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Developing a Fuzzy Logic and Sensitivity Analysis Model to Estimate Financial Loss from Social Conflict and Natural Disaster Risks in Hillside Construction Project

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ABSTRACT

Hillside construction projects face external risks from community issues and slope problems such as landslides, which often cause cost overruns. However, current tools like risk matrices do not provide accurate cost estimates. This study develops a model that converts expert judgments on social conflict (RS) and natural-disaster risks (RB) into expected financial loss as a percentage cost overrun. The model used frequency and consequence ratings from 30 stakeholders, validated by six experts (I-CVI: 0.83–1.00; S-CVI/Ave: 0.90–0.92). Internal consistency was confirmed (Cronbach's α: 0.759–0.873). Scores were combined using weighted geometric mean ($\omega\_F = 0.318$; $\omega\_C = 0.682$) and processed by a Mamdani fuzzy inference system with triangular/trapezoidal membership functions and a 3×3 rule base. Tested on a hillside villa project in Lombok, Indonesia, the model estimated loss at 12.75%, close to the actual overrun of 11.65% (MAPE = 9.42%). Sensitivity analysis shows RB dominates near baseline, while RS exhibits threshold effects at higher levels. Cost-benefit analysis reveals mitigation value depends on how much KF can be reduced per mitigation cost. This framework enables integration of qualitative risk assessment into early contingency planning for hillside construction projects.

INTRODUCTION

Cost overruns are common in construction, especially when projects face unpredictable outside factors. This problem is worse in areas with difficult terrain and sensitive social settings (Al-Nahhas et al., 2024; Topal & Atasoylu, 2022). Evidence from across industries, including ADB-funded road projects, shows that external factors commonly affect project budgets (Youssefi & Celik, 2024). In hillside construction, costs are affected by technical and environmental factors, such as intense rainfall, slope instability, and landslides, as well as by social factors, including site access, procurement, and local stakeholder expectations. These aspects may interact; for example, weather delays may increase community pressure on project schedules, and supply chain problems can lead to local disputes. As a result, planners must deal with many sources of uncertainty, most of which are hard to measure (Tariq & Gardezi, 2023).

Standard 5 × 5 risk matrices are widely used, but they provide only rough rankings and can hide important patterns and interactions among risks (Duijm, 2015). For social conflict and hillside natural-disaster risks, information is often classified as low, medium, or high, which is not sufficiently precise. Fuzzy set theory is well-suited here because it allows partial membership, facilitates interpretation, and enables descriptive evaluations to be translated into numerical values using clear rules (Idrus et al., 2011). Recent studies indicate that Mamdani-type fuzzy inference systems can effectively estimate construction risks, provided the process is transparent and subject to review (Al-Nahhas et al., 2024).

This study builds an integrated workflow that: (1) checks RS and RB indicators for content validity and reliability, (2) sets expert weights for frequency and consequence with a structured method, (3) estimates KF using a Mamdani fuzzy inference system, (4) tests robustness and finds main drivers with one-at-a-time sensitivity analysis (OAT), and (5) links the loss estimate to mitigation options using a simple cost–benefit analysis. Accordingly, the objective of this study is to develop and test a fuzzy logic–based model that converts social conflict (RS) and hillside natural-disaster risk (RB) into expected financial loss for a hillside villa project in Lombok, Indonesia.

The benefits of this research are both practical and methodological. Practically, the proposed model provides project owners, contractors, and risk managers with a standardized and auditable tool to translate qualitative risk assessments into quantitative contingency estimates during early project planning (Andrić et al., 2019; Sun & Wang, 2025). This enables more informed decision-making regarding budget allocation, risk mitigation prioritization, and resource planning for hillside construction projects. Specifically, the cost–benefit analysis framework allows practitioners to evaluate whether proposed mitigation measures, such as slope reinforcement or stakeholder engagement programs, are economically justified based on their expected reduction in financial exposure (Aregbesola et al., 2025; Ibeh et al., 2025). Methodologically, this study contributes to the construction risk management literature by demonstrating how fuzzy logic, weighted geometric means, and sensitivity analysis can be integrated into a coherent workflow that addresses the limitations of traditional risk matrices. The validation process using content validity indices and reliability testing offers a replicable approach for future research seeking to develop evidence-based risk assessment tools. Furthermore, the threshold effects revealed through sensitivity analysis provide theoretical insight into how social and natural-disaster risks interact non-linearly to influence project outcomes.

