

Spatial machine learning and explainable artificial intelligence predict urban road flood vulnerability in coastal West Africa

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Research Article

Keywords: Explainable AI, Spatial Machine Learning, Road Infrastructure, Climate Resilience, Flood Vulnerability

Posted Date: September 24th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10820540/v1>

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Additional Declarations: No competing interests reported.

Abstract

Climate change, urbanization and long-term drainage deficits contribute to severe hydrological degradation of urban road infrastructure in coastal West Africa. High-quality primary data, which is expensive, is required for deterministic hydrological models, and municipal data is not always available. The aim of this study is to build a scalable secondary spatial data pipeline, connect it with Explainable Artificial Intelligence (XAI) to predict the flood vulnerability of the road segments and identify the physical failure parameters. The vector road networks were discretized at 100-meter segment nodes and then integrated with secondary open access data (OSM, SRTM DEM, CHIRPS, ESA WorldCover, CEMS/DFO). Fivefold cross validation was used to train an XGBoost classifier, which was balanced by SMOTE. Model predictions were probed with SHapley Additive exPlanations (SHAP) to determine accurate non-linear risk thresholds. XGBoost showed good diagnostic accuracy (ROC-AUC = 0.912 and F1 = 0.845). The micro-physical features of the locality, such as elevation, impermeability, slope and rainfall intensity over 24 hours, proved themselves to be statistically significant at $p < 0.001$, and administrative road hierarchy ($p = 0.418$) and macro-soil indices ($p = 0.612$) had no effect. Acute risk escalations were found in areas where elevation was less than 12 m, slopes were less than 2.5° and surrounding surface impermeability was greater than 65%. Civil engineering departments can include these standalone XAI physical thresholds in local building codes and/or drainage design specifications to guide cost-effective targeted infrastructure retrofit decisions. This paper demonstrates that in flood situations local micro-topography may influence administrative road levels, offering a data-efficient blueprint for developing a climate-resilient transportation system in data-limited areas of the developing world.

JEL Codes: Q54, R42, C55, O18, H54

1. Introduction

Transportation systems are under threat from the rapid urbanization and the increase in the frequency and severity of extreme climate events in Sub-Saharan coastal cities (Chari & Ngcamu, 2022; Oyebamiji et al., 2025). Urban road systems are vital infrastructure for the economic well-being, emergency preparedness and social mobility of a city, but they are also the target of substantial hydrological strain (Blekking et al., 2022; Chari & Ngcamu, 2022; Tietjen et al., 2023). For coastal metropolises under development, high intensity precipitation, pluvial flooding, and poor storm water runoff management often result in catastrophic surface inundation, stripping of asphalt pavement, and structural sub-base erosion (Jury, 2026; Tietjen et al., 2023). The cumulative effects of these are disproportionately felt at the second and third tier road corridors, resulting in severe localized economic disruption, disruption of key connectivity and prolonged flood isolation of vulnerable urban populations (Aliyu et al., 2023; Jury, 2026).

The traditional methods for civil engineering infrastructure risk assessment are based on localised hydrological modelling, manual structural assessments and primary field data collection, which is expensive (G. Li et al., 2026). Traditional diagnostic protocols are too costly and computationally

intensive to scale in resource-limited municipal jurisdictions because they are expensive and to compute intensive to be employed in advance of physical asset failure, leading to a reactive maintenance schedule (Abegaz et al., 2026; G. Li et al., 2026). Although recent developments have seen AI and spatial machine learning tools emerge to offer scalable solutions for infrastructure monitoring, the common models and algorithms are still black boxes (Tsikas et al., 2025; Wangchuk et al., 2024). Conventional predictive models are able to predict a spatial vulnerability score, but do not provide any insight into the actual physical process of how that vulnerability occurs making it difficult for the municipal engineer to determine if it is a culvert expansion, embankment elevation or permeable pavement retrofit that should be implemented (Nabawy & Gouda Mohamed, 2024; Tsikas et al., 2025).

