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Research article

Integrating Eco-DRR into landslide susceptibility assessment: The critical role of eco-environmental factors

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ABSTRACT

Understanding the factors driving landslide susceptibility is essential for improving risk assessment and disaster management. Traditional assessments often emphasize structural factors such as topography and geology, while overlooking eco-environmental variables. In this case study from western Rwanda, we propose a multidimensional landslide susceptibility assessment framework grounded in Ecosystem-based Disaster Risk Reduction (Eco-DRR) principles, using a Random Forest model. The framework integrates 60 variables across nine interrelated dimensions, including structural (topography, geology, hydrology) and eco-environmental factors (soil health parameters, vegetation indices, landscape composition, and temporal dynamics). We use six model configurations combining different sets of these dimensions to assess their contribution to model performance. Our results show that models integrating both structural and eco-environmental factors achieve higher accuracy (up to 93 %) than those using only structural factors (83 %). Key predictors included traditional factors like slopes, alongside eco-environmental variables such as soil moisture or land use transition. These findings highlight the value of incorporating Eco-DRR principles in landslide susceptibility assessment by identifying key eco-environmental indicators that improve predictive accuracy. This provides actionable insights for decision-makers to design targeted ecosystem-based interventions. We provide quantitative evidence supporting recent conceptual frameworks that emphasize the importance of eco-environmental factors in landslide processes. By demonstrating the added predictive value of a multi-dimensional approach, this study provides a strong empirical foundation for enhancing disaster prevention, landscape management, and the practical implementation of Eco-DRR strategies in landslide-prone areas in landslide-prone regions like Rwanda.

1. Introduction

Landslides are among the most devastating natural hazards worldwide, occurring when masses of earth, rocks, or debris move downslope (Cruden, 1991). Their occurrence and impacts are significantly influenced by the interaction between land use patterns and ecological processes (Brander et al., 2018; Froude and Petley, 2018). For instance, urbanization and resource consumption accelerate landscape alteration, weaken ecosystems' resilience, and disrupt essential regulating ecosystem services (Foley et al., 2005; Liu et al., 2024). Such degradation increases both the likelihood and severity of landslides, which in turn further damage ecosystems, creating a destructive feedback loop (Doko et al., 2016; Faivre et al., 2018). To address this cycle, ecosystems, habitat, and biodiversity must be seen as critical assets that need to be preserved or restored (Kasada et al., 2022).

Ecosystem-based Disaster Risk Reduction (Eco-DRR) emphasizes the role of natural systems in reducing disaster risks by maintaining or restoring ecological functions (Anderson et al., 2021; Cohen-Shacham et al., 2016; Sudmeier-Rieux et al., 2013; UNDRR, 2020). Interest in Eco-DRR has grown significantly over the past two decades, particularly after the 2004 Indian Ocean tsunami, which highlighted the protective role of ecosystems against coastal hazards (Chang et al., 2006; Chatenoux and Peduzzi, 2007). Its recognition in international frameworks such as the Sendai Framework for Disaster Risk Reduction (UNDRR,

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2015) and the 2030 Agenda for Sustainable Development (United Nations, 2015) underscores its global relevance. However, its widespread adoption is hindered by limited understanding, low acceptance, and a lack of trust among decision-makers (McVittie et al., 2018; Ruangpan et al., 2019; Sudmeier-Rieux et al., 2021). Conflicting land-use priorities also hamper Eco-DRR initiatives (Imamura et al., 2016). These challenges arise from the inherent nature and complexity of ecosystems. While ecosystems provide beneficial effects, their risk reduction benefits may not be immediate, and they are not a universal solution for disaster prevention (Walz et al., 2021). Addressing these barriers requires targeted research to provide robust empirical evidence supporting Eco-DRR strategies and their practical implementation (de Jesús Arce-Mojica et al., 2019).

This study builds on the evolution of Landslide Susceptibility Assessment (LSA), a critical tool for predicting landslide-prone areas by analyzing conditioning and triggering factors (Dai et al., 2002; Yong et al., 2022). LSA has traditionally focused on static, structural predictors like slope, lithology, and curvature geology (Guzzetti et al., 1999). While foundational, these factors often fail to account for dynamic eco-environmental drivers shaped by land use and climate change (Badgley et al., 2017). Recent studies have begun to recognize the influence of eco-0environmental variables, such as Land Use Land Cover (LULC), Normalized Difference Vegetation Index (NDVI), or deforestation patterns (Huang et al., 2021; Pacheco Quevedo et al., 2023; Reichenbach et al., 2018). However, approaches remain fragmented, with these variables often used in isolation or as proxies rather than being systematically structured within a conceptual framework that captures ecological complexity and temporal variability (Broquet et al., 2024; Pisano et al., 2017). For example, while LULC and NDVI are both widely used in LSAs to capture the combined effects of human activity and environmental degradation on landslide risk (Ferchichi et al., 2022; Pacheco Quevedo et al., 2023), their temporal fluctuations, and thus their evolving influence on landslide dynamics, are often overlooked (Alexander, 1992; Hasan et al., 2020; Tyagi et al., 2023). Moreover, although the inclusion of such variables is becoming more common, factor selection remains inconsistent and fragmented, with no standardized methodology (Huang et al., 2022; Pourghasemi et al., 2018). While factor analysis is commonly employed to select influencing factors of landslides, existing studies tend to focus more on the performance of statistical and machine learning tools than on models' performance based on selected factors (Bui et al., 2016; Yalcin, 2008). However, the comprehensive and structured integration of eco-environmental dimensions remains underdeveloped (Arrogante-Funes et al., 2021, 2022).

Traditional LSA approaches rely heavily on static structural factors like slope, lithology, and geology, which primarily support reactive or avoidance-based DRR strategies, such as building barriers or restricting development in high-risk zones (Spiker and Gori, 2003; UNDRR, 2015). In contrast, the Eco-DRR framework promotes proactive prevention through ecosystem-based interventions that can modify landscape conditions and reduce vulnerability (Renaud et al., 2016). While integrating eco-environmental variables into LSA models holds promise for advancing this paradigm, empirical validation is needed to demonstrate that such integration meaningfully improves both prediction and prevention (Sudmeier-Rieux et al., 2021).

Conceptual advances such as Sidle's ecological framing of landslides (Sidle and Bogaard, 2016) and Reichenbach's support for multidimensional factor integration (Reichenbach et al., 2018) have laid important foundations. However, these efforts often stop short of embedding eco-environmental dimensions into predictive LSA models. Similarly, while ecosystem health frameworks like Pressure-State-Response, Vigor-Organization-Resilience, or InVEST offer valuable insights, they are rarely operationalized in landslide modeling (Aneseyee et al., 2020; Bao et al., 2022; Fu et al., 2021; Zhang et al., 2023). Despite the shared use of remote sensing and spatial modeling in both LSA and ecosystem assessment, the two domains remain largely disconnected (Guzzetti et al., 2012; Kumar et al., 2021; Renaud et al., 2016). Yet, ecosystem assessments also face challenges due to the absence of standardized approaches and the complexity of models (Eason et al., 2016; Soubry et al., 2021). This complexity notably arises from the need to balance multiple eco-environmental variables, which can vary significantly across different landscapes and conditions (Wang et al., 2022). This points to a critical gap between theoretical potential and practical application of Eco-DRR within LSA.

To address this, our study proposes a multidimensional, conceptually grounded LSA framework that integrates Eco-DRR principles. Rather than treating eco-environmental variables as peripheral or static, we embed them alongside structural predictors, reflecting their dynamic and systemic roles in landslide processes. It represents a logical progression of emerging trends that increasingly recognize the role of eco-environmental factors in landslide dynamics. Inspired by structural equation modeling, we organize 60 variables into nine interrelated dimensions, spanning both structural and eco-environmental domains, a significant advancement over previous studies that typically examined limited factor sets in isolation. To analyze the interplay of diverse and often correlated eco-environmental and structural factors, we employed a Random Forest (RF) model. RF is widely recognized for its applicability in geospatial and environmental modeling, offering strong predictive performance and interpretability across heterogeneous landscapes (Al-Wardy et al., 2025). Compared to other tree-based models, RF provides a balance of robustness, scalability, and resilience to noise and multicollinearity, features especially valuable in complex, multi-dimensional datasets characteristic of LSA (Belgiu and Drăgu, 2016; Rodriguez-Galiano et al., 2015). Its ensemble nature ensures reliable performance without extensive tuning, making it a methodologically and pragmatically suitable choice for integrating ecological and structural variables within an Eco-DRR framework (Cutler et al., 2007; Merghadi et al., 2020).

This conceptual shift motivates our central research question: How does integrating eco-environmental factors enhance the performance of LSA models within an Eco-DRR framework? To address this, we tested two hypotheses. First, models incorporating eco-environmental factors predict landslide susceptibility more accurately than traditional models focused on static factors. Second, dynamic eco-environmental factors are key predictors of landslide risk. In our study, Accordingly, the study pursues two main objectives: (1) to empirically evaluate whether models incorporating eco-environmental factors outperform traditional models and (2) to explore methodologically which, and how, eco-environmental factors influence landslide susceptibility. We test our framework through a case study in Rwanda, a region with high landslide susceptibility and pronounced eco-environmental pressures. By bridging structural and ecological perspectives, this research advances LSA methodology and lays a foundation for more effective Eco-DRR applications.

