DOCTORAL PROGRAMME

Information Management

ENHANCING ECOSYSTEM-BASED DISASTER RISK REDUCTION THROUGH GEOINFORMATICS: INTEGRATING ECOLOGICAL FACTORS INTO ASSESSMENT PRACTICES

Melanie Broquet

A thesis submitted in partial fulfillment of the requirements for the degree of Doctor in Information Management

NOVA Information Management School
Instituto Superior de Estatística e Gestão de Informação
Universidade Nova de Lisboa

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September 2025

STATEMENT OF INTEGRITY

I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism or any form of undue use of information or falsification of results along the process leading to its elaboration. I further declare that I have fully acknowledge the Rules of Conduct and Code of Honor from the NOVA Information Management School.

Lyon, France, 22 September 2025

DEDICATION

For 25 years, my professional life as a humanitarian worker has been shaped by responding to crises, a path marked by intensity, resilience, and meaning. Along the way, my career gave me the opportunity to travel across our incredible planet, discovering stunning landscapes, remarkable biodiversity, and meaningful human connections, while also witnessing the concerning footprint of human activity on diverse environments. These experiences have stayed with me, and it is perhaps no surprise that my thesis brings together disasters and ecosystems, two themes that have been central to my journey across the globe.

I am mindful of the privilege of having been given the chance to undertake this professional and personal journey, and I dedicate this thesis to those whose journeys were interrupted or who never had the chance to begin.

While this path has been meaningful, it has also carried moments of obstacles, emotional weight and disillusionment. Luckily, determination and conviction, together with the support of family, friends, and colleagues always helped overcome the challenges.

I am grateful for the everyday presence of my close ones, those who, even after three years, might not fully understand why I chose to do a thesis or what it is really about (despite their Post-it notes!). Thank you all for being there, sharing good food, drinks, and life stories.

Top honors go to Sandrine, the very best companion for those moments of work/PhD decompression, and to Vero, my indispensable boost throughout my Parisian transits.

A dedication goes to Nadine, who inspired my love for whales, which actually initially led me to learn Geographical Information Systems (GIS) for conservation work, and who has remained a lifelong, steadfast presence.

Finally, I dedicate this achievement to my beloved parents. They gave me the chance to pursue an education, challenged me when needed but never overruled my choices, and have been my greatest supporters every step of the way through both my academic, professional and personal life.

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My thanks go as well to NOVA Information Management School for their excellent teaching and support services, and for fostering an environment that welcomes international and experienced students. The courses were both demanding and rigorous, contributing greatly to my growth during this journey.

This doctoral path represents a significant step in a career shaped by earlier professional experiences and personal encounters. I am deeply grateful to all those who have guided and supported me since the beginning of my career, teaching me persistence, the importance of reconsidering my opinions, and the courage to pursue my ambitions.

In particular, I wish to acknowledge Mr. Olivier Desmars, without whom I might not have reached this stage today. We crossed paths about ten years ago over a Nescafé in Gaziantep, Turkey. At the time, I was a beginner in GIS, but thanks to his patience and teaching, he passed on to me his passion for the discipline.

ABSTRACT

Ecosystem-based Disaster Risk Reduction (Eco-DRR) leverages ecosystem conservation and restoration to mitigate natural disaster risks by providing regulatory services that reduce their intensity and lower the vulnerability of exposed communities and ecosystems. Despite growing recognition, especially after the 2004 Indian Ocean tsunami, Eco-DRR faces key barriers: limited consensus on ecosystem effectiveness, inconsistent methodologies, data scarcity, and the absence of standardized frameworks that integrate ecological factors into disaster risk assessments. This study addresses these gaps by using landslide hazard as a case study to strengthen the credibility and acceptance of Eco-DRR through empirical evidence and improved assessment practices. Three inter-connected objectives guided the work: (1) identifying ecological factors relevant for landslide susceptibility assessment (LSA) through literature review; (2) examining the relationship between Land Use/Land Cover (LULC) and habitat quality as indicators of hazard-prone landscapes using the InVEST Habitat Quality model; and (3) testing whether integrating ecological variables into LSA frameworks improves predictive performance using Random Forests. Findings show that eco-environmental factors, especially dynamic ones, remain underutilized in LSAs. LULC change was strongly correlated with ecological degradation, supporting the use of integrative indicators such as habitat quality for characterizing vulnerable landscapes. Integrated models combining structural and ecological variables, particularly dynamic ones, significantly outperformed conventional LSA models. These results confirm that eco-environmental variables play a critical role in shaping landslide susceptibility and should be systematically integrated into risk assessments. Overall, this research strengthens Eco-DRR's scientific foundation by moving beyond static, hazard-centric approaches. It introduces evidence-based methodologies that are applicable even in data-scarce contexts, replicable across settings. By promoting cross-disciplinary integration and efficiency, the work helps bridge the knowledge–action gap, enhances policy relevance, and underscores ecosystems as critical assets whose protection and restoration are essential for breaking the cycle of degradation and disaster risk.

