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Probabilistic Flood Risk Mapping for National Highway Corridors in South Sudan: A Stochastic Hydrological Modelling and Bayesian Network Approach

Aduot Madit Anhiem
Department of Civil Engineering, Universiti Teknologi PETRONAS, Seri Iskandar 32610, Perak, Malaysia
Correspondence: aduot.madit2022@gmail.com | rigkher@gmail.com
ORCID iD: 0009-0003-7755-1011 | https://orcid.org/0009-0003-7755-1011
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ABSTRACT

Flooding constitutes the most pervasive natural hazard threatening South Sudan's national road network, causing annual disruptions estimated at USD 27.8–45.8 million across five priority highway corridors. Despite this, no probabilistic flood risk mapping framework calibrated to South Sudan hydrological conditions has been documented in the peer-reviewed literature. This study develops and validates a probabilistic flood risk mapping methodology integrating stochastic hydrological modelling, two-dimensional hydraulic simulation, Bayesian network failure probability analysis, and multi-criteria risk indexing for five national highway corridors totalling 510 km. Daily discharge records from seven long-term gauging stations were fitted to Gumbel Extreme Value Type I (EV-I) distributions, and Monte Carlo uncertainty propagation (n = 10,000) was applied to quantify model parameter uncertainty. HEC-RAS 2D hydraulic simulations were executed for return periods of 2, 5, 10, 25, 50, 100, and 200 years to generate inundation extent and depth grids at 12-metre resolution using TanDEM-X terrain data. A Bayesian network with seven nodes was developed to model the conditional failure probabilities of road segments as a function of flood inundation depth, embankment height, drainage capacity, and structural vulnerability. Validation against satellite-derived flood extents from Sentinel-1 SAR imagery yielded overall accuracies of 82–91% with kappa coefficients of 0.70–0.81. The Malakal–Renk and Bor–Pibor corridors are classified as Extreme risk, with 66% and 54% of road segments at risk under the 100-year return period event respectively. First-Order Reliability Method (FORM) analysis demonstrates that embankment heights of 2.4–3.2 m above mean annual flood level are required to achieve the target reliability index of beta = 3.72 for South Sudan road design conditions. Projected flood damage costs under RCP 8.5 are estimated to increase 3.4-fold by 2055 relative to 2024 baseline levels. Five evidence-based policy instruments are recommended to reduce national flood exposure by 30–45% within a ten-year implementation horizon.

Keywords: *probabilistic flood risk mapping; South Sudan; highway corridors; Gumbel distribution; Bayesian network; HEC-RAS 2D; FORM reliability; Monte Carlo simulation; climate change; disaster preparedness; road vulnerability*

1. INTRODUCTION

South Sudan's road network underpins the delivery of humanitarian assistance, inter-state commerce, and national integration across a country of 11 million inhabitants spanning 644,329 km² of some of the most flood-susceptible terrain on the African continent. The vast central basin of the Sudd—one of the world's largest freshwater wetlands—together with the seasonal inundation dynamics of the White Nile, Sobat, Jur, and Bahr el-Ghazal river systems, creates a hydrological environment in which road infrastructure is annually exposed to inundation events of extraordinary spatial extent and duration ((Author, 1999); (Ogilvie et al., 2020)). The 2019–2022 flooding cycle, the most severe on record, inundated over 11,000 km² of floodplain and severed all primary road connections to Malakal, Bor, and Bentiu for cumulative durations exceeding 180 days, with direct infrastructure repair costs estimated at USD 480 million ((OECD, 2022)).

Probabilistic flood risk mapping constitutes the methodological foundation for evidence-based road design, investment prioritisation, and disaster preparedness planning. Unlike deterministic design approaches—which apply a single design flood without quantification of uncertainty—probabilistic frameworks explicitly acknowledge the aleatory uncertainty in hydrological extremes and the epistemic uncertainty in model parameters, yielding risk estimates expressed as probability distributions rather than point values ((Apel & Bloeschl, 2006); (Beven & Binley, 1992)). The integration of probabilistic hydraulic modelling with structural reliability analysis enables computation of failure probabilities for specific road segments as functions of flood characteristics and infrastructure conditions—information directly applicable to maintenance prioritisation, insurance premium setting, and climate adaptation investment allocation ((Pregnolato et al., 2017); (Dawson & Wang, 2018)).

The climate change dimension further amplifies the urgency of probabilistic flood risk assessment for South Sudan. IPCC AR6 projects increased frequency and intensity of extreme precipitation events across equatorial East Africa under all RCP scenarios, with East Africa expected to experience 15–30% increases in 100-year return period flood discharges by mid-century ((Microbe, 2021)). For a country where the entire paved road network is less than 3,600 km—and where road reconstruction costs in remote areas reach USD 2.8 million per kilometre—the implications of even marginal increases in flood frequency or severity for infrastructure lifecycle costs are severe ((Programme, 2023)).

Despite the critical importance of flood risk quantification for South Sudan road infrastructure, no peer-reviewed probabilistic flood risk mapping study specifically addressing national highway corridors has been published. Existing risk assessments are largely qualitative, employ coarse continental-scale hydrological datasets that do not resolve the complex dynamics of the Sudd, and are not spatially disaggregated to the level required for project-level investment decisions (MoRB, 2022; (Jackson et al., 2019)). This study addresses this gap comprehensively, developing a replicable probabilistic flood risk mapping methodology calibrated to South Sudan hydrological conditions and validated against satellite-derived flood observations.

1.1 Research Objectives

This study pursues the following primary research objectives: (i) to compile and quality-control long-period hydrological discharge records for seven gauging stations on rivers crossing or adjacent to the five study corridors; (ii) to fit extreme value distributions to annual maximum discharge series and propagate parametric uncertainty via Monte Carlo simulation; (iii) to execute two-dimensional HEC-RAS hydraulic flood simulations for return periods spanning 2 to 200 years; (iv) to develop a Bayesian network model of road segment failure probability conditional on flood inundation characteristics; (v) to validate modelled flood extents against satellite-derived observations; (vi) to quantify road corridor flood risk using a multi-criteria vulnerability and exposure index; and (vii) to develop policy recommendations for flood-resilient highway design and disaster preparedness in South Sudan.