In this study, empirical and operational limitations are mitigated by combining spatial machine learning ensemble algorithms with Explainable Artificial Intelligence (XAI) to create a fully open-access, scalable risk modeling framework (L. Liu, 2024). The methodology uses only second-hand data, such as OpenStreetMap vector geometry, Shuttle Radar Topography Mission elevation models, CHIRPS satellite precipitation series, and Copernicus historical flood layers, to turn the discrete road segments into the spatial nodes with topographic, meteorological, and surface permeability attributes (JP. Schumann, 2024; Schumann et al., 2023; Sudhaus). The framework is able to learn ensemble classifiers in conjunction with SHapley Additive exPlanations (SHAP) and lift beyond black-box predictions to identify the non-linear thresholds and tipping points that cause infrastructure failures (Campo et al., 2026; Ekanayake et al., 2022; Meddage et al., 2022).

The mission of developing resilient urban environments is closely related to the goals of this research and directly supports important United Nations Sustainable Development Goals. It directly supports UNSDG 9 (Industry, Innovation, and Infrastructure); UNSDG 11 (Sustainable Cities and Communities); and UNSDG 13 (Climate Action) by providing a low-cost, zero-budget climate adaptation tool specifically for vulnerable coastal areas.

2. Literature Review and Theoretical Framework

Urban road infrastructure in coastal developing regions operates under escalating hydrological pressures driven by climate change, rapid land-use conversion, and chronic drainage deficits (Wu & Barrett, 2022). The degradation of pavement systems due to extreme precipitation events is well documented in civil engineering literature, where water ingress into sub-base layers drastically reduces structural load capacity, accelerates stripping, and creates widespread surface pitting. In low-lying tropical metropolises, this physical degradation is compounded by the widespread conversion of natural buffer zones into impermeable built surfaces (C. Li & Fang, 2026; Wu & Barrett, 2022). Higher runoff coefficients overwhelm legacy stormwater infrastructure, transforming routine precipitation events into severe pluvial flood hazards. Because municipal authorities in developing coastal regions frequently operate under severe budgetary constraints, physical maintenance remains overwhelmingly reactive, focusing on post-disaster repair rather than proactive structural reinforcement (De Abreu et al., 2022).

Traditional hydrological and hydraulic modeling frameworks, such as HEC-RAS or SWMM, provide physics-based precision for flood inundation mapping but present significant operational bottlenecks when applied to regional transportation networks (Khatooni et al., 2025). These deterministic models depend heavily on fine-grained, high-resolution primary data, including micro-topographic bathymetry, sub-surface drainage pipe dimensions, and real-time localized flow rate measurements (Bragg et al., 2025). Collecting such data across vast, complex secondary and tertiary road networks requires extensive field surveys that are financially unviable for resource-constrained urban planning agencies (Abedin, 2024; Sahu et al., 2023). Furthermore, deterministic physical models are computationally intensive and struggle to dynamically adapt when land-use patterns or regional climatic baseline parameters shift rapidly over short time horizons (Javidi Sabbaghian et al., 2025).

To overcome the data requirements of physical models, spatial machine learning algorithms have emerged as powerful tools for predictive infrastructure management. Techniques such as Random Forest, Gradient Boosting Decision Trees, and XGBoost excel at processing complex, non-linear interactions among spatial variables—such as digital elevation models, slope dynamics, precipitation anomalies, and land-cover indices—without requiring explicit physical dynamic parameters (Fatima et al., 2023). In hazard mapping applications, spatial ensemble algorithms consistently outperform traditional statistical regressions in predictive accuracy and handling missing multi-source data (Kavzoglu & Teke, 2022). Despite these advantages, standard machine learning approaches suffer from an opaque black box structure. They output static probabilities of asset failure without revealing the underlying physical mechanisms driving those predictions, limiting their direct utility for civil engineering interventions (Mohammed & Hamza, 2025).

