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Development of the Field–Based Maintenance Management Prediction Model for Reducing Landslides along Mountainous District Roads: A Case of Mufindi District

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ABSTRACT

Mountainous district roads in Tanzania, particularly in Mufindi District, are frequently disrupted by landslides triggered by heavy rainfall, poor drainage, and inadequate maintenance. These hazards increase costs, endanger communities and expose weaknesses in current maintenance planning, which lacks predictive, field-based tools. This study aimed to identify and rank critical landslide-contributing factors, develop a robust landslide risk maintenance management prediction model and validate its applicability for integration into TARURA's planning framework.

A mixed-methods approach was employed. Field surveys and expert questionnaires provided primary data. The Relative Importance Index (RII) ranked contributing factors, while a Binary Logistic Regression Model (BLRM) quantified predictive relationships among hydrological, maintenance, geological, and road-condition indices. Validation combined statistical metrics Accuracy, ROC-AUC, Sensitivity, Specificity, Precision and F_1-score with expert ratings to confirm reliability and operational relevance. Results showed that hydrological factors (RII = 0.868) and maintenance management (RII = 0.858) influenced landslide occurrence more than static geological conditions, highlighting rainfall-induced pore-water pressure and neglected drainage as primary drivers of slope instability. BLRM outputs confirmed hydrological indices (OR = 6.162, p = 0.033) and maintenance indices (OR = 4.206, p = 0.007) as statistically significant predictors. The model demonstrated robust predictive performance, achieving 90% accuracy, ROC-

AUC = 0.9399, Sensitivity = 90.9%, Specificity = 89.3% and F_1-score = 0.889. External validation reinforced these outcomes, with expert satisfaction ratings between 4.4 and 4.8 out of 5, consistent with international benchmarks.

The study provides TARURA with a validated, cost-effective predictive tool that shifts maintenance planning from reactive to proactive. By relying on simple, field-observable indices rather than expensive remote-sensing data, the BLRM enables prioritization of drainage management and routine inspections. Theoretically, the study advances predictive maintenance modelling in civil engineering; practically, it enhances infrastructure resilience, optimizes resource allocation and safeguards communities in Tanzania's mountainous districts.

TARURA must prioritize mountain water control through regular drainage clearing and culvert desilting before and during rains, while shifting road management from reactive emergency repairs to planned preventive maintenance schedules. Additionally, road edges and steep slopes require routine inspections for early landslide warning signs, and future research should integrate and upscale this predictive tool into a national framework.

Keywords: Binary Logistic Regression, Landslide Prediction, Mountainous Roads, Mufindi District, TARURA, risk-based maintenance management.

1. INTRODUCTION

This chapter introduces the research context, establishes the background of the study, and presents the statement of the problem, objectives, research questions, significance, and scope of the study on developing a prediction model for early landslide detection and improved maintenance management in mountainous road networks.

Landslides are globally recognised as one of the most devastating geohazards affecting mountainous transportation infrastructure, particularly road networks through steep, geologically vulnerable terrain. Petley (2012) confirms that landslides kill thousands of people each year and cost the economy billions of dollars through infrastructural destruction, traffic congestion, and emergency interventions. Mountainous roads are uniquely susceptible due to a combination of steep slopes, complex geology, intense rainfall, and persistent anthropogenic disruptions during construction and maintenance.

To address these challenges, developed countries embrace predictive maintenance management systems integrating geospatial technologies, remote sensing, and data-driven modelling to project slope failures before they occur (Emmanuel, 2025). Driven by advances in machine learning, previous landslide susceptibility models incorporate meteorological data, soil/rock properties, topographic variables, and historical records to predict potential hazards accurately (Thomas & Weiss, 2021). These preventive measures significantly reduce infrastructure failure, improve maintenance allocation, and enhance road user safety.

Although the world is advancing, most developing nations still rely on reactive maintenance approaches, which only address landslides after they have occurred. This leads to prolonged road closures, high economic losses, and loss of lives due to the lack of real-time monitoring and predictive tools tailored to local complex terrains. Therefore, this study develops an early landslide prediction model to bridge this gap, enhancing timely maintenance interventions and infrastructure resilience.

1.1 Statement of the Problem

Landslides along mountainous roads severely damage infrastructure and increase costs. The World Bank (2020) and Federal Highway Administration (FHWA) (2009) emphasize that proactive risk management and drainage maintenance are vital to prevent erosion and slope failures.

In Mufindi District, the maintenance challenge is severe. According to the Iringa Regional Road Board (2025), the district has 1,788 km of roads, with 67% located in mountainous areas, and 28% becoming impassable during rainy seasons. Between the 2020/2021 and 2024/2025 financial years, TZS 3.7 billion allocated for planned maintenance was reallocated to emergency works. Consequently, 81 km of periodic maintenance and 246 km of routine/recurrent maintenance were left unimplemented (Iringa Regional Road Board, 2025).

Relying on emergency repairs rather than systematic, risk-based maintenance prevents road authorities from anticipating failures. Currently, Mufindi District lacks a locally validated, field-based model to predict landslide occurrence and prioritize maintenance.

This study bridges this gap by developing and validating a field-based landslide risk maintenance management prediction model for Mufindi's mountainous roads. Integrating hydrological, geological, and maintenance factors, the model provides an evidence-based approach to optimize resource allocation and improve road network reliability.

1.2 Research Objectives

- **Main Objective:** Develop a field-based landslide risk maintenance management model to predict vulnerable sections on mountainous roads in Mufindi District.
- **Specific Objectives:**
  - Identify and rank key factors contributing to landslides.
  - Construct a prediction model achieving at least 80% accuracy.
  - Validate the model (AUC ≥ 0.8) and secure TARURA's approval for maintenance planning.

2. LITERATURE REVIEW

2.1 Contributing Factors to Road-Related Landslides

Research shows that landslide occurrence along transportation infrastructure is driven by a combination of geotechnical, topographical, and hydrological factors. Adhikari and Dhakal (2026) highlight that weak geological conditions, steep slopes, rainfall exposure, and proximity to drainage systems significantly influence slope failures along road cut slopes. Similarly, Moon et al. (2024) emphasize the importance of measurable geotechnical properties, demonstrating that soil depth, friction angle, and porosity are critical indicators of landslide risk near road corridors.

On a broader scale, He et al. (2025) explain that highway landslide risk varies dynamically with altitude, slope curvature, lithology, vegetation index, and distance to water bodies. Furthermore, Robson et al. (2025) establish a strong link between landslide events and engineering practices, noting that failures along road networks are frequently caused by inadequate road cut-slope design guidance.