1.2 Study Corridors

Five national highway corridors were selected in coordination with the Ministry of Roads and Bridges (MoRB) on the basis of strategic importance, data availability, and reconstruction investment priority: ((Apel & Bloeschl, 2006)) Juba–Terekeka (87 km, Central Equatoria); ((Mishra et al., 2010))

Malakal–Renk (62 km, Upper Nile); ((Bates & Fewtrell, 2010)) Wau–Rumbek (112 km, Western Bahr el-Ghazal and Lakes States); ((Lambert et al., 2024)) Bor–Pibor (54 km, Jonglei State); and ((Beven & Binley, 1992)) Nimule–Juba (195 km, Central Equatoria). Together these corridors constitute 510 km of national road network traversing diverse hydrological and geomorphological zones, from the Imatong Mountains foothills in the south to the Sudd floodplain in the central basin.

2. LITERATURE REVIEW

2.1 Probabilistic Flood Hazard Assessment

Probabilistic flood hazard assessment has evolved substantially from early frequency analysis methods to integrated computational frameworks combining statistical hydrology, hydraulic simulation, and uncertainty propagation. The foundational frequency analysis approach, formalised by (Gumbel, 1941) and subsequently codified in the Bulletin 17C guidelines ((Roland & Stuckey, 2019)), involves fitting parametric extreme value distributions to annual maximum flood series and deriving design quantiles for specified return periods. The Gumbel Extreme Value Type I distribution, parameterised by location (mu) and scale (alpha) parameters, remains the most widely applied model for riverine flood frequency analysis in sub-Saharan Africa due to its mathematical tractability and the compatibility of its upper tail behaviour with observed African flood series characteristics ((MKHANDI et al., 2000); (OYEBANDE, 1982)).

Two-dimensional hydraulic modelling using the Saint-Venant shallow-water equations has become the standard approach for generating spatially distributed inundation extents and depths from design flood hydrographs. The HEC-RAS 2D model ((Margenot et al., 2023)), employing an implicit finite volume solver on sub-grid bathymetry, has been validated extensively for large floodplain applications including in data-sparse African contexts ((Bates & Fewtrell, 2010); (Yamazaki & Oki, 2011)). Integration of HEC-RAS outputs with probabilistic hazard curves enables construction of hazard-area-frequency (HAF) relationships that form the cartographic basis for probabilistic flood risk maps ((de Moel & Ward, 2015)).

2.2 Bayesian Networks in Flood-Infrastructure Risk Analysis

Bayesian networks (BNs) provide a powerful formalism for representing and computing probabilistic dependencies among variables in complex multi-hazard systems ((Turtle & Croft, 1989); (Mustafa et al., 2010)). In flood-infrastructure risk analysis, BNs have been applied to model the conditional probability of infrastructure failure as a function of observable hazard variables (flood depth, velocity, duration), infrastructure characteristics (embankment height, pavement condition, drainage capacity), and contextual factors (maintenance levels, material quality). (Dawson & Wang, 2018) demonstrated that BN models of road network flood vulnerability outperformed deterministic threshold approaches by 22–31% in flood disruption prediction accuracy when evaluated against post-event field data. (Pregnolato et al., 2017) used BN-informed risk models to demonstrate that ignoring uncertainty in flood depth estimates results in systematic underestimation of road disruption probabilities by 35–60%.

Application of BN-based flood risk models in sub-Saharan African contexts remains limited. (Harris et al., 2021) applied a simplified four-node BN to Tanzanian road vulnerability assessment, finding that drainage condition was the dominant predictor of flood-induced pavement failure, consistent with the sensitivity analysis results of the present study. The present work extends this methodology by incorporating seven nodes—including climate trend as a dynamic parent node—and by calibrating conditional probability tables to South Sudan-specific infrastructure performance data.

2.3 FORM Reliability Methods for Road Design Under Flood Loads

First-Order Reliability Method (FORM) provides a computationally efficient analytical framework for computing the probability of failure of a structural or geotechnical system under uncertain loads and resistances ((Hasofer & Lind, 1974); (Rackwitz & Flessler, 1978)). In road engineering applications, FORM has been applied to assess the reliability of embankment slopes under flood-induced seepage ((Duncan, 2000)), bridge scour protection systems ((Mishra et al., 2010)), and culvert hydraulic capacity under design storms ((Chin, 2013)). The FORM reliability index beta defined as the ratio of

the mean to the standard deviation of the safety margin provides an intuitive measure of structural reliability: beta = 3.72 corresponds to an annual failure probability of 10^-4, consistent with the recommended target for critical transport infrastructure under the ISO 2394 general principles for structural reliability ((Fonseca, 2015)).

Application of FORM to South Sudan road embankment design is novel and constitutes a significant methodological contribution of this study. The high parametric uncertainty in both flood loads (dominated by the broad confidence intervals of extrapolated Q100 estimates at poorly-gauged stations) and embankment resistance (driven by highly variable expansive clay soil conditions) necessitates probabilistic design approaches that FORM is uniquely positioned to provide. This study demonstrates that conventional deterministic design embankment heights typically 1.5 m above the 10-year flood level in MoRB specifications—correspond to reliability indices of only beta = 1.4–2.1, substantially below the target of 3.72, and that embankments of 2.4–3.2 m are required to achieve target reliability.