METHOD

Subsequent sections describe the model and data collection methods, present the results of baseline validation and sensitivity analysis, and discuss their significance for risk monitoring and mitigation planning in hillside construction projects. Data were collected from stakeholders directly involved in the project, including owner representatives, contractor managers, site engineers, and key subcontractors. An expert panel also reviewed the selected indicators, as well as the wording and interpretation of the frequency and consequence ratings. To validate the model, project records comparing actual costs with the base contract value were used to calculate the observed cost overrun, which served as the benchmark (Table 1).

The study looks at two main risks: social conflict (RS) and hillside natural disasters (RB). Each risk was initially assessed using 10 indicators. For each indicator, respondents rated frequency (F) and consequence (C) on a Likert scale from 1 (very low/rare) to 5 (very high/very frequent). These ratings were then converted to a 0–25–50–75–100 scale to fit the fuzzy inference system. This approach preserves the order of responses and facilitates the use of membership functions while minimizing the need for repeated normalization (Norman, 2010).

The model is tested using data from a hillside villa development (Villa RH) in Lombok, Indonesia, where construction activities occur on a sloping site.

Frequency and consequence ratings were obtained from 30 respondents (owner representatives, contractor managers, site engineers, and key subcontractors). An expert panel of six senior practitioners and academics in geotechnical engineering and construction management assessed item relevance and provided pairwise comparisons for the AHP weighting.

RS indicators (RS1–RS10). The social-conflict indicators capture recurring stakeholder and governance frictions in project delivery: RS1 dominance of certain groups in material procurement; RS2 pressure to employ local labor; RS3 rejection/boycott of external vendors; RS4 interests of village officials or customary leaders affecting project operations; RS5 land or access-road disputes with residents; RS6 pressure for informal/non-official compensation; RS7 identity politics or group influence in project decision-making; RS8 informal actors influencing tender/subcontract processes; RS9 conflict potential due to exclusive distribution of work/material; and RS10 requests for informal incentives or project contributions by local authorities. After content validity screening, items RS6–RS8 were removed, and the remaining items were retained for modelling.

RB indicators (RB1–RB10). The hillside natural-disaster indicators emphasize rainfall, slope response, and landslide-related production impacts: RB1 rate of intense rainfall (>150 mm/day); RB2 rainfall disruption to work activities; RB3 rainfall impact on site conditions (slipperiness, erosion, ponding); RB4 geotechnical slope stability; RB5 felt earthquake exposure at the project location; RB6 annual landslide frequency around the site; RB7 landslide impact on work progress; RB8 damage due to landslide events; RB9 limited project capability in landslide mitigation; and RB10 disaster impact on labor productivity. After screening, RB1, RB2, and RB5 were removed while the remaining items were retained for modelling.

The relevance of each item was assessed using the content validity index (CVI). Experts rated each item on a 4-point scale, and both item-level (I-CVI) and average scale-level (S-CVI/Ave) scores were calculated. Items that did not meet standard thresholds were revised or removed to improve coverage and clarity. The internal consistency of the remaining items was assessed using Cronbach's alpha, with a minimum of 0.70 for each risk type. Reliability was also assessed using composite reliability to avoid over- or underestimating reliability. Content validation and reliability assessment were performed by an expert panel of six senior practitioners and academics in geotechnical engineering and construction management.

For each indicator, frequency and consequence scores were combined using a weighted geometric mean (WGM) to reflect better how risks multiply and to avoid giving too much weight to extreme values (Kreinovich et al., 2020): $R_i = (F_i^{\omega_F} \times C_i^{\omega_C})$, with $\omega_F + \omega_C = 1$. The weights for frequency and consequence (ω_F, ω_C) were set using a simple AHP pairwise comparison and normalized to $\omega_F = 0.31849$ and $\omega_C = 0.68151$. The risk scores for each indicator were then combined to get RS_{group} and RB_{group}. At baseline, $RS_F = 36.786$ and $RS_C = 24.167$ gave $RS_{group} = 27.626$, while $RB_F = 42.976$ and $RB_C = 70.714$ gave $RB_{group} = 60.343$.

Fuzzy inference system (Mamdani 3×3). The two combined inputs (RS_{group} and RB_{group}) were mapped to three categories (Low, Medium, High) on a 0–100 scale using trapezoidal and triangular membership functions. The output is the estimated financial loss percentage (KF), which is grouped into Low, Medium, and High. A 3×3 rule base employs expert reasoning to demonstrate how RS and RB jointly affect loss, applying min–max inference as in a Mamdani system (Idrus et al., 2011; Shafique & Warren, 2016). The final KF value is calculated using centroid of area (COA) defuzzification, which is popular for its smooth and precise results.