2.2. Landslide Prediction and Modelling Approaches

Statistical and machine learning methods are widely used to estimate landslide probability. Puente-Sotomayor et al. (2021) demonstrate that binary logistic regression effectively estimates landslide probability in hazard-prone areas by utilizing conditioning factors. Shang et al. (2023) expand on this, showing that logistic regression can be integrated with other models to classify risk levels, though their work focused primarily on spatial susceptibility mapping rather than specific corridors.

However, data source limitations remain a challenge. Prathom and Sujitapan (2024) note that while logistic regression remains useful when appropriate variables are selected, many existing models rely heavily on GIS and remote sensing. Additionally, Al-kordi et al. (2025) point out that geospatial landslide models often remain basin-based, showing limited connection to actual road network management needs.

2.3 Validation Metrics for Susceptibility Models

To ensure practical reliability, robust validation is essential. Alvioli et al. (2024) argue that model validation should incorporate comprehensive classification metrics including ROC-AUC, accuracy, precision, recall, F1-score, and Kappa rather than relying on a single statistic. Qiu et al. (2024) support this by showing that interpretable validation models help correctly distinguish between landslide and non-landslide areas.

Moreover, Abdelkader and Csámer (2025) emphasize interpreting ROC-AUC alongside precision and F1-scores, pointing out that past studies have validated spatial models rather than road-specific corridors. Finally, Taherdangkoo et al. (2026) recommend using probabilistic measures such as AUC, average precision, and the Brier score to assess the reliability of advanced machine-learning prediction models.

2.4 Research gap

Existing literature focuses primarily on GIS-based spatial susceptibility and remote sensing (Adhikari & Dhakal, 2026; Moon et al., 2024; Puente-Sotomayor et al., 2021; Robson et al., 2025; Shang et al., 2023). However, a practical gap remains district road authorities lack an integrated, field-based model that translates observable road conditions into clear maintenance priorities. This study addresses this gap by developing a localized field-based landslide prediction model.

2.5 Conceptual Framework

The conceptual framework analyzes how field-based indicators-geotechnical, hydrological, road condition, and maintenance factors-influence landslide occurrence along Mufindi's mountainous roads. The dependent variable is landslide occurrence (0 = no landslide, 1 = landslide occurred). In this study, maintenance prioritization is not a secondary dependent variable. Instead, the model first predicts landslide probability based on these indicators. This probability is then converted into a landslide risk score (0 to 1), which finally categorizes road sections into low, moderate, high, and very high-risk levels to practically prioritize maintenance resource allocation.

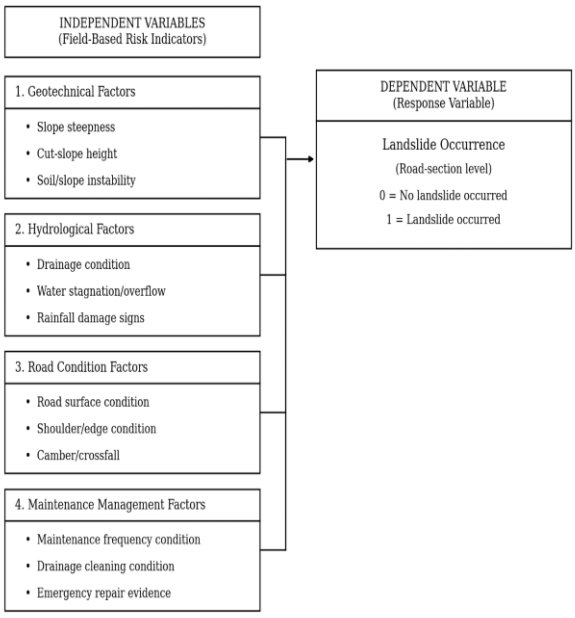


Figure 1: Conceptual Framework

3. RESEARCH METHODS

3.1 Introduction

This chapter outlines the research design, approach, study area, target population, sampling procedures, data collection methods, and analytical techniques used to develop and validate the landslide risk maintenance management model for mountainous roads in Mufindi District.

3.2 Research Design

This study adopted a quantitative-dominant mixed-methods research design with an embedded qualitative component, executed in three distinct stages:

Stage 1. Factor Identification and Ranking: Landslide-contributing factors were identified and grouped into four categories: geotechnical, hydrological, road condition, and maintenance management. Data from field observations and structured questionnaires were analysed using descriptive statistics and the Relative Importance Index (RII).

Stage 2. Model Development: Composite indices were constructed for each factor category and entered a Binary Logistic Regression model using Stata 17. Landslide occurrence served as the binary output dependent variable coded 0 for no landslide and 1 for landslide occurrence

Stage 3. Validation and Practical Assessment: The model was validated using classification metrics (overall accuracy, sensitivity, specificity, precision, F1-score, and ROC-AUC) alongside Spearman correlation to compare model outputs with expert rankings. Key informant interviews assessed the model's practical relevance to TARURA's maintenance prioritization.

3.3 Research Approach

A pragmatic research approach was employed to bridge physical data with institutional practices. The quantitative approach measured physical road conditions, calculated composite indices, and ran the regression model to estimate landslide probability. The qualitative approach gathered professional experiences from key informants and expert validators to interpret findings and contextualize the model within real-world constraints.

3.4 Area of Study

The study was conducted in Mufindi District, Iringa Region, within Tanzania's Southern Highlands. The district covers approximately 7,123 km² with mountainous elevations ranging from 1,200 to over 2,600 meters above sea level. It receives a mean annual rainfall of 1,200–1,600 mm (predominantly between November and May), with slopes exceeding a 30% gradient, accelerating erosion and slope instability.

Mufindi was selected due to severe landslide impacts on its 1,788 km road network, where 67% of roads are mountainous and 28% become impassable during the rainy season. Between financial year 2020/2021 and 2024/2025, TZS 3.7 billion of planned maintenance funds was redirected to emergency works, leaving 81 km of periodic maintenance and 246 km of routine/recurrent maintenance unimplemented (Iringa Regional Road Board, 2025). Sampling focused on TARURA-managed road sections with slopes above 15 degrees and elevations above 1,200 meters.