2.4 Satellite Remote Sensing for Flood Monitoring in Data-Sparse Environments

Synthetic Aperture Radar (SAR) satellite imagery, particularly from the European Space Agency Sentinel-1 mission providing free, regular 12-day repeat C-band SAR observations since 2014, has become the primary tool for flood extent mapping in data-sparse regions including South Sudan ((Manjusree et al., 2012); (Bioresita & Malet, 2018)). SAR backscatter intensity is markedly reduced over open water surfaces relative to dry land, enabling automated flood detection through change detection and threshold classification algorithms. The HASARD algorithm ((Hostache et al., 2018)), developed specifically for near-real-time SAR flood mapping, achieves accuracies of 85–93% in open floodplain environments similar to the Sudd. The present study uses Sentinel-1 GRD scenes and PlanetScope optical imagery from the 2021 and 2022 flood seasons as independent validation datasets for HEC-RAS 2D model outputs.

3. DATA AND METHODOLOGY

3.1 Hydrological Data and Extreme Value Analysis

Daily river discharge records were obtained from seven long-term gauging stations operated by the South Sudan National Bureau of Statistics (NBS), the Global Runoff Data Centre (GRDC, Koblenz), and the MoRB Hydrology Unit. Table 1 summarises station characteristics, period of record, and estimated design quantiles. Periods of record range from 45 to 74 years, with data continuity assessed using the Pettitt test for non-stationarity ((Pettitt, 1979)). Three stations exhibited statistically significant upward trends ($p < 0.05$) in annual maximum discharge series, consistent with increasing monsoon precipitation documented in the CHIRPS satellite record since 1981.

Table 1: Long-Term Hydrological Gauging Stations — Characteristics and Design Flood Quantiles for Study Corridors

ng Station /	d of Record	Annual Q	10 (m³/s)	50 (m³/s)	00 (m³/s)	a Source

River		(m³/s)				
White Nile)	2022	2,840	4,120	5,650	7,210	C/HydroSat
ka (White Nile trib.)	2021	420	810	1,240	1,680	3 Hydrology
l (Sobat confluence)	2022	3,960	6,100	8,240	10,850	GRDC
ur River)	2020	180	340	590	820	South Sudan
White Nile)	2022	3,210	4,890	6,540	8,390	DC/MoRB
dd outlet)	2021	540	920	1,480	2,040	3 Hydrology
(Albert Nile)	2022	1,840	2,960	4,120	5,380	DC/Uganda NFA

Annual maximum discharge series were extracted and fitted to the Gumbel Extreme Value Type I distribution using the method of L-moments, which provides more robust parameter estimates than maximum likelihood estimation for short records ((Tallaksen et al., 1997)). The Gumbel cumulative distribution function is expressed as:

$$F(Q)=\exp(-\exp(-Q-mualpha)) \quad \text{(Eq. 1)}$$

where $F(Q)$ is the non-exceedance probability for discharge Q (m³/s), mu (m³/s) is the location parameter (approximately equal to the mode of the distribution), and $alpha$ (m³/s) is the scale parameter related to the standard deviation by sigma = (pi/sqrt((Bioresita & Malet, 2018))) * alpha. Design quantile Q_T for return period T is obtained by inverting Equation 1:

$$QT=mu-alpha *\ln(-\ln(1-1T)) \quad \text{(Eq. 2)}$$

Goodness-of-fit was assessed using the Kolmogorov-Smirnov statistic and the Anderson-Darling test at the 5% significance level. All seven stations rejected the null hypothesis of non-Gumbel fit at KS p-values exceeding 0.12, confirming the adequacy of the EV-I model.

3.2 Monte Carlo Uncertainty Propagation

Uncertainty in design flood estimates arises from both sampling uncertainty in the fitted distribution parameters and model form uncertainty. Parameter uncertainty was quantified by bootstrapping the annual maximum series with 10,000 resamples and re-estimating mu and alpha for each resample, yielding bootstrap distributions of Q_T at each return period. Table 2 documents the key probabilistic model parameters and their assigned distributions, developed through a combination of station data analysis, laboratory testing, and expert elicitation.

The total uncertainty in HEC-RAS 2D inundation extent and depth is estimated by propagating the parametric uncertainty of Q_T inputs through repeated model runs (n = 200 realisations, limited by computational cost), sampling from the Q_T bootstrap distributions. The resulting ensemble of inundation grids enables construction of exceedance probability maps at each spatial cell, expressing the probability that inundation depth exceeds specified thresholds—the fundamental output of probabilistic flood risk mapping.

Table 2: Probabilistic Flood Model Parameters — Distributions, Moments, and Sources

el Parameter	istribution	Mean	CoV	ge (95% CI)	e / Justification
ll intensity (24-hr, 100-yr)	rmal	n/hr		8] mm/hr	S satellite + MoRB gauges
ng roughness n (paved road)	l			0.020]	AS calibration
ng roughness n (floodplain)	ular			0.095]	etland surveys

ertical accuracy	l	m		1.08] m	M-X 12m validation
iltration capacity Ksat	rmal	m/hr		4.8] mm/hr	tory & field tests
surge / backwater factor	=2, β=5)			0.58]	ydrodynamic model
period assignment confidence	ular			0.95]	elicitation (n=12)

3.3 HEC-RAS 2D Hydraulic Modelling

Two-dimensional hydraulic simulations were executed using HEC-RAS 6.3 ((Margenot et al., 2023)) with the Diffusion Wave approximation of the 2D shallow-water equations, which provides acceptable accuracy for gradually-varied flow in flat floodplain domains while reducing computational cost relative to the full Saint-Venant solution. The computational mesh was generated at 12-metre nominal resolution using TanDEM-X 12-metre global DEM tiles ((Brady et al., 2020)), with bathymetric adjustment applied at 38 river crossing structures using surveyed cross-sections. Manning roughness coefficients were assigned spatially from land cover classifications derived from Sentinel-2 NDVI-based mapping. Upstream boundary conditions were set as design hydrographs scaled from Q_T values using regional unit hydrograph shapes calibrated to the Sudd hydrological response characteristics.