KEYWORDS

Remote Sensing; Geographic Information Systems; Ecosystem-Based Disaster Risk Reduction; Landslide Susceptibility Assessment; Nature-based Solutions

Sustainable Development Goals (SGD):

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LIST OF ABBREVIATIONS AND ACRONYMS

ALOS	Advanced Land Observing Satellite
BAU	Business-As-Usual
DEM	Digital Elevation Model
DRR	Disaster Risk Reduction
DSM	Digital Surface Model
Eco-DRR	Ecosystem-based Disaster Risk Reduction
EecA	Ecosystem Extent and Condition Assessment
EO	Earth Observation
EVI	Enhanced Vegetation Index
FVC	Fractional Vegetation Cover
GIS	Geographical Information Systems
GLCM	Grey Level Co-occurrence Matrix
HQM	Habitat Quality Model
InVEST	Integrated Valuation of Ecosystem Services and Tradeoffs
LAI	Leaf Area Index
LCM	Land Change Modeler
LiDAR	Light Detection and Ranging
LSA	Landslide Susceptibility Assessment
LST	Land Surface Temperature
LULC	Land Use Land Cover
MCC	Matthews Correlation Coefficient
MCDM	Multi-Criteria Decision Making
NbS	Nature-based Solutions
NDBI	Normalized Difference Built-Up Index
NDVI	Normalized Difference Vegetation Index
NDWI	Normalized Difference Water Index
NPP	Net Primary Productivity
PRISMA	Preferred Reporting Items for Systematic Review and Meta-Analysis
PSR	Pressure-State-Response
RF	Random Forest
RMSE	Root Mean Square Error
RUSLE	Revised Universal Soil Loss Equation
SAR	Synthetic-Aperture Radar
SAVI	Soil Adjusted Vegetation Index
SEEA-EA	System of Environmental-Economic Accounting for Ecosystem Accounting
SEM	Structural Equation Modelling
SPI	Stream Power Index
TWI	Topographic Wetness Index
UPRB	Upper Paraguay River Basin
VIF	Variance Inflation Factor
VOR	Vigor, Organization, and Resilience

1. INTRODUCTION

1.1. SCOPE OF THE RESEARCH

Ecosystem-based Disaster Risk Reduction (Eco-DRR) emphasizes the conservation and restoration of ecosystems to provide regulatory services that mitigate the risk and impact of natural disasters (Cohen-Shacham et al., 2016; Renaud et al., 2013; UNDRR, 2020). Eco-DRR encompasses two fundamental concepts: Disaster Risk Reduction (DRR), which focuses on preventing new disaster risks, reducing existing ones, managing residual risks, and minimizing losses and damages resulting from a disaster (Sudmeier-Rieux et al., 2019; UNDRR, 2015); and ecosystem-based approaches, which emphasize the role of ecosystems as natural capital providing essential for human well-being (Hernández-Blanco et al., 2022; Millennium Ecosystem Assessment, 2005; Veerkamp C et al., 2021). Disaster risk commonly conceptualized as a function of three dimensions: hazard, exposure, and vulnerability (Ward et al., 2020).

Eco-DRR aligns with the broader concept of Nature-based Solutions (NbS), formally endorsed by the United Nations Environment Assembly in 2022 (Eggermont et al., 2015; UNEP, 2022). NbS promote ecosystem conservation, sustainable management, and restoration to address various societal challenges, particularly those exacerbated by environmental degradation, such as natural disasters and climate change (Cohen-Shacham et al., 2016; IUCN, 2016; Raymond et al., 2017; Sowińska-Świerkosz & García, 2022; UNEP, 2022).

As a form of NbS, Eco-DRR specifically targets disaster-related challenges by leveraging ecological infrastructure to reduce disaster risk by moderating hazard intensity and lowering exposure and vulnerability (Bimrah et al., 2022; Renaud et al., 2016; Sudmeier-Rieux et al., 2008; UNDRR, 2020). Interest in Eco-DRR has grew significantly following the devastating Indian Ocean tsunami in December 2004 (S. E. Chang et al., 2006; Mattsson et al., 2009). This event highlighted the protective roles of ecosystems, after observations that some communities shielded by mangroves experienced less damage due to their function as natural barriers that attenuate coastal flooding (Danielsen et al., 2005; Gijsman et al., 2021; Murti & Mathez-Stiefel, 2019; Sudmeier-Rieux et al., 2019). Similarly, coral reefs contribute to the dissipation of the waves and attenuating their energy, and so their degradation can increase the risk and severity of coastal flooding (Beck et al., 2018). Likewise, on lands, the protection and restoration of forests can help stabilize soil, slow water runoff, and reduce the risk of landslides and floods (Y. Zhang et al., 2022). Beyond regulating services, ecosystems also offer provisioning functions that strengthen community resilience during and after disasters, thus addressing the vulnerability aspect of the disaster risk (Paudel et al., 2023).

This recognition contributed to the integration of Eco-DRR in global policy frameworks such as the Sendai Framework for Disaster Risk Reduction and the 2030 Agenda for Sustainable Development (UNDRR, 2015; United Nations, 2015).

The emphasis on Eco-DRR is of critical for two significant reasons. First, the incidence and intensity of natural disasters have increased over recent decades, with an estimated annual global death toll estimated at 45,000 per year in the last decade (Buszta et al., 2023; Ritchie & Rosado, 2022). Among these, landslides are particularly destructive due to their potential, rapid onset, localized impact, and high potential for human and economic loss (Perera et al., 2018). Accordingly, Landslide Susceptibility

Assessment (LSA) becomes vital for identifying risk-prone areas and informing prevention and mitigation strategies.