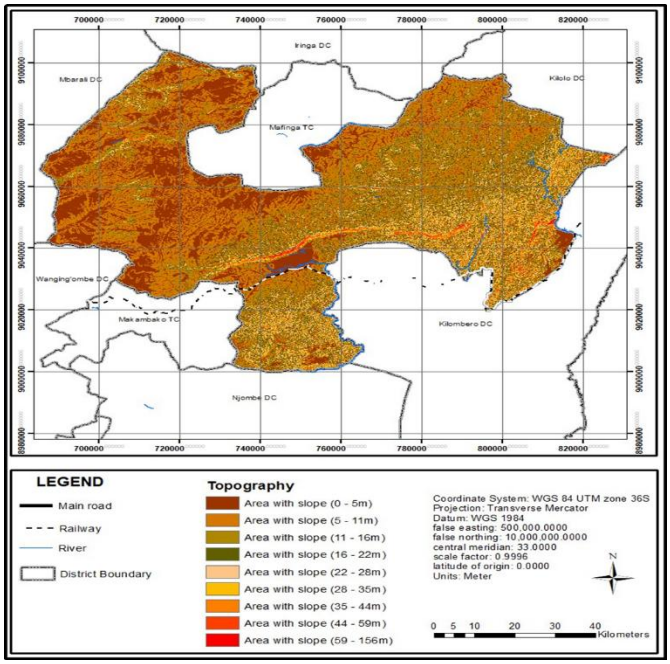


Figure 2: Mufindi District topography

Source: Mufindi District Council Library (2021)

3.5 Study Population

The study target population comprised three main components:

- Road Sections: TARURA-managed mountainous road segments vulnerable to slope instability, drainage failure, and road-edge degradation.
- Technical Personnel: A population of 73 personnel (25 road engineers/technicians, 40 maintenance supervisors/workers, and 8 meteorological officers) with field experience in landslide responses (Creswell, 2018).
- Qualitative and Historical Records: Comprising 12 key informants, 10 expert validators, and 50 documentary records (maintenance registers, emergency works reports, and road inspection logs).

3.6 Sample and Sampling Techniques

3.6.1 Sample Size Determination

The sample sizes were defined based on the data stream and analytical requirements:

50 road sections were selected across mountainous corridors to provide balanced landslide and non-landslide cases for binary logistic regression.

Technical Respondents were calculated using Yamane's (1967) formula at a 5% margin of error (e = 0.05) from the known population (N = 73)

$$n = \frac{N}{1 + N(e)^2}$$

Using proportional allocation, the final technical sample size of 62 respondents was distributed as shown below:

Table 1: Proportional Allocation of Technical Respondents

Respondent Category	**Population (N)**	**Sample Size (n)**
Road engineers and technicians	25	21
Maintenance supervisors/workers	40	34
Meteorological officers	8	7
Total	**73**	**62**

The study further integrated 12 key informants, 50 historical documentary records, and 10 expert validators to finalize the qualitative and validation data streams.

3.6.2 Sampling Techniques

The study utilized tailored sampling techniques for different data needs in Mufindi District:

Purposive Sampling: Used to select 50 mountainous district road sections exhibiting landslide risk indicators (slope instability, drainage issues, rainfall damage, edge failure, and maintenance challenges), alongside key informants, expert validators, and relevant documentary records.

Proportionate Sampling: Allocated technical respondents across road engineers/technicians, maintenance supervisors/workers, and meteorological officers based on direct operational involvement.

3.7 Types of Data and Data Collection Methods

Five methods collected primary and secondary data:

Field Observation: Used a checklist across the 50 road sections to record 12 observable indicators: slope steepness, cut-slope height, soil/slope instability, drainage condition, water stagnation/overflow, rainfall damage signs, road surface condition, shoulder/edge condition, camber/crossfall, maintenance frequency, drainage cleaning condition, and emergency repair evidence.

Structured Questionnaire: Administered to technical respondents using a 5-point Likert scale to rate geotechnical, hydrological, road-condition, and maintenance-management landslide factors, plus professional experience.

Key Informant Interviews: Gathered qualitative insights on perceived landslide causes, maintenance practices, management challenges, and model applicability.

Documentary Review: Examined secondary records (TARURA maintenance registers, emergency works, road inspection, and district road board reports) to verify landslide histories and repair costs.

Expert Validation: Used a checklist to evaluate the model's relevance, factor adequacy, practical/maintenance applicability, priority ranking, decision support, cost relevance, ease of use, reliability, and integration potential.

3.8 Data Analysis Methods

Quantitative data were analyzed in Stata 17, and qualitative data underwent thematic analysis across four themes (causes, practices, challenges, and applicability).

3.8.1 Factor Ranking

Descriptive statistics and the Relative Importance Index (RII) ranked landslide factors (Scale: 0.000–0.199 very low; 0.200–0.399 low; 0.400–0.599 moderate; 0.600–0.799 high; 0.800–1.000 very high):

$$\text{RII} = \sum \frac{W}{A \, x \, N} \tag{3.2}$$

Where: W = respondent weight, A = The highest possible weight, N = total respondents.

3.8.2 Reliability & Composite Indices

Internal consistency required Cronbach's alpha value of 0.70. Three indicators each were averaged into four composite indices: Geotechnical (GTF), Hydrological (HYF), Road Condition (RCF), and Maintenance Management (MMF):

$$\text{Index}=\frac{X1+X2+X3}{3} \tag{3.3}$$

Where X_1, X_2 and X_3 represent the field-based indicators under each composite variable

3.8.3 Model Development and Operation

Binary logistic regression predicted dichotomous landslide occurrence (0 = none, 1 =occurred):

$$logit(P_\text{i}) = \ln\left(\frac{P_\text{i}}{1-P_\text{i}}\right) = \beta_0 + \beta_1 GTF_\text{i} + \beta_2 HYF_\text{i} + \beta_3 RCF_\text{i} + \beta_4 MMF_\text{i} \tag{3.4}$$

Where:

P_i = the probability of landslide occurrence for road section i;

GTF_i = the geotechnical factor index for road section i;

HYF_i = the hydrological factor index for road section i;

RCF_i = the road condition factor index for road section i;

MMF_i = the maintenance management factor index for road section i;

β_0 = the constant term; and

β_1–β_4 = the regression coefficients indicating the direction and magnitude of influence of the predictor indices.

