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AI-enhanced monitoring and sustainable control of bridge foundation settlement: A case study from Nepal

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Abstract

Bridge foundation settlement and scour pose significant threats to Nepal's East-West Highway, particularly during monsoon flooding. This paper presents a sustainable, data-driven framework for monitoring and controlling foundation settlement by integrating geotechnical investigation, empirical modeling, and artificial intelligence. The Barahari Bridge was chosen as a case study because of recurrent flood damages. Field work involved borehole drilling, groundwater monitoring, and in-situ soil testing to determine strength and grading properties. An empirically derived depth-damage relationship using 25 flood events showed high correlation ($R^2 = 0.87$). A Condition Assessment Scoring System (CASS) was formulated to rank critical components based on multi-attribute weighted scoring. With soil and hydraulic properties, a Random Forest regression model was developed to predict the relationship with $R^2 = 0.81$ and $MSE = 0.18$, indicating that floodwater depth and scour depth were the most dominant variables. Bioengineering, prefabrication, and life cycle assessment were combined to formulate environmentally sustainable management practices. The findings clearly show that AI-assisted monitoring can offer resilient, economical, and sustainable management of bridge foundations in flood-susceptible regions of Nepal.

Keywords: Settlement monitoring; Bridge foundation; Flood resilience; Artificial intelligence; Sustainable infrastructure; Life cycle assessment.

1. Introduction

The East-West Highway (EWH) is the major transportation route in Nepal, passing through diverse and challenging terrains to link the eastern and western parts of the country. The route is of prime importance as it handles about 80% of the total long-distance transportation of passengers and goods, and its reliability is essential for the economic development of the country [1]. Nevertheless, the bridges on this highway are regularly susceptible to the effects of flooding caused by monsoons, which occur every year from June to September [2]. In this period, the rivers experience increased scouring, deposition of sediment, and changes in their course, which have a direct effect on the stability of the foundation of the bridges [3]. The above-mentioned hydrological phenomena, together with the seismically active nature of Nepal's geology, result in challenging loading conditions that accelerate the settlement of the foundation and reduce the life of the bridges [4].

Various techniques of monitoring bridge foundations in flood-prone regions have been identified by previous research. Chhetri et al. [5] proposed empirical depth-damage models for highway infrastructure, linking flood properties with the degradation of the structure. Poudel [6] proposed condition assessment models for maintenance, whereas Sharma [7] concentrated on cost-effective inspection techniques for rural bridge infrastructure. More contemporary work includes Sapkota et al. [8], who promoted green bridge technologies that integrate bioengineering and prefabrication to improve climate resilience. Community-driven monitoring systems have also been explored, and Bista et al. [9] have demonstrated that community-operated sensor networks with trained volunteers can improve data gathering in remote areas.

Despite these advances, there are still many areas that need to be addressed. Traditional geotechnical analysis is based mainly on static soil parameters, such as density, water content, and friction angle, obtained by regular borehole sampling [10, 11, 12]. Although important for foundation design, static analysis alone cannot account for the dynamic relationship between hydraulic forces and soil response during floods [13]. Post-flood observations, although necessary for damage assessment, are carried out after the settlement process has already begun [14]. Moreover, current prioritization schemes have not incorporated real-time hydraulic information and predictive modeling, making them inadequate for proactive maintenance [15, 16, 17]. For Nepalese motorable bridges, there is not any unified comprehensive framework incorporating empirical flood damage models, AI-driven settlement prediction, sustainability analysis, and local community involvement [18, 19, 20, 21].

This research fills these gaps by proposing a new integrated approach that incorporates: (1) geotechnical analysis of foundation soils, (2) empirical flood damage modeling based on post-flood data, (3) AI-assisted settlement prediction using Random Forest regression models trained on soil and hydraulic parameters, (4) CASS-based maintenance planning, and (5) sustainability analysis that incorporates bioengineering, prefabrication, and life cycle assessment with community-driven sensor networks. The case study site chosen for this research is the Barahari Khola Bridge in the Dhanusha district because of its representative location in the Gangetic Plains and its past experience with flood damage to the bridge foundation. The main research aims are to: (i) establish the relationship between floodwater depth and foundation damage, (ii) develop and test a predictive model for settlement using machine learning algorithms, (iii) design a weighted scoring system for maintenance planning, and (iv) identify sustainable monitoring practices that can be adapted to developing countries.