2. Methods

2.1. Overview of the research methodological approach

To achieve the study's objectives, a structured six-stage workflow was implemented (Fig. 1), following a standard LSA process. The workflow begins with a landslide inventory, documenting past landslide locations (Guzzetti et al., 2012). In the second stage, conditioning factors were identified and categorized into nine dimensions, spanning ecological processes, environmental conditions, and LULC change which bridges both domains. In our study, the term "eco-environmental" was adopted to encompass this full spectrum of interrelated factors, acknowledging that landslide susceptibility emerges from complex interactions between living systems and their physical context. Based on these dimensions, six multi-dimensional models were developed in the third stage, while each dimension also formed a single-dimensional model, as illustrated in the fourth step. In the fifth stage, all models were trained and evaluated using RF. Finally, their performance was

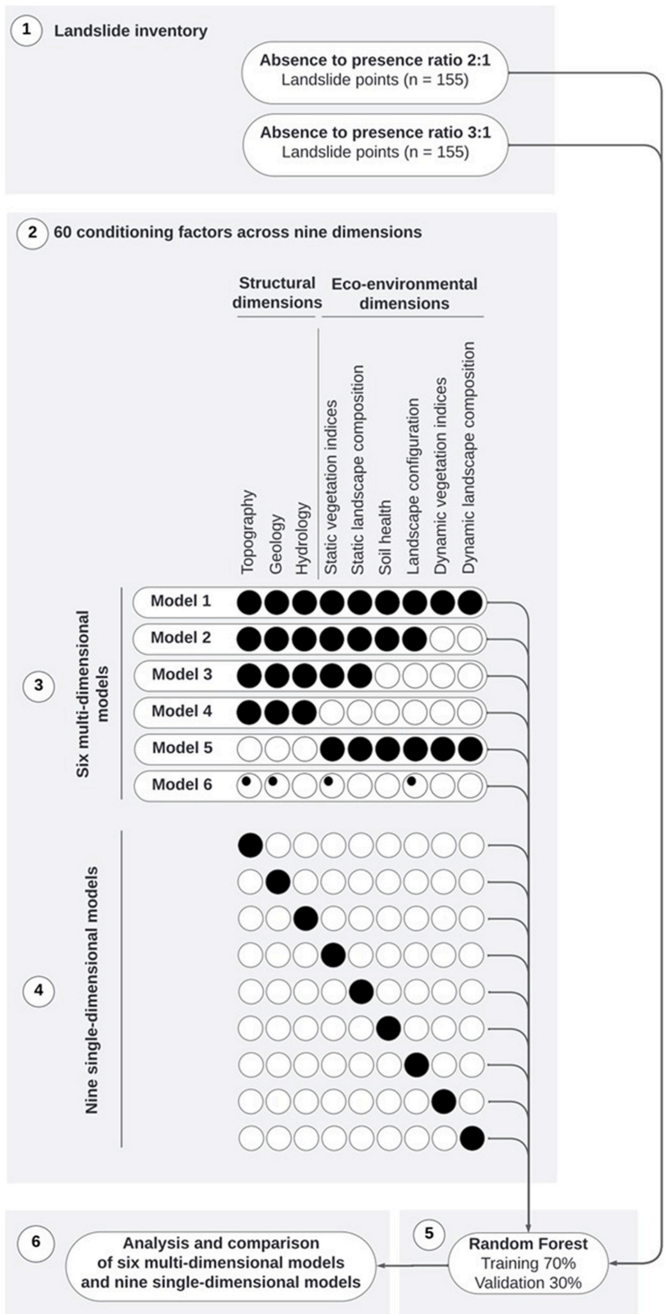

Fig. 1. Overview of the research methodological approach. This figure illustrates the six main steps of the study: (1) preparation of the landslide inventory; (2) preparation of conditioning factors across nine dimensions; (3) and (4) development of six multi-dimensional and nine single-dimensional models; (5) running of models using Random Forest (RF); and (6) analysis and comparison of models.

compared in the last stage to assess their effectiveness and the relative contribution of different factor dimensions to landslide prediction performance. To address our specific research questions, following (Goetz et al., 2015), we focused our methodological approach on comparative model performance and factor importance analysis rather than to produce a comprehensive susceptibility zonation map.

2.2. Study area

Rwanda, located in Central-East Africa, is highly susceptible to landslides due to its predominantly mountainous terrain and intense seasonal rainfall, the dominant triggering mechanism for landslides in the region (Dewitte et al., 2021; Uwihirwe et al., 2022). Over the past decade, a growing body of research has examined the physical, environmental, and anthropogenic drivers of landslides in the region. A key focus of many studies has been on the environmental drivers, environmental factors such as deforestation dynamics (Depicker et al., 2021a) and land cover changes (Safari Kagabo et al., 2024); anthropogenic influence such as agricultural terracing practices (Sibomana et al., 2025) and population density (Imasiku and Ntagwirumugara, 2020). Research methodologies have evolved alongside the growing understanding of these factors. A variety of modeling techniques have been employed to assess landslide susceptibility in the region (Li et al., 2022b; Nsengiyumva et al., 2019; Nsengiyumva and Valentino, 2020).

However, while these studies have made significant contributions to understanding the drivers of landslides, they often examine individual factors in isolation or as static inputs, Notably, while previous research recognizes various eco-environmental factors, it generally approaches them from hazard assessment or geomorphological perspectives rather than conceptualizing ecosystems as integrated solutions for disaster risk reduction within an Eco-DRR framework.To our knowledge, this is one of the first empirical studies in Rwanda to evaluate a comprehensive set of eco-environmental factors and assess their relative importance for landslide susceptibility through an Eco-DRR lens. Given the diversity and complexity of influencing factors, Rwanda presents an ideal empirical setting to test a multidimensional approach to LSA. This study builds on the region's existing research foundation while advancing an integrative framework that explicitly incorporates eco-environmental dimensions into landslide modeling within the Eco-DRR paradigm.

This study focuses on West Rwanda, specifically the districts of Rubavu, Rutsiro, and Karongi, which border Lake Kivu. These districts were among the hardest hit by a torrential rainfall event during the first ten days of May 2023, which triggered landslides and flooding. This disaster resulted in at least 130 deaths, widespread destruction of homes and infrastructure, and the displacement of thousands of people. The study area lies between longitudes 28.861731° E to 30.899747° E and latitudes 1.047167° N to −2.840230° S, covering an area of 1789 km2 (Fig. 2). Elevation ranges from 1456 to 2913 m above sea level. According to the 2023 LULC map from the Esri Sentinel-2 Land Cover Explorer, the area consists of cropland (45 %), rangeland (24 %), trees (19 %), and built area (12 %).

The region serves as an ideal test case for our methodological framework due to its complex interplay of topographic, climatic, ecological, and anthropogenic factors affecting landslide susceptibility. Rather than focusing on site-specific applications, our research uses this diverse landscape to test theoretical approaches for integrating multidimensional eco-environmental factors into landslide susceptibility models—approaches that can potentially be adapted to various geographic contexts worldwide.

2.3. Landslide inventory

A single event-based landslide inventory dataset was used, ensuring that all presence points correspond to the same event, i.e., a torrential rainfall episode in Rwanda in early May 2023. This methodological choice was intentional to minimize temporal bias by focusing on the immediate influences of a specific rainfall event on relevant conditions that contributed to the landslides, such as vegetation cover and soil moisture at the time of the event (Ma et al., 2024; Oliveira et al., 2024). In contrast, using historical data from multiple landslide events may not accurately reflect environmental conditions during each event, potentially introducing bias and variability due to the changes from deforestation or urbanization (Li et al., 2022a). This focus aligns with the principles of Eco-DRR and is crucial for our study's emphasis on conditioning factors.

The landslide inventory, counting 155 evidence points, was obtained

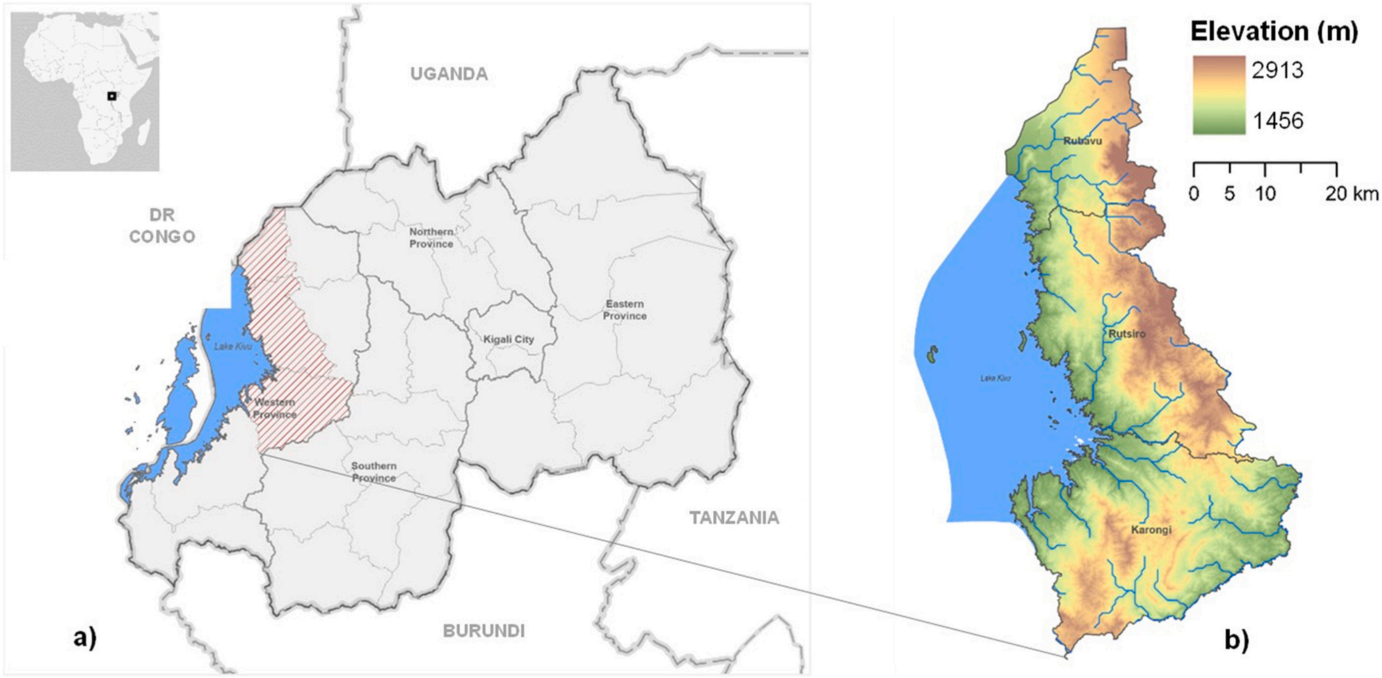

Fig. 2. Study area. a) Administrative map of Rwanda with the study area outlined in red dashes; b) Elevation map (in meters) of the study area, covering the districts of Rubavu, Rutsiro and Karongi.

from the Global Landslide Catalog (GLC) (Kirschbaum et al., 2010, 2015). While the dataset has known limitations (including a modest sample size, potential spatial inaccuracies, and a lack of detail on landslide types or sizes), it is well-suited to the scale and goal of our analysis, which focuses on identifying general patterns of landslide susceptibility instead of trying to predict exact landslide locations. As noted by Petschko et al. (2014), while larger inventories are preferable, smaller samples can still provide reliable insights into factor importance and relative susceptibility patterns when appropriately analyzed.