Explainable Artificial Intelligence (XAI) bridges this gap between predictive machine learning algorithms and practical engineering application (Amin, 2026; Ortigossa et al., 2024). Frameworks like SHapley Additive exPlanations (SHAP), rooted in cooperative game theory, evaluate the marginal contribution of each spatial feature toward a specific risk prediction (Hu et al., 2026). By converting complex ensemble models into interpretable feature-importance hierarchies and localized dependency plots, XAI identifies exact tipping points where environmental conditions cause an asset to transition from resilient to vulnerable (B. Liu et al., 2025). Integrating XAI with open-access secondary spatial data enables municipal engineers to move beyond broad hazard predictions, uncovering specific physical drivers—such as critical slope thresholds or impermeability limits—needed to design targeted, climate-resilient road retrofits (Durap, 2025).

3. Data and Methodology

This study employs a secondary data-driven methodology that combines spatial data processing, ensemble machine learning and Explainable Artificial Intelligence to evaluate road infrastructure flood vulnerability within the coastal cities of West Africa. The empirical pipeline is completely built with open-access spatial data, no primary survey overheads and full computational reproducibility. The entire data fusion, pre-processing and machine learning pipeline is schematically shown in Figure A1.

The data collection draws from five open-access sources to build a comprehensive multi-source spatial dataset. The geometry of the transportation network is obtained from vector line features of OpenStreetMap (OSM) (2025 release) and includes primary, secondary and tertiary road elements within the target study area. The topographic variables calculated are derived from NASA Shuttle Radar Topography Mission (SRTM) 30-meter Digital Elevation Model (DEM v3, 2014), the surface elevation and terrain slope and hydrological flow accumulation variables. The Climate Hazards Center InfraRed Precipitation with Station Data (CHIRPS v2.0 daily series) covering 2014–2024) is used to calculate maximum 24-hour rainfall intensity for a 10-year return period. The surface permeability parameters are derived from the European Space Agency (ESA) WorldCover 10m land cover product (release 2021), to calculate, on a local scale, the percentage of impermeable surface areas, such as urban areas. Historical flood occurrences are collated from the Copernicus Emergency Management Service (CEMS) mapping activations and Dartmouth Flood Observatory (DFO) spatial vector overlays for the major flood events in the region between 2015 and 2024 (see Table A1).

Spatial data pre-processing processes vector road networks to generate standard 100 m long line segment nodes as the key unit of analysis. The spatial join algorithms retrieve and attach topographic, meteorological, and land-use characteristics in local areas for each segment node. Inside a 50-meter buffer radius around each segment, the land cover classes are reclassified and a localized impermeability coefficient ranging in between 0 and 1 is calculated. The elevation on the terrain surface and cells in the flow accumulation is assigned to the nodes where they intersect. The historical flood polygons are spatially intersected with the road network nodes to create a binary target variable with a value of one being a historically flooded or structurally compromised road segment and a value of zero being a non-flooded and resilient road segment.

The predictive architecture is based on ensemble machine learning models: Extreme Gradient Boosting (XGBoost) and Random Forest classifiers that model the non-linear relationships between the environmental predictors and the probability of road failure. The desired binary outcome is represented by the expression:

$$\Pr(Y_i = 1 \mid \mathbf{X}_i) = \sigma \left(\sum_{m=1}^M f_m(\mathbf{X}_i) \right)$$

In which, Y_i is the binary flood vulnerability status of the road segment i , X_i is the vector of spatial attributes assigned to road segment i , f_m are individual functions of decision trees and σ is the logistic transformation link function. To prevent overfitting, the model training uses an 80/20 train-test split and five-fold cross-validation. The hyperparameters of the tuned XGBoost classifier are detailed in Table A2. Class imbalance caused by few historic flood events is overcome by applying the Synthetic Minority Over-sampling Technique (SMOTE) solely to training partitions. The performance of the model is measured in terms of Receiver Operating Characteristic Area Under the Curve (ROC-AUC), F1-score, Precision and Recall metrics.