One-at-a-time (OAT) sensitivity analysis was done in two ways. First, RS_{group} and RB_{group} were reversed relative to the baseline to assess how the results changed and to identify any thresholds. Second, at the indicator level, one item was shifted up or down by one Likert level (equal to ±25 points after mapping), and the combined inputs and KF output were recalculated. To link the model to mitigation decisions, expected financial exposure was set as E = KF × contract value, and mitigation options were judged by the benefit–cost ratio BCR = ΔE/MC, where MC is the mitigation cost. The model's accuracy was checked by comparing $KF_{estiamted}$ to the actual cost overrun and calculating the mean absolute percentage error (MAPE).

The model's results were compared with the actual project cost overrun, defined as the difference between the final cost and the base contract value. Accuracy was measured using mean absolute percentage error (MAPE): MAPE = $|KF_{estiamted} - KF_{actual}| / KF_{actual} \times 100\%$.

RESULT AND DISCUSSION

Table 1. Model validation against observed cost overrun (baseline condition)

Contract value (Rp)	RS_{group}	RB_{group}	$KF_{estiamted}$ (%)	KF_{actual} (%)	MAPE (%)
20,209,054,526	27.626	60.343	12.75	11.65	9.42

Source: Author's calculation based on project records and fuzzy inference system, 2025

Table 1 shows that the model's estimation is close to the actual cost overrun in the case-study project. With 〖RS〗group = 27.626 and 〖RB〗group = 60.343, the fuzzy system estimates KF at 12.75%, while the actual overrun is 11.65%. The error (MAPE = 9.42%) suggests that the model is a helpful planning tool in uncertain contexts, but testing it on a single project does not cover all possible future situations.

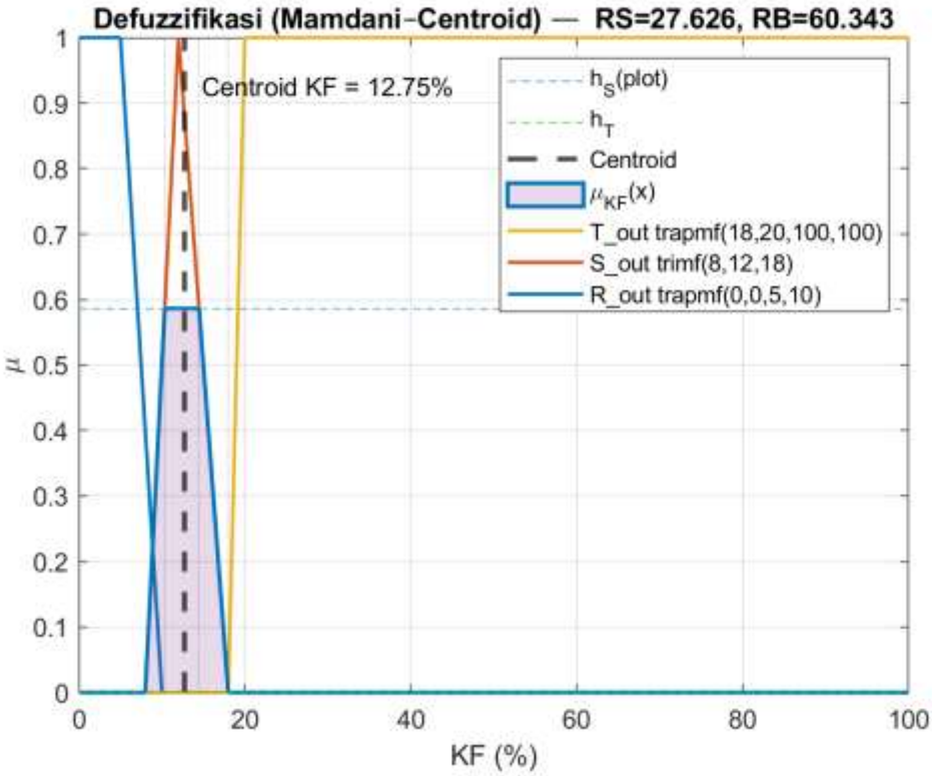

Figure 1. Defuzzification result (Mamdani–Centroid) at baseline inputs (〖RS〗_group=27.626, 〖RB〗_group=60.343).