Second, as human populations grow, urbanize and participate in consumer-driven society, the demand for natural resources increases, often leading to their unsustainable use (Ahmed et al., 2020; Huo & Peng, 2023). Land-use activities such as deforestation, agriculture, or mining alter landscapes, disrupt the ecological balance, and weaken ecosystem's natural resilience and ability to provide essential services (Hasan et al., 2020). For instance, the replacement of natural vegetation with impervious surfaces significantly contributes to urban flooding (Jacobson, 2011). Moreover, growing populations, particularly in urban centers, lead to increased exposure to natural hazards (Anelli et al., 2022; Ehrlich et al., 2018).

Overall, the impact of anthropogenic pressure, characterized by the exhaustion of natural resources and environmental degradation, contributes to climate change, extreme weather events, and more frequent natural disasters (Fig. 1) (Abbass et al., 2022). In turn, disasters such as landslides further damage ecosystems, creating a destructive feedback loop that increases overall disaster risk (Doko et al., 2016; Faivre et al., 2018; UNDRR, 2020). Breaking this cycle requires recognizing ecosystems, habitats, and biodiversity as at-risk assets in need of urgent protection and restoration (Kasada et al., 2022).

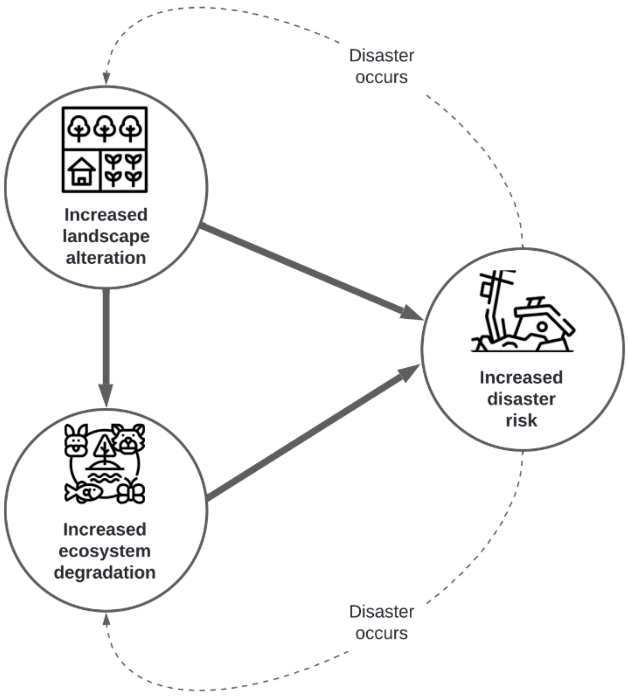

Figure 1 – Feedback loop between landscape alteration, ecosystem degradation, and disaster risk. Increased landscape alteration leads to greater ecosystem degradation and higher disaster risk. In turn, disasters can exacerbate both landscape alteration and ecosystem degradation, creating a reinforcing cycle

1.2. Relevance of the research

Despite its recognized advantages and the growing interest for it, Eco-DRR still faces significant limitations (Anderson et al., 2022; Seddon et al., 2020; Sudmeier-Rieux et al., 2019). A key challenge lies in the limited understanding, acceptability, and trust from policymakers, which can impede investment in Eco-DRR approaches (Anderson et al., 2022; McVittie et al., 2018). This may stem from a lack of evidence regarding the effectiveness of ecosystems in mitigating the extent and impact of natural hazards, with no clear scientific consensus on the matter (de Jesús Arce-Mojica et al., 2019; Marois & Mitsch, 2015; Stolton et al., 2008).

On one hand, Eco-DRR benefits may not be rigorously assessed; available evidence tends to be limited, context-specific, or focused on small-scale projects (Anderson et al., 2022; Ruangpan et al., 2019; Seddon et al., 2020; Sudmeier-Rieux et al., 2021; Sutton-Grier et al., 2015). On the other hand, the inherent complexity of ecosystems complicates measurement; benefits may take time to materialize; while valuable, ecosystems are not a 'miracle' solution against disasters (Walz et al., 2021). Moreover, competing land use interest can also obstruct Eco-DRR initiatives (Anderson et al., 2022; McVittie et al., 2018).

These challenges highlight the need for more empirical research and context-specific case studies to reinforce the scientific foundation of Eco-DRR (de Jesús Arce-Mojica et al., 2019; Sudmeier-Rieux et al., 2019). In particular, more work is needed to better integrate ecological dimensions into disaster risk information systems and to fully acknowledge their role in DRR (Peduzzi, 2019; Ruckelshaus et al., 2020; Walz et al., 2021).

Disaster risk assessment, the process of analyzing hazard likelihood, exposure, and vulnerability, is a valuable instrument for analyzing and guiding effective risk mitigation (P. Cui et al., 2021). Eco-DRR emphasizes the role of environmental degradation as a driver of disaster risk, calling for the integration of ecological factors into assessment frameworks (Peduzzi, 2019). Yet, the incorporation of ecological components within assessment frameworks remains constrained by several challenges.

First, the processes influencing an area's vulnerability are highly complex and difficult to quantify (Hochrainer-Stigler et al., 2023; Simpson et al., 2021). Land conversion often leads to habitat fragmentation, biodiversity loss, and decline in ecosystem services (Haddad et al., 2015). These changes weaken natural buffers and increase susceptibility to hazards such as floods, wildfires, or landslides (Liang & Song, 2022). In this context, habitat quality, which captures the condition and functioning of ecosystems in response to land use, fragmentation, and degradation, emerges as a critical variable. Assessing habitat quality may offer a valuable entry point for identifying ecologically degraded landscapes that may be more vulnerable to disasters.