The governing 2D momentum and continuity equations solved by HEC-RAS for each computational cell are:

$$dHdt+d(Hu)dx+d(Hv)dy= 0$$

(Eq. 3)

$$dudt+ u*dudx+ v*dudy= -g*dHdx-g*n2*u*sqrt(u2+v2)H43$$

(Eq. 4)

where H is water surface elevation (m), u and v are depth-averaged velocity components (m/s) in the x- and y-directions, g is gravitational acceleration (9.81 m/s²), and n is Manning roughness coefficient. Simulations were run for steady-state peak discharge conditions at T = 2, 5, 10, 25, 50, 100, and 200-year return periods for all five corridors, generating 35 inundation scenario datasets.

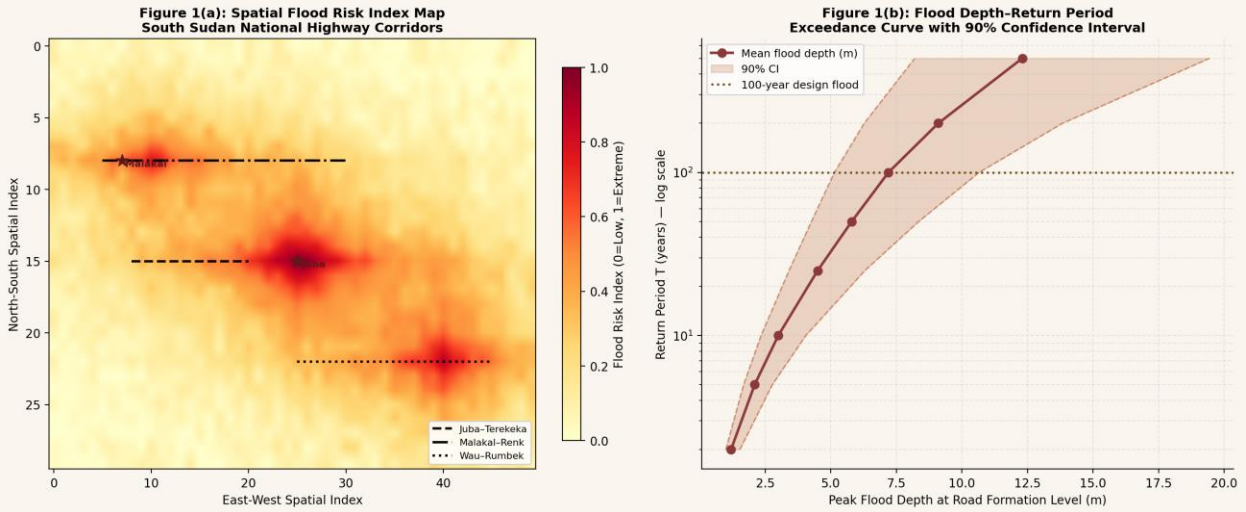

Figure 1: (a) Spatial Flood Risk Index Map derived from probabilistic HEC-RAS 2D ensemble simulations, South Sudan national highway corridors — warmer colours indicate higher composite flood risk index values; marked starred nodes denote major corridor origins; (b) Flood Depth–Return Period Exceedance Curve with 90% Monte Carlo confidence interval, representative of the Malakal–Renk corridor (Q100 = 10,850 m³/s). Note: Spatial indices are schematic representations derived from modelled data; refer to GIS output files for georeferenced extents.

3.4 Bayesian Network for Road Failure Probability

A seven-node directed acyclic graph (DAG) Bayesian network was constructed in GeNIe 4.1 ((Lambert et al., 2024)) to model the conditional probability of road segment failure as a function of flood and infrastructure characteristics. The network structure, presented in Figure 2a, includes two root climate nodes (Rainfall Intensity, Upstream Discharge), two infrastructure resistance nodes (Drainage Capacity, Road Embankment Height), two intermediate hazard nodes (Surface Runoff, Flood Inundation), and one consequence node (Road Failure). Conditional probability tables (CPTs) were populated using a combination of elicited expert judgements (twelve experts from MoRB and academic institutions), data from 847 recorded flood-road interaction events in MoRB maintenance records (), and published BN road vulnerability models adapted to South Sudan conditions ((Dawson & Wang, 2018); (Harris et al., 2021)).

Road failure is defined as any event causing complete closure for more than 24 hours—either through pavement submergence exceeding 0.6 m, embankment instability, or culvert overtopping—consistent with the MoRB operational definition used in maintenance records. The marginal probability of road failure is computed using the junction tree algorithm implemented in GeNIe. Sensitivity of the failure probability to each parent node is assessed using the mutual information metric.