Source: Author's calculation using Mamdani fuzzy inference system with centroid defuzzification method, 2025

At the baseline (〖RS〗 group = 27.626; 〖RB〗 group = 60.343), fuzzification gives μ_RS(Low) = 0.89494 and μ_RS(Medium) = 0.10506. RB falls between Medium and High, with μ_RB(Medium) = 0.52478 and μ_RB(High) = 0.47522. The 3×3 rule base activates four rules: (RS=Low, RB=Medium) → KF=Medium; (RS=Low, RB=High) → KF=Medium; (RS=Medium, RB=Medium) → KF=Medium; and (RS=Medium, RB=High) → KF=Medium. Since social risk is mostly Low and natural-disaster risk is not fully High, the output is primarily in the "Medium" loss category. Centroid defuzzification gives a final 〖KF〗_estimated of 12.75% (Figure 1). This means that, under these conditions, the project is expected to incur a moderate loss, mainly due to interruptions to the hillside rather than severe social issues.

Table 2. One-at-a-time (OAT) sensitivity at variable level (selected points).

Scenario	RS_{group}	RB_{group}	KF (%)	ΔKF (pp)	|ΔKF| (pp)
Baseline	27.626	60.343	12.75	–	–
RB −30	27.626	30.343	6.031	−6.716	6.716
RB −25	27.626	35.343	7.613	−5.134	5.134
RB −20	27.626	40.343	9.020	−3.727	3.727
RB −10	27.626	50.343	12.673	−0.074	0.074
RB +10	27.626	70.343	12.686	−0.061	0.061
RS −20	7.626	60.343	12.748	0.000	0.000

Scenario	RS_{group}	RB_{group}	KF (%)	ΔKF (pp)	|ΔKF| (pp)
RS +10	37.626	60.343	12.776	0.028	0.028
RS +25	52.626	60.343	44.024	31.277	31.277
RS +30	57.626	60.343	52.562	39.814	39.814

Source: Author's calculation using one-at-a-time sensitivity analysis, 2025

Table 2 summarizes the one-at-a-time (OAT) scenarios used to assess local sensitivity near the baseline. In each scenario, only one combined input modification is made, while the others remain unchanged. This method shows how the Mamdani surface responds to small changes in RS or RB.

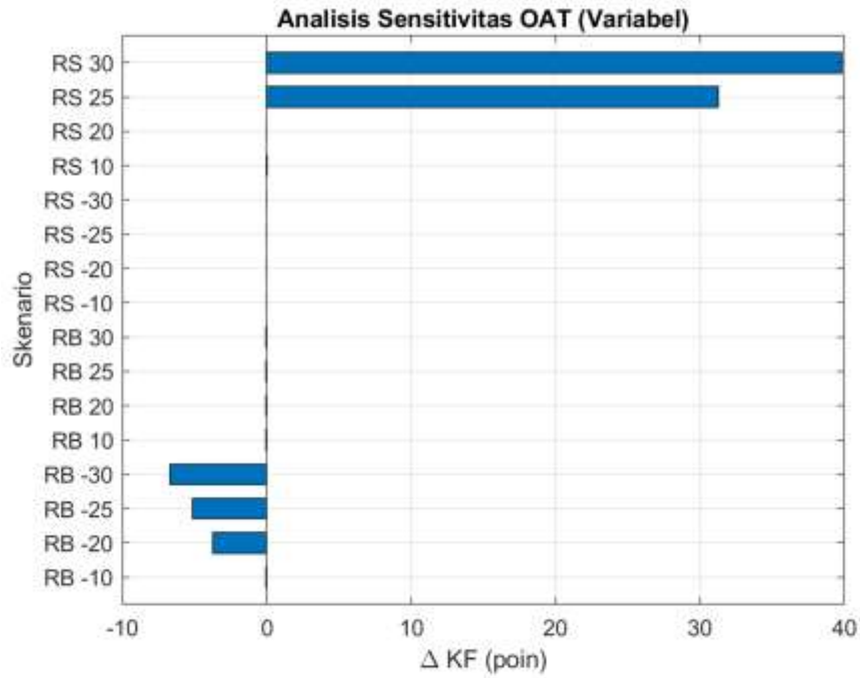

Figure 2. Tornado chart of variable-level OAT sensitivity (ΔKF in percentage points).

Source: Author's calculation using one-at-a-time sensitivity analysis, 2025

OAT sensitivity analysis results at the variable level show a non-linear, threshold-based response (Table 2 and Figure 2). Near the baseline, RB has the most significant effect: lowering 〖RB〗_group by 20–30 points reduce KF by approximately 3.73–6.72 percentage points. This is consistent with the hillside context, where technical measures such as drainage, shotcrete, retaining walls, or sequential excavation can reduce slope risks (Ardianto & Makarim, 2021; Kim et al., 2021). In contrast, changing 〖RS〗_group by ±20 points have little effect on KF, since the rule base treats low-to-medium social disruption the same regardless of whether the project continues. But when 〖RS〗_groupoup gets very high (for example, RS +25 or +30), KF rises sharply (over 40%), showing that severe social disruption may cause significant losses. Other studies also show that unresolved stakeholder conflicts can create major project problems if there is no local support and good negotiation (Shafique & Warren, 2016; Tariq & Gardezi, 2023; Yuan et al., 2018).