Incorporating landslide absence data improves predictive accuracy, mitigates bias, and enhances the model's ability to distinguish between susceptible and non-susceptible areas (Zhu et al., 2018). In this study, non-landslide sample points were randomly generated within the study area using two absence/presence ratios. A higher ratio (3:1) provides more information on non-landslide conditions, thereby improving the model's ability to generalize, while a lower ratio (2:1) prevents the model from being overwhelmed by absence points, thus maintaining the influence of presence points. A 500-m exclusion buffer was applied around the evidence points (Hong, 2023) to reduce the likelihood of selecting areas too close to the landslide sites, avoiding spatial bias and ensuring better differentiation between landslide and non-landslide conditions. In the 2:1 ratio scenario, 310 absence points were randomly generated; however, four points were excluded because they fell within a 500-m exclusion buffer around landslide points resulting in a final dataset of 461 points (306 absence and 155 presence). In the 3:1 ratio scenario, 465 absence points were generated, with eight points excluded, leading to a final dataset of 612 points (457 absence and 155 presence).

2.4. Landslide conditioning factors

The subsequent step in the LSA process involved identifying the key factors influencing landslide occurrence, given the absence of a universally established list in the existing literature. A common distinction is drawn between triggering factors, which are linked to short-term events such as intense rainfall, and conditioning factors, which determine landslide susceptibility under longer-term conditions (Meena et al., 2022a). In this study, conditioning factors were selected based on their documented influence on landslide susceptibility and their capacity to reflect and influence ecosystem health. They were categorized into nine dimensions, each grouping a unique combination of conceptually linked factors. Each dimension reflected either structural or eco-environmental aspects of landslide dynamics (Broquet et al., 2024). A detailed description of the 60 factors, along with their relevance within an Eco-DRR framework, is provided in Supplementary Material 1.

Three "structural" dimensions refer to inherent, stable physical characteristics of the landscape that are less influenced by human intervention or short-term environmental changes: topography, geology, and hydrology (Kayastha et al., 2013). These topographic, hydrological, and geology-related factors are key drivers of landscape stability and eco-environmental health, particularly in the Eco-DRR context, where physical stability, water dynamics, and soil characteristics are interrelated (Pepin and Lundquist, 2008; Shiqiang et al., 2024; Yang et al., 2020). Lastly, proximity to fault lines, while not directly triggering landslides, can increase their likelihood by altering hydrological processes and making slopes more vulnerable to seismic activity (Rahman et al., 2022). This is particularly relevant for Rwanda, which lies in an active tectonic region near the East African Rift System (Oth et al., 2017).

In contrast, six "eco-environmental" dimensions represent dynamic and human-modified characteristics that influence how landscapes respond to environmental changes: soil health, static vegetation indices, dynamic vegetation indices (temporal changes over years), static landscape composition, dynamic landscape composition (temporal changes over years), and landscape configuration (Li and Duan, 2024; Pacheco Quevedo et al., 2023). For example, soil health factors, although less commonly used in traditional LSAs, play a critical role in Eco-DRR. Chemical soil elements, such as Soil Organic Carbon (SOC), pH, and nitrogen levels, influence vegetation growth and slope stability (Cao et al., 2024). Similarly, vegetation indices provide valuable insights; while the NDVI is widely used for its simplicity, alternative indices offer a better assessment of vegetation health, density, and ecological conditions across varying environments (Huang et al., 2021; Vélez et al., 2023). Static vegetation indices from 2023 highlight areas with low vegetation prone to erosion, while dynamic factors like vegetation loss (2008–2023) and proximity to land cover changes highlight the evolution of land cover linked to landslides (Law et al., 2024). Landscape composition, configuration and dynamics are crucial in understanding landslide susceptibility as they influence slope stability, hydrological processes, soil erosion, vegetation health, and water retention (Pacheco Quevedo et al., 2023). In this study, static landscape composition was defined by LULC types at the time of the landslide event. Population density was considered as a factor that reflects how densely populated areas may alter landscapes through construction, deforestation, which can exacerbate landslide susceptibility (WorldPop). Dynamic LULC transitions from 2017 to 2023 (e.g., 'Trees to Built area'; 'Crops to Built area'; 'Rangeland to Built area'; The 'Trees to Crops') revealed how human activities and ecological changes reduce stabilizing vegetation, increase impervious surfaces, and weaken soil stability, driving erosion and runoff. Finally, the spatial configuration of LULC plays an important role in landslide susceptibility. Forest fragmentation and logging, for instance, significantly increase landslide susceptibility in non-protected areas (Shirvani, 2020). Four landscape configuration metrics were analyzed, including distance to roads, distance to patch diversity (measuring surrounding pixels with varied LULC types within a perimeter three times the pixel size), and distance to critical patches. Larger patches of trees, crops, or rangeland stabilize slopes more effectively than smaller ones due to their stronger root systems.

All datasets needed to evaluate the conclusions in the paper (see Supplementary Material 2) were downloaded in September 2024 from open-source repositories, ensuring reproducibility. To address potential data issues and maintain consistency, all raster datasets were processed into the same projected coordinate reference system (WGS, 1984 UTM Zone 35S), spatially aligned, and resampled to a common 30m spatial resolution to ensure consistent pixel correspondence across layers (Fig. 3). Vector datasets were converted to raster format at 30m resolution for inclusion in the modeling framework. This resolution was chosen as a compromise between preserving detail in high-resolution datasets while accommodating the lower resolution of some global products. Subsequently, where missing values were present, they were filled using a focal statistics approach based on the majority value within a 25 × 25 cell window. The 25 × 25 window size was selected as a compromise between capturing sufficient contextual information and maintaining spatial detail, consistent with established practices for categorical raster smoothing and gap-filling (Chen et al., 2017; Maxwell et al., 2018). The use of RF modeling, known for its robustness to resolution disparities, helps address the trade-offs involved in combining datasets of varying original resolutions into a common 30m scale (Goetz et al., 2015). All data processing and modeling in this study were performed using ArcGIS Pro version 3.3 (ESRI, 2024).

After this preliminary analysis, 60 factors were retained across the nine dimensions. While the factors within each dimension are inherently related, they also complement each other to represent the complexity of the landscape. The nine dimensions were organized into six main models incorporating structural and eco-environmental dimensions to varying degrees (Table 1). Model 1 was the most comprehensive model, including all structural and eco-environmental factors across the nine dimensions. Model 2 focused on all static variables, excluding the two

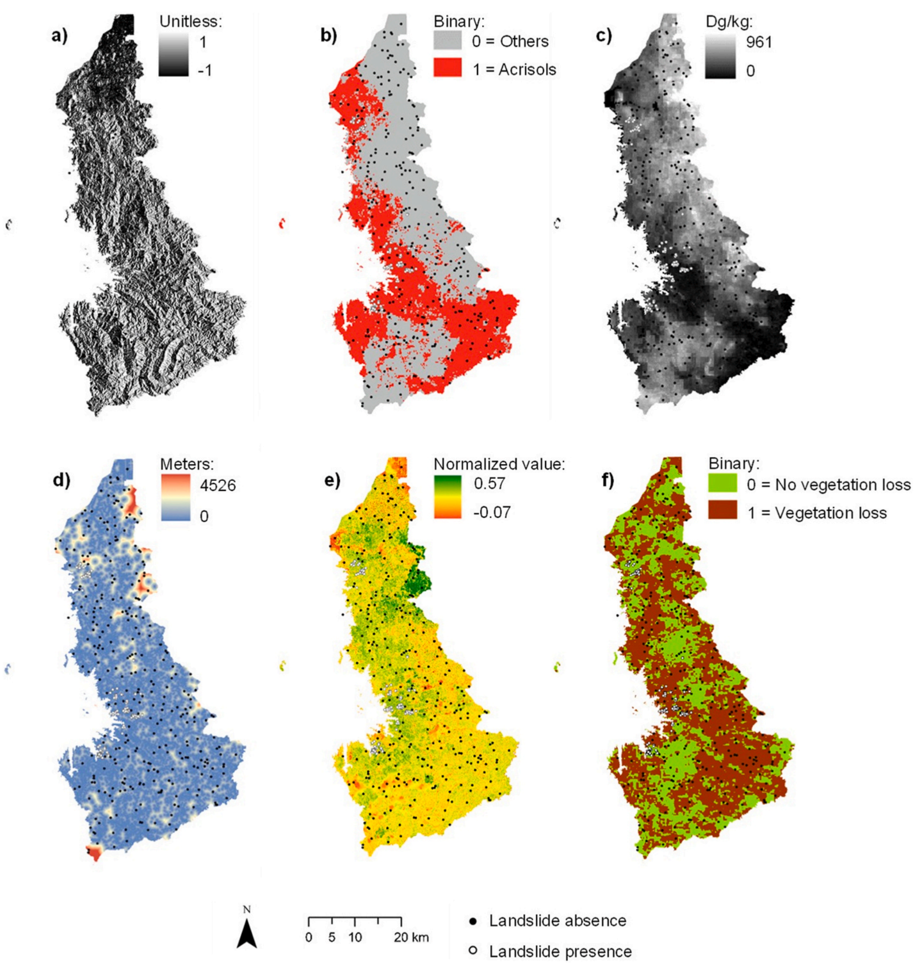

Fig. 3. Example maps of landslide conditioning factors. a) Aspect Sin (unitless); b) Acrisols (binary, where 1 = Acrisols, and 0 = Other soil classes); c) SOC (in dg/kg); d) Distance to a critical patch (in meters); e) NDVI 2023 [Landsat] (normalized value); f) NDVI negative change 2008–2023 (binary, where 1 = Vegetation loss and 0 = No vegetation loss).