Secondly, the diversity of ecosystems, hazards, and interacting drivers creates a wide range of scenarios, complicating the development of standardized Eco-DRR approaches (Cremen et al., 2022; Fisher et al., 2009). This is further intensified by the multidimensional nature of disaster risk (combining hazard, exposure, and vulnerability) and the need to engage diverse stakeholders across disciplines, sectors, and governance levels (Murti & Mathez-Stiefel, 2019). To address these challenges in a focused and manageable way, this research uses landslides as a case study hazard, allowing for a targeted exploration of how ecological factors influence disaster risk within a specific hazard context.

Thirdly, data scarcity, particularly in low-income regions, remains a major barrier to comprehensive Eco-DRR assessments (Dang et al., 2021; Ruckelshaus et al., 2020; Sudmeier-Rieux et al., 2021; UNDRR, 2021). In these contexts, data poverty may not only impede risk assessment but may also reinforce broader development challenges (Aaronson, 2019; Hein et al., 2020; Sudmeier-Rieux et al., 2019). Here, geoinformatics, including Earth Observation (EO), geospatial analysis, and spatial modeling techniques, offer valuable tools. These methods are extensively applied in both ecosystem and disaster risk assessments (Chrysoulakis et al., 2021; Cord et al., 2017; De Araujo Barbosa et al., 2015; Le Cozannet et al., 2020; Ramirez-Reyes et al., 2019), and Eco-DRR assessment often takes the form of risk maps (Sudmeier-Rieux et al., 2019). As such, geoinformatics provide a solid foundation for integrating ecological data into disaster assessments and facilitating a more nuanced understanding of risk. However, despite their widespread use in both ecosystem and DRR domains, geospatial approaches are rarely fully integrated across ecosystem and DRR assessments, and often lack standardization (Kumar et al., 2021; Renaud et al., 2016; Sutherby & Tomaszewski, 2018).

These gaps and challenges highlight the need for a framework that incorporates ecological degradation into disaster risk assessment while improving the robustness and standardization of such assessments.

1.3. Research objectives

The primary objective of this research thesis is to enhance the credibility and acceptance of Eco-DRR by providing stronger evidence and advancing assessment practices. Eco-DRR operates on the premise that ecological degradation, as indicated by proxy measures such as habitat quality loss, increases disaster risk by reducing critical ecosystem services. Additionally, landscape alteration acts as a common underlying factor that both drives ecological degradation and amplifies risk. Applied to landslides, our central hypothesis posits that integrating ecological factors into a comprehensive LSA framework will provide a more nuanced characterization of at-risk areas and enhance the effectiveness and benefits of Eco-DRR interventions. To achieve this overarching objective and test the hypothesis, the research addresses three interconnected questions that that complement and inform one another.

The first research question examines what ecological factors should be integrated into LSA to support Eco-DRR. Given the lack of standardization and integration between DRR and ecosystem assessment tools, this investigation explores the extent to which ecological factors are currently incorporated into the LSAs. Through a comprehensive literature review, it examines existing LSA literature, assesses overlaps of factors between ecosystem assessments and LSAs, identifies gaps where relevant ecological factors are not currently incorporated into LSA practices, and evaluates the feasibility of using open-source EO data for these factors in data-scarce contexts. This first objective, to identify and evaluate the ecological factors currently used in LSAs, is addressed in the research study presented in the Chapter 2, titled "*What ecological factors to integrate in landslide susceptibility mapping? An exploratory review of current trends in support of Eco-DRR.*"

Building upon the identification of ecological factors and gaps revealed in the literature review, the second research question shifts focus to empirically examining the relationship between two key ecological indicators, Land Use/Land Cover (LULC) and habitat quality, that emerged as both promising and underutilized in current LSA practices. It assesses their empirical relationship and tests their utility in evaluating degraded landscapes, which can serve as proxies for identifying locations potentially susceptible to hazards such as landslides. This proxy approach may help reducing the reliance on complex disaster risk assessments, a critical advantage given the inherent complexity of DRR–ecosystem integration and the data limitations that often preclude comprehensive hazard modeling. This objective, to empirically analyze the relationship between LULC and habitat quality, and validate their use as proxies for identifying degraded landscapes that are more vulnerable to disasters, is addressed in the study presented in Chapter 3, *"Habitat quality on the edge of anthropogenic pressures: predicting the impact of land use changes in the Brazilian Upper Paraguay River Basin."*

The third and final research question addresses whether integrating ecological factors improves LSA compared to conventional approaches, thereby validating the central research hypothesis. To achieve this, we propose LSA assessment models that integrate ecological factors and compare their performance against more conventional models that excludes ecological components. Different models are evaluated based on their ability to predict hazard events using historical hazard inventory data, with the assessment framework utilizing geoinformatics tools and open-source remote sensing data to ensure applicability and replicability even in data-scarce environments. This objective, to assess whether these models that incorporate ecological factors outperform conventional approaches in predicting landslide susceptibility, is addressed in the study presented in Chapter 4, "*Integrating Eco-DRR into landslide susceptibility assessment: The critical role of eco-environmental factors.*"

Each chapter directly addresses one or more of these objectives: the review (Chapter 2) identifies knowledge gaps (Objective 1), the proxy-based case study (Chapter 3) tests methodological approaches (Objective 2), and the predictive models (Chapter 4) integrate these findings (Objective 3).