Predicted probabilities 0 to 1 serve as risk scores guiding maintenance prioritization divided into four results range as indicated in Table 2

Table 2: Classification of Predicted Landslide Risk and Recommended Maintenance Response

Predicted Probability	**Risk Category**	**Recommended Maintenance Response**
0.00–0.25	Low risk	Routine monitoring and scheduled inspection
0.26–0.50	Moderate risk	Regular inspection and drainage cleaning
0.51–0.75	High risk	Preventive maintenance and targeted slope or drainage improvement
0.76–1.00	Very high risk	Immediate inspection and priority maintenance intervention

3.8.4 Model Validation

Classification of metrics was found using TP, TN, FP, FN, AUC-ROC was used to assess the model's overall discriminative ability where the value of 0.50 = none; 0.70–0.79 = acceptable; 0.80–0.89 = good; 0.90 or above indicated excellent descrimination. Spearman's rank correlation, and expert validation (means and standard deviations) confirmed validity:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (3.5)$$

$$Sensitivity = \frac{TP}{TP + FN} \quad (3.6)$$

$$Specificity = \frac{TN}{TN + FP} \quad (3.7)$$

$$Precision = \frac{TP}{TP + FP} \quad (3.8)$$

$$Fi = 2 \times \frac{Precision \times Sensitivity}{Precision + Sensitivity} \quad (3.9)$$

Where:

TP = true positives, referring to road sections where landslides occurred and were correctly predicted by the model;

TN = true negatives, referring to road sections where no landslide occurred and were correctly predicted by the model;

FP = false positives, referring to road sections predicted as landslide cases although no landslide occurred; and

FN = false negatives, referring to road sections predicted as non-landslide cases although a landslide occurred.

Table 3: Summary of Model Validation Measures

Validation Measure	**What it Assesses**	**Interpretation**
Accuracy	Overall classification correctness	Higher values indicate better overall classification.
Sensitivity	Correct landslide section ID	Higher values indicate fewer missed landslide cases.
Specificity	Correct non-landslide section ID	Higher values indicate fewer false alarms.
Precision	Correctness of predicted cases	Higher values indicate dependable landslide predictions.
F1-score	Balance of precision & sensitivity	Higher values indicate stronger balanced performance.
AUC-ROC	Overall discriminative ability	Values \(\ge 0.80\) indicate good discrimination.

Spearman correlation	Model vs. expert ranking agreement	Strong positive coefficient indicates consistency.
Expert validation	Practical relevance & usability	High means & low SD indicate strong agreement.

Table 4: Methodology Matrix

Specific Objective	Data Collected	Collection Methods & Tools	Analysis & Tools	Expected Outcome
Identify & rank landslide factors	Technical ratings across 4 factor groups; experience	Questionnaire & observation (Questionnaire & checklist)	Descriptive stats & RII (**Stata 17**)	Ranked landslide factors by category & overall
Develop field based BLR risk model	Road-section landslide occurrence & 12 field indicators	Observation & document review (Checklists)	Reliability, indices, BLR & risk scoring (**Stata 17**)	Field-based BLR model, risk scores & categories
Validate developed risk model	Predictions, observations, expert scores & views	Model/expert validation & KIIs (Checklist & interview guide)	Classification metrics, ROC/AUC, Spearman, descriptive & thematic (**Stata 17**)	Validated model for maintenance prioritization

4. DATA COLLECTION AND ANALYSIS

4.1 Introduction

This chapter presents data collection and analysis for developing a field-based landslide risk maintenance management model to predict vulnerable road sections in Mufindi District. It covers response rates, data coverage, technical respondent profiles, descriptive characteristics of road sections, reliability results, factor rankings, binary logistic model development, risk score prediction, section classification, and model validation.

4.2 Demographic Information of Technical Respondents

The study evaluated professional categories and working experience to ensure respondents possessed direct technical involvement and field exposure to landslide conditions. Table 5 summarizes this data.

Table 5: Demographic information of technical respondents

Profile variable	Category	Frequency	Percentage (%)
Professional category	Maintenance supervisor/worker	34	54.84
	Road engineer/technician	21	33.87
	Meteorological officer	7	11.29
	Total	**62**	**100**
Years of experience	0–5 years	15	24.19
	6–10 years	21	33.87
	11–15 years	15	24.19
	Above 15 years	11	17.74
	Total	**62**	**100**

Source: Field data analysed using Stata 17, 2026

Maintenance supervisors/workers form the largest group (54.84%). They frequently observe active issues like drainage blockages, slope movements, and edge failures. Road engineers/technicians (33.87%) and meteorological officers (11.29%) contribute structural and rainfall expertise. A balanced experience structure exists, with 33.87% having 6–10 years of experience, and 41.93% possessing over 11 years. This ensures deep memory of seasonal cycles and repeated failures. Empirical studies support leveraging experienced field personnel to validate risk zones and analyse infrastructure vulnerability (Salini & Rahul, 2024; Ozer Genc et al., 2026; Yao et al., 2023; Yousefi et al., 2022).

4.3 Descriptive Characteristics of Observed Road Sections

4.3.1 Landslide Occurrence among Observed Road Sections

Out of 50 observed mountainous road sections, 44.00% (22 sections) had experienced landslides, while 56.00% (28 sections) had not. This high occurrence rate shows that landslide risk widespread across the road network.

Table 6: Distribution of Road Sections by Landslide Occurrence

Landslide occurrence	Frequency	Percentage (%)
No landslide	28	56
Landslide occurred	22	44
Total	**50**	**100**

Source: Field data analysed using Stata 17, 2026

Risk Shift: The 44.00% baseline proves the need to shift from reactive maintenance to risk-based preventive maintenance planning.

Literature Alignment: Similar patterns of terrain and geological factors driving road-network damage are documented internationally (Ubaidulloev et al., 2021; Woldearegay, 2025).

4.3.2 Descriptive Statistics of Field-Based Landslide Risk Indicators

Analysis of the risk indicators showed that landslide vulnerability is multidimensional, influenced by hydrological, geotechnical, road condition, and maintenance management indices.

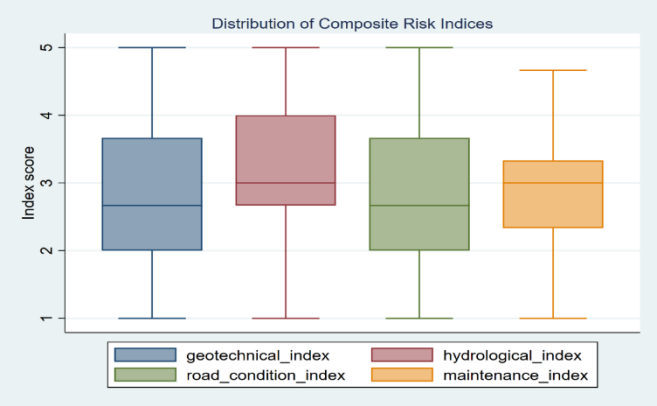


Figure 3: Distribution of composite field-based landslide risk indices. adapted from tsheten et al. (2021)

Boxplot analysis (Figure 3) and numerical mean scores established that hydrological risks and maintenance weaknesses are the most centrally concentrated drivers of vulnerability.