Table 1
Structural ([S]) and eco-environmental ([E]) factors selected. The 60 factors are classified into nine dimensions and assigned to six multidimensional models.

Dimension	Factor	Model					
		1	2	3	4	5	6
Topography[S]	Elevation	●	●	●	●	–	–
	Slope	●	●	●	●	–	●
	Aspect Sin	●	●	●	●	–	●
	Aspect Cos	●	●	●	●	–	●
	Profile curvature	●	●	●	●	–	●
	Plan curvature	●	●	●	●	–	●
	Terrain Ruggedness Index (TRI)	●	●	●	●	–	–
	Vector Ruggedness Measure (VRM)	●	●	●	●	–	–
Geology[S]	Lithology – basic volcanics	●	●	●	●	–	–
	Lithology – metamorphics	●	●	●	●	–	●
	Lithology – unconsolidated sediments	●	●	●	●	–	–
	Soil class – Acrisols	●	●	●	●	–	–
	Soil class – Andosols	●	●	●	●	–	–
	Soil class – Cambisols	●	●	●	●	–	–
	Soil class – Ferrasols	●	●	●	●	–	–
	Soil class - Luvisols	●	●	●	●	–	–
	Physical soil – Clay content at depth 0–30 cm	●	●	●	●	–	–
	Physical soil – Sand content at depth 0–30 cm	●	●	●	●	–	–
	Physical soil – Silt content at depth 0–30 cm	●	●	●	●	–	–
	Physical soil - Coarse fragments at depth 0–30 cm	●	●	●	●	–	–
	Distance to fault	●	●	●	●	–	●
Hydrology[S]	Distance to river	●	●	●	●	–	–
	Distance to lake	●	●	●	●	–	–
	Topographic Wetness Index (TWI)	●	●	●	●	–	–
	Stream Power Index (SPI)	●	●	●	●	–	–
	Sediment Transport Index (STI)	●	●	●	●	–	–
Static vegetation indices[E]	NDVI 2023 [MODIS]	●	●	●	–	●	●
	Enhanced Vegetation Index (EVI) 2023	●	●	●	–	●	–
	Net Primary Productivity (NPP) 2023	●	●	●	–	●	–
	Leaf Area Index (LAI) 2023	●	●	●	–	●	–
	NDVI 2023 [Landsat]	●	●	●	–	●	●
	Soil-Adjusted Vegetation Index (SAVI) 2023	●	●	●	–	●	–
Static landscape composition[E]	LULC 2023 - Water	●	●	●	–	●	–
	LULC 2023 - Trees	●	●	●	–	●	–
	LULC 2023 - Flooded vegetation	●	●	●	–	●	–
	LULC 2023 - Crops	●	●	●	–	●	–
	LULC 2023 - Built area	●	●	●	–	●	–
	LULC 2023 - Bareground	●	●	●	–	●	–
	LULC 2023 - Rangeland	●	●	●	–	●	–
	Population density	●	●	●	–	●	–
Soil health[E]	Chemical soil - pH water at depth 0–30 cm	●	●	–	–	●	–
	Chemical soil - Nitrogen at depth 0–30 cm	●	●	–	–	●	–
	Chemical soil - SOC at depth 0–30 cm	●	●	–	–	●	–
	Normalized Difference Moisture Index (NDMI) 2023	●	●	–	–	●	–
Landscape configuration[E]	Distance to a critical patch	●	●	–	–	●	–
	Distance to patch diversity	●	●	–	–	●	–
	Distance to roads (all types)	●	●	–	–	●	●
	Distance to roads (only highway, primary, secondary, tertiary)	●	●	–	–	●	●
Dynamic vegetation indices[E]	NDVI negative change 2008–2023	●	–	–	–	●	–
	Distance to NDVI negative change 2008–2023	●	–	–	–	●	–
	EVI negative change 2008–2023	●	–	–	–	●	–
	Distance to EVI negative change 2008–2023	●	–	–	–	●	–
	NPP negative change 2008–2023	●	–	–	–	●	–
	Distance to NPP negative change 2008–2023	●	–	–	–	●	–
	LAI negative change 2008–2023	●	–	–	–	●	–
	Distance to LAI negative change 2008–2023	●	–	–	–	●	–
Dynamic landscape composition[E]	Distance to transition 2017–2023 from (Trees) to (Built area)	●	–	–	–	●	–
	Distance to transition 2017–2023 from (Crops) to (Built area)	●	–	–	–	●	–
	Distance to transition 2017–2023 from (Rangeland) to (Built)	●	–	–	–	●	–
	Distance to transition 2017–2023 from (Trees) to (Crops)	●	–	–	–	●	–

dimensions reflecting dynamic eco-environmental factors over time. Model 3 incorporated the three structural dimensions along with two eco-environmental dimensions: "Static vegetation indices" and "Landscape composition", including the traditionally used NDVI and LULC factors. However, it excluded dynamic dimensions, as in Model 2, as well as "Soil health" and "Landscape configuration" dimensions, which are less commonly used than NDVI- and LULC-related factors. Model 4 included only the three traditionally used structural factors: "Topography", "Geology", and "Hydrology". Model 5 isolated exclusively eco-environmental factors while excluding structural dimensions ("Topography", "Geology", and "Hydrology"). While all previous models used the same set of factors for each dimension, Model 6 selected the traditionally most commonly used conditioning factors in certain dimensions (e.g., slope, aspect, curvature, lithology, distance to fault, NDVI, and distance to roads).

2.5. Modeling and performance analysis

Random Forest (RF) is a widely used ensemble learning algorithm suitable for both classification and regression tasks (Schonlau and Zou, 2020). It constructs multiple decision trees using bootstrapped datasets and introduces random feature selection at each node split, promoting model diversity, reducing overfitting and enhancing model generalization. It estimates feature importance using permutation importance, which measures the increase in prediction error when a feature's values are randomly permuted while all other features remain unchanged (Al-Wardy et al., 2025). The final output is derived from the aggregated predictions of all trees in the ensemble. Empirical research in geospatial modeling consistently demonstrates RF's robustness, strong predictive performance, and adaptability in environmental applications, particularly in LSAs (Goetz et al., 2015; Hengl et al., 2018).

In this study, RF was selected due to its methodological advantages in addressing key challenges posed by the dataset: a limited sample size (155 landslide presence points), class imbalance (306 or 457 pseudo-absence points in two scenarios), and high predictor dimensionality (60 variables). A key reason for RF's selection is its inherent robustness to overfitting and multicollinearity. Unlike linear regression models, where multicollinearity can destabilize coefficient estimates and reduce interpretability, or single decision trees, which tend to overfit by repeatedly selecting dominant or correlated features, RF offers a more robust approach. It addresses these issues by averaging predictions across multiple decorrelated trees, each built on bootstrapped samples and random subsets of features (Breiman, 2001; Merghadi et al., 2020). This randomization framework not only regularizes the model but also enhances generalizability, a particularly important advantage when working with one-event landslide datasets that often exhibit spatial sparsity and underrepresent variability across the landscape (Breiman, 2001; Brenning, 2005). Moreover, studies have shown that removing correlated variables based on multicollinearity criteria may not always improve RF performance, as correlated features may contribute complementary information, especially in ecological contexts models (Genuer et al., 2010; Gregorutti et al., 2017).

RF is also more resilient to noise and outliers than other tree-based approaches. Since each tree is trained on a different subset of the data, the influence of noisy or extreme values is diluted across the ensemble. In contrast, gradient boosting methods, for instance, which build trees sequentially to correct previous errors, can overemphasize such anomalies, potentially destabilizing the model and reducing generalization performance (Dou et al., 2019). Additionally, boosting approaches often require more careful hyperparameter tuning and larger sample sizes to avoid overfitting in small-to-medium datasets (Probst and Boulesteix, 2017).

To isolate the impact of different factor combinations, we treated the predictor sets as the primary variable of interest while holding all other parameters constant. This controlled approach ensured that variations in model performance could be attributed solely to the input variables rather than model settings. The RF model parameters (number of trees: 500; tree depth: 30; leaf size: 5) were selected based on established best practices in environmental modeling and study-specific considerations (Belgiu and Drăgu, 2016; Merghadi et al., 2020; Probst and Boulesteix, 2017; Taalab et al., 2018). These parameter values were chosen to offer an optimal balance between model complexity, generalization ability, overfitting risk and computational efficiency of geospatial applications. These parameters were consistently applied across all models in accordance with established methodologies for comparative model evaluation (Goetz et al., 2015). Given that our study's primary objective was to systematically compare the performance of different multi-dimensional sets of conditioning factors rather than achieving maximum predictive performance for a single model configuration, we deliberately did not employ an hyperparameter optimization method of the RF model. Hyperparameter optimization could introduce bias, making it unclear whether performance differences were due to the variables themselves or the tuning process (Probst and Boulesteix, 2017). This intentional standardization was critical to ensure that performance variations could be attributed solely to differences in predictor variable sets by eliminating bias from model-specific optimization (Probst et al., 2019). This approach aligns with established protocols for controlled experimental design in machine learning, where parameter standardization is essential for valid comparisons (Boulesteix et al., 2013). Additionally, RF is widely recognized for its robustness to hyperparameter settings, often delivering strong predictive performance across a range of domains with minimal tuning (Fernández-Delgado et al., 2014). In the context of small-to-medium sample sizes, as in our study, the expected performance gains from hyperparameter optimization are likely to be marginal relative to the increased computational burden and risk of overfitting associated with nested cross-validation across multiple predictor sets. The datasets were divided between training (70 %) and validation (30 %) subsets (Dou et al., 2019).