1.4. RESEARCH FRAMEWORK

The thesis is organized in five chapters:

- Chapter 1 serves as the introduction, which outlines the scope, relevance, and objectives of the thesis.
- Chapters 2, 3 and 4 present detailed research studies conducted to address to the specific objectives.
- Although our work is presented as a collection of separate research papers, each study is interconnected and contributes to the overarching goal of the thesis. Therefore, Chapter 5 summarizes the research findings, highlights the main contributions, discusses the limitations encountered, and suggests directions for future research.

The details and status of each research study are presented in Table 1. Three studies have been published in Q1 international journals following a peer-review process.

Table 1 – Scientific production

Research study title	**Journal**	**Status** DOI	**Impact Factor (Quartile)**	**Publication date**	**Chapter**
What ecological factors to integrate in landslide susceptibility mapping? An exploratory review of current trends in support of Eco-DRR	**Progress in Disaster Science**	**Published** https://doi.org/10.1016/j.pdisas.2024.100328	**Impact factor JCR: 3.8 (Q1, ESCI) SCOPUS Q1**	April 2024	2
Habitat quality on the edge of anthropogenic pressures: predicting the impact of land use changes in the Brazilian Upper Paraguay River Basin	**Journal of Cleaner Production**	**Published** https://doi.org/10.1016/j.jclepro.2024.142546	**Impact factor JCR: 10.0 (Q1, SCIE) SCOPUS Q1**	June 2024	3
Integrating Eco-DRR into landslide susceptibility assessment: The critical role of eco-environmental factors	**Journal of Environmental Management**	**Published** https://doi.org/10.1016/j.jenvman.2025.127043	**Impact factor JCR: 8.4 (Q1, SCIE) SCOPUS Q1**	October 2025	4

2. WHAT ECOLOGICAL FACTORS TO INTEGRATE IN LANDSLIDE SUSCEPTIBILITY MAPPING? AN EXPLANATORY REVIEW OF CURRENT TRENDS IN SUPPORT TO ECO-DRR

Chapter abstract: Eco-DRR reflects the important role that natural ecosystems play in reducing the likelihood, severity, and impact of environmental disasters such as landslides. However, landslide risk assessments often lack explicit references to Eco-DRR and unified frameworks, notably for its LSA. Here, we assess how ecological factors are integrated into LSAs and the feasibility of measuring them, using open EO data. We conduct an exploratory review for identifying the factors used in LSAs and ecosystem assessments, determining their commonalities. Key findings indicate that standardization is more lacking in ecosystem assessments than in LSAs, with the former exhibiting a higher dispersion of factors—195 identified across 41 papers—compared to the latter, where only 46 factors were identified across 30 studies. LSAs and ecosystem assessments shared 19 common factors, with only two, the Normalized Differential Vegetation Index (NDVI) and LULC, being widely accepted criteria. Our study contributes to advancing Eco-DRR practices by proposing concrete measures to expand the ecological perspective in LSAs and fostering collaboration between DRR and conservation domains. Ultimately, it raises awareness of the pivotal role that healthy ecosystems play in mitigating disasters and addressing societal challenges.

Broquet, M., Cabral, P., & Campos, F. S. (2024). What ecological factors to integrate in landslide susceptibility mapping? An exploratory review of current trends in support of eco-DRR. *Progress in Disaster Science* (Vol. 22). Elsevier Ltd. https://doi.org/10.1016/j.pdisas.2024.100328

2.1. INTRODUCTION

The concept of Eco-DRR reflects the role that natural ecosystems play in reducing the likelihood, severity, and impact of disasters (Sudmeier-Rieux et al., 2008). Eco-DRR encompasses two broad concepts – disaster risk and ecosystem-based approaches (UNDRR, 2020). Disaster risk is conceptualized as a function of three dimensions: the hazard that occurs in a specific location and at a specific time; the exposure of objects, such as people or infrastructures, to the hazard; and finally, the vulnerability, meaning the potential for the exposed objects to be adversely impacted by the hazard (Hallegatte et al., 2020; Ward et al., 2020). The hazard is a component of disaster risk, not the risk (Cardona et al., 2012). On the other hand, ecosystem-based approaches are linked to the interrelated concepts of ecosystem services and NbS (Almenar et al., 2021). Ecosystem services refer to the benefits that natural ecosystems provide to humans (Millennium Ecosystem Assessment, 2005). NbS, for which the United Nations adopted a resolution in 2022, refer to the strategies that promote their conservation, sustainable management, and restoration as solutions to societal challenges (Sowińska-Świerkosz & García, 2022). In this context, Eco-DRR is the NbS that addresses challenges related natural disasters (Cohen-Shacham et al., 2016; Walz et al., 2021), based on the assumption that environmental degradation is a factor of disaster risk (Peduzzi, 2019).