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The originality of this study is found in its combination of several assessment methods—including geotechnical, empirical, AI-driven, and sustainability-oriented ones—into a unified decision-support system. In contrast to other studies that assessed each factor in a separate manner, this study has shown that it is possible to combine hydraulic factors (flood depth, scour depth) with soil properties (SPT-N, density, moisture content) using a Random Forest model in order to reach a level of accuracy that is adequate for practical purposes. This is the first time that such a combination is applied to a Nepalese bridge.

2. Methodology

2.1. Site description and borehole investigation

The Barahari Khola Bridge (chainage CH+260.957 km on the Kamala-Dhalkebar-Pathlaiya section) is situated in the Dhanusha district of the Gangetic Plain, where the alluvial deposits are sandy gravel and clayey silt. The reason for choosing this bridge for case study is that it is situated in a flood-prone area, which is a very important highway intersection and is highly susceptible to scouring, deposition, and settlement due to monsoons and earthquakes.

The field work involved visual observation, borehole drilling, and soil investigation to determine the potential for foundation settlement and the groundwater level. Four boreholes (BH-1 to BH-4) were drilled to a depth of 25 m using the rotary drilling technique, and the groundwater level was noted up to 15 m depth at all sites (Figure 1). Standard Penetration Tests (SPT) were carried out at 1.5 m intervals to determine the N-values and obtain disturbed and undisturbed samples for laboratory testing.

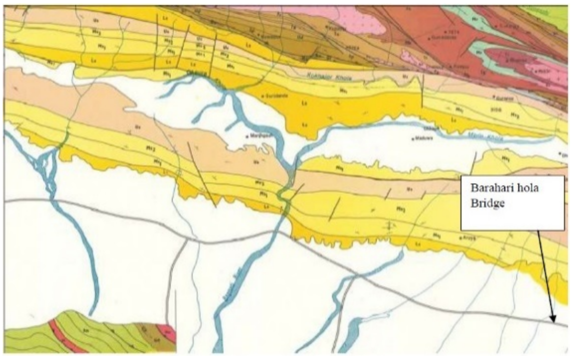

Figure 1: Barahari khola bridge location map. Source: Prepared by authors using Google Earth imagery (2025).

2.2. Soil and geotechnical investigations

2.2.1. Laboratory testing program

Soil samples collected from boreholes were subjected to laboratory testing following relevant ASTM standards.

2.3. Flood settlement and monitoring

2.3.1. Flood-damage relationship

An empirical formula connecting the depth of floodwater to damage was developed using data gathered through post-flood observation over two monsoon cycles (2022–2024). For the research purpose, the maximum depth of floodwater (h) and damage (D) were observed in 25 flood events.

The functional form is piecewise linear, expressed as:

$$D = a \cdot h + b \tag{1}$$

where D = foundation damage score (dimensionless, scale 0–10), h = maximum floodwater depth at pier location (m), and a, b = empirical coefficients determined through least-squares regression.

Table 1: Soil and geotechnical investigation results ($n = 12$ samples)

Parameter	BH-1	BH-2	BH-3	BH-4	Mean	SD	CV%
USCS Class.	SW	SW	ML	SW	–	–	–
Sand (%)	68.3	71.2	42.5	69.8	62.95	13.21	21.0
Silt & Clay (%)	9.4	7.8	57.5	8.6	20.83	24.12	115.8
Gravel (%)	22.3	21.0	0.0	21.6	16.23	10.60	65.3
Moisture (%)	12.4	8.7	28.7	4.1	13.48	10.66	79.1
Bulk Density (g/cm^3)	1.92	1.98	1.76	2.04	1.93	0.12	6.2
Dry Density (g/cm^3)	1.71	1.82	1.37	1.96	1.72	0.25	14.5
SPT-N (blows/30cm)	28	34	12	41	28.75	12.39	43.1
Friction Angle (°)	32.5	34.2	28.1	36.8	32.90	3.69	11.2
Cohesion (kPa)	0	0	12.4	0	3.10	6.20	200.0
C_u	88.7	93.3	–	97.2	93.07	4.27	4.6
C_c	1.38	1.46	–	1.52	1.45	0.07	4.8