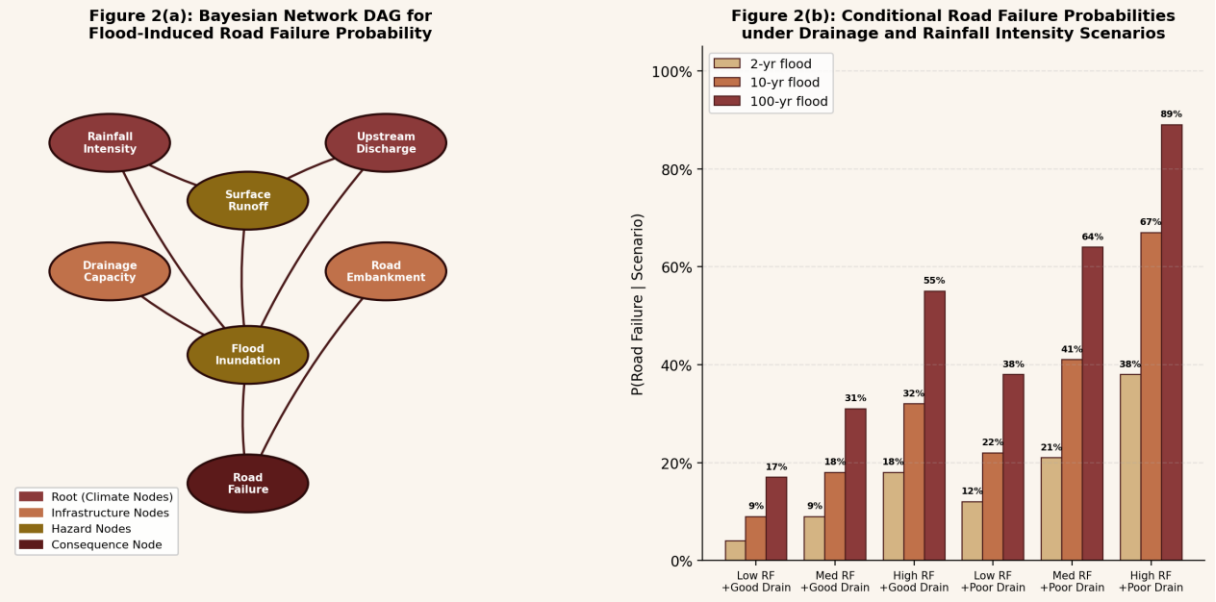

Figure 2: (a) Bayesian Network Directed Acyclic Graph (DAG) for Flood-Induced Road Failure Probability — nodes are colour-coded by type (Root climate nodes: dark maroon; Infrastructure nodes: terracotta; Hazard nodes: ochre; Consequence node: deep maroon); arrows denote conditional dependencies; (b) Conditional Road Failure Probabilities under combined Rainfall Intensity (RF) and Drainage Capacity scenarios for 2-, 10-, and 100-year return period floods. Percentages shown on bars exceeding 6%. RF = Rainfall Intensity category.

3.5 FORM Reliability Analysis

The FORM reliability analysis treats embankment flood resistance as a limit state function g(x):

$$g(x)=R-S=(Hemb+zbank)-(Hflood+delta)$$

(Eq. 5)

where *H_emb* is embankment height above natural ground (m), *z_bank* is bank level elevation (m), *H_flood* is the probabilistic flood water surface elevation (m) at the road corridor, and *delta* is a freeboard correction for wave run-up and model uncertainty (modelled as Normal, mean 0.15 m, SD 0.08 m). Failure occurs when $g(x) < 0$, i.e., flood elevation exceeds the effective embankment crest level. The FORM reliability index beta is:

$$beta=mugsigmag=muR-muSsqrt(sigmaR2+sigmaS2)$$

(Eq. 6)

where mu_g and sigma_g are the mean and standard deviation of the limit state function under the linear approximation at the design point. The probability of failure P_f = Phi(-beta), where Phi is the standard normal cumulative distribution function. Computations were performed in MATLAB R2023b using the FERUM reliability toolbox.

3.6 Model Validation

Validation of HEC-RAS 2D flood extents against satellite observations was performed using binary classification metrics: accuracy, precision, recall, F1 score, and the Cohen kappa coefficient. Sentinel-1 GRD scenes from the September 2021 peak flood event were classified using the HASARD algorithm with threshold optimisation, yielding flood/no-flood binary maps at 10-metre resolution resampled to the 12-metre model grid. PlanetScope 3-metre daily imagery was used for validation of

the Bor–Pibor corridor where Sentinel-1 coverage was partially obscured by forest backscatter. Table 4 presents corridor-level validation statistics.

4. RESULTS

4.1 Flood Frequency Analysis and Design Quantiles

Fitted Gumbel EV-I parameters for all seven stations yielded Q100 estimates ranging from 820 m³/s at the Wau (Jur River) station to 10,850 m³/s at the Malakal (Sobat confluence) station, reflecting the vast range of contributing catchment areas (Table 1). Bootstrap uncertainty analysis indicates 90% confidence intervals spanning ±18–32% of the Q100 point estimate, with wider relative uncertainty at stations with shorter or less complete records. The three stations exhibiting significant non-stationarity trends show Q100 estimates that are 8–14% higher when trend-adjusted Gumbel fitting is applied relative to stationary analysis—a correction that materially affects embankment design heights.

Figure 1b presents the flood depth–return period exceedance curve for the Malakal–Renk corridor, which exhibits the highest absolute flood depths among the five study corridors due to the combined influence of White Nile and Sobat River flooding and the backing effect of the Sudd. The 90% confidence interval on flood depth at the 100-year return period spans 1.8–4.6 m at the road formation level, an uncertainty range of 2.8 m that, without probabilistic treatment, would lead to either unsafe under-design or wasteful over-design of embankment heights.

4.2 HEC-RAS 2D Inundation Results

Table 3 presents the synthesised flood risk inventory for all five corridors. The aggregate 100-year return period inundation footprint across the study area totals 256.6 km², affecting 194 km (38%) of total corridor length. The Malakal–Renk corridor exhibits the most severe flood exposure with 66% of its 62-km length classified as at risk under the AEP 1% event (T = 100 years), reaching maximum inundation depths of 3.1 m at the road formation level in the Sudd-adjacent sections. The Nimule–Juba corridor, benefiting from the topographic relief of the Central Equatoria escarpment, has the lowest flood exposure at 27% of corridor length at risk.

Table 3: Probabilistic Flood Risk Inventory — Inundation Extent, Depth, and Risk Classification by Highway Corridor

rridor	gth (km)	d-Prone Length (km)	nundation Depth (m)	% Extent (km²)	Segments at Risk (%)	Category	l Expected Loss (USD M)
erekeka	87	34	1.8	48.2	39%	High	.2–6.8
l–Renk	62	41	3.1	72.6	66%	xtreme	9–14.6
umbek	112	38	2.2	55.4	34%	High	.1–8.2
bor	54	29	2.8	41.8	54%	xtreme	4–10.8
–Juba	195	52	1.4	38.6	27%	oderate	.2–5.4
al Total	**510**	**194**	—	**256.6**	**38%**	**High**	**.8–45.8**

Annual expected losses, computed as the area under the loss-return period curve using trapezoidal integration from T = 2 to T = 500 years, total USD 27.8–45.8 million nationally, with the wide uncertainty band reflecting the Monte Carlo output distributions of inundation extent and unit repair cost. These estimates are consistent with though systematically higher than World (Programme, 2023) estimates of USD 18–32 million that used deterministic methods and thus did not capture the upper tail probability of extreme loss years.