Ecosystems provide regulating services in relation to the hazard component of disaster risk (Bimrah et al., 2022). For instance, restoring and protecting forests can help stabilizing soil, slowing water runoff, and reducing the likelihood of landslides and floods (Y. Zhang et al., 2022). In terms of exposure, ecosystems, habitat, and biodiversity must be seen as at-risk assets that need to be preserved since healthy ecosystems are essential for the long-term supply of ecosystem services (Kasada et al., 2022). Regarding the vulnerability dimension of disaster risk, ecosystems represent a valuable resource for building the resilience of exposed or affected populations (Paudel et al., 2023). The roles that ecosystems play in mitigating disasters gained much attention in the aftermath of the 2004 Indian Ocean tsunami, after the observation that some communities were less affected than others because of the protective effect of mangroves (Chatenoux & Peduzzi, 2007; Danielsen et al., 2005). Other devastating events have prompted an increase in scientific studies exploring ecosystem-based approaches to DRR as they highlight the effectiveness of natural systems in mitigating hazards, leading to a growing recognition of their value for resilience and the need for further research (Sudmeier-Rieux et al., 2021). Although disaster risk cannot be totally avoided, it can be reduced (K. Smith & Petley, 2009). Therefore, disaster risk assessment is a valuable instrument to analyze and orientate actions to mitigate the effects of disasters (P. Cui et al., 2021).

In this paper, the focus is on one type of natural hazard – the landslides, given that it is one of the most devastating natural hazards worldwide (Froude & Petley, 2018). The disaster risk assessment, applied to landslides, is called landslide risk assessment (F. C. Dai et al., 2002). It generally consists of three key elements representing the tripartite dimensions of disaster risk: the likelihood of hazard (LSA), the identification and quantification of vulnerable assets, and the projected extent of damage to these assets (Guo et al., 2020; Sim et al., 2022). In the scope of Eco-DRR, ecological aspects should be included in the evaluation of the landslide risk assessment, and notably in the LSA (Sutherby & Tomaszewski, 2018; Veerkamp et al., 2021).

Both ecosystem and disaster risk assessment methods frequently make use of remote sensing, geospatial analysis, and modelling techniques (Le Cozannet et al., 2020; Ramirez-Reyes et al., 2019).

As a result, they are regarded as suitable methods in the field of Eco-DRR (Chrysoulakis et al., 2021). However, their applications are rarely merged (Renaud et al., 2016) and the integration of ecological factors into DRR information management and research is recommended (Ruckelshaus et al., 2020). Another major challenge in the disaster risk assessment under Eco-DRR intervention is the lack of data (Sudmeier-Rieux et al., 2021). In this regard, remotely sensed data is particularly suitable because of the availability and performance of open-source data, and modelling software. It makes these tools applicable in either rich or poor data environments (Harris & Baumann, 2015). These tools enable spatial analysis over large areas, the spatiotemporal reproducibility and comparability of analyses, as well as the extrapolation of models' parameters (Van Bodegom et al., 2020). Their capabilities allow to capture the dynamic nature of ecosystems and its effects on disaster risk (Cremen et al., 2022). If these challenges are common to all types of disasters, each natural hazard or disaster is driven by specific factors, with some that may be common to different threats (P. Cui et al., 2021).

In the context of landslide risk assessments, certain case studies incorporate environmental factors like topography or climate. However, they often overlook explicit references to Eco-DRR (Sutherby & Tomaszewski, 2018; Veerkamp C et al., 2021) or NbS (Modugno et al., 2022; Rusk et al., 2022; Zhou et al., 2022). In the limited number of studies that spot ecological factors as a distinct element within landslide risk assessment, various approaches are observed. For instance, (Chen & Alexander, 2022) incorporates environmental factors into the LSA, while other researchers regard them as a constituent of vulnerability (Anderson et al., 2021; Arrogante-Funes et al., 2021; X. Liu & Chen, 2020). The absence of standardization within the Eco-DRR approach can originally stem from the non-standardized nature of ecosystem and landslide risk assessments when conducted independently, where these assessments often utilize variable sets that vary from one study to another (Soubry et al., 2021). Some reviews have already examined the use of remotely sensed variables for ecosystem or landslide assessment, respectively (De Araujo Barbosa et al., 2015; Z. Li et al., 2014). However, to the best of our knowledge, no study has been conducted to analyse how the factors related to ecosystem and landslides are connected.

Creating a unified Eco-DRR framework for landslide risk assessment from two fields already lacking standardization may introduce additional complexity into the analysis (Okhuysen & Bonardi, 2011). Moreover, due to the varying implications of ecosystems across the three dimensions of landslide risk (Bimrah et al., 2022; Kasada et al., 2022; Paudel et al., 2023), it is crucial to address ecological factors separately for each dimension in the risk assessment process. In this study, our primary focus lies on the LSA segment of landslide risk assessment. We justify this focused approach on one specific dimension by recognizing the intricacies and expansiveness of landslide risk assessment, which necessitate a concentrated examination to enhance understanding and interpretation of outcomes. Additionally, LSA holds significant relevance in the context of landslide risk assessment, offering potential for valuable contributions to the field (F. C. Dai et al., 2002; De Araujo Barbosa et al., 2015; Z. Li et al., 2014).

Our main research objective is to determine from the most recent practices the extent to which ecological factors, measurable from open-source EO data, are incorporated into the factors influencing the landslide susceptibility. To achieve this, a three-steps exploratory review is conducted responding the following questions: (i) What factors are used to assess the likelihood of landslide? (ii) What are those used to assess the ecosystem? (iii) What are the factors used to assess the ecosystems that are also used to measure the LSA? The expected outcome is to provide a foundation for understanding, harmonizing, and improving the selection of the appropriate ecological factors for LSA. It can serve as a precursor to a systematic review and to inform future Eco-DRR and NbS discussion and research. This will be beneficial to promote Eco-DRR to professionals that generally have expertise in their own domain and operate independently (Renaud et al., 2013). Additionally, it will help the ecosystem-based disaster risk assessment, at least for its hazard dimension, to be more replicable and comparable, notably in data-scarce environments. This is crucial given that most scientific studies on Eco-DRR are concentrated in North American and European contexts (Sudmeier-Rieux et al., 2021) and because data scarcity is a 'development issue' because it may hinder evidence-based decision-making (Leidig et al., 2015).