Table 7: Descriptive Statistics of Field-Based Landslide Risk Indicators

Variable	Minimum	Maximum	Mean	Standard deviation
Slope steepness	1	5	2.96	1.142
Cut-slope height	1	5	2.90	1.216
Soil/slope instability	1	5	2.98	1.220
Drainage condition	1	5	3.08	1.104
Water stagnation/overflow	1	5	3.16	1.017
Rainfall damage signs	1	5	3.14	1.069
Road surface condition	1	5	2.76	1.001
Shoulder/edge condition	1	5	2.96	1.142
Camber/crossfall	1	5	2.84	1.017
Maintenance frequency condition	1	5	2.84	0.997
Drainage cleaning condition	1	5	3.14	0.926
Emergency repairs evidence	1	4	2.72	0.784
Geotechnical index	1	5	2.947	1.138
Hydrological index	1	5	3.127	0.992
Road condition index	1	5	2.853	0.969
Maintenance management index	1	4.667	2.900	0.826

Source: Field data analysed using Stata 17, 2026

The hydrological index registered the highest composite meaning (3.127). At the indicator level, water stagnation/overflow (3.160), rainfall damage signs (3.140), and drainage cleaning condition (3.140) scored the highest.The wide spread of geotechnical (2.947) and road condition (2.853) indicates localized severity. The compact maintenance management distribution (2.900) implies widespread maintenance challenges.Poor water control (blocked drains, water stagnation, delayed cleaning) is the primary pathway accelerating slope vulnerability. Road sections must be assessed using integrated metrics rather than surface defects alone.Multidimensional risk indexing aligns with regional and global landslide susceptibility frameworks (Sisay et al., 2024; Nurwatik et al., 2022; Muhimbula et al., 2025; Adhikari & Dhakal, 2026).

4.4 Reliability and Construction of Composite Indices

Following individual descriptor analysis, internal consistency tests were necessary to ensure the items within each risk category reliably measured their respective underlying dimensions before building the composite indices.

4.5 Reliability Test

The internal consistency of indicators for geotechnical, hydrological, road condition, and maintenance management risk categories—as well as the overall field risk scale—was evaluated using Cronbach's alpha. A threshold value of $\alpha \geq 0.70$ was set as acceptable for internal consistency. Table 8 presents the results.

Table 8: Reliability Test Results for Field-Based Model Variables

Variable category	Number of items	Cronbach's alpha	Interpretation
Geotechnical factors	3	0.950	Acceptable
Hydrological factors	3	0.925	Acceptable

Road condition factors	3	0.907	Acceptable
Maintenance management factors	3	0.897	Acceptable
Overall field risk scale	**12**	**0.911**	**Acceptable**

Source: Field data analysed using Stata 17, 2026

All Cronbach's alpha values exceeded the conventional 0.70 standard (all achieved $\alpha > 0.80$), confirming strong internal consistency. These results statistically justify constructing the four composite indices for the subsequent binary logistic regression model.

4.6 Factors Contributing to Landslides Along Mountainous District Roads

Technical respondents (N = 62) rated potential landslide-contributing factors along mountainous district roads in Mufindi District using a 5-point Likert scale (5 = Very high, 4 = High, 3 = Moderate, 2 = Low, 1 = Very low contribution). The Relative Importance Index (RII) was computed to rank the factors using Formula 4.1:

$$RII = \Sigma W / (A \times N) \quad (4.1)$$

Where:

Σ W = Sum of weights assigned by respondents

A = Highest scale weight (5)

N = Total respondents (62)

Denominator (A × N) = 5 × 62 = 310

RII values range from 0 to 1. Scores ≥ 0.80 indicate a "very high contribution," while scores between 0.60 and 0.79 indicate a "high contribution." Table 9 summarizes the ranking results.

Table 9: RII Ranking of Factors Contributing to Landslides along Mountainous District Roads

Category	Factor	5	4	3	2	1	ΣW	RII	Rank	Interpretation
Hydrol.	Heavy rainfall	31	23	6	2	0	269	.868	1	Very high
Hydrol.	Poor drainage condition	30	23	7	2	0	267	.861	2	Very high
Maint.	Inadequate drainage cleaning	29	24	7	2	0	266	.858	3	Very high
Hydrol.	Blocked drains & culverts	28	23	9	2	0	263	.848	4	Very high
Maint.	Irregular road maintenance	27	24	9	2	0	262	.845	5	Very high
Hydrol.	Water stagnation & overflow	25	24	10	3	0	257	.829	6	Very high
Geotech.	Cut-slope height	25	23	11	3	0	256	.826	7	Very high
Geotech.	Slope steepness	24	23	12	3	0	254	.819	8	Very high
Maint.	Limited preventive maintenance	23	25	11	3	0	254	.819	8	Very high
Maint.	Emergency maintenance dependence	23	23	13	3	0	252	.813	10	Very high
Maint.	Delayed repair works	22	24	13	3	0	251	.810	11	Very high
Geotech.	Visible cracks & erosion signs	22	23	14	3	0	250	.806	12	Very high
Road cond.	Road edge failure	21	24	14	3	0	249	.803	13	Very high
Geotech.	Weak/loose soil material	21	23	15	3	0	248	.800	14	Very high
Road cond.	Poor road camber/crossfall	18	22	18	3	1	239	.771	15	High
Road cond.	Shoulder damage	16	22	20	3	1	235	.758	16	High
Road cond.	Road surface deterioration	16	22	19	4	1	234	.755	17	High

Source: Field data analysed using Stata 17, 2026

4.7 Key Analysis of Contributing Factors

Hydrological Dominance: Hydrological drivers top the hierarchy, led by heavy rainfall (RII = 0.868, Rank 1) and poor drainage conditions (RII = 0.861, Rank 2). Heavy intense rainfall raises pore-water pressure via infiltration. Concurrently, blocked infrastructure or inadequate designs (RII = 0.848) trigger localized water stagnation and structural overflow (RII = 0.829). These forces weaken natural slope profiles and accelerate slope failure, demonstrating that aggressive drainage management must anchor regional risk reduction.

