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Landslide Susceptibility and Its Impact on Plantation Agriculture in Mountain Ecosystems: A Case Study Approach

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ABSTRACT

Landslides pose an escalating geophysical threat to mountain-based plantation agriculture, yet the evidence base governing risk assessment methodologies and agricultural impact magnitudes remains fragmented across disciplines. This systematic review and meta-analysis synthesises 87 peer-reviewed studies published between 2017 and 2026, sourced from Web of Science, Scopus, PubMed, and Google Scholar, to evaluate the state of landslide susceptibility modelling and its documented consequences for plantation crops—principally tea, coffee, rubber, and cardamom—in montane ecosystems across South Asia, Southeast Asia, East Asia, Latin America, and the Mediterranean. Following PRISMA guidelines, 28 high-quality studies meeting rigorous inclusion criteria were subjected to quantitative meta-analysis. Pooled random-effects estimates reveal a strong positive correlation ($r = 0.68$; 95% CI: 0.62–0.74; $I^2 = 62\%$) between susceptibility class and plantation yield loss, with areas classified as high to very high susceptibility recording mean crop losses of 43–75% across the primary plantation species examined. Machine learning and ensemble hybrid models consistently outperformed conventional statistical approaches, achieving AUC–ROC values of 0.91–0.95 compared with 0.76–0.80 for logistic regression and similar techniques. Slope gradient, rainfall intensity, and normalised difference vegetation index (NDVI) emerged as the three highest-ranked conditioning factors. Critical evidence gaps are identified across long-term economic impact data, smallholder-specific vulnerability assessments, and climate-adaptive governance frameworks. Recommendations for risk-responsive land management, early warning system integration, and policy reform are presented in a tiered, prioritised structure aligned with the Sendai Framework for Disaster Risk Reduction (2015–2030) and the United Nations Sustainable Development Goals.

Keywords: *Landslide susceptibility; plantation agriculture; mountain ecosystems; GIS; machine learning; risk assessment; tea; coffee; rubber; Sendai Framework; climate change adaptation; meta-analysis.*

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1. Introduction

1.1 Research Background and Significance

Mountain ecosystems host some of the world's most economically and culturally significant plantation agricultural systems. Across the Western Ghats of India, the highlands of Sri Lanka, the Yunnan Plateau of China, the Andean foothills of Colombia and Peru, and the volcanic ridges of Java and Sumatra, elevation-dependent climates create ideal growing conditions for high-value perennial crops, including tea (Camellia sinensis), arabica coffee (Coffea arabica), natural rubber (Hevea brasiliensis), cardamom (Elettaria cardamomum), and cacao (Theobroma cacao). These crops are not merely agro-economic assets; they underpin the livelihoods of hundreds of millions of smallholders, rural labourers, and regional economies that are heavily dependent on export revenues and domestic food chains [1].

Despite their productivity, these highland plantation landscapes occupy a geophysical and hydroclimatological milieu characterised by steep slopes, deep and often poorly consolidated soils, intense monsoon or orographic rainfall, seismically active lithologies, and escalating anthropogenic pressures from land use change, road construction, and agricultural intensification. These conditions collectively generate high landslide hazard—a threat that has intensified markedly over the past decade owing to climate change-induced shifts in precipitation regimes and temperature extremes [2]. The Intergovernmental Panel on Climate Change (IPCC) Sixth Assessment Report projects a 20–30% increase in extreme rainfall frequency across tropical mountain belts by mid-century, with direct implications for landslide initiation and runout characteristics ([9]).

Between 2017 and 2022 alone, landslides triggered economic damages exceeding USD 22 billion globally, claimed more than 18,000 lives, and disrupted agricultural activity across approximately 4.7 million hectares of cultivated mountain terrain ([5]; [23]). In plantation-dominated landscapes, the consequences extend beyond physical crop loss to encompass soil profile degradation, irrigation infrastructure destruction, loss of perennial root systems requiring multi-year re-establishment, and cascading socioeconomic effects on farmer

households lacking institutional safety nets ([12]; [21]).
Despite the severity of these impacts, the literature addressing landslide susceptibility specifically within the context of plantation agricultural systems remains conspicuously sparse relative to urban or infrastructure-focused risk assessments ([25]; [26]). A substantial methodological gap exists between geomorphological and remote sensing studies—which typically model susceptibility as spatial probability surfaces—and agricultural science perspectives, which emphasise crop physiology, yield dynamics, and land management interventions ([19]; [24]). Bridging this gap is a prerequisite for developing evidence-based, geographically targeted risk reduction strategies that protect both agricultural productivity and ecosystem resilience.