2.2. METHODS

A three-step methodology was designed to enable the identification of the current interdisciplinary practices that could answer our research questions and objective. Such an exploratory review, which differs from a systematic review, may be useful to explore the bridge between unidimensional perspectives (Aryana et al., 2019; Pybus et al., 2022). This is illustrated in the graphical abstract (Fig. 2).

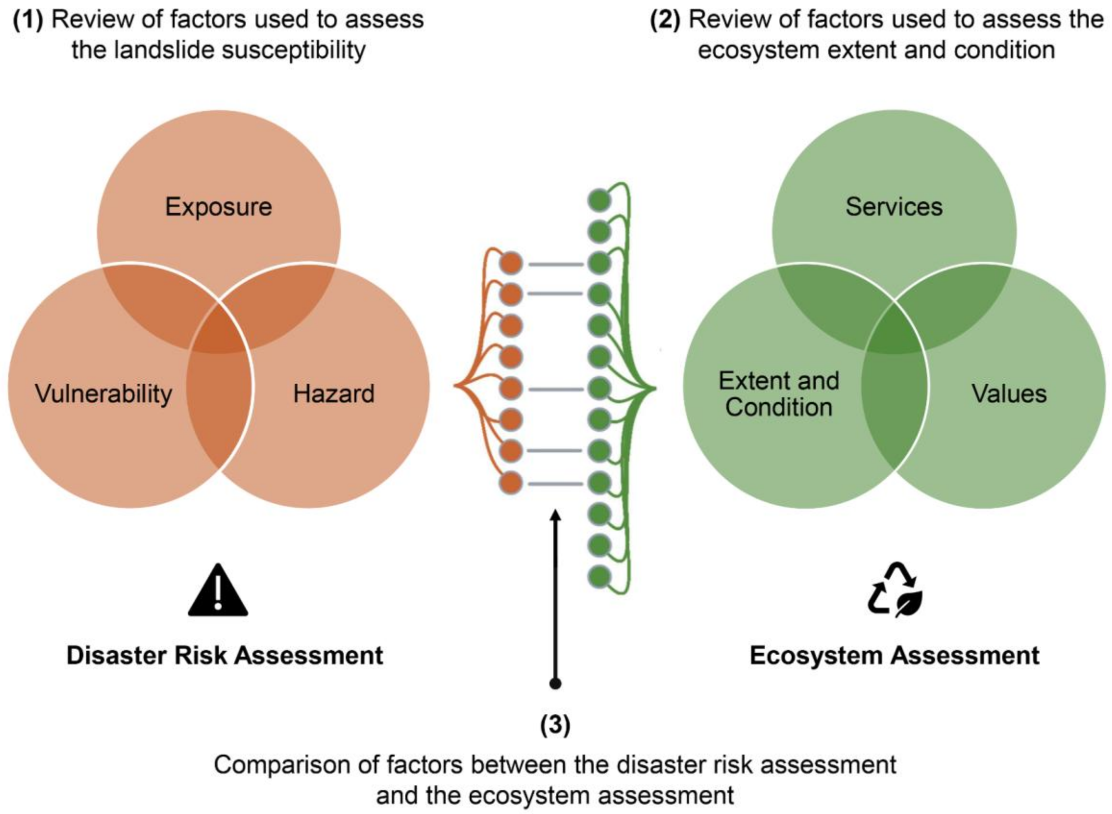

Figure 2 – Graphical abstract

2.2.1. Review of the factors used in landslide susceptibility assessment

2.2.1.1. Conceptual framework

The LSA is a tool to analyze where the hazard is likely to occur. A preliminary step to it is the development of a landslide inventory that indicates the locations and geographical extent of landslides (Guzzetti et al., 2012). The second step is the selection of the relevant factors that condition the occurrence of the landslide since there is no established list of factors in the literature (Pourghasemi et al., 2018). The distinction is sometimes made between the conditioning factors that affect the chance of a hazard under long-term circumstances, such as the geology and the triggering factors that considers the short-term impact of, for instance, rainfall (Lombardo et al., 2020). For better readability, the term “conditioning factors” will be further used in this paper without distinction between conditioning and triggering factors. Then, the landslide susceptibility is modelled using different methods, such as machine learning or Multi-Criteria Decision Making (MCDM) (Shano et al., 2020). Landslide susceptibility maps are derived from this information, reflecting the likelihood of a landslide occurring in a particular location based on the local conditioning factors that cause them. The LSAs can be combined with additional information on exposure and vulnerability to inform the disaster risk management (Bourenane et al., 2021). The primary focus of our review was the second step of the LSA, which is the selection of the factors influencing the likelihood of the landslide.