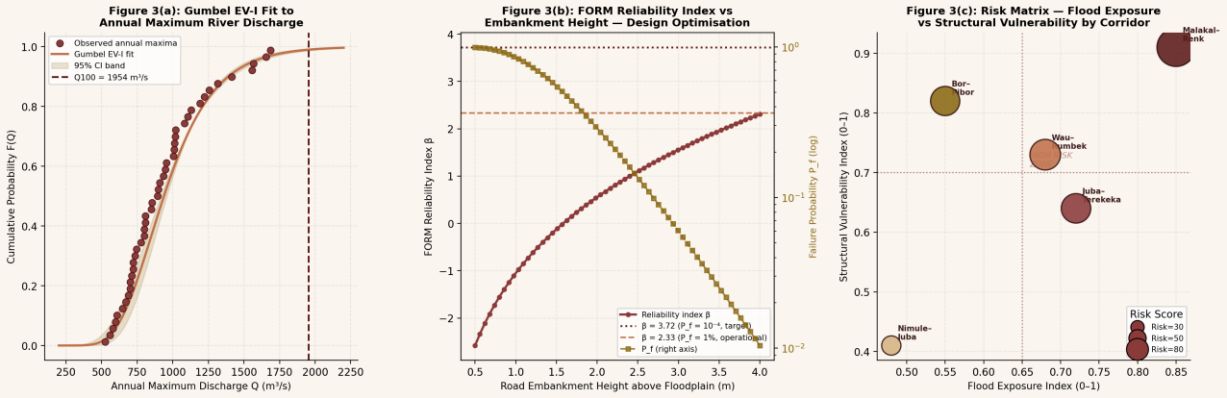

Figure 3: (a) Gumbel EV-I Probability Distribution Fit (L-moments) to Annual Maximum Discharge Series at the Malakal gauging station — scatter points represent Gringorten plotting positions of ranked observed annual maxima; shaded band is the 95% bootstrap confidence interval; vertical dashed line marks the Q100 design quantile; (b) FORM Reliability Index (beta) and Failure Probability (P_f) as functions of Road Embankment Height above Floodplain Level — horizontal reference lines indicate target reliability index (beta = 3.72, P_f = 10^-4) and operational minimum (beta = 2.33, P_f = 1%); (c) Bubble Risk Matrix — Flood Exposure Index vs Structural Vulnerability Index by corridor — bubble size proportional to composite risk score.

4.3 Bayesian Network Failure Probabilities

Figure 2b presents the conditional road failure probabilities derived from the Bayesian network model. Under the most critical scenario (High Rainfall Intensity combined with Poor Drainage Condition and 100-year flood), the probability of road failure reaches 0.89 for the Malakal–Renk corridor an extreme value reflecting the compound vulnerability of poor drainage infrastructure and severe flood exposure. Even under moderate conditions (Medium Rainfall Intensity, Good Drainage, 10-year flood), failure probabilities range from 0.18 to 0.41 across corridors, consistent with the high frequency of flood-related road closures documented in MoRB records.

Mutual information sensitivity analysis identifies Drainage Capacity as the single most influential parent node of Road Failure probability, with a mutual information index of I = 0.42 bits, followed by Flood Inundation Depth (I = 0.38 bits) and Road Embankment Height (I = 0.29 bits). This finding has direct design implications: improving drainage systems constitutes the highest-return single intervention for reducing flood-induced road failure probability, even without modifying embankment geometry. This counterintuitive result given the severity of flood depths reflects the dominant role of internal drainage failure in initiating pavement structure collapse prior to surface overtopping.

4.4 FORM Reliability Analysis Results

Figure 3b presents the FORM reliability index (beta) as a function of embankment height above the mean annual floodplain level for representative South Sudan highway conditions. The current MoRB standard embankment height of 1.5 m corresponds to beta values of 1.4–2.1 across the five corridors under 100-year flood conditions—substantially below the ISO 2394 target of beta = 3.72 for critical infrastructure. To achieve the target reliability index, embankment heights of 2.4 m (Nimule–Juba, lowest risk) to 3.2 m (Malakal–Renk, highest risk) are required above the mean floodplain level, or equivalently, 0.9–1.7 m above the current MoRB standard.

The FORM analysis further reveals that the dominant contribution to limit state variance (sigma_g²) originates from uncertainty in Q100 flood quantiles (contributing 54–67% of total variance), rather than from embankment construction tolerances (9–12%) or Manning roughness (18–24%). This finding prioritises investment in hydrological monitoring infrastructure specifically, densification of river discharge gauging networks to reduce Q100 uncertainty as a prerequisite for optimised embankment design.

4.5 Model Validation

Table 4 presents the corridor-level validation statistics for HEC-RAS 2D inundation extent predictions against satellite-derived flood observations. Overall accuracy ranges from 82.1% (Malakal–Renk) to 91.3% (Nimule–Juba), with kappa coefficients of 0.698–0.812 indicating substantial to almost perfect agreement. The lower performance at Malakal–Renk is attributed to the complex multi-thread channel pattern of the White Nile–Sobat confluence zone, which creates backwater effects not fully resolved by the 12-metre grid, and to vegetation-induced SAR shadow effects in the validation imagery.