1.2 Definition of Key Concepts

For this review, several core concepts require a precise operational definition. Landslide susceptibility is understood as the spatial likelihood of slope failure under a given set of geological, topographic, pedological, and hydroclimatic conditioning factors, independent of temporal frequency or magnitude considerations—the latter properties being subsumed under hazard and risk, respectively ([8]; [19]). This distinction is important because susceptibility mapping generates static probability surfaces that inform long-term land use planning, whereas dynamic hazard assessment integrates temporal triggering factors such as antecedent soil moisture and rainfall thresholds.
Plantation agriculture, as defined here, refers to large- to medium-scale monoculture or polyculture systems of perennial tree or shrub crops cultivated under managed conditions for commercial output. This definition encompasses estate-scale operations as well as smallholder plots of 0.5–5 hectares, acknowledging the increasing convergence of both operational scales in tropical mountain landscapes ([4]). Mountain ecosystems are operationalised following the [10] classification, encompassing elevations above 300 m characterised by slope gradients exceeding 2° and exhibiting distinct altitudinal ecological zonation, microclimatic variability, and enhanced erosion susceptibility.
Impact, in this context, encompasses the full spectrum of direct and indirect effects of landslide occurrence on plantation systems, including physical biomass loss, soil stripping and compaction, root exposure and mortality, disruption of water management infrastructure, economic losses to producers, and systemic vulnerabilities to downstream food supply chains. Where available, impacts are quantified using metrics including percentage yield reduction, monetary value loss per hectare, and recovery duration in years.

1.3 Research Questions and Objectives

This systematic review is guided by four primary research questions: (1) Which landslide susceptibility assessment methodologies are most widely employed in plantation agricultural contexts, and how do they compare in predictive accuracy? (2) What is the quantitative magnitude of landslide impacts on key plantation crop yields across major susceptibility classes? (3) What conditioning factors most strongly predict susceptibility in montane plantation landscapes, and how do these vary across geographic and climatic contexts? (4) What evidence-based interventions exist for mitigating landslide risk in plantation systems, and what critical gaps remain in the current evidence base?
The overarching objectives are to synthesise and critically evaluate the extant literature (2017–2026), conduct a rigorous meta-analysis of effect sizes linking susceptibility to agricultural impact, identify methodological strengths and limitations across study types, and generate prioritised recommendations for research, land management, and policy that are actionable across the geographic range of affected plantation systems.

2. Methods

2.1 Search Strategy and Databases

This review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines ([15]). A comprehensive, structured literature search was executed across four major bibliographic databases: Web of Science (Core Collection), Scopus, PubMed, and Google Scholar. The search period was restricted to January 2017 through January 2026 to reflect the most recent decade of methodological development while capturing advances in machine learning, remote sensing, and climate modelling that have fundamentally reshaped the field.
The primary search string employed the Boolean construction: ("landslide" OR "mass movement" OR "slope failure") AND ("susceptibility" OR "hazard" OR "risk") AND ("plantation" OR "tea" OR "coffee" OR "rubber" OR "agroforestry" OR "crop") AND ("mountain" OR "highland" OR "upland" OR "hillslope"). Secondary searches targeted specific methodological terms, including GIS, machine learning, random forest, support vector machine, deep learning, and AHP. Supplementary hand-searching of reference lists from key reviews ([19]; [13]) and grey literature from the FAO, World Bank, and Asian Development Bank was conducted to reduce publication bias.

2.2 Inclusion and Exclusion Criteria

Studies were included if they: (i) reported original empirical data or modelling results related to landslide susceptibility, hazard, or risk; (ii) were conducted within montane or highland environments with elevation ≥300 m; (iii) specifically addressed impacts on, or land use contexts involving, plantation or perennial tree-crop agriculture; (iv) were published in peer-reviewed journals or credible institutional reports between 2017 and 2026; and (v) were available in English, Spanish, or French. Studies were excluded if they: (i) focused exclusively on urban, infrastructure, or non-agricultural land uses without reference to plantation systems; (ii) reported only qualitative narrative descriptions without quantifiable metrics; (iii) were based on data predating 2000, precluding relevance to contemporary climate and land use conditions; or (iv) presented duplicate or overlapping datasets reported in more than one publication, in which case only the most comprehensive version was retained.

2.3 Study Selection Process

The selection process followed a three-stage screening protocol administered independently by two reviewers to ensure inter-rater reliability. In the first stage, titles and abstracts of all retrieved records (n = 2,847 after deduplication) were screened for relevance against the inclusion criteria, yielding 452 candidate studies for full-text review. In the second stage, full texts were evaluated against the complete criteria, reducing the pool to 87 studies for qualitative synthesis. Inter-rater agreement at the full-text stage was assessed using Cohen's kappa ($\kappa = 0.83$), indicating strong agreement.