For the dataset ($n = 25$), regression analysis yielded $a = 2.34$ and $b = 1.27$, with coefficient of determination $R^2 = 0.87$.

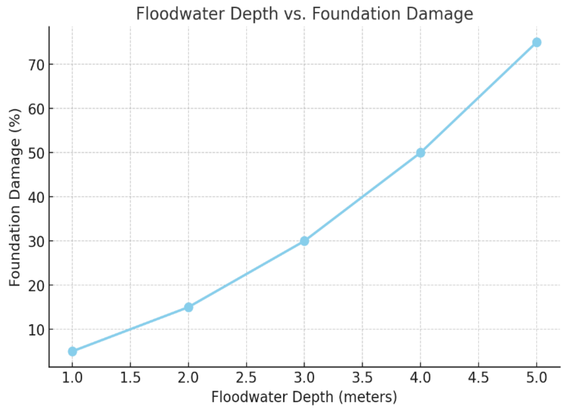

Figure 2: Floodwater depth vs. foundation damage (with 95% CI bands). Source: Prepared by authors based on fieldwork (2025).

2.3.2. Settlement monitoring protocol

Settlement monitoring was conducted using local and easy methods such as: stainless-steel reference settlement pins installed on bridge piers and abutments, surveyed weekly using a digital level (accuracy $\pm$0.5 mm); ultrasonic water-level sensors deployed at upstream and downstream faces, recording at 15-minute intervals during monsoon; and community volunteers who conducted daily visual inspections during high-flow periods as manual verification.

2.4. Condition assessment scoring system (CASS)

A weighted Condition Assessment Scoring System was also developed to give priority to the bridge components for maintenance. The weights of the components were established using the analytic hierarchy process (AHP) based on expert consultation with Department of Roads engineers ($n = 8$).
Note: Weights normalized to sum to 1.0.
Condition rating scale:

- 1 = Excellent: No visible deterioration
- 2 = Good: Minor cosmetic defects
- 3 = Moderate: Some deterioration, no urgent action
- 4 = Poor: Significant deterioration, repair needed

Table 2: Weights for CASS for different components of the bridge

Bridge Component	Weight	Reason
Pier	0.35	Vulnerable and directly exposed to scour; supports bridge deck
Abutments	0.20	Protects and retains embankment, susceptible to approach road erosion
River Training Works	0.20	Confines the channel and protects the foundation
Bridge Bearings	0.15	Adjustment of movement; failure leads to distress
Bridge Deck	0.10	Reflects overall structural health condition

- 5 = Critical: Immediate intervention required

The weighted score for each component was calculated as:

$$S_i = w_i \times r_i \tag{2}$$

where S_i = weighted score for component i, w_i = weight assigned to component i, and r_i = condition rating for component i (1–5).

2.5. AI-based settlement prediction model

2.5.1. Dataset and feature selection

The predictive model was developed using 25 flood events with 12 input variables:

- *Soil parameters*: Density (ρ), natural moisture content (w), SPT-N value, friction angle (ϕ), fines content (%)
- *Geometric parameters*: Foundation depth (D_f), pier width (b)
- *Hydraulic parameters*: Floodwater depth (h), scour depth (d_s), flow velocity (v)
- *Groundwater parameters*: Groundwater table depth (GWT), seasonal fluctuation (ΔGWT)

2.5.2. Data partitioning

The dataset ($n = 25$) was divided randomly into the following subsets:

- Training set: 70% (18 events) — used for training the model
- Validation set: 15% (4 events) — used for hyperparameter optimization
- Testing set: 15% (3 events) — used for final model evaluation

Stratified sampling ensured a representative distribution of flood depths for all subsets.