2.2.1.2. Search, screening and analysis processes

The review method was guided by the standards of the Preferred Reporting Items for Systematic Review and Meta-Analysis (PRISMA) Statement (Page et al., 2021). A targeted search strategy was used to summarize the best available evidence. To create a custom search string, the Boolean operators "AND" and "OR" were added between various terms. The search was also restricted to the title, abstract and keywords of the article, or to the title only. The final search query string was: (TITLE ("landslide susceptibility") AND TITLE-ABS-KEY ("conditioning factor*" OR "driving factor*" OR "triggering factors")) AND (LIMIT-TO (DOCTYPE, "ar")) AND (LIMIT-TO (LANGUAGE, "English")).

Our query did not include the terms remote sensing or earth observation as the landslide susceptibility mapping method relies by nature on spatial data. The keywords landslide hazard or landslide risk were intentionally not included as they retrieved articles not focusing specifically on the landslide susceptibility but on broader topics. The keyword co-occurrence analysis was carried out using the software VOSviewer 1.6.19 (van Eck & Waltman, 2010).

The search using the final query string was conducted on Scopus database on April 29th, 2023. Another filter was applied to the publication date to sort out all the 2023 publications (from 2023, 1st January until the date of search, 2023, 29th April). As landslide susceptibility case studies are subject to an abundant literature, it would have been neither possible in practice, nor relevant to review integrally. Indeed, two literature reviews already investigated the conditioning factors used in landslide susceptibility-related articles, one for the period 2001-2020 (1,142 papers reviewed), the other for the period 2005-2016 (469 papers reviewed) (J. Huang et al., 2022; Pourghasemi et al., 2018). Although using different approaches, both papers came to comparable findings with J. Huang et al. (2022) and Pourghasemi et al. (2018) identifying 17 and 18 most used conditioning factors, respectively, among which 16 were common variables. Given that, we anticipated that the set of factors that we would identify could be similar to these findings even on a more restricted paper set. Consequently, this short time window was considered sufficient to obtain a quantity of information representative enough of the most recent practices while being practically manageable. This was also driven in view of the study's purpose, which was not to conduct a systematic review of the landslide conditioning factors, but to investigate how they were currently integrating ecosystem-related factors.

There was a total of 31 articles found that met the search criteria. They were all manually screened to confirm their eligibility in the study. Exclusion criteria were defined to keep for analysis only the most relevant articles. Hence, the following articles were excluded: the ones that study the impact of landslide on ecosystems, and not the impact of ecosystems on landslides; the ones that were not case studies; and the ones not ranked as Q1 or Q2 journals according to the SCImago Journal Rank indicator accessed on 2023, May 6 (https://www.scimagojr.com/). The screening led to the exclusion of one article because it was published in a Q4 journal. Therefore, a total of 30 articles were finally eligible for analysis (Appendix A).

Both qualitative and quantitative methods were used to examine the selected paper set. The analysis comprised two parts. Firstly, we analyzed the main characteristics of the selected papers: publication venues; keywords occurrence; study area; mention of the term ecosystem or Eco-DRR; objective of the research; and methods. Then, we made a detailed examination of the factors used. For that, we first listed all the factors from the information provided in the selected articles, and we specified for each factor the author(s) who used them. When a factor was named differently although referring to the same measure, such as precipitation or rainfall, only one denomination was kept. Afterwards, each factor was associated with one of the following seven categories: topography, geology, hydrology, LULC, climate, human interference, and ecology-related factors. In the absence of a standardized classification, these categories were defined and refined as the analysis progressed according to the proposals made by the authors. After being enumerated and assigned to a main criterion, the factors were analyzed. It consisted of counting the total number of factors found, how many times they appeared in the 30 selected articles, and how they were distributed across the primary criteria.

2.2.2. Review of the factors used in ecosystem extent and condition assessment

2.2.2.1. Conceptual framework

The reference framework for this review on ecosystem assessment is the System of Environmental-Economic Accounting for Ecosystem Accounting (SEEA-EA) (United Nations, 2021). In this framework, the ecosystem extent and condition are measured first, the supply and use of the ecosystem services they produce second, and the monetary value of the ecosystems and ecosystem services is estimated last (Farrell et al., 2021; Grammatikopoulou et al., 2023). However, the quantification and valuation of ecosystem services are challenging and most commonly rely on the initial measurements and joint analysis of the ecosystem extent and condition (La Notte et al., 2022; United Nations, 2021). For this reason, our review focused on the ecosystem extent and condition components.

The ecosystem extent refers to the composition of the landscape, which includes the type, number, area and proportion of the different land cover and land use types in a geographic area (Petersen et al., 2022). Two primary inputs for the assessment of ecosystem extent are the ecosystem classification, and the LULC map (Bruzón et al., 2022). On the other hand, the ecosystem condition, which is also referred to as ecosystem health, reflects the quality of an ecosystem as measured through its abiotic and biotic characteristics (Rapport et al., 1998). The SEEA-EA states that the condition of an ecosystem is dependent on three aspects: the ecosystem characteristics, its integrity, and its drivers of change (United Nations, 2021). The ecosystem characteristics are, for instance, the biomass and soil for a terrestrial ecosystem (Maes et al., 2018). The ecosystem integrity refers to the landscape configuration, that is the spatial arrangement and distribution of the different land cover classes. Examples of this include the shape, fragmentation, or connectivity of landscape's patches (Beita et al., 2021). Finally, the drivers of change are those which impose pressure on ecosystems, such as climate change, habitat conversion and degradation, overuse, pollution, and invasive species (Sahana et al., 2022). Despite this framework, there