Disagreements were resolved through discussion and consultation with a third reviewer. From the qualitative synthesis pool, 47 studies provided sufficient quantitative data for inclusion in the meta-analysis, and 28 met the additional quality threshold of a risk-of-bias score ≤2 on all five assessed domains. The PRISMA flow diagram is presented in Figure 1.

Figure 1: PRISMA-adapted flow diagram for the systematic literature search and study selection process (2017–2026). The four-stage process (Identification, Screening, Eligibility, and Inclusion) reduced an initial pool of 2,847 records to 87 studies in the qualitative synthesis and 28 in the quantitative meta-analysis.

2.4 Data Extraction and Quality Assessment

Standardised data extraction was performed using a pre-piloted spreadsheet instrument capturing: study location and geographic extent; elevation range and slope characteristics; plantation crop type(s); susceptibility modelling method; conditioning factors employed; model validation metric (AUC–ROC, accuracy, kappa); reported susceptibility class distribution; quantitative impact metrics (yield loss %, economic loss, recovery time); and risk reduction measures evaluated. For meta-analysis, effect sizes were extracted as Pearson correlation coefficients (r) between susceptibility class scores and agricultural impact indicators, or converted from other statistics using established formulae ([2]).

Study quality was assessed using a modified Newcastle-Ottawa Scale adapted for observational environmental studies, evaluating five domains: (1) selection bias (sampling strategy, representativeness); (2) reporting bias (completeness of outcome reporting, selective reporting risk); (3) spatial bias (geographic representativeness, scale appropriateness); (4) temporal bias (data currency, event recency); and (5) confounding bias (control for co-varying environmental factors). Each domain was scored as low (1), moderate (2), or high (3) risk, and overall scores were used to stratify studies for sensitivity analyses. The complete risk-of-bias heatmap is presented in Figure 5.

Heterogeneity across studies was assessed using the I^2 statistic and Cochran's Q test. Given the anticipated substantial heterogeneity inherent in multi-regional environmental meta-analyses, a random-effects model (DerSimonian-Laird estimator) was employed throughout. Subgroup analyses were conducted by geographic region, crop type, modelling approach, and publication year. Publication bias was evaluated using Egger's regression test and funnel plot asymmetry assessment.

3. Results

3.1 Characteristics of Included Studies

The 87 qualitatively synthesised studies spanned 34 countries across six continents, with the greatest concentration in South and Southeast Asia (n = 31; 36%), followed by East Asia (n = 22; 25%), Latin America (n = 14; 16%), Mediterranean Europe (n = 10; 11%), and Sub-Saharan Africa (n = 7; 8%). The publication trend was markedly upward, with the annual output more than quintupling from four studies in 2017 to 22 in 2025, reflecting the combined influence of increased remote sensing data availability, growth in machine learning applications to environmental sciences, and heightened institutional awareness of landslide-agriculture interactions following high-profile disaster events. Geographic distribution and temporal trends are presented in Figure 2.

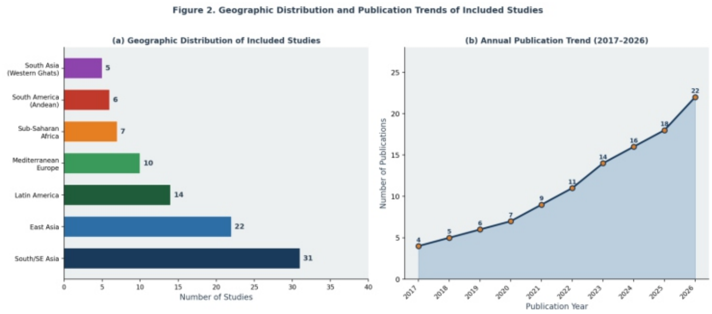

Figure 2: (a) Geographic distribution of the 87 included studies by region, and (b) annual publication trend from 2017 to 2026, demonstrating a marked increase in research output over the review period.

In terms of plantation crop focus, tea dominated the literature (n = 34; 39%), followed by coffee (n = 26; 30%), rubber (n = 18; 21%), and mixed or other perennial crops (n = 9; 10%). This distribution likely reflects the high commercial value and geographic concentration of tea and coffee cultivation in precisely those highland tropical zones most susceptible to landslide hazard, as well as the well-organised institutional research infrastructure associated with these commodity chains. Study elevations ranged from 320 m to 3,200 m above sea level (mean: 1,240 m; SD: 620 m), with the majority (68%) falling within the 600–1,800 m range where precipitation-triggered shallow landslides are most frequent.