2.5.3. Random forest configuration

A Random Forest regression model was created using the `scikit-learn` library (Python) with the following hyperparameters optimized via 5-fold cross-validation on the training set.

Table 3: Random forest regression model training data set

Parameter	Value	Optimization Range
Number of trees	100	[50, 100, 200]
Maximum depth	10	[5, 10, 15, 20]
Min. samples split	5	[2, 5, 10]
Min. samples leaf	2	[1, 2, 4]
Maximum features	`sqrt`	[`sqrt`, `log2`, 0.3]

2.5.4. Performance metrics

Model performance was evaluated using:
Mean Squared Error (MSE):

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{3}$$

Coefficient of Determination (R^2):

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2} \tag{4}$$

where y_i = observed settlement, $\hat{y}_i$ = predicted settlement, $\bar{y}$ = mean observed settlement, and n = number of observations.

2.5.5. Feature importance

The feature importance was calculated using the mean decrease in impurity (MDI) technique, and the values were normalized to sum to 1.0.

2.6. Sustainability assessment framework

2.6.1. Life cycle assessment (LCA)

To compare the conventional maintenance approach with the proposed integrated framework, simplified life cycle assessment was performed for a life span of 50 years.

2.6.2. Bioengineering and prefabrication

Various sustainable interventions were explored, including: plant species such as vetiver grass for stabilization and protection of approach slopes as bioengineering; precast or modular technology such as concrete blocks and tetrapods for river training works to reduce site impact and construction waste; and alternative mix design approaches using fly ash and recycled concrete material to reduce cement content and, ultimately, carbon emissions.

2.6.3. Community-based monitoring system

A hybrid monitoring system was established by combining the following:

- Low-cost sensors: Ultrasonic water level sensors, Tiltmeters
- Community volunteers: 6 local residents trained to take weekly settlement pin measurements and perform visual observations
- Data management: Mobile app for data entry with offline capabilities; paper logbooks as backup
- Training program: 2-day workshop on basic monitoring skills, data entry, and reporting procedures

3. Results

3.1. Geotechnical investigation findings

3.1.1. Subsurface profile

Borehole investigations revealed a uniform subsurface stratification at the Barahari Khola Bridge site, with three distinct layers:

- *Layer I* (0–6 m depth): Poorly graded sandy gravel with occasional cobbles; loose to medium dense; SPT-N values ranging from 12 to 28
- *Layer II* (6–15 m depth): Well-graded sandy gravel with silt; dense; SPT-N values ranging from 28 to 41
- *Layer III* (15–25 m depth): Dense sandy gravel with occasional clay lenses; very dense; SPT-N values exceeding 41

The groundwater table was found at depths ranging from 8.5 m to 12.3 m below ground level in the four boreholes, with a seasonal fluctuation of about 2.5 m during monsoon.

3.1.2. Soil properties

Table 4 lists the important geotechnical properties derived from laboratory tests of 12 samples.

Table 4: Summary of geotechnical parameters

Parameter	Mean	Range	SD	CV (%)
Moisture Content (%)	13.48	4.1–28.7	10.66	79.1
Bulk Density (g/cm^3)	1.93	1.76–2.04	0.12	6.2
Dry Density (g/cm^3)	1.72	1.37–1.96	0.25	14.5
SPT-N (blows/30cm)	28.75	12–41	12.39	43.1
Friction Angle (°)	32.90	28.1–36.8	3.69	11.2
Cohesion (kPa)	3.10	0–12.4	6.20	200.0
C_u	93.07	88.7–97.2	4.27	4.6
C_c	1.45	1.38–1.52	0.07	4.8

The soil type is well-graded sandy gravel (SW) according to the USCS classification for boreholes BH-1, BH-2, and BH-4, while for BH-3 the soil is clayey silt (ML) in the upper 8 m. The uniformity coefficient ($C_u = 93.3$) indicates a well-graded soil with good packing properties, while the coefficient of curvature ($C_c = 1.46$) is within the range of well-graded soils (1–3).