Models were evaluated using three metrics: accuracy, Matthews Correlation Coefficient (MCC), F1-score. The formulas for these metrics are provided in Supplementary Material 3. Thresholds were determined based on insights from a comprehensive literature review (Meena et al., 2022b; Sharma et al., 2024). Accuracy corresponds to the percentage of correct predictions made by the model. A high accuracy indicates good overall performance, with 70 % or higher considered acceptable. MCC measures the quality of binary classifications by considering true and false positives and negatives (Chicco and Jurman, 2020). It ranges from −1 (total disagreement) to 1 (perfect prediction). An MCC value of 0 indicates random guessing; above 0.5, MCC is indicative of a good model performance; while values closer to 1 signify a strong predictive ability. F1-score balances precision and recall, making it particularly useful in cases of imbalanced data (e.g., comparing landslide presence vs. absence). It ranges from 0 to 1, with 1 indicating a perfect balance between precision (the proportion of true positives among all positive predictions) and recall (the proportion of true positives among all actual positives). An F1-score above 0.5 is considered acceptable, while scores above 0.7 indicate good model performance. In addition to accuracy, MCC, and F1-score, we also calculated sensitivity, specificity, and precision to provide a more detailed assessment of model performance. Definitions and results for these additional metrics are provided in Supplementary Material 4. No formal statistical significance testing was conducted between models; therefore, the observed differences in performance metrics should be interpreted as indicative of potential patterns rather than definitive statistical conclusions. At the factor level, the "Top Variable Importance" table generated by the RF tool in ArcGIS Pro was used to analyze the 20 factors with the highest contribution to the most performant model's predictive accuracy.

3. Results

3.1. Performance of multi-dimensional models

Results begin with an evaluation of six multi-dimensional models and a comparison among them (Fig. 4). Prediction maps for landslide susceptibility were generated for each model, showcasing the selected predictive accuracies to illustrate the variability in predictions across the tested models (Fig. 5).

Model 1 exhibited excellent overall performance in both the 2:1 and 3:1 scenarios (Fig. 5). With accuracy values of 92 % and 93 % respectively, the model demonstrated reliable predictions. The MCC of 0.82 in the 2:1 scenario, which increased to 0.84 in the 3:1 scenario, highlights its robust predictive ability by considering both true and false positives and negatives. The F1-scores of 0.91 and 0.92 further emphasize the model's excellent balance between precision and recall. Overall, the 3:1 scenario showed a slight improvement over the 2:1 scenario for Model 1, but both perform excellently. As the most comprehensive model, incorporating structural and eco-environmental factors across dimensions, Model 1 outperformed the other models under both scenarios.

Model 2 also showed very strong performance in both absence/presence scenarios, with, respectively, accuracy values of 93 % and 91 %, MCC values of 0.84 and 0.79, and F1-scores of 0.92 and 0.89. Overall, Model 2, which includes all static dimensions but excludes dynamic eco-environmental ones, performed excellently as well. It performed better than Model 1 in the 2:1 scenario but showed a slight decline in performance metrics in the 3:1 scenario, making it the second highest performing model.

Model 3 achieved good and consistent results in both scenarios, with an accuracy of 87 %, MCC of 0.71, and F1-score of 0.85. These results indicate steady performance across both scenarios. This model, which includes fewer eco-environmental dimensions than Models 1 and 2, demonstrates lower performance.

Model 4 focuses solely on traditional structural dimensions ("Topography", "Geology", and "Hydrology"). It yielded, for the 2:1 and 3:1 ratios, accuracy of 83 % and 83 %, MCC of 0.61 and 0.59, and F1-

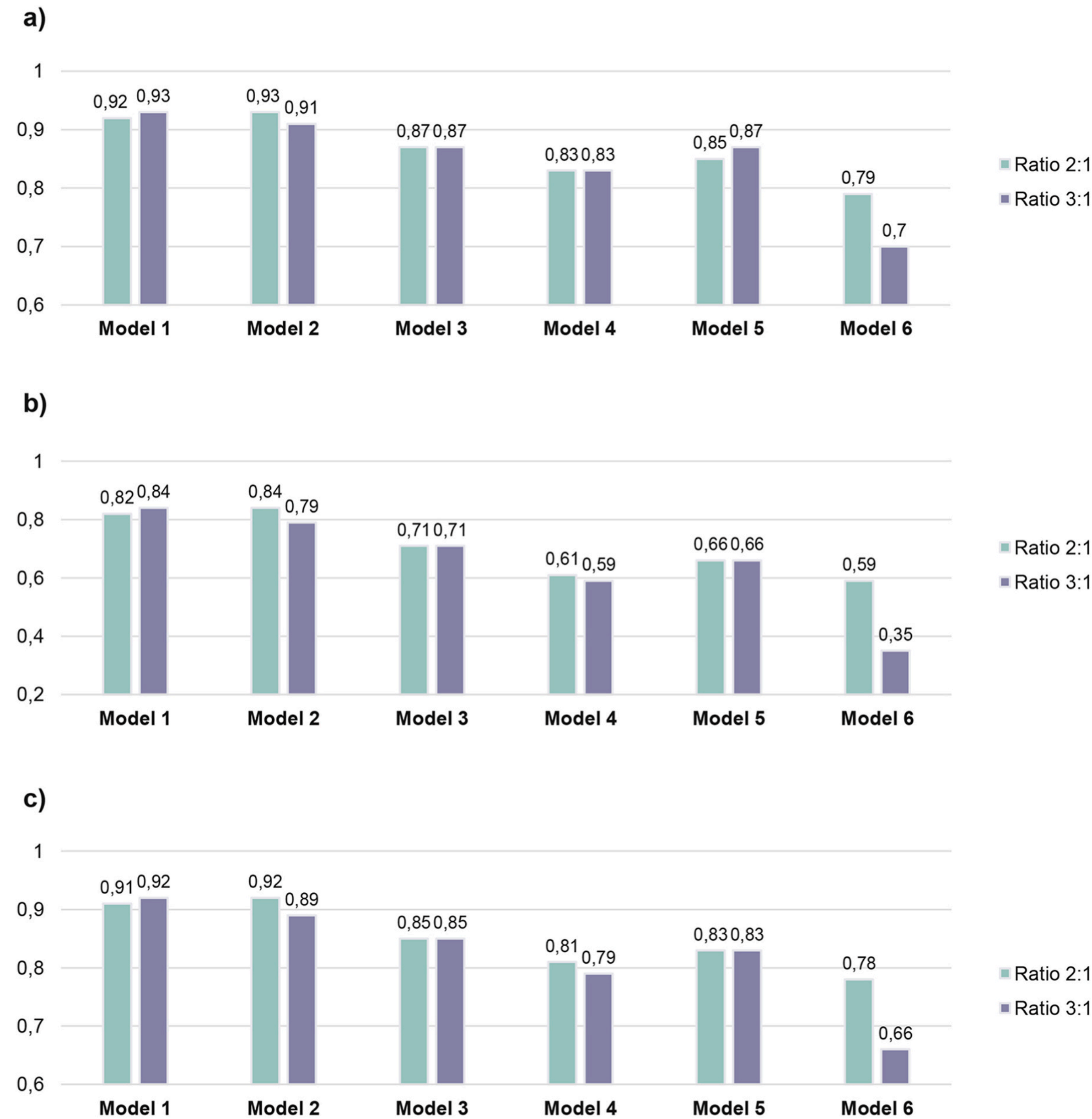

Fig. 4. Performance results across three metrics. Histograms of a) Accuracy, b) MCC, and c) F1-score for the six multi-dimensional models under absence/presence scenarios 2:1 and 3:1.

score of 0.81 and 0.79. This model's performance is acceptable, but notably lower than the three previous models that included eco-environmental dimensions.

Model 5, which isolates eco-environmental dimensions, performed reasonably (with accuracy of 85 % and 87 %, MCC of 0.66 and 0.66, and F1-score of 0.83 and 0.83, respectively, for both ratios). Its performance is better than for Model 4, but did not surpass the more comprehensive Models 1, 2 and 3.

Finally, Model 6, which uses a simplified set of conditioning factors, showed the lowest performance across all metrics, particularly in the 3:1 scenario. Its accuracy dropped from 79 % (2:1 ratio) to 70 % (3:1 ratio), while its MCC declined from 0.59 to 0.35, and its F1-score from 0.78 to 0.66.

3.2. *Single-dimensional model performance*

The performance of each of the nine single-dimensional models was evaluated using the same three metrics, which collectively provide insight into each model's predictive ability (Fig. 6). The general trends showed that the "Soil health" dimension consistently outperformed other models across both scenarios, achieving the highest metrics: accuracy (81 %), MCC (0.62), and F1-score (0.80) in the 2:1 ratio, and accuracy (80 %), MCC (0.55), and F1-score (0.76) in the 3:1 ratio. This suggests that soil health is highly effective in identifying landslide susceptibility.

Six other dimensions, namely "Topography", "Geology", "Hydrology", "Static vegetation indices", "Static landscape composition" and "Dynamic landscape composition" demonstrated relatively similar and acceptable performance. Accuracies ranged from 66 % ("Static landscape composition" in the 2:1 scenario) to 78 % ("Hydrology" in the 3:1 scenario). Similarly, F1-scores varied from 0.65 ("Hydrology" and "Static landscape composition" in the 2:1 scenario) to 0.74 ("Static vegetation indices") in 2:1 scenario and "Geology" in the 3:1 scenario). However, MCC values remain low, peaking at 0.53 ("Geology" in the 3:1 scenario) and dropping as low as 0.32 ("Static landscape composition" in the 2:1 scenario).