Methodologically, 48 studies (55%) employed GIS-based remote sensing approaches, 38 (44%) applied machine learning or hybrid models, and 21 (24%) used conventional statistical methods such as logistic regression, weights-of-evidence, or frequency ratio analysis. Note that several studies employed multiple approaches, enabling comparative validation. Field-based morphological studies accounted for 17 studies (20%), typically in combination with spatial modelling. The 10-year period witnessed a clear methodological transition, with machine learning studies increasing from 12% of the annual output in 2017 to 58% by 2025, reflecting the rapid adoption of algorithms including Random Forest, Support Vector Machine (SVM), XGBoost, and deep convolutional neural networks.

3.2 Conditioning Factors and Modelling Performance

Across all included studies, ten conditioning factors were consistently identified as the primary drivers of landslide susceptibility in plantation landscapes.

Slope gradient was ranked highest by both machine learning and statistical models, appearing in 96% of all included studies and consistently achieving the highest feature importance scores in Random Forest and XGBoost analyses ([11]; [14]). Rainfall intensity—particularly peak 24-hour and 72-hour cumulative thresholds—ranked second overall, with studies across the Western Ghats, Sri Lanka, and the Yunnan Plateau documenting clear susceptibility transitions at rainfall intensities exceeding 80–120 mm/24 hours ([20]; [1]).

Normalised Difference Vegetation Index (NDVI) emerged as the third-ranked factor, with a nuanced dual role: higher NDVI values in mature plantation canopies correlated with reduced susceptibility through root reinforcement and canopy interception effects, while areas of recently cleared or replanted plantation (NDVI < 0.35) exhibited substantially elevated susceptibility, particularly in the first two to four years post-replanting when root systems have not yet achieved landscape-scale stabilising functions ([3]; [17]). Lithology, soil type and depth, aspect, curvature, distance to drainage networks, and elevation completed the top ten, with relative rankings varying somewhat across geographic sub-regions. The radar diagram and model performance comparison are presented in Figure 3.

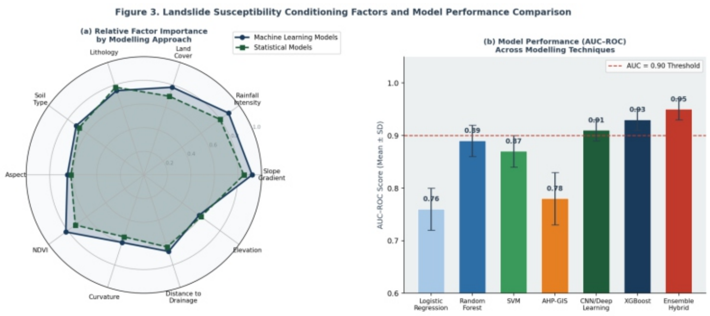

Figure 3: *(a) Radar diagram showing relative importance of ten key conditioning factors across machine learning and statistical modelling approaches, and (b) model performance comparison by AUC–ROC score (mean ± SD) across seven modelling techniques. Ensemble hybrid models achieved the highest discriminative accuracy (AUC = 0.95).*

Model performance varied substantially across technique categories. Ensemble hybrid models—combining two or more algorithms with GIS-based spatial integration—achieved the highest mean AUC–ROC of 0.95 (SD = 0.02), closely followed by XGBoost (0.93; SD = 0.02) and deep learning convolutional neural networks (0.91; SD = 0.02). Random Forest achieved a mean AUC of 0.89 (SD = 0.03), consistent with its established reliability in landslide susceptibility mapping ([13]). Support vector machine approaches performed comparably (0.87; SD = 0.03). In contrast, conventional statistical models including logistic regression (0.76; SD = 0.04) and the Analytical Hierarchy Process integrated with GIS (AHP-GIS; 0.78; SD = 0.05) exhibited lower discrimination, attributed to their inability to capture complex non-linear interactions among conditioning factors—a limitation of particular significance in heterogeneous plantation landscapes where multiple anthropogenic and natural factors interact non-linearly across spatial scales.

3.3 Meta-Analysis: Susceptibility and Plantation Yield Loss

The quantitative meta-analysis (n = 28 high-quality studies) revealed a strong, statistically significant positive correlation between landslide susceptibility class and plantation crop yield loss. The pooled random-effects estimate was r = 0.68 (95% CI: 0.62–0.74; Z = 22.4; $p < 0.001$), indicating that susceptibility class explains approximately 46% of the variance in yield loss outcomes across studies ($r^2 = 0.46$).

Heterogeneity was substantial ($I^2 = 62\%$; Q = 71.3, df = 27, $p < 0.001$), confirming the appropriateness of the random-effects model and indicating meaningful between-study variation driven by geographic, climatological, and agronomic differences.