The OAT sensitivity analysis method can also be applied at the indicator level by changing individual survey items and recalculating 〖RS〗_group or 〖RB〗_group before rerunning the fuzzy system. This helps set monitoring priorities, since indicators that can move RS or RB between Low, Medium, and High need special attention. In this case study, indicators such as slope stability, landslide events, readiness for mitigation, and productivity losses are most helpful in mitigating short-term losses. Social indicators act as early warnings; problems with procurement access, informal pressure, or stakeholder actions are linked to rapid increases in financial risk in the model. So, risk mitigation approaches should combine technical measures (such as drainage and slope protection) with governance actions (such as transparent procurement and organized stakeholder engagement) to prevent problems from worsening (Sanggoro et al., 2021; Yuan et al., 2018).

Table 3. Cost–benefit analysis (CBA) of slope reinforcement mitigation scenarios.

Scenario	**RS_{group}**	**RB_{group}**	**KF (%)**	**ΔKF (pp)**	**Exposure E (Rp)**	**ΔE (Rp)**	**MC (Rp)**	**BCR**
Baseline (KF_0)	27.63	60.34	12.75	–	2,576,654,452	–	–	–
Mitigation RB −20 (KF_1)	27.63	40.34	9.02	−3.73	1,822,856,718	753,797,734	947,243,400	0.80
Mitigation RB −25 (KF_2)	27.63	35.34	7.61	−5.13	1,537,909,049	1,038,745,403	947,243,400	1.10
Mitigation RB −30 (KF_3)	27.63	30.34	6.03	−6.72	1,358,048,464	1,218,605,988	947,243,400	1.29

Source: Author's calculation based on fuzzy inference system output and mitigation cost assumptions, 2025

Table 3 evaluates three mitigation scenarios that reduce 〖RB〗_group by 20, 25, and 30 points, representing progressively stronger slope-reinforcement and site-protection packages. The mitigation cost (MC) is treated as constant across scenarios for illustrative purposes, whereas the benefit is measured as the reduction in expected financial exposure (ΔE) implied by the decrease in KF.

The cost–benefit analysis illustrates that the fuzzy output can serve as a decision anchor rather than a single deterministic forecast. At baseline (〖KF〗_0 = 12.75%), the expected financial exposure is approximately Rp2.58 billion for the case-study contract value. A mitigation package that reduces 〖RB〗_group by 20 points decreases KF to 9.02% and lowers exposure by approximately Rp753.80 million; however, with a mitigation cost of Rp947.24 million, the benefit–cost ratio is below 1 (BCR = 0.80), suggesting limited economic attractiveness under this assumption set. When the RB reduction reaches 25–30 points, the implied exposure reduction becomes larger (Rp1.04–1.22 billion), increasing the BCR to 1.10–1.29. In practice, this means that modest technical measures may not justify their cost if they do not shift RB across a meaningful membership boundary. In contrast, more comprehensive packages can become attractive once the project moves into a lower expected-loss regime. The same framework can be used to compare alternative mitigation options or phased interventions, provided that cost estimates are updated and the assumed effect on RB is supported by engineering judgement and site monitoring.

CONCLUSION

This study proposes a standardized, auditable workflow to estimate project financial losses from the combined effects of social-conflict risk (RS) and hillside natural-disaster risk (RB). The technique integrates indicator-based measurement with expert input and validation, employs weighted geometric means to combine frequency and consequence, and applies a transparent Mamdani fuzzy inference system to transform risk conditions into an expected loss percentage (KF). In the case study, the model produced a moderate loss estimate (〖KF〗 estimated = 12.75%) with an error of 9.42% relative to the actual cost overrun, suggesting it can support early planning in the presence of uncertainty. Sensitivity analysis indicates that small changes within a risk category have little effect, whereas significant changes, especially in social conditions, can significantly increase expected losses. Cost–benefit analysis helps determine whether mitigation measures sufficiently reduce risk. Further investigations should test the model on additional projects, refine membership functions using larger datasets, and expand the framework to include schedule impacts and real-time updates as new monitoring data become available. For practitioners, the model can be embedded in early-stage risk workshops to translate qualitative RS and RB assessments into provisional contingency allowances and to screen mitigation packages by benefit–cost ratio.

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