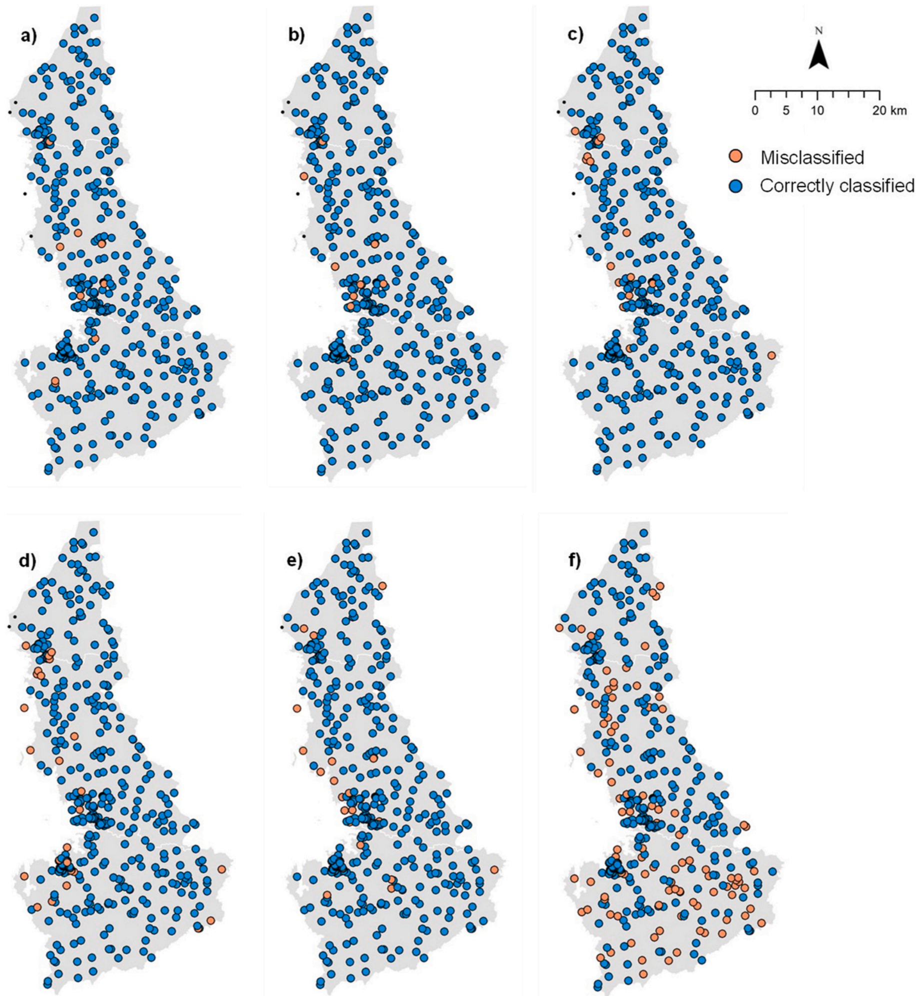

Fig. 5. Landslide susceptibility prediction maps. Maps illustrate correctly classified (blue) and misclassified (red) prediction points, under a 2:1 absence/presence points scenario, for a) Model 1 (accuracy: 0.92), b) Model 2 (accuracy: 0.93), c) Model 3 (accuracy: 0.87), d) Model 4 (accuracy: 0.83), e) Model 5 (accuracy: 0.85), and f) Model 6 (accuracy: 0.79).

Overall, these six single-dimensional models showed slightly better performance under the 3:1 scenario. The last two dimensions, "Landscape configuration" and "Dynamic vegetation indices", were the least effective models in both scenarios. The highest accuracy was 60 % ("Landscape configuration in the 2:1 scenario); F1-scores ranged from 0.46 to 0.58 across both dimensions and scenarios; and MCC values did not exceed 0.32. These two single-dimensional models showed slightly better performance under the 2:1 scenario. Comparing the performance of single-dimensional models with multi-dimensional models, the former generally exhibited lower metrics in the 2:1 scenario, except for the "Soil Health" model. With accuracy, MCC, and F1-score values of 0.81, 0.62, and 0.80, respectively, the "Soil Health" model outperformed Model 6, the lowest-performing multi-dimensional model. In the 3:1 scenario, while most single-dimensional models (excluding "Topography," "Landscape configuration," and "Dynamic vegetation indices") achieved better performance than Model 6, their metrics remained lower than those of all other multi-dimensional models.

3.3. Factor importance

The analysis of the factor importance is based on the results of the best performing Model 1 (Fig. 7). In both absence/presence scenarios, factors related to the nine dimensions were represented, with at least one factor included from each dimension (see Supplementary Materials 5 and 6). The following 15 individual factors were consistently ranked among the 20 most important factors across both scenarios.

- Within the "Topography" dimension (2 factors): 'Slope' and 'VRM'.
- Within the "Geology" dimension (3 factors): 'Coarse fragments', 'Soil class – Acrisols', and 'Physical soil - Clay'.
- Within the "Hydrology" dimension (1 factor): 'SPI'.
- Within the "Static vegetation indices" dimension (4 factors): NDVI 2023 [MODIS], EVI 2023, NPP 2023; SAVI 2023.
- Within the "Static landscape composition" dimension (1 factor): 'Population density'.
- Within the "Soil health" dimension (1 factor): 'NDMI 2023', identified as a top influential factor, ranked 1st with the ratio 2:1 and 2nd with the ratio 3:1.
- Within the "Landscape configuration" dimension (1 factor): 'Distance to roads (only highway, primary, secondary, tertiary)'.
- Within the "Dynamic vegetation indices" dimension (1 factor): 'Distance to NPP negative change 2008–2023'.
- Within the "Dynamic landscape composition" dimension (1 factor): 'Distance to transition 2017–2023 from (Trees) to (Crops).

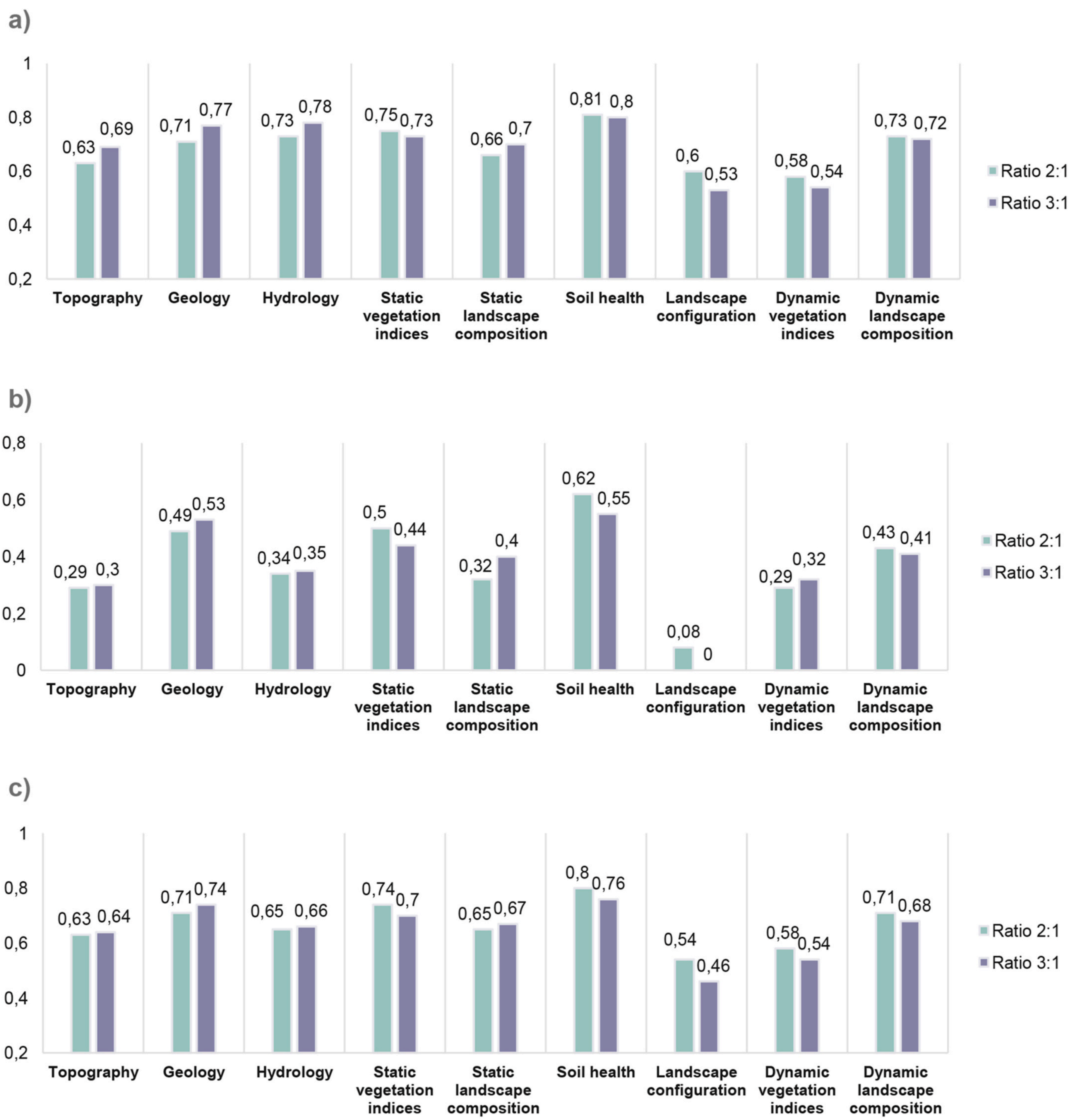

Fig. 6. Performance results across three metrics. Histograms of a) Accuracy, b) MCC, and c) F1-score for the nine single-dimensional models under absence/presence scenarios 2:1 and 3:1.

4. Discussion

4.1. Models integrating eco-environmental dimensions provide more accurate predictions

Based on the empirical results from the Rwanda study area, Models 1 and 2, which integrated the most comprehensive set of structural and eco-environmental factors, demonstrated the highest performance across all evaluation metrics. Model 3, which included fewer eco-environmental dimensions, underperformed compared to Models 1 and 2. Model 4, which relied solely on structural dimensions, achieved the lowest performance among the first four models. This indicated that the progressive removal of eco-environmental dimensions led to a corresponding decline in predictive capability. Model 5, focusing exclusively on eco-environmental dimensions, performed better than Model 4 but did not surpass the more comprehensive Models 1, 2, or 3. Model 6, using a simplified set of conditioning factors, achieved the lowest performance of the six models.