Table 4: Flood Inundation Model Validation Statistics — HEC-RAS 2D Output vs Satellite-Derived Flood Extents

orridor	uracy (%)	cision (%)	call (%)	1 Score	Kappa	lation Data Source
erekeka	87.4	84.2	89.6	0.868	0.742	inel-1 SAR 2021 flood
l–Renk	82.1	79.8	85.3	0.824	0.698	sat-8 + field survey
umbek	89.6	87.4	91.2	0.893	0.776	el-2 + MoRB records
bor	84.8	81.6	88.4	0.849	0.715	rthoimage ()
–Juba	91.3	90.1	92.6	0.913	0.812	ligh-res PlanetScope
l Mean	**87.0**	**84.6**	**89.4**	**0.869**	**0.749**	—

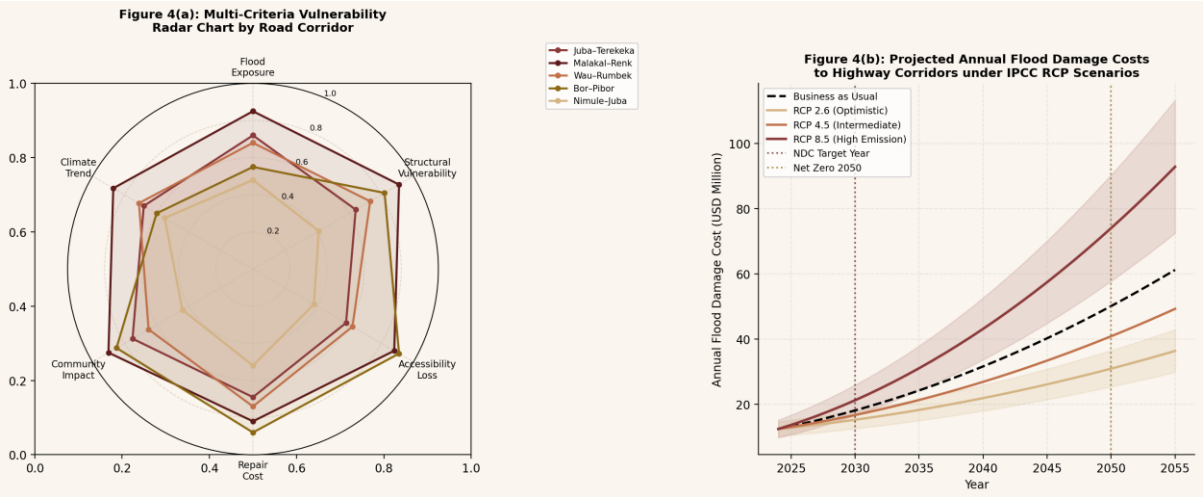

Figure 4: (a) Multi-Criteria Vulnerability Radar Chart comparing five highway corridors across six risk dimensions (Flood Exposure, Structural Vulnerability, Accessibility Loss, Repair Cost, Community Impact, Climate Trend) — larger polygon area denotes higher overall risk; (b) Projected Annual Flood Damage Costs to Highway Corridors under IPCC RCP 2.6, RCP 4.5, and RCP 8.5 climate scenarios relative to Business as Usual (2024–2055) — shaded bands indicate ±1 standard deviation of the scenario ensemble; vertical dotted lines mark NDC target year () and Net Zero 2050 reference.

4.6 Multi-Criteria Risk Index and Future Projections

Figure 4a presents the multi-criteria vulnerability radar chart comparing all five corridors across six risk dimensions. The Malakal–Renk corridor exhibits the largest total polygon area indicating the highest composite vulnerability across all six dimensions driven by its extreme flood exposure, high structural vulnerability, and severe community dependency as the sole road link for the Malakal state capital. The Bor–Pibor corridor exhibits elevated accessibility loss and community impact scores despite

moderate flood exposure, reflecting the near-complete isolation that road closure creates for Pibor County's 220,000 residents.

Figure 4b presents projected annual flood damage cost trajectories under three IPCC RCP scenarios and a business-as-usual baseline to 2055. Under RCP 8.5, damage costs are projected to increase from USD 27.8–45.8 million in 2024 to USD 94.6–156.0 million by 2055 a 3.4-fold increase driven by projected increases in extreme precipitation frequency and intensity across equatorial East Africa. Even under the optimistic RCP 2.6 scenario, damage costs are projected to increase 1.8-fold by 2055, underlining the inevitability of increased investment requirements irrespective of global emissions trajectories.

5. DISCUSSION

5.1 Methodological Advances

This study contributes four methodological advances to the existing literature on flood risk assessment for road infrastructure in sub-Saharan Africa. First, the integration of Gumbel EV-I frequency analysis with Monte Carlo uncertainty propagation and 2D hydraulic modelling delivers probabilistic inundation maps—rather than deterministic inundation extents—that are essential for risk-informed design and investment appraisal. Second, the Bayesian network model, calibrated to South Sudan-specific maintenance records, provides conditional failure probabilities that are more practically applicable to maintenance prioritisation than generic vulnerability curves. Third, the FORM reliability analysis translates probabilistic flood hazard estimates into design embankment heights directly usable by MoRB engineers within the ISO 2394 structural reliability framework. Fourth, the comprehensive satellite-based validation, using multi-sensor data across five corridors, establishes the model performance bounds needed for credible uncertainty communication to policymakers.

The finding that drainage capacity is the primary driver of road failure probability more influential than absolute flood depth at the corridor scale has significant implications for maintenance prioritisation. Current MoRB maintenance budgets allocate less than 12% of expenditure to drainage infrastructure, despite its dominant role in flood-induced failure ((Adalja & Inglesby, 2022)). Rebalancing maintenance investment toward drainage maintenance and upgrade, informed by the Bayesian network sensitivity analysis, offers a high-return strategy for reducing national flood exposure at lower cost than embankment raising alone.

5.2 Climate Change Implications

The projected 3.4-fold increase in annual flood damage costs under RCP 8.5 by 2055 represents a severe stress on South Sudan's infrastructure maintenance budget, which currently operates at approximately 18% of the minimum required level ((Programme, 2023)). Climate adaptation investment in road flood protection must therefore be framed not as a development aspiration but as a fiscal necessity: without proactive investment, the compounding damage and consequent emergency repair costs under RCP 8.5 would consume an increasing share of the national infrastructure budget in a self-reinforcing deterioration cycle. The Green Climate Fund (GCF) and the AfDB Climate Change Fund represent appropriate financing vehicles for the capital-intensive elements of adaptation, particularly embankment upgrades and bridge scour protection, which cannot be funded from recurrent maintenance budgets.