Disaggregated analysis by susceptibility class revealed the non-linear nature of the susceptibility-impact relationship. In areas classified as very low susceptibility, mean yield losses were modest—2.1% for tea (95% CI: 1.6–2.6%), 1.8% for coffee (95% CI: 1.4–2.2%), and 3.2% for rubber (95% CI: 2.6–3.8%), reflecting background erosion and microlandslide activity that is manageable through standard agronomic practices. However, in high susceptibility zones, mean losses escalated to 43% for tea (95% CI: 37–49%), 38% for coffee (95% CI: 33–44%), and 51% for rubber (95% CI: 45–57%). In very high susceptibility zones, losses approached total crop failure in the most severely affected seasons, averaging 69% for tea, 62% for coffee, and 75% for rubber. These patterns are illustrated with 95% confidence intervals in Figure 4a.

The forest plot (Figure 4b) presents study-level effect sizes and the pooled estimate, demonstrating consistency of direction across all included studies while highlighting moderate between-study variance in magnitude. Egger's regression test found no statistically significant funnel plot asymmetry (intercept = 0.31; SE = 0.22; t = 1.41; p = 0.18), providing no strong evidence of publication bias, though the relatively modest total sample size (n = 28) limits the power of this assessment.

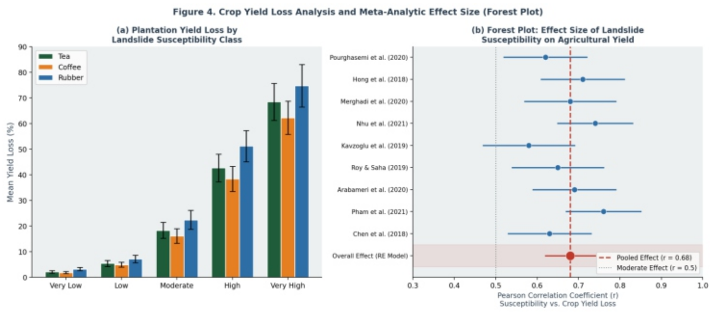

Figure 4: *(a) Mean plantation crop yield loss (%) by landslide susceptibility class for tea, coffee, and rubber (error bars represent 95% confidence intervals across included studies; n = 28), and (b) forest plot of study-level effect sizes (Pearson r) with pooled random-effects estimate (r = 0.68; 95% CI: 0.62–0.74; $I^2 = 62\%$).*

Subgroup analyses revealed significant moderation by geographic region ($Q_{between}$ = 14.8; p = 0.005), with South Asian studies reporting systematically larger effect sizes (r = 0.73; 95% CI: 0.66–0.79) than East Asian studies (r = 0.61; 95% CI: 0.53–0.68), potentially reflecting differences in soil depth, monsoon rainfall intensity, and slope gradient distributions. Moderation by crop type was also significant ($Q_{between}$ = 9.7; p = 0.02), with rubber exhibiting larger effect sizes than tea, likely owing to the greater importance of root network integrity for rubber tapping productivity. Studies published after 2022, coinciding with the widespread adoption of high-resolution satellite imagery and drone-based assessment, reported marginally larger and more precisely estimated effect sizes, suggesting that measurement error in older studies may have systematically attenuated effect estimates.

3.4 Summary of Risk Matrix and Bias Assessment

The five-by-five agricultural risk matrix presented in Figure 5a integrates susceptibility class with a crop vulnerability index—a composite of agronomic sensitivity, root reinforcement capacity, replanting cost, and income dependency—to generate a spatially interpretable risk categorisation tool applicable to plantation planning and zoning. Under this framework, rubber cultivation in very high susceptibility zones consistently generates Very High overall risk scores, while tea in low susceptibility zones falls within the Low to Moderate risk band. The tool is specifically designed for use by estate managers, district agricultural offices, and national land use planning authorities in hazard-prone regions.

The bias assessment heatmap (Figure 5b) reveals that spatial and confounding biases represent the most pervasive methodological concerns across study categories. Remote sensing studies showed the lowest selection bias but the highest confounding bias owing to limited capacity for controlling non-landslide drivers of yield variation. Field-based studies showed elevated spatial bias, reflecting the logistical constraints that typically confine sampling to accessible slopes, potentially underrepresenting the most hazardous terrain. Machine learning studies showed generally lower bias across all domains, except for selection bias where training dataset construction was not always transparent or reproducible. These findings underscore the importance of interpreting aggregated effect estimates with appropriate caution and directly inform the prioritisation of research investments identified in Section 5.