Maintenance Management Pitfalls: Systemic maintenance shortfalls severely aggravate risks. Key challenges include inadequate drainage cleaning (RII = 0.858, Rank 3), irregular maintenance (RII = 0.845), and highly reactive workflows such as overdependence on emergency maintenance (RII = 0.813) and delayed repairs (RII = 0.810). Uncleaned catchpits tie back directly into the hydrological failure loop. These indicators suggest the infrastructure system operates reactively rather than proactively, prioritizing emergency interventions after disasters instead of mitigating minor faults early.

Geotechnical Geometry: Geometric variables indicate high vulnerability, with cut-slope height (RII = 0.826) and slope steepness (RII = 0.819) ranking prominently. Taller, steeper cut-slope designs generate extreme mechanical instability, especially when dealing with weak or loose soil profiles (RII = 0.800). Progressive slope decay is visibly signaled by secondary surface cracks and structural erosion (RII = 0.806). Close index spreads emphasize that geotechnical failures operate symmetrically rather than in isolation, establishing slope geometry as a crucial early warning metric.

Road Condition Indicators: Structural Road metrics registered the lowest relative index weights, though they remain substantial. Road edge failure (RII = 0.803) presents a very high-risk contribution. Meanwhile, geometric parameters such as poor road camber (RII = 0.771), shoulder damage (RII = 0.758), and surface deterioration (RII = 0.755) are categorized as high contributions.

4.8 Factors Contributing to Landslides Along Mountainous District Roads

This section presents the ranking of factors contributing to landslides along mountainous district roads in Mufindi District. Technical respondents (N = 62) rated each factor on a five-point Likert scale, where 5 = very high contribution, 4 = high, 3 = moderate, 2 = low and 1 = very low contribution. The Relative Importance Index (RII) was then computed to rank the factors using the formula:

$$RII = \Sigma W / (A \times N) \quad (4.1)$$

where ΣW is the sum of the weights given to each factor by all respondents, A is the highest weight on the scale (5), and N is the total number of respondents (62). Thus, the denominator is 5 × 62 = 310. RII values range from 0 to 1, with higher values indicating a greater contribution to landslide occurrence. Values of 0.80 and above were interpreted as a very high contribution, while values between 0.60 and 0.79 were interpreted as a high contribution. The results are summarised in Table 10

Table 10: RII Ranking of Factors Contributing to Landslides

Category	Factor	5	4	3	2	1	∑W	RII	Rank
Hydrol.	Heavy rainfall	31	23	6	2	0	269	.868	1
Hydrol.	Poor drainage condition	30	23	7	2	0	267	.861	2
Maint.	Inadequate drainage cleaning	29	24	7	2	0	266	.858	3
Hydrol.	Blocked drains & culverts	28	23	9	2	0	263	.848	4
Maint.	Irregular road maintenance	27	24	9	2	0	262	.845	5
Hydrol.	Water stagnation & overflow	25	24	10	3	0	257	.829	6
Geotech.	Cut-slope height	25	23	11	3	0	256	.826	7
Geotech.	Slope steepness	24	23	12	3	0	254	.819	8
Maint.	Limited preventive maintenance	23	25	11	3	0	254	.819	8
Maint.	Emergency maintenance dependence	23	23	13	3	0	252	.813	10

Maint.	Delayed repair works	22	24	13	3	0	251	.810	11
Geotech.	Visible cracks & erosion signs	22	23	14	3	0	250	.806	12
Road cond.	Road edge failure	21	24	14	3	0	249	.803	13
Geotech.	Weak/loose soil material	21	23	15	3	0	248	.800	14
Road cond.	Poor road camber/crossfall	18	22	18	3	1	239	.771	15
Road cond.	Shoulder damage	16	22	20	3	1	235	.758	16
Road cond.	Road surface deterioration	16	22	19	4	1	234	.755	17

Source: Field data analysed using Stata 17, 2026

Ranks 1–14 indicate very high contribution; Ranks 15–17 indicate high contribution.

Hydrological and maintenance management factors dominated, demonstrating that intense rainfall infiltrates slopes and triggers failure primarily where reactive maintenance and blocked drains persist. Geotechnical geometry/material weaknesses and road-edge/camber defects compound runoff erosion. These empirical rankings (noting Table 9/text reference to Table 12) justify all four categories for predictive model development.

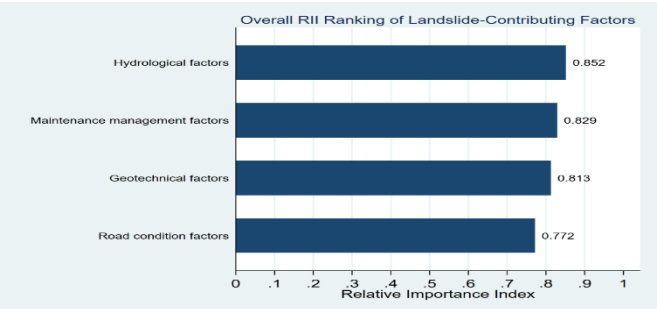


Figure 4: Overall RII Ranking of Landslide-Contributing Factors

Source: Field data plotted using Stata 17, 2026

4.9 Development of the Field-Based Binary Logistic Landslide Risk Maintenance Management Model

4.9.1 Model Summary

To meet the second specific objective, a binary logistic regression model was estimated in Stata 17 using 50 mountainous road sections in Mufindi District. Landslide occurrence 1 = occurred, 0 = none served as the dependent variable, predicted by four composite indices: Geotechnical (GTF), Hydrological (HYF), Road Condition (RCF), and Maintenance Management (MMF). The model demonstrated strong fit and predictive adequacy (explaining 54.71% of variation).

Table 11: Model Summary and Diagnostic Tests

Statistic	Value
Number of observations	50
Log pseudolikelihood	-15.5324
Pseudo R^2	0.5471
Hosmer–Lemeshow test (df = 8)	5.18 (p = 0.738)
Area under ROC curve	0.9399
Classification accuracy	90.00%
Sensitivity	90.90%
Specificity	89.30%

Source: Field data analysed using Stata 17, 2026

4.9.2 Overall Significance and Regression Coefficients

Table 11 presents the test of overall model significance. The Wald chi-square value of 17.01 with 4 degrees of freedom and a p-value of 0.002 shows that the model was statistically significant at the 1% level (Table 4.7). Hydrological B = 1.819, p = 0.033 and maintenance management B = 1.437, p = 0.007 indices were statistically significant, increasing landslide odds by 6.162 and 4.206 times per unit increase, respectively. Geotechnical p = 0.408 and road condition p = 0.816 indices had positive but statistically insignificant independent effects.