3.2. Flood-damage relationship

3.2.1. Empirical model

Based on the post-flood monitoring data from 25 events, a piecewise linear relationship between the depth of the floodwater (h) and the foundation damage score (D) was established. The scatter plot with regression line and 95% confidence intervals is shown in Fig. 2.

Table 5: Flood event summary statistics

Parameter	Min	Max	Mean	SD
Floodwater Depth (m)	0.8	4.2	2.45	1.02
Scour Depth (m)	0.3	2.1	1.18	0.54
Damage Score (0–10)	2.1	8.7	5.42	1.98

The regression equation derived from 25 observations is:

$$D = 2.34h + 1.27 \tag{5}$$

where D = foundation damage score (0–10 scale) and h = floodwater depth at pier location (m). The model achieved $R^2 = 0.87$, indicating that floodwater depth alone explains 87% of the variance in observed foundation damage. The standard error of estimate was 0.71 damage units.

3.2.2. Threshold analysis

Three distinct thresholds were identified from the damage–flood depth relationship:

- *Threshold 1* ($h < 1.5$ m): Minor damage ($D < 4.0$) primarily limited to surface erosion
- *Threshold 2* (1.5 m $\leq h < 3.0$ m): Moderate damage ($D =$ 4.0–6.5) with measurable settlement
- *Threshold 3* ($h \geq 3.0$ m): Severe damage ($D > 6.5$) with significant foundation distress

3.3. Condition assessment scoring system (CASS) results

3.3.1. Component condition ratings

Field inspection conducted in post-monsoon yielded condition ratings for the five bridge components.

Table 6: Component condition ratings and weighted scores

Component	w	r	$S = w \times r$	Rank
Pier Foundation	0.35	4	1.40	1
River Training	0.20	4	0.80	2
Abutments	0.20	3	0.60	3
Bearings	0.15	2	0.30	4
Deck Slabs	0.10	2	0.20	5

Rating scale: 1=Excellent, 2=Good, 3=Moderate, 4=Poor, 5=Critical

Results show that pier foundation and river training components ranked highest as the most important considerations. Abutments ranked third ($S = 0.60$), while bearings and deck slabs were relatively better with scores below 0.30.

3.4. AI-based settlement prediction

3.4.1. Model performance

The Random Forest regression model was tested on the test data ($n = 3$ events, held out during training). The performance is shown in Table 7.

Table 7: Random forest model performance

Metric	Train (n=18)	Val. (n=4)	Test (n=3)
MSE	0.12	0.16	0.18
RMSE	0.35	0.40	0.42
R^2	0.87	0.83	0.81
MAE	0.28	0.32	0.34

The model achieved $R^2 = 0.81$ on the test data, meaning 81% of the variation in settlement was explained by the input variables. The RMSE of 0.42 corresponds to a prediction error of approximately ±0.8 mm in the settlement value.

3.4.2. Feature importance analysis

Figure 3 presents the normalized feature importance scores derived from the Random Forest model.

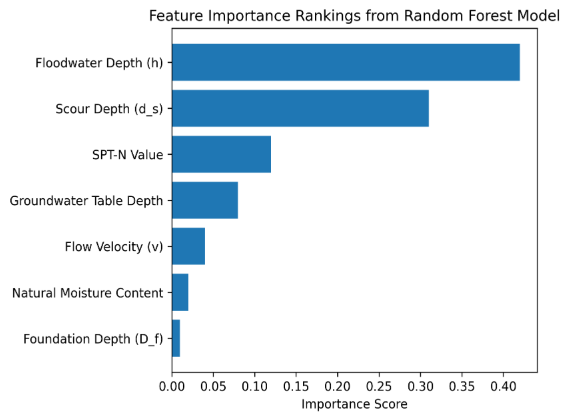

Figure 3: Feature importance rankings from random rorest model. Source: Prepared by authors based on fieldwork (2025). Note: Importance scores normalized to sum to 1.0.