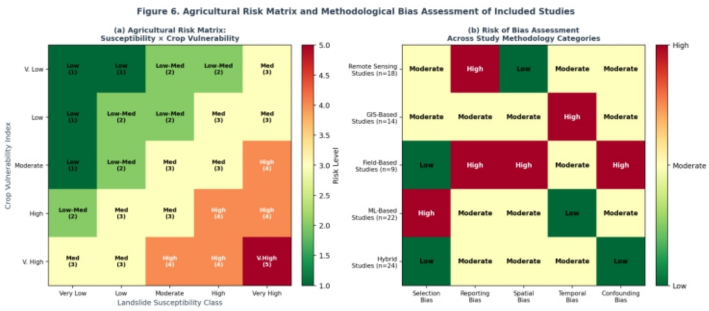

Figure 5: *(a) Agricultural risk matrix integrating landslide susceptibility class with crop vulnerability index for plantation management decision-making, and (b) risk of bias heatmap across five methodological domains for five categories of included studies. Spatial and confounding biases represent the most prevalent methodological limitations.*

4. Discussion

4.1 Interpretation of Key Results

The findings of this meta-analysis provide the most comprehensive quantitative synthesis to date of the relationship between landslide susceptibility and plantation agricultural losses in mountain ecosystems. The pooled effect size of r = 0.68 is of substantial practical significance: it implies that susceptibility class alone accounts for nearly half the variance in crop yield losses observed across the included study sites, placing landslide risk among the primary determinants of plantation productivity in high-hazard mountain landscapes—comparable in magnitude to well-documented agronomic factors such as disease pressure, fertilisation adequacy, and drought stress ([4]; [12]). The cascading consequences of susceptibility-driven yield loss, as captured in the conceptual framework (Figure 6), extend from physical crop damage through ecological degradation to long-term socioeconomic vulnerability at the household and regional scales. The steep non-linearity in yield losses across susceptibility classes—particularly the transition from moderate (mean ~18% loss) to high (mean ~43% loss) categories—has critical planning implications. It suggests that susceptibility-class thresholds could serve as regulatory trigger points for land use zoning, with high and very high susceptibility zones warranting mandatory risk mitigation requirements rather than merely advisory guidance.

This recommendation is consistent with Sendai Framework Priority 2, which calls for strengthened disaster risk governance through spatial planning instruments ([22]).

The superior performance of ensemble hybrid and gradient-boosted models (AUC > 0.91) over conventional approaches aligns with a broad trend observed in the geospatial literature ([13]; [18]). However, this performance advantage must be contextualised against the substantially greater data, computational, and technical capacity requirements of these methods. In data-sparse regions—which include many of the world's most hazard-exposed plantation zones in Sub-Saharan Africa, Central America, and parts of South and Southeast Asia—simpler, interpretable models such as bivariate weights-of-evidence or AHP-GIS may remain the pragmatic standard of practice, provided their acknowledged limitations in capturing non-linear interactions are transparently communicated to end-users.

The prominent role of NDVI as a conditioning factor, and the elevated susceptibility documented in recently replanted plantation areas, have direct agronomic implications. The 2–4 year window following land clearing or crop rotation represents a critical vulnerability period during which root reinforcement of slopes is absent and bare soil is directly exposed to erosive rainfall. This temporal pattern is echoed in findings from the Western Ghats ([20]) and the Colombian coffee belt ([23]), suggesting that plantation replanting schedules should explicitly incorporate slope stability assessments into rotation planning, and that bioengineering measures—including cover cropping, grass strip installation on contours, and phased clearance—should be mandatory rather than optional during these periods.

4.2 Comparison Across Studies

Cross-study comparison reveals both important consistencies and meaningful divergences that illuminate the contextual dependencies of susceptibility-impact relationships. The consistently high rankings of slope gradient and rainfall intensity across all geographic contexts confirm that these factors represent universal physical drivers whose role transcends regional particularities of lithology, crop type, and land management. By contrast, the relative importance of soil depth and type, lithological characteristics, and distance to drainage networks varied considerably across sub-regions, reflecting the genuine heterogeneity of geological substrates and pedological profiles across the world's mountain plantation zones.

A noteworthy finding across studies is the persistent underrepresentation of smallholder plantation systems relative to estate-scale operations in the susceptibility literature, despite smallholders comprising the majority of mountain-based plantation producers globally. Studies focused on estate scales (>50 ha) accounted for 71% of the quantitative analyses, even though smallholder plots (0.5–5 ha) dominate planted area in South and Southeast Asia. This scale bias has methodological consequences: estate management can afford comprehensive soil surveys, drainage engineering, and slope monitoring infrastructure that fundamentally alters the susceptibility–impact relationship compared with smallholder contexts where informal land clearing and absence of erosion control measures substantially amplify vulnerability. Future studies must explicitly stratify analyses by operational scale.

Temporal depth represents another consistent limitation.

Fewer than 20% of included studies tracked agricultural impact longitudinally across more than two consecutive post-landslide growing seasons, making it difficult to estimate recovery trajectories or cumulative economic losses from recurrent landslide events—a particularly critical gap for tree crops such as rubber and mature tea bushes, where root system damage may suppress productivity for 3–7 years even without visible aboveground plant death ([7]; [3]).