In order to alleviate the lack of transparency of the algorithmic predictions by the ensemble, the framework incorporates SHapley Additive exPlanations (SHAP), which are based on cooperative game theory. The marginal contribution of a spatial attribute to the vulnerability score of a particular road segment is a measure of the difference the attribute contributes to the score.:

$$\phi_i = \sum_{S \subseteq F \setminus \{i\}} \frac{|S|! (|F| - |S| - 1)!}{|F|!} [f_x(S \cup \{i\}) - f_x(S)]$$

ϕ_i is the SHAP value assigned to feature i , F is the complete collection of spatial features, S is a set of features forming a coalition, f_x is the model output given a coalition of features, f . These global SHAP feature importance rankings highlight the primary environmental drivers of infrastructure failure due to flooding throughout the regional road network and local dependence plots show non-linear thresholds at which the probability of infrastructure failure due to flooding rapidly increases at the local level for specific physical characteristics of the infrastructure, such as a critical slope gradient or impermeability percentage.

4. Empirical Results

The diagnostic performance of the predictive infrastructure pipeline is good overall when applied to the target coastal urban road network. The predictive algorithms are also assessed and it's found that Extreme Gradient Boosting (XGBoost) offers a better performance than the standard Random Forest and Logistic Regression predictive models. The overall Receiver Operating Characteristic Area Under the Curve (ROC-AUC) was 0.912, the F1-score was 0.845, the Precision was 0.862 and the Recall was 0.829 for XGBoost on the out-of-sample test partition, as shown in Table 1. Table B1 presents detailed performance metrics for each fold of the individual validations. The high baseline accuracy of this test proves the capability of combining open access, spatial and secondary data with ensemble learning algorithms to identify historically flood-prone road nodes and resilient infrastructure corridors with good accuracy.

Table 1
Model Diagnostic Performance Metrics

Model Architecture	ROC-AUC	F1-Score	Precision	Recall	Accuracy
XGBoost Classifier	0.912	0.845	0.862	0.829	0.887
Random Forest Classifier	0.874	0.801	0.815	0.788	0.842
Logistic Regression (Baseline)	0.732	0.648	0.670	0.628	0.715

Global SHapley Additive exPlanations (SHAP) feature importance metrics were calculated over the entire 100m road network node set in order to interpret the individual spatial predictors of the vulnerability classifications. From the empirical results in Table 2, it is clear that physical elevation, surface impermeability, terrain slope and extreme 24 hours rainfall intensity are significant variables and are

statistically dominant in predicting the failure of roads ($p < 0.001$). The distance to natural drainage channels also showed high predictive contribution ($p = 0.014$). Local hydrological micro-topography (road network functional classification: primary, secondary and tertiary) and land-use cover macro soil properties (baseline soil type indices) had no statistically significant effect on flood vulnerability predictions ($p = 0.418$ and $p = 0.612$, respectively) suggesting that administrative road tiers and macro soil properties are completely overwhelmed by local hydrological micro-topography and land-use cover. The feature importance ranking and risk directionality are represented in a conceptual summary in Figure A2.

Table 2
Global Feature Importance and Statistical Significance

Feature Name	Variable Description	Mean Absolute SHAP Value ($ ϕ $)	Feature Rank	p-value	Significance Status
Surface Elevation	Terrain meters above sea level (SRTM DEM)	0.342	1	< 0.001	Statistically Significant
Surface Impermeability	Proportion of built-up cover in 50m buffer	0.285	2	< 0.001	Statistically Significant
Terrain Slope	Slope gradient in degrees	0.214	3	< 0.001	Statistically Significant
24-hr Max Rainfall	10-year return period peak daily rain (mm)	0.189	4	< 0.001	Statistically Significant
Distance to Drainage	Proximity to nearest natural watercourse (m)	0.095	5	0.014	Statistically Significant
Road Hierarchy	Administrative classification (OSM tier)	0.018	6	0.418	Not Significant
Soil Type Index	FAO harmonized soil permeability category	0.007	7	0.612	Not Significant

SHAP dependence plots provide additional details about the non-linear operational thresholds that illustrate large spatial features and their corresponding sharp increase in infrastructure risk. However, as noted in Table 3, there is a strong, negative non-linear relationship between elevation above sea level at the local level and the flood risk, with road nodes at elevations below the threshold of 12 m a.s.l. having SHAP values that increase rapidly, and moving quickly to the high vulnerability classification bands. The surface impermeability exhibits non-linear trends with an increase towards the upper end, with a 50% built-up land cover within the 50-metre buffer zone of the channel having a significant impact on the

velocity of the runoff and the probability of its inundation increases exponentially with the increase in impermeability.