These findings support the study’s hypothesis that integrating eco-environmental dimensions alongside structural ones provides a more

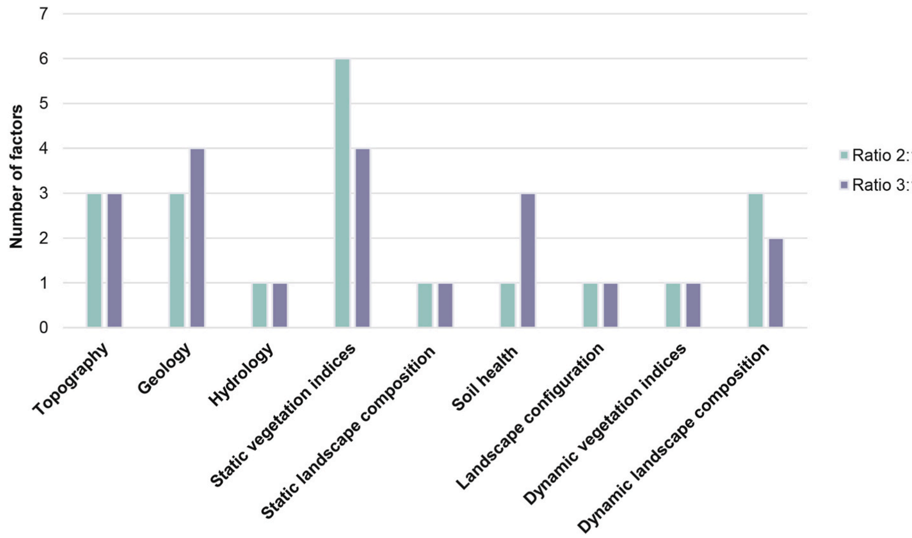

Fig. 7. Distribution of the 20 most important factors across single dimensions under absence/presence scenario 2:1 and 3:1.

holistic representation of the contributing factors, thereby enhancing the predictive performance of LSA models. They also empirically validate conceptual frameworks proposed by recent studies examining the role of eco-environmental factors in landslide processes (Sidle and Bogaard, 2016).

The systematic multi-dimensional approach employed in this study represents a structured implementation of ideas that have existed in fragmented form across literature. For instance, Dou et al. (2019) demonstrated that integrated approaches incorporating diverse factors generally outperform simpler models, but their analysis focused primarily on algorithmic optimization rather than systematic factor integration. Our framework extends this work by organizing factors into conceptual dimensions that reflect landscape functioning rather than simply maximizing input variables. Furthermore, Lima et al. (2023) highlighted how conventional landslide susceptibility models may underestimate impact areas by failing to account for complex relationships between factors. Our multi-dimensional approach directly addresses this limitation by explicitly capturing ecological interactions that mediate landslide processes.

In contrast, Sterlacchini et al. (2011) compared various combinations of explanatory factors, but their analysis, which was limited to topography, geology, and LULC, reported statistically similar predictive outcomes. This discrepancy may reflect recent advancements in understanding ecological influences on slope stability, as documented by Zhao et al. (2023).

While our results demonstrate notable differences in performance metrics between models that include eco-environmental variables and those relying solely on structural factors, formal statistical significance tests were not performed. This is consistent with common practice in landslide susceptibility modeling, where comparisons are often based on point estimates rather than inferential statistics (Shmueli, 2010). Furthermore, using RF, we did not perform multicollinearity analysis, since RF tree-based models inherently robust to multicollinearity due to their ensemble of decision trees and random feature selection at each split (Biau and Scornet, 2016; Breiman, 2001; Goetz et al., 2015). Nevertheless, the observed improvement in accuracy, along with consistent gains across other performance metrics, suggests a meaningful enhancement in predictive performance attributable to the inclusion of eco-environmental variables. The stability of these metrics also implies that overfitting was likely minimal, despite the increased number of input factors, aligning with recent methodological observations by Pourghasemi and Rahmati (2018) regarding model parsimony in LSA.

4.2. Eco-environmental factors, particularly dynamic ones, are key predictors of landslides

In the Rwanda case study, models incorporating eco-environmental variables consistently outperformed those with fewer or no eco-environmental dimensions. While this study is centered on Rwanda, its findings have broader implications for landslide-prone regions worldwide. Similar eco-environmental interactions influence landslide susceptibility in other mountainous and tropical landscapes, such as the Andean Cordillera, the Himalayas, and the East African Rift (Sepúlveda and Petley, 2015). The integration of eco-environmental factors into LSA models could enhance predictive accuracy in regions where land-use change, deforestation, and extreme weather events exacerbate landslide risks (Sepúlveda and Petley, 2015).

Our results demonstrate that integrating eco-environmental variables into LSA models not only improves predictive accuracy but also reveals, through factor importance ranking, that variables such as deforestation, soil degradation, and land use transitions are key contributors to landslide susceptibility. This insight enables practitioners to identify the specific drivers of risk in a given area, supporting the strategic prioritization of targeted ecological interventions, such as reforestation, erosion control, and soil restoration, in zones where modifiable risk factors converge.

Moreover, the comparison between Model 1 (all dimensions) and Model 2 (all dimensions except dynamic factors) showed the slight superiority of Model 1, suggesting that excluding dynamic factors marginally reduces predictive performance. Factor importance analysis further emphasized the critical role of dynamic factors in enhancing model accuracy. For example, while static indices like NDVI and EVI provide snapshot of ecosystem health, NPP captures long-term degradation linked to landslide drivers like deforestation, urbanization, and climate change. As such, it serves as a crucial eco-environmental indicator reflecting climate change, human activities, and ecological dynamics (Zhou et al., 2023). This emphasizes the value of using multiple indices that capture both vegetation characteristics and dynamics, aligning with the hypothesis that combining all factors, particularly dynamic ones, leads to more effective LSA result.

4.3. Contextualizing findings within Rwanda's specific landslide dynamics

Our empirical findings both confirm and expand upon local knowledge on landslide processes in western Rwanda. Several factors previously identified as key predictors, such as slope and LULC, emerged as top predictors in our models as well, aligning with earlier studies in the region (Mind'je et al., 2020; Nsengiyumva et al., 2019; Uwihirwe et al., 2022). Similarly, the relevance of soil properties echoes findings from the adjacent Lake Kivu region, where soil characteristics were found to be key differentiators between stable and unstable slopes (Maki Mateso et al., 2023). Depicker et al. (2021b) did demonstrate that forest cover changes (deforestation) over years increase landslide risk in the Kivu Rift region.

Beyond reaffirming the importance of individual factors, our study provides robust evidence that integrating multiple eco-environmental dimensions, in West Rwanda's context, enhances model performance. For example, Model 5, which relied solely on eco-environmental variables, showed better performance metrics than Model 4, which included only structural variables. When we combined all nine dimensions, including six eco-environmental ones, these variables consistently ranked among the top predictors, highlighting their critical role in understanding landslide susceptibility, particularly when use in combination.

Importantly, we provide quantitative evidence on the relative influence of these variables. Land-use transitions, especially forest-to-cropland conversion, emerged as among the most influential predictors, supporting Sibomana et al. (2025)'s findings on the impacts of agricultural expansion. Notably, the proximity to forest-cropland transition zones proved more predictive than static land cover or many traditional structural variables, a novel insight in the context of Rwanda-specific landslide research.

These findings suggest that future LSAs in the region would benefit from incorporating a broader range of eco-environmental variables, including those capturing dynamic landscape changes and soil-vegetation-water interactions. Such variables appear to more accurately capture landslide susceptibility in Rwanda's tropical, mountainous terrain. This has direct implications for local risk management, indicating that monitoring many eco-environmental variables may offer earlier and more effective warning signs than relying solely on few factors, or only on static factors like slope or geology. These insights directly support the development of an Eco-DRR monitoring strategy that is proactive, dynamic, and grounded in ecosystem change.

Most importantly, our integrated models confirm that combining structural and eco-environmental variables improves predictive accuracy. Although rooted in Rwanda's context, these findings demonstrate the broader applicability of our methodological approach for uncovering hidden drivers of landslide susceptibility in similarly complex terrains elsewhere. Thus, the study contributes both localized insights and generalizable evidence supporting Eco-DRR-informed LSA frameworks.

4.4. The synergy of multi-dimensional conditioning factors is key to enhancing LSAs within an Eco-DRR framework

Model 4, which relied solely on structural dimensions, achieved the lowest performance among the first four models. In contrast, Model 5, which focused exclusively on eco-environmental dimensions, performed better than Model 4 but did not surpass more comprehensive Models 1, 2, or 3. Similarly, Model 6, failing to incorporate a comprehensive range of eco-environmental and structural dimensions, led to suboptimal outcomes. On the other hand, single-dimensional models consistently underperformed compared to multi-dimensional ones. These findings emphasize that within ecosystem-based approaches, combining factors across different dimensions—and within each dimension—is crucial for reflecting landscape complexity and improving LSA modeling accuracy. Although integrating diverse dimensions may not strictly qualify as an ensemble model, it follows a similar principle by leveraging the complementary contributions of each dimension (Sharma et al., 2024).

For instance, the study reaffirmed the established importance of structural terrain aspects in LSAs. Structural factors, reflecting soil stability, water flow patterns, and erosion potential, are fundamental in determining landslide risk, as they directly influence the physical environment (Djukem et al., 2020).

Moreover, factors related to soil health and static vegetation indices emerged as key drivers of landslide susceptibility in this study. Their prominence underscored the role they play in stabilizing slopes, preventing erosion, and improving soil structure through root networks, enhanced rainfall interception, and regulated water flow (Fusun et al., 2013). However, this is a double-edged sword in Eco-DRR, as excessive soil moisture can weaken soil strength, and high fertility may lead to land-use changes that destabilize slopes (Chen et al., 2021; Hales and Miniat, 2017). The benefits of soil health and vegetation generally outweigh these risks when part of a well-managed ecosystem, emphasizing the importance of ecosystem monitoring and sustainable management.