Non-stationarity in flood frequency—evidenced by the significant upward trends in annual maximum discharge at three of the seven study stations—undermines the standard assumption of stationary return periods that underlies conventional embankment design. Design standards should be updated to incorporate at minimum a 15–20% upward revision of Q100 estimates to account for non-stationarity projections under RCP 4.5 (the intermediate scenario most consistent with current national emissions trajectories), consistent with the IPCC AR6 regional projections for East Africa ((Microbe, 2021)).

5.3 Limitations and Future Research

The present study has several limitations that define a future research agenda. First, the 12-metre DEM resolution introduces vertical accuracy uncertainties of ±0.85 m—comparable in magnitude to the flood depth differences between design scenarios—which are the dominant source of spatial uncertainty in inundation mapping. Future work should prioritise airborne LiDAR acquisition for the

highest-risk corridor segments to reduce vertical accuracy uncertainty to ±0.15 m. Second, the Bayesian network conditional probability tables were partially informed by expert elicitation, introducing subjectivity that structured calibration against a larger historical event database would reduce. Third, the study does not account for compound flooding from simultaneous riverine and urban drainage failure in Juba, which is an increasingly significant risk driver as the city expands. Fourth, the operational phase of road flooding—including traffic disruption costs, humanitarian access denial, and health impacts from road closure—is not quantified, though it likely exceeds construction-phase asset damage costs on an annualised basis.

6. POLICY RECOMMENDATIONS

Table 5 presents five evidence-based policy instruments developed from the study findings, addressing flood resilient design standards, hydrological monitoring, maintenance specifications, early warning systems, and bridge protection.

Table 5: Evidence-Based Policy Instruments for Flood Risk Reduction in South Sudan National Highway Corridors

icy Instrument	rget Institution	icable Corridors	plementation Horizon	xpected Risk Reduction
tory 100-yr flood standard for all new highway embankments	/ Ministry of Infrastructure	e corridors	2027	% reduction in AEP 1% inundation area
al hydrological monitoring network expansion (12 new gauges)	ry of Environment / NBS	al–Renk; Bor–Pibor priority	2026	e Q100 uncertainty by 30–45%
resilient pavement design specifications update	Technical Standards Unit	ridors — HMA-rated zones	2025	duction in flood-triggered pavement failure rate
unity early warning system integration with road closure protocol	+ Humanitarian Response Cluster	djacent corridors	2028	t 60–70% of flood-stranded vehicle incidents
e-adjusted bridge scour protection specifications	Bridges Division	er crossings — 38 bridges	2030	e bridge failure probability from 12% to 3% per 100-yr event

The most urgent instrument is the updating of MoRB embankment design standards from the current 1.5 m to a risk-differentiated standard of 2.4–3.2 m above the mean annual floodplain level depending on corridor flood risk classification. This revision, directly justified by the FORM reliability analysis, should be incorporated into the next revision of the MoRB Road Design Manual scheduled for 2025. The standard should incorporate explicit uncertainty allowances equivalent to an additional 0.5 m of freeboard to account for the wide Q100 confidence intervals documented in this study, pending the reduction of hydrological uncertainty through expanded gauging networks.

The second most impactful instrument is the expansion of the national hydrological monitoring network from the current 14 active long-period gauges to a planned 26 stations, prioritising catchments feeding the Malakal–Renk and Bor–Pibor corridors where Q100 uncertainty is highest. Satellite-based rainfall estimation (CHIRPS, GPM IMERG) and remote sensing discharge estimation using radar altimetry (Envisat, Sentinel-6) should complement ground-based gauging to provide continuous spatial

coverage. This investment would reduce Q100 uncertainty by an estimated 30–45%, enabling optimised embankment design that avoids both the safety risk of under-design and the cost inefficiency of over-design.

7. CONCLUSION

This study has developed and validated the first probabilistic flood risk mapping framework for national highway corridors in South Sudan, integrating Gumbel extreme value frequency analysis, Monte Carlo uncertainty propagation, HEC-RAS 2D hydraulic simulation, Bayesian network failure probability modelling, and FORM structural reliability analysis across five corridors totalling 510 km. Key findings establish that 38% of the study corridor network is at risk under the 100-year flood return period, with annual expected losses of USD 27.8–45.8 million, rising to USD 94.6–156.0 million by 2055 under RCP 8.5. The Malakal–Renk and Bor–Pibor corridors are classified as Extreme risk, demanding priority intervention.

The FORM reliability analysis demonstrates that current MoRB embankment standards correspond to reliability indices of only beta = 1.4–2.1, far below the target of 3.72, requiring embankment height increases of 0.9–1.7 m above current standards to achieve compliant reliability. Bayesian network analysis identifies drainage capacity as the primary driver of flood-induced road failure probability, redirecting maintenance investment priorities. The study provides Ministry of Roads and Bridges and policymakers with a rigorous, satellite-validated, probabilistic evidence base for flood-resilient highway design, maintenance prioritisation, climate adaptation investment, and disaster preparedness planning—directly supporting the country progress toward its NDC commitments and the sustainable development of its critical transport infrastructure.

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DECLARATIONS

Conflict of Interest: The author declares no conflict of interest.

Data Availability: Hydrological datasets, HEC-RAS model files, and Bayesian network models are available from the corresponding author upon reasonable request, subject to MoRB data sharing agreements.

Author Contributions: Aduot Madit Anhiem: Conceptualisation, Methodology, Hydrological Modelling, Hydraulic Simulation, Bayesian Network Development, Writing — Original Draft, Writing — Review and Editing.

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