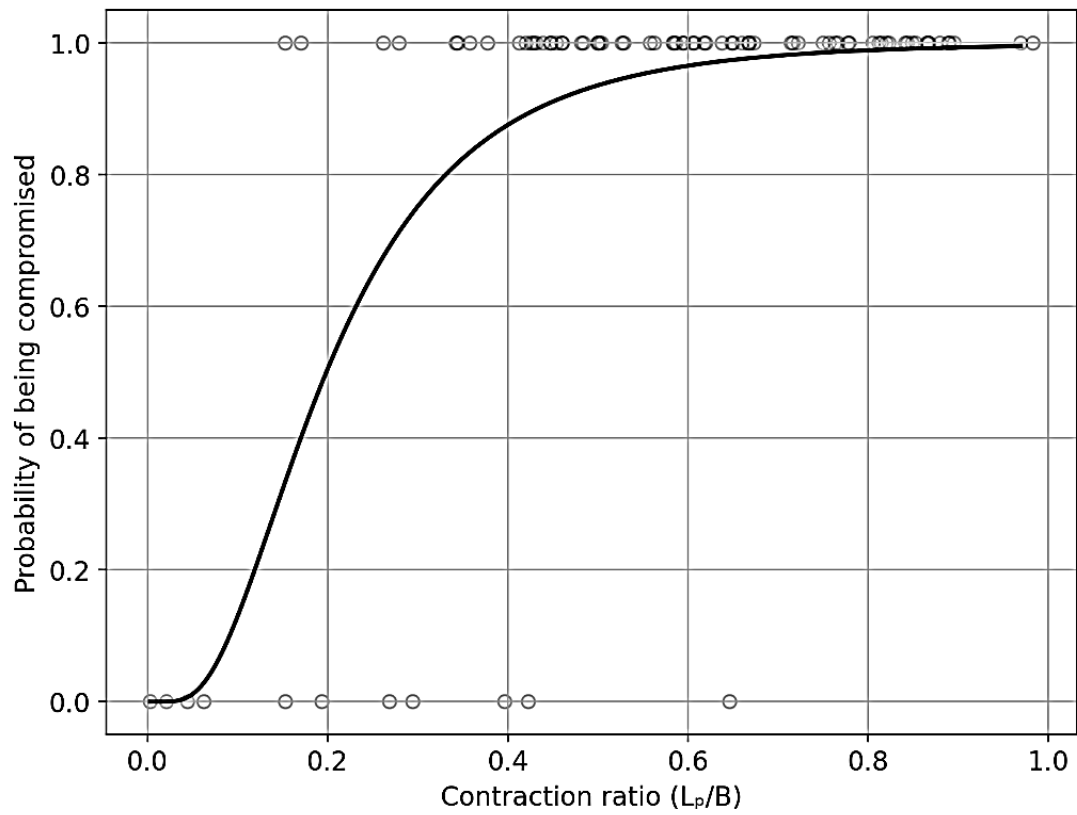


Figure 5: Fragility curve fit using both the benchmark and the test dataset (shown as individual data points). Corresponding median and dispersion values are 0.19 and 0.61, respectively.

DISCUSSIONS AND CONCLUSIONS

This study provides a framework that demonstrates the potential of leveraging satellite-imagery to support assessment of bridge vulnerability to floods. A key contribution of this work is the development and validation of a new intensity measure, the contraction ratio (L_p/B). This metric captures the interaction of flood flow paths and bridge geometry, without the need for hydrodynamic modelling or the extensive monitoring networks typically required to estimate traditional flood intensity measures like velocity or depth. The metric statistically separates bridges classified as compromised from those not compromised in the same flood event, supporting the feasibility of deriving defensible flood fragility functions under data-scarce conditions. Building on this finding, the final output of this study is a fragility function relating contraction ratio to the probability of bridge compromise, calibrated on the performance of 84 bridges in five flood events across six regions.

The insights of this work offer practical value for decision-makers responsible for infrastructure planning, emergency response, and recovery, particularly in regions with limited flood risk monitoring capacity. When used alongside global flood maps, the proposed fragility function enables rapid identification of bridges likely to be compromised during flood events, supporting large-scale screening of bridges at risk for prioritisation of inspections and recovery resources.

Although the results are encouraging, some challenges remain. The L_p/B value is not meaningful for engineered or channelized river systems. In these systems, flow is confined by levees, embankments, or straightened channels, preventing lateral inundation and natural activation of the floodplain. This disruption of natural river-floodplain interactions makes it difficult to define the floodplain. The temporal resolution of freely available imagery is irregular, ranging from days to months before or after a flood event. As a result, expert judgment and informed assumptions are often necessary to determine the most appropriate time to extract flood conditions (Demissie et al., 2023; Nhangumbe et al., 2023; Shoko & Dube, 2024). Furthermore, image acquisition does not always align with peak flooding, hence flood impacts may be underestimated. Additionally, intermittent lower-magnitude events may be overlooked, even though they could cumulatively contribute to structural damage, thereby contributing to uncertainty in damage attribution. Finally, this study did not account for variations in bridge characteristics such as structural type, construction materials, deck width, or foundation design.

The continued expansion of the underlying datasets and integration of additional remotely derived hazard and/or damage indicators will further strengthen the applicability of this framework and the resulting approximate vulnerability models in future flood risk management efforts. For instance, such developments could facilitate a transition from a binary damage classification (i.e., compromised or not compromised) to a multi-state fragility model, thereby enhancing the precision of vulnerability estimates. Future work may also explore the integration of machine learning methods for automated extraction of hazard and bridge information from satellite imagery, enabling scalable, near-real-time application of the proposed fragility framework.

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