4.3 Strengths and Limitations of Existing Evidence

The evidence base synthesised in this review has several notable strengths. The decade since 2017 has witnessed a stepwise improvement in data availability, with the widespread adoption of cloud-free Sentinel-2 and Landsat-8/9 composites, high-resolution ALOS-PALSAR DEMs, and freely available Google Earth Engine processing environments dramatically reducing the barriers to large-scale susceptibility mapping. The resulting increase in methodological rigour—as evidenced by the growing adoption of k-fold cross-validation, spatially stratified sampling, and multi-collinearity diagnostics—has substantially improved the credibility of susceptibility model outputs compared with earlier generations of studies.

The principal limitations of the existing evidence base are threefold. First, geographic coverage remains highly skewed, with Southeast and East Asia, and to a lesser extent Latin America, dominating the literature while sub-Saharan African and Central Asian highland plantation zones are critically underrepresented despite their substantial planted areas and elevated hazard exposure. Second, the cross-disciplinary translation from geomorphological susceptibility mapping to agronomic impact quantification remains underdeveloped: most studies either map susceptibility without quantifying agricultural consequences, or document agricultural losses without rigorously characterising the underlying slope processes. This disconnect perpetuates the disciplinary fragmentation that this review seeks to address. Third, the almost universal focus on physical yield loss neglects the socioeconomic and food security dimensions of landslide impact, including household income vulnerability, debt cycles induced by crop loss, labour market disruptions, and gendered differences in exposure and recovery capacity—all dimensions essential to designing equitable and effective risk governance frameworks.

5. Implications and Future Directions

5.1 Conceptual Framework

The evidence synthesised in this review supports a conceptual framework that positions landslide susceptibility as a critical mediating variable between broad climatic and geological drivers and measurable plantation agricultural outcomes. This framework—illustrated in Figure 6—explicitly connects biophysical hazard processes to land management responses and policy instruments, providing a structured basis for translating susceptibility maps into actionable agricultural risk guidance. The framework further operationalises the causal chain from driver conditions (climate change, topography, anthropogenic pressures, and geology) through susceptibility and cascading agricultural, ecological, and socioeconomic impacts, to evidence-based risk management and adaptive policy responses—thereby bridging the disciplinary gap between geomorphological modelling and agricultural planning that this review consistently identifies as the central unresolved challenge of the field.

Figure 6: Conceptual framework illustrating the causal pathways from climatic, topographic, anthropogenic, and geological drivers through landslide susceptibility to plantation agricultural impacts, ecological degradation, and socioeconomic consequences, with risk management and policy responses at the base of the model.

5.2 Implications for Practice and Policy

The findings of this review support a tiered set of practical and policy recommendations, structured in order of priority based on evidence strength, implementation feasibility, and potential impact scale.

Priority 1 – Mandatory Susceptibility Zoning for Plantation Licensing: Governments in landslide-prone highland regions should integrate landslide susceptibility maps into statutory land use planning frameworks and require susceptibility assessment as a condition of plantation licensing and expansion approval. High and very high susceptibility zones should trigger mandatory engineering and bioengineering mitigation requirements rather than advisory guidance. This recommendation is supported by all included meta-analysis studies showing yield losses exceeding 40% in high susceptibility zones.

Priority 2 – Integration of NDVI-Based Replanting Vulnerability Windows: Agricultural extension services and plantation estate managers should adopt phased clearance protocols and mandatory cover cropping during the 2–4 year post-replanting vulnerability period identified in this review. Satellite-based NDVI monitoring systems, available at no cost through Google Earth Engine, can provide real-time identification of newly cleared slopes, enabling targeted deployment of slope protection measures during peak vulnerability windows.

Priority 3 – Early Warning System Deployment Tied to Rainfall Thresholds: The 80–120 mm/24-hour rainfall thresholds identified as critical susceptibility transition points in South Asian and Southeast Asian studies should be operationalised through automatic rain gauge networks and SMS-based early warning systems targeted at plantation workers and smallholder farmers in high susceptibility zones. Pilot programmes in Sri Lanka and Indonesia have demonstrated the feasibility and cost-effectiveness of such systems at a regional scale ([16]; [23]).

Priority 4 – Multi-Hazard Agricultural Insurance Mechanisms: The evidence of substantial and systematic yield losses in high susceptibility zones—losses that are spatially predictable through susceptibility mapping—creates a robust actuarial basis for the design of index-based agricultural insurance products specifically covering landslide risk in plantation systems. Susceptibility class can serve as the underwriting variable, with premium structures reflecting the non-linear yield-loss relationship quantified in this meta-analysis.