Table 12: Binary Logistic Regression Coefficients for Landslide Occurrence

Variable	B	Robust Std. Error	\(z\)-value	Sig.
Constant	-12.306***	2.912	-4.23	0.000
Geotechnical index	0.573	0.692	0.83	0.408
Hydrological index	1.819**	0.855	2.13	0.033
Road condition index	0.120	0.514	0.23	0.816
Maintenance management index	1.437***	0.536	2.68	0.007

Source: Field data analysed using Stata 17, 2026.
Note: * p < 0.10; ** p < 0.0); *** p < 0.01.

4.9.3 The Estimated Regression Equation

Aligning with prior Relative Importance Index (RII) rankings, the estimated model is specified as:

$$Logit\ (P_i) = -12.3059 + 0.5726GTF_i + 1.8185HYF_i + 0.1197RCF_i + 1.4365MMF_i$$

Where:

P_i = probability of landslide occurrence in road section i

GTF_i = geotechnical index

HYF_i = hydrological index

RCF_i = road condition index

MMF_i = maintenance management index

4.10 Validation of the Field-Based Landslide Risk Maintenance Management Model

4.10.1 Introduction and Classification Performance

Statistical and practical validations assessed the model's ability to distinguish landslides from non-landslide sections. The model correctly classified 25 of 28 non-landslide sections (89.30%, 3 false alarms) and 20 of 22 landslide sections (90.90%, 2 missed cases), yielding 90.00% overall accuracy

Table 13: Classification Performance of the Binary Logistic Regression Model

Observed outcome	Predicted no landslide	Predicted landslide	Percentage correctly classified
Observed: No landslide	25	3	89.3
Observed: A landslide occurred	2	20	90.9
Overall classification			**90**

Source: Field data analysed using Stata 17, 2026.

4.10.2 Sensitivity, Specificity and Overall Accuracy

High sensitivity (0.909), high specificity (0.893), and a balanced F1-score (0.889) confirm reliable classification with low false negative (0.091) and false positive (0.107) rates, minimizing unattended safety hazards.

Table 14: Sensitivity, Specificity and Accuracy Statistics of the BLR Model

Performance Measure	Value	Interpretation
Sensitivity/Recall	0.909	Correctly identifies landslide sections (90.90%)
Specificity	0.893	Correctly identifies non-landslide sections (89.30%)
Overall accuracy	0.900	Overall correct classification rate (90.00%)
Precision	0.870	Correctness among predicted landslide sections
F1-score	0.889	Balance between precision and sensitivity
False positive rate	0.107	Non-landslide sections misclassified as risky
False negative rate	0.091	Landslide sections missed by the model

Source: Field data analysed using Stata 17, 2026

4.10.3 ROC Curve and Area under the Curve

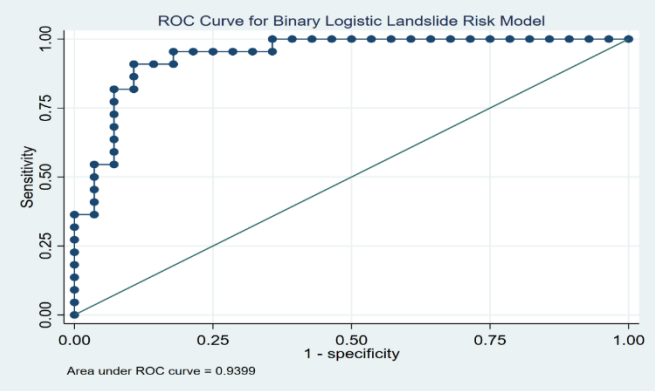


Figure 5: ROC curve for the binary logistic landslide risk model

Figure 4.3 (ROC curve for the binary logistic landslide risk model) shows the curve positioned well above the diagonal reference line (AUC = 0.9399), confirming excellent discrimination.

5. DISCUSSION OF RESULTS

5.1 Introduction

This chapter discusses the findings presented in Chapter Four in relation to the study objectives and existing empirical literature. The discussion is organized into three core thematic areas: factors contributing to landslides along mountainous district roads; development of the field-based binary logistic regression model; and model validation.

The findings are interpreted using descriptive statistics, the Relative Importance Index (RII), regression coefficients B, odds ratios OR classification results, the Receiver Operating Characteristic (ROC) curve, and expert validation results to identify areas of agreement, differences, and practical implications for road maintenance management.

5.2 Factors Contributing to Landslides along Mountainous District Roads

The first objective identified and ranked seventeen landslide-contributing factors based on technical respondents' N = 62 assessments. The RII results revealed that heavy rainfall ranked first (RII = 0.868), followed by:

- Poor drainage conditions: RII = 0.861 (Rank 2)
- Inadequate drainage cleaning: RII = 0.858 (Rank 3)
- Irregular road maintenance: RII = 0.845 (Rank 4)
- Cut-slope height (Geotechnical): RII = 0.826 (Rank 7)
- Slope steepness (Geotechnical): RII = 0.819 (Rank 8)
- Road-edge failure (Road Condition): RII = 0.803 (Rank 13)

Ranking heavy rainfall as the leading factor underscores the critical role of water-related conditions in Mufindi District. Rainfall raises soil moisture and pore-water pressure, reducing the shear strength of susceptible slopes. This aligns with Mwakapesa et al. (2023) on multi-factor machine-learning susceptibility, and Ayele et al. (2025), who identified rainfall and drainage variables as primary hazard drivers in Ethiopia's Sile-Sago watershed.

The high ranking of poor drainage conditions (RII = 0.861) underscores the danger of surface runoff. Blocked channels cause water accumulation, accelerated erosion, and slope material decay. This interaction between environmental exposure and infrastructure condition mirrors the unpaved road climate-vulnerability framework proposed by Kamara et al. (2025) in Sierra Leone.

Unlike natural hazard factors (rainfall and slope topography), road authorities can directly control drainage cleaning (RII = 0.858) and maintenance intervals (RII = 0.845). Transitioning from a reactive to a proactive inspection regime allows TARURA to mitigate minor drainage defects before they escalate into catastrophic slope failures.

critical mechanical triggers. While these RII rankings reflect perceived relative field importance rather than direct mathematical causality, they match broader literature confirming that terrain cutting heavily conditions slope instability (Mwakapesa et al., 2023; Ayele et al., 2025).