Additionally, the impact of landscape composition, configuration and evolution was highlighted, with human-driven ecological-to-anthropogenic transitions influencing landslide susceptibility (Rabby et al., 2022). For example, population density emerged as a key proxy for human influence in LSAs, consistent with the findings of Sepúlveda and Petley (2015). On the other hand, while LULC class is a widely acknowledged factor in LSA, it is not always the primary driver, especially in contexts where other environmental or anthropogenic factors play a stronger role. Studies showed that LULC data can be overshadowed by more dominant factors (Chen et al., 2019; Meneses et al., 2019). It emphasizes the importance of considering landscape-related factors within the broader context of LULC and ecosystem changes when assessing landslide susceptibility, to better understand the still not fully understood effects of LULC dynamics on landslides, as noted by Shu et al. (2019). Although dimensions like "Dynamic Landscape Composition" and "Landscape Configuration" underperformed as standalone predictors, their integration with other dimensions significantly enhanced the predictive capability of the models. It further underscores the importance of considering both structural and eco-environmental factors, particularly the dynamic ones, in landslide susceptibility (Reichenbach et al., 2014). This is aligned with the conclusion of Jien et al. (2023), which illustrated the complex interaction between reforestation, reduced landslide areas, and decreased soil erosion.

4.5. Translating findings into Eco-DRR implementation

Our research contributes to bridging the gap between scientific knowledge and practical Eco-DRR strategies, addressing a key gap identified by Sudmeier-Rieux et al. (2021). At a local level, the detailed understanding of factor importance provided by this study supports more targeted interventions. Instead of applying uniform mitigation measures, decision-makers could prioritize ecological restoration in areas where high-risk factors converge. This aligns with the recommendations of de Jesús Arce-Mojica et al. (2019), who advocated for site-specific Nature-based Solutions for landslide risk reduction. Local and national stakeholders can use our factor-ranking outputs to target areas with critical deforestation or soil degradation for restoration or erosion control, improving resource allocation efficiency. Furthermore, integrating these insights into early warning systems can enhance the timeliness and ecological relevance of advisories, making them more responsive to dynamic environmental changes.

For example, soil moisture (NDMI) emerged as a top predictor, extending Mirus et al. (2018) work by incorporating vegetation-mediated hydrological dynamics. Additionally, our findings show that forest-to-cropland transitions significantly influenced susceptibility, quantitatively supporting the observations on that land-use changes enhance landslide activity made by Muenchow et al. Muenchow et al. (2012). These insights suggest that early warning systems should monitor eco-environmental indicators alongside traditional factors (Lima et al., 2023).

By providing this empirical foundation, this study supports the implementation of evidence-based Eco-DRR strategies, helping to close the policy-practice gap identified by McVittie et al. McVittie et al.

(2018), and reinforcing the case for incorporating ecological processes into disaster risk planning.

4.6. Effect of absence/presence ratio on model performance

Testing different scenarios of absence/presence points primarily served to evaluate the consistency of results. Since all models were evaluated under identical conditions, i.e., the same absence/presence ratios and similar spatial clustering patterns, the observed performance differences between models remained valid across both scenarios. Furthermore, the consistent trends in performance metrics, such as F1-score and MCC, which are particularly relevant for imbalanced datasets, confirmed the robustness of the findings.

The analysis also provided insight into how varying the number of absence points influenced model performance. The 2:1 scenario tended to perform slightly better across the six multi-dimensional models. This aligns with prior research, which suggested that balanced datasets enhance the identification of landslides (Steen et al., 2021; Wu et al., 2024). The differences in model performance reflected not only predictive accuracy but also the ability to address challenges related to data imbalance and spatial clustering. Given the prevalence of these issues in real-world landslide mapping, the findings offer valuable insights for practical applications.

4.7. Limitations and future directions

The empirical findings from this case study in Rwanda hold significant implications for LSA and, more broadly, for Eco-DRR. However, certain limitations must be acknowledged as they may have influenced the results and their interpretation.

This study compared comprehensive LSA models, incorporating up to 60 factors across nine dimensions, which may raise concerns about multicollinearity and overfitting, especially in complex models like Model 1. To address these issues, mitigation strategies such as random sampling of absence points and leveraging RF's robustness to multicollinearity were employed. Although RF's structure inherently mitigates multicollinearity concerns, the study adopted a permissive approach to multicollinearity, accepting some noise in exchange for richer insights into the interactions between variables, which was essential for meeting the research objectives.

While the NASA GLC enabled a regional-scale analysis, we acknowledge its spatial limitations, including potential location inaccuracies and bias toward high-impact, reported events. However, these limitations are partly offset by our focus on broader susceptibility patterns and factor comparison rather than local-scale prediction. Additionally, the relatively small number of presence points ($n = 155$) in the landslide inventory may limit model robustness and generalizability, particularly for fine-scale predictions. Future studies could address these data limitations by incorporating higher-resolution or field-validated inventories with larger sample sizes to improve spatial accuracy and model stability.

The methodological approach by dimensions has been inspired by Structural Equation Modelling approach, allowing for a more structured exploration of abstract dimensions and complex relationships between landslide factors, which is an innovative approach (Akhand et al., 2024). By demonstrating the value of combining factors from multiple dimensions in LSA to capture the complexity of landslide processes, this study highlights a path for future research. Future studies could refine this approach by retaining only the most critical factors within each dimension. This approach would help reduce overfitting and address the computational demands of high-dimensional models, while also offering some mitigation of multicollinearity (though the latter is less critical for RF due to its inherent robustness to correlated predictors). A comprehensive spatial analysis of susceptibility patterns would be a valuable direction for future research building upon our methodological findings, particularly one incorporating more detailed geomorphological interpretation to contextualize the ecological-physical processes suggested by our factor importance results. This aligns with Reichenbach et al. (2018)'s observation that methodologically focused landslide studies often prioritize statistical validation over detailed geomorphological interpretation, while both approaches provide complementary insights for comprehensive hazard assessment. Additionally, since the relative importance of conditioning factors varies across different contexts, we should prioritize identifying consistently influential variables, ultimately guiding the development of a standardized framework for LSA. Future studies could compare LSA models with habitat quality assessments, such as the InVEST Habitat Quality model (Sharp et al., 2020), as potential proxies for eco-environmental factors. This approach may be relevant since habitat quality integrates dimensions that overlap with eco-environmental factors, such as LULC and human-induced threats. Additionally, habitat quality could be explored as a summary indicator of eco-environmental factors, enhancing predictive capabilities.

Exploring the synergies between eco-environmental parameters and traditional factors could improve disaster risk management and resilience strategies in Rwanda, making it a relevant case study area for Eco-DRR applications. While the findings are promising, they are derived from the specific conditions of western Rwanda, which may limit their applicability to other geographic or environmental contexts. Furthermore, as this study focused on a landslide inventory triggered by a torrential rainfall event, the model's applicability might also be limited to similar triggering event types and may require further validation for landslides triggered by other mechanisms, such as seismic activity. Adapting these findings to other settings would necessarily involve collaboration with local scientific experts who understand regional geomorphological processes, ecological dynamics, and socioeconomic patterns. This contextual knowledge is essential for translating the methodological framework into locally relevant applications. Therefore, while the results may be applicable to areas with similar environmental and socio-economic conditions, the uniqueness of West Rwanda's topography, land-use dynamics, and climate patterns requires cautious interpretation and adaptation when considering their relevance in different settings. Expanding the study to more diverse geographical areas, with varying elevations, land covers, and socio-economic conditions, could enhance the generalizability and relevance of the results, providing a broader understanding of landslide susceptibility in various contexts. Methodologically, this study demonstrates a replicable approach for assessing key variables across multiple dimensions to develop comprehensive, yet parsimonious, models that represent the complexity of landscape dynamics. By demonstrating the importance of eco-environmental factors in LSA, this study paves the way for future research and practical applications in disaster risk reduction. This research provides a robust foundation for improving Eco-DRR strategies and advancing more holistic approaches to landslide risk reduction. It also underscores the need for future work to refine conditioning factor selection, improve the measurement of dynamic variables, and address redundancies to enhance landslide risk understanding and inform mitigation strategies.

5. Conclusion

This case study in western Rwanda developed a multidimensional LSA framework, integrating Eco-DRR principles. Findings show that incorporating eco-environmental variables, especially dynamic factors like land-use transitions, significantly improves model performance. Models combining both ecological and structural factors consistently outperformed those relying solely on traditional structural elements such as slope. This highlights that landslide susceptibility is shaped by complex and dynamic interactions between ecological processes and physical landscapes, rather than by static physical conditions alone. It builds on recent eco-environmental research, reinforces the value of holistic, cross-disciplinary methods in disaster risk management, and strengthens the foundation for applying Eco-DRR by quantifying how these variables affect susceptibility. Additionally, the proposed framework offers a scalable, replicable method for more nuanced risk assessments in other landslide-prone regions. It offers policymakers clear priorities: integrating dynamic eco-environmental factors into LSA, aligning early warning systems with ecosystem indicators, and updating Eco-DRR policies to include ecosystem monitoring for targeted risk zoning. This approach aligns with global frameworks like Sendai by promoting nature-based solutions that address environmental vulnerability. Looking forward, further research should refine the selection of eco-environmental variables across different regions and incorporate more comprehensive temporal analyses to capture seasonal and long-term changes. Simplifying models while preserving predictive accuracy, such as using proxy indicators like habitat quality, could be explored for enhancing models' usability. By bridging ecological science and disaster risk reduction, this study supports more sustainable, effective, evidence-based strategies for predicting landslides and managing risk in Rwanda and beyond.

CRediT authorship contribution statement

Mélanie Broquet: Writing – original draft, Visualization, Methodology, Investigation, Conceptualization. **Pedro Cabral:** Writing – review & editing, Supervision, Methodology, Investigation. **Felipe S. Campos:** Writing – review & editing, Visualization, Supervision, Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2025.127043.

Data availability

Data will be made available on request.

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