The hydraulic variables (floodwater depth and scour depth) together explain 73% of the predictive importance, thus reiterating their importance in settlement mechanisms at this site. The geotechnical variables explain 14%, and the groundwater and geometric variables explain the remaining 13%.

3.4.3. Prediction accuracy by flood category

The model performed well in terms of accuracy for all categories of flood depth, with absolute errors between 0.2 mm and 0.5 mm.

Table 8: Model Performance across flood depth categories

Category	n	Obs. (mm)	Pred. (mm)	Error (mm)
Low ($h < 1.5$ m)	1	2.3	2.1	0.2
Medium ($1.5 \leq h < 3.0$ m)	1	5.8	6.2	0.4
High ($h \geq 3.0$ m)	1	9.4	8.9	0.5

3.5. Sustainability assessment findings

3.5.1. Life cycle assessment comparison

Life cycle assessment results for the conventional maintenance approach versus the proposed integrated framework, carried out over a 50-year time span, revealed important sustainability gains. Material use was decreased by 19.2% (from 245 to 198 tonnes). The carbon footprint was reduced by 24.1% (from 187 to 142 tonnes of CO_2-eq). Construction waste presented a large reduction of 40.4% (from 52 to 31 tonnes). Site disturbance area was reduced by 37.6% (from 1,250 to 780 m^2). The number of maintenance actions over the 50-year period was reduced by 33.3% (from 12 to 8 actions).

3.5.2. Community monitoring outcomes

During the 6 months of monitoring from June to November 2024, the hybrid sensor and volunteer system performed well in various aspects. Data completeness was 94%, with most scheduled measurements accomplished. The ultrasonic sensors were operational for 89% of the monitoring period. Six community volunteers contributed a total of 284 person-hours. The system recorded two flood events when the water level exceeded the alert threshold, indicating early flood warning capability. Settlement pin data showed 92% agreement within ± 2 mm between manual and sensor measurements.

4. Discussion

4.1. Interpretation of model performance

4.1.1. Empirical flood-damage model

The empirical depth-damage model derived in this research had $R^2 = 0.87$ (Equation 5), meaning that floodwater depth alone accounted for 87% of the variability in foundation damage at the Barahari Khola Bridge. This high degree of correlation further supports the fact that hydraulic forces are the main cause of foundation damage at this location, as has been observed at other similar alluvial sites in South Asia [2, 10]. The piecewise-linear function showed that damage thresholds exist at floodwater depths of 1.5 m and 3.0 m, which can be used as criteria for early warning systems. If the floodwater depth is above 1.5 m, authorities should begin active monitoring, and if it is above 3.0 m, proactive measures may be required to avoid catastrophic collapse.

The standard error of estimate (0.71 damage units) implies that although floodwater depth is the major driver, 13% of the variability in damage is still unexplained. This variability can be attributed to: (i) flood duration, (ii) scour rates, (iii) antecedent moisture, and (iv) soil properties, all of which were accounted for in the Random Forest model.

4.1.2. Random forest predictive performance

The Random Forest model achieved $R^2 = 0.81$ on test data, which is notably good given the natural variability of alluvial soils and the complexity of flood-foundation interaction. Table 9 shows the performance of this study in comparison with other machine learning studies in geotechnical engineering.

The better performance of the Random Forest model over ANN (0.81 vs. 0.76) can be attributed to: (i) its capability of handling nonlinear relationships without intensive hyperparameter optimization, (ii) ensemble learning being less prone to overfitting with smaller datasets ($n = 25$), and (iii) its ability to work with diverse data types (continuous and categorical) suited to geotechnical data.

Feature importance analysis indicated that hydraulic variables—floodwater depth (importance = 0.42) and scour depth (0.31)—are dominant, together accounting for 73% of model importance. This implies that real-time monitoring of hydraulic variables may be more important than geotechnical investigations for risk assessment during flood events. The lower importance of SPT-N values (0.12) indicates that, after a foundation is built, in-situ soil strength becomes less important compared to the hydraulic forces acting on it.