5.3 Development of the Field-Based Landslide Risk Maintenance Management Model

The second objective established a field-based binary logistic regression model to predict landslide occurrence (1 = landslide occurred), (0 = no landslide) across 50 observed road sections. The model incorporated four composite predictor indices: Geotechnical Factor Index (GTF), Hydrological Factor Index (HYF), Road Condition Factor Index (RCF), and Maintenance Management Factor Index (MMF).

5.3.1 Model Fit and Statistical Significance

(i) Overall Model Significance: Wald chi2 = 17.01, p = 0.002

(ii) Pseudo- R2: 0.5471

The joint significance indicators confirm that the predictor indices effectively explain the observed distribution of road-section landslides, though the pseudo-R2 represents likelihood improvement rather than direct ordinary least-squares variance representation.

5.3.2 Regression Coefficients and Odds Ratios Analysis

Hydrological Factor Index (HYF): (B = 1.819, p = 0.033, OR = 6.162)

A one-unit increase in the adverse conditions of the hydrological index is associated with approximately 6.16 times higher odds of landslide occurrence, holding all other variables constant.

Maintenance Management Factor Index (MMF): (B = 1.437, p = 0.007, OR = 4.206)

A one-unit increase in adverse maintenance management weaknesses is associated with approximately 4.21 times higher odds of landslide occurrence, holding other indices constant.

Geotechnical (GTF) & Road Condition (RCF) Indices: Recorded positive coefficients (B = 0.573) and (B = 0.120), respectively but were not statistically significant in this model context. This indicates a lack of sufficient empirical evidence to establish their independent statistical contributions once hydrological and maintenance factors are controlled, rather than implying slope geometry is irrelevant.

5.3.3 Literature Integration and Practical Implication:

The strong regression path for hydrological risk matches the hazard assessments of Ayele et al. (2025) and complements the multi-factor conditioning methodologies of Mwakapesa et al. (2023).

Crucially, this model extends traditional susceptibility frameworks by explicitly integrating operational maintenance management indicators (MMF) with physical environmental

variables (HYF), (GTF), (RCF). This integration provides TARURA with a practical, field-based toolkit to mathematically prioritize road sections for preventative funding before seasonal slope failure occurs.

5.4 Validation of the Developed Field-Based Landslide Risk Maintenance Management Model

Statistical Performance: The model correctly classified 25 of 28 non-landslide sections and 20 of 22 landslide sections, achieving 90.0% accuracy, 90.9% sensitivity, 89.3% specificity, ~87.0% precision, and an F1-score of 0.889. High sensitivity prevents unattended hazards, while high specificity avoids misallocating limited funds. It achieved strong discrimination (AUC = 0.9399; cf. Ganga et al., 2022) and acceptable calibration (Hosmer–Lemeshow $p = 0.738$). Like Mwakapesa et al. (2023), numerical comparisons require matching metrics, and external data testing is needed before routine deployment.

Practical Validation: Model risk rankings correlated strongly with expert priorities (Spearman's $\rho = 0.758$, $p < 0.001$), while expert ratings ranged from 4.400 (ease of use) to 4.800 (practical/maintenance applicability; cf. Ayele et al., 2025).

5.5 Summary of the Discussion

Hydrological (heavy rainfall, poor drainage) and maintenance management factors dominated both RII rankings and logistic regression results. Consistent with Ganga et al. (2022), Mwakapesa et al. (2023), and Ayele et al. (2025), the study uniquely integrates environmental field evidence with maintenance management indicators into a validated screening tool for Mufindi District.

Table 14: Overall Model Validation Results Summary

Validation Metric	Mufindi Model	Published Comparison	Discussion
Accuracy	**90.0%**	**89%** (susceptibility study)	Comparable accuracy, though datasets/methods may differ.
Sensitivity	**90.9%**	**92%** (testing dataset)	Identifies most landslide cases closely to published results.
Specificity	**89.3%**	**81%** (testing dataset)	Better non-landslide ID; dataset/threshold differences apply.
Precision	**87.0%**	**82%** (testing dataset)	Favourable predictions, dependent on dataset prevalence.
F1-score	**0.889**	Not reported	Direct comparison impossible without matching metrics.
ROC-AUC	**0.9399**	**0.92** (testing dataset)	Strong discrimination; Mufindi reports higher AUC.
Expert validation	**4.4–4.8/5**	Not established	Confirms practical utility; distinct from statistical metrics.

Source: Field data analysed using Stata 17 (2026).

6. CONCLUSIONS AND RECOMMENDATIONS

6.1 Conclusions

This study successfully developed and validated a field-based landslide risk maintenance prediction model tailored for mountainous district roads in Mufindi District. The empirical findings show that roadside landslides are not merely unavoidable natural occurrences; rather, they are heavily driven by poor drainage maintenance and inadequate routine inspections. The Relative Importance Index explicitly highlighted hydrological constraints (RII = 0.868) and maintenance gaps (RII = 0.858) as dominant risk factors.

By using Binary Logistic Regression, the study produced a robust mathematical model that accurately assesses section-level risk with 90% overall accuracy and an outstanding ROC-AUC of 0.9399. Shifting from traditional reactive operations to this predictive model allows road maintenance agencies to identify high-risk zones early using basic, field-observable indicators, bypassing the need for costly geospatial monitoring tools.

6.2 Recommendations

Based on the study's conclusions, the following interventions are recommended for implementation:

6.2.1 Adopt Proactive Maintenance Planning

TARURA should formally integrate the developed binary logistic prediction model into its annual road asset maintenance planning framework to shift resources from post-disaster repair to proactive hazard mitigation.

6.2.2 Prioritize Hydrological and Drainage Infrastructure

Immediate interventions must prioritize clearing unlined side drains, constructing reinforced miter drains, and clearing debris from culverts along high-risk mountainous corridors.

6.2.3 Establish Field-Based Inspection Protocols

Maintenance technicians should use standardized field forms to record observable indices (such as water stagnation and road-edge cracking) to maintain up-to-date risk scores for the road network.

6.2.4 Scale and Recalibrate the Prediction Model

While highly optimized for the environmental conditions of Mufindi District, TARURA should scale this cost-effective,

field-based framework to other mountainous districts across Tanzania's Southern Highlands.

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