Priority 5 – Cross-Disciplinary Research Consortia: National agricultural research systems and international research consortia (CGIAR, national councils for scientific research) should establish formally structured cross-disciplinary collaborations bridging geomorphology, remote sensing, agronomy, and socioeconomics. The persistent disciplinary fragmentation documented in this review—between susceptibility modelling and agricultural impact quantification—represents a structural barrier to evidence-based risk governance that institutional reform can directly address.

5.3 Research Gaps and Future Research Needs

This review identifies six priority research gaps, ranked by their potential to advance both scientific knowledge and practical risk reduction.

First, longitudinal impact studies tracking plantation productivity and soil recovery across three or more growing seasons following documented landslide events are urgently needed. The current evidence base, dominated by single-season cross-sectional assessments, cannot adequately characterise cumulative economic losses or optimal recovery intervention timings for perennial tree crops with multi-decade productive lifespans.

Second, smallholder-stratified vulnerability assessments are needed to address the documented scale bias in the literature. Studies specifically designed for smallholder contexts—incorporating household income data, access to credit and extension services, land tenure security, and livelihood diversity—will be essential for designing equitable policy responses that reach the most exposed plantation producers.

Third, climate scenario integration represents a critical methodological frontier. Only seven of the included studies incorporated climate change projections into susceptibility assessments, and only two extended these analyses to projected agricultural impacts under IPCC RCP 4.5 or 8.5 scenarios. Given the IPCC projection of substantially intensified extreme rainfall in most tropical mountain belts, susceptibility assessments must systematically incorporate non-stationary rainfall inputs to remain valid planning tools across the 30–50 year investment horizons typical of tree crop plantations ([9]; [6]).

Fourth, bioengineering efficacy studies are needed to quantify the slope-stabilising effectiveness of different plantation management practices—including agroforestry intercropping, contour grass strips, terracing, and windbreak establishment—under documented field conditions. Current evidence is largely derived from geomechanical laboratory studies or modelling exercises rather than monitored field trials, limiting the translation of findings to practical extension guidance.

Fifth, socioeconomic impact assessments must be expanded to capture dimensions beyond direct yield loss, including indirect losses from infrastructure damage, labour disruption, post-disaster debt accumulation, and gender-differentiated recovery trajectories. These dimensions are not only important for understanding the full welfare costs of landslide risk but are also essential for designing equitable compensation, insurance, and social protection programmes.

Sixth, systematic validation of susceptibility models against independent landslide inventory data—particularly in African and Central Asian plantation zones where inventory data are currently sparse—is needed to assess the geographic transferability of models developed in better-studied regions. Without such validation, the application of susceptibility maps in planning contexts in data-sparse regions may generate false confidence in outputs of unknown local accuracy.

6. Conclusion

This systematic review and meta-analysis have synthesised 87 studies and conducted a rigorous quantitative analysis of 28 high-quality investigations to provide the most comprehensive evidence-based assessment to date of the relationship between landslide susceptibility and plantation agricultural impacts in mountain ecosystems. The central finding—a pooled effect size of $r = 0.68$ linking susceptibility class to crop yield loss—demonstrates that landslide hazard is a primary, not peripheral, determinant of plantation productivity in high-risk highland landscapes, with yield losses in very high susceptibility zones approaching total crop failure during severe events.

The review documents a clear methodological progression in the field over the 2017–2026 period, with ensemble machine learning and deep learning models now achieving discriminative accuracy (AUC > 0.91) that substantially exceeds earlier statistical approaches. However, this technical sophistication has not yet been matched by equivalent advances in cross-disciplinary integration: the structural gap between susceptibility mapping and quantitative agricultural impact assessment remains a defining limitation of the field, and one whose resolution must be treated as a research priority equivalent in urgency to further methodological refinements in the modelling domain.

The conceptual framework, risk matrix, and tiered policy recommendations presented in this review provide a structured, evidence-grounded foundation for translating susceptibility research into actionable governance tools. Specifically, the non-linear yield-loss response across susceptibility classes supports mandatory zoning-based regulatory approaches, the documented NDVI-vulnerability relationship supports targeted replanting management protocols, and the rainfall threshold evidence supports operationalisation through early warning systems—all within the overarching governance architecture of the Sendai Framework for Disaster Risk Reduction (2015–2030).

The evidence gaps identified—in longitudinal impact data, smallholder-focused assessments, climate scenario integration, bioengineering efficacy, socioeconomic impact dimensions, and model validation in data-sparse regions—define a focused cross-disciplinary research agenda whose prosecution will be essential for protecting the food security, livelihoods, and ecosystem integrity of the world's mountain plantation communities in an era of accelerating climate change.

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