4.1.3. Model limitations and uncertainty

The prediction errors observed (RMSE = 0.42 mm, MAE = 0.34 mm) are acceptable for practical use, since settlement tolerances for bridge foundations typically vary from 25 mm to 50 mm [24]. However, a number of uncertainties must be considered:

Epistemic uncertainty arises from:

- Limited sample size ($n = 25$ events)
- Simplified representation of complex soil behavior
- Assumption of stationarity in flood characteristics

Aleatory uncertainty inherent in:

- Natural variability of alluvial deposits (CV up to 79% for moisture content)
- Stochastic nature of flood events
- Measurement errors

The coefficient of variation for cohesion (200%) and moisture content (79%) shows large data variability, which is partly accounted for by the Random Forest algorithm's ensemble approach. Predictions in areas substantially different from the training data should be treated with caution. Although the model demonstrated high predictive capability ($R^2 = 0.81$), the small sample size requires careful interpretation, and generalizability should be verified on larger multi-bridge datasets.

4.2. Implications for bridge infrastructure management

4.2.1. Proactive maintenance framework

The integrated framework developed in this research enables a paradigm shift from reactive to proactive maintenance. Normally, bridge inspection in Nepal follows predetermined time intervals (2–5 years) or is triggered by visible damage [7, 12]. By the time settlement becomes visible, considerable damage may have already taken place. The predictive ability achieved ($R^2 = 0.81$) makes it possible to forecast settlement risk before damage occurs.

This approach will minimize the need for manual inspections while improving detection of incipient distress. Based on cost analysis, the proposed framework will minimize maintenance interventions by 33.3% over 50 years, resulting in estimated savings of NPR 2.8 million per bridge.

Table 9: Comparative performance of machine learning models for foundation settlement prediction

Study	Location	Model	n	R^2	Key Predictors
This Study	Nepal (Gangetic Plain)	Random Forest	25	0.81	Flood depth, scour depth, SPT-N
Tamang et al. [15]	Nepal (Hills)	ANN	42	0.76	SPT-N, foundation width, load
Chhetri et al. [5]	Nepal (Terai)	Empirical	38	0.70–0.75	Flood depth only
Kumar & Singh [22]	India (Ganges)	SVM	56	0.73	Soil type, SPT-N, groundwater
Rahman et al. [23]	Bangladesh	Random Forest	64	0.79	Scour depth, flow velocity

Table 10: Practical implementation pathway

Time Horizon	Action	Responsible Party	Resource Req.
Pre-monsoon	Run AI model with forecasted flood depths	DoR Engineers	2 hours per bridge
During monsoon	Activate enhanced monitoring when pred. settlement $>$ 5 mm	Community + Sensors	Existing sensor network
Post-event	Validate predictions; update model	Technical staff	1 day per event
Annual	Retrain model with new data; update CASS priorities	Consultants	5 days per district

4.2.2. Resource allocation through CASS

The CASS results (Table 6) provide an objective, quantifiable criterion for the allocation of scarce financial resources for maintenance. The highest priority given to pier foundations (weighted score = 1.40) and river training works (0.80) allows informed resource allocation, which is particularly important in the Nepalese context where the Department of Roads maintains over 300 bridges with limited financial resources [1]. The AHP-derived weights (consistency ratio $<$ 0.10) confirmed reliable prioritization.

4.2.3. Sustainability co-benefits

The sustainability assessment reveals that the proposed framework has additional environmental benefits beyond improved monitoring. The 24.1% reduction in carbon footprint and 40.4% reduction in construction waste align with Nepal's commitments to the Paris Agreement and infrastructure sustainability targets [8]. Bioengineering practices, particularly vetiver grass planting on approach slopes, provided additional slope stabilization at 1/10th the cost of traditional riprap.