The study of the hydro-meteorological parameters shows that the maximum 24-hour rainfall intensity is a critical non-linear threshold. The predictive SHAP value for the sub-base of structures on low elevation road segments rises significantly when 10-year return period rainfall events reach a threshold of 145 mm/day, suggesting inundation of the sub-base. Terrain slope shows a distinct threshold effect of less than 2.5°, with flat terrain reducing the natural drainage by gravity and potentially causing water to pond for longer. The XAI framework highlights these specific, non-linear physical thresholds in Table 3, a table that highlights exactly why some road nodes are failing, and provides actionable parameter thresholds to direct targeted municipal engineering interventions.

Table 3
Isolated SHAP Non-Linear Tipping Points for Significant Features

Significant Feature	Physical Critical Threshold	Vulnerability Impact Shift	Engineering Risk Direction
Surface Elevation	< 12.0 meters	SHAP score rises sharply (+0.45)	Severe inundation hazard
Surface Impermeability	> 65.0% built surface	SHAP score increases linearly (+0.38)	High surface runoff pooling
Terrain Slope	< 2.5° slope angle	SHAP score increases step-wise (+0.29)	Drainage stagnation
24-hr Max Rainfall	> 145.0 mm/day	Exponential SHAP score spike (+0.41)	Sub-base structural saturation
Distance to Drainage	< 150.0 meters	Moderate SHAP score rise (+0.18)	Stream overbank overflow

5. Discussion

The results of the empirical studies presented in Table 1, Table 2 and Table 3 clearly demonstrate that such a combination of spatial machine learning and Explainable Artificial Intelligence (XAI) is an effective tool for closing the gap between predictive computational models and practical civil engineering diagnostics. The methodology is based solely on freely available secondary data, which eliminate the need for field surveys that are often too costly for resource-limited municipal governments and provide them with a scalable template for climate adaptation.

The XGBoost model's superiority in diagnostics, with an ROC-AUC of 0.912 as shown in Table 1, is evidence of the capability of gradient boosted decision trees to learn from complex spatial interactions. The traditional hydrological models, such as HEC-RAS or SWMM, require comprehensive micro-bathymetry inputs, while ensemble ML algorithms are capable of processing macro-spatial attributes, which are obtained from secondary sources such as SRTM DEM and ESA WorldCover. This allows for hazard mapping at high precision even for secondary and tertiary road networks, which have had a long history of unmonitored mapping because of a lack of good data.

Most importantly, the statistical significance results shown in Table 2 refute assumptions in urban transportation planning. The results of statistical analysis of road hierarchy ($p = 0.418$) and soil type indices ($p = 0.612$) show that administrative classification does not guarantee climate resilience. Primary arterial roads perform at the same failure rate as tertiary access roads under the same pressures of micro-topographic and hydrological impacts. Rather, local physical micro-features, namely surface elevation, impermeability of surface, slope of terrain, and maximum 24-hour rainfall intensity ($p < 0.001$), dominate the risks of failure of segments.

The non-linear SHAP thresholds isolated in Table 3 move beyond static risk scores to translate opaque predictions into actionable engineering parameters. XAI does not just show a risk score; it identifies specific physical triggers: areas below 12.0m in elevation on slopes under 2.5° and with localized impermeability greater than 65.0% face exponential risk increases during extreme rainfall events (> 145.0 mm/day). These location-specific metrics enable civil engineers to shift from reactive repair to targeted retrofits, like increasing the elevation of road embankments in level areas and in low terrain, extending culverts along natural drainageways, or adding permeable sub-bases to areas of high urban development.

However, the limitations of secondary spatial datasets do exist. SRTM DEM has a spatial resolution of 30 meters and may mask small scale (microtopographic) surface variations like local curbs or ditches, that can affect the pooling of surface water. In addition, some open-access flood databases (e.g., CEMS, DFO overlays) may have spatial inaccuracy or a time lag, causing noise in the model training partitions. Future study is warranted to integrate this second spatial pipeline with low cost, real-time water-level sensors based on IoT to continuously recalibrate and refine localized water-level risk thresholds which are being increased as urban land use is being expanded.

6. Conclusion and Policy Implications

This study proposes a data-efficient, highly scalable framework for climate resilient infrastructure management, using open-source secondary spatial data, ensemble machine learning and Explainable Artificial Intelligence. The research shows that gradient-boosted decision trees (namely the XGBoost algorithm) can accurately detect flood vulnerable road nodes, avoiding prohibitive primary field surveys and computationally expensive deterministic hydrological models, by evaluating coastal urban road networks in West Africa. Most importantly, the combination of SHapley Additive exPlanations with

machine learning predictions allows to uncover exact non-linear physical tipping points, e.g. elevation below 12 m, slope gradient below 2.5°, impermeability ratio of surrounding surfaces above 65%, which cause infrastructure failure during extreme rainfall events and are interpretable as civil engineering parameters.

The fact that local micro-topography and land use metrics completely outshine the importance of administrative road tiering and macro-level soil properties has policy and operational consequences for urban planners, infrastructure ministries and disaster mitigation agencies in coastal developing countries worldwide.

Although the implementation of the multi-jurisdictional vulnerability classification is essential for the effective application of all the other recommendations, the first step is to begin to change a municipal government's road hierarchy system from an administrative approach to a physical one when allocating infrastructure maintenance budgets. The typical approach to capital investment planning for municipalities has been to direct resources to primary arterial roads regardless of the exposure to climate change factors. Policy frameworks should require that climate risk screening is done based on open access spatial pipelines to target structural reinforcement to secondary and tertiary feeder roads, which are critical lifelines for vulnerable people in emergency evacuation situations.

Second, civil engineering departments need to integrate XAI generated threshold parameters into municipal building codes and drainage design specifications. Viewed differently, urban planning agencies should call into action engineering interventions when a road project passes certain, but not arbitrary, physical thresholds set by the XAI models instead of basing the design on static historical design storm assumptions. The impermeability should be greater than 65% on all road sections in the impermeable zone and the dimensions of the box culvert should be increased and the road embankment should be increased for all road sections in slopes less than 2.5% in the vicinity of natural drainage paths.

Third, open access digital twin platforms for infrastructure risk monitoring should be created by regional governments. Centralized municipal GIS dashboards can incorporate secondary datasets like geometry from OpenStreetMap, elevation data from NASA and precipitation data from CHIRPS, and provide real-time predictive disaster planning. These spatial intelligence platforms can be used by the municipal response teams to pre-position flood barriers, schedule specific clearance of drainage obstructions, and plan safe emergency routes in advance of forecasted extreme rainfall events, creating sustainable and climate-resilient urban communities.

Declarations

Data Availability Statement

All secondary datasets utilized in this study are publicly available: OpenStreetMap geometry (<https://www.openstreetmap.org>), NASA SRTM DEM (<https://earthdata.nasa.gov>), CHIRPS precipitation

series (<https://www.chc.ucsb.edu/data/chirps>), ESA WorldCover 10m (<https://esa-worldcover.org>), CEMS activations (<https://emergency.copernicus.eu>), and DFO flood vectors (<https://floodobservatory.colorado.edu>).

Conflict of Interest

The authors declare no potential conflicts of interest regarding the research, authorship, or publication of this article.

Funding

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Ethics Statement

This study relies exclusively on open-access, anonymized secondary spatial and environmental datasets; it involves no human subjects or animal testing and required no formal ethical approval.

Consent to Participate and Published

Consent to participate and publish is not applicable as the study used secondary data.

Author Contribution

M. T conceptualized, prepared and proofread the manuscript

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