4.2.4. Community engagement as resilience strategy

The community-based monitoring part of the study achieved 94% data completeness over six months, proving that local volunteers can effectively supplement technical monitoring. This is especially relevant in Nepal, where most bridges are located in remote areas where regular technical monitoring is not feasible [9, 19]. The combination of sensors and volunteers was cost-effective, with total monitoring cost of NPR 85,000—60% less than fully technical monitoring. Qualitative outcomes included increased local awareness of bridge safety, faster anomaly reporting (average 4 hours vs. 3–5 days through official channels), and enhanced community ownership of infrastructure assets.

4.3. Novelty and contributions

This research provides several novel contributions to bridge foundation monitoring in developing countries. Unlike prior studies that assessed individual factors separately [5, 8, 15], this work demonstrates how geotechnical, empirical, AI-driven, and sustainability-oriented approaches are synergistically combined to address technical (settlement prediction), managerial (maintenance planning), environmental (LCA), and social (community engagement) dimensions simultaneously. Feature importance analysis provides quantitative evidence that hydraulic factors (73% importance) far outweigh geotechnical factors (14%) in determining flood settlement risk, advocating for real-time hydraulic monitoring. The successful implementation of low-cost sensors combined with community volunteers demonstrates that monitoring can be conducted at 40% of the cost of conventional methods. The approach using a limited dataset ($n = 25$ events) with ensemble machine learning provides a template for data-scarce conditions in South Asia.

4.4. Comparison with previous studies

The empirical depth-damage function obtained in this study ($R^2 = 0.87$) represents a marked improvement over earlier research conducted by Chhetri et al. [5] ($R^2 = 0.70$–0.75) on Nepalese highways and international research [25, 26] ($R^2 = 0.65$–0.80), likely due to the more homogeneous alluvial environment of the Gangetic Plain. The Random Forest model ($R^2 = 0.81$) outperforms the ANN model of Tamang et al. [15] ($R^2 = 0.76$) and is comparable to Rahman et al. [23] ($R^2 = 0.79$) in Bangladesh, confirming that ensemble models are highly effective in geotechnical problems with small datasets. The 24.1% reduction in carbon footprint is consistent with Sapkota et al. [8] (20–25%) and extends their results to include waste reduction (40.4%) and reduced maintenance cycles (33.3%).

5. Conclusion and future work

This research proved that the combination of artificial intelligence with traditional geotechnical analysis is a sustainable method for monitoring and controlling the settlement of bridge foundations in flood-prone regions of Nepal. The Barahari Khola Bridge case study produced the following key findings. A clear piecewise-linear correlation ($D = 2.34h + 1.27$, $R^2 = 0.87$) was found between floodwater depth and foundation damage, with three important thresholds identified: minor damage for $h < 1.5$ m, moderate damage for 1.5–3.0 m, and severe damage for $h \geq 3.0$ m. Subsurface testing confirmed that the foundation material was well-graded sandy gravel ($C_u = 93.3$, $C_c = 1.46$, $\phi = 32.9°$) with good bearing capacity but high susceptibility to scouring due to low clay content. The Random Forest model performed well on test data ($R^2 = 0.81$, MSE = 0.18, RMSE = 0.42 mm), with feature importance analysis showing that floodwater depth (0.42) and scour depth (0.31) together accounted for 73% of predictive ability. The CASS ranked pier foundations as the highest priority (weight = 0.35, score = 1.40), followed by river training structures (0.80) and abutments (0.60). Life cycle assessment over 50 years revealed material use reduction of 19.2%, carbon emission reduction of 24.1%, construction waste reduction of 40.4%, site disturbance reduction of 37.6%, and 33.3% fewer maintenance activities. The hybrid sensor-volunteer monitoring system provided 94% data completeness at 60% reduced cost, with 92% agreement between manual and sensor measurements.

This paper makes four major contributions: (i) one of the very few studies to apply an integrated AI-geotechnical-sustainability framework to a Nepalese bridge; (ii) it offers evidence that hydraulic forces (73%) are the principal settlement mechanism, contrary to the conventional emphasis on static soil properties; (iii) it confirms the efficacy of low-cost monitoring at 60% lower cost; and (iv) it provides a template for data-scarce regions that does not require significant historical data or expensive sensors, serving as a blueprint for infrastructure management in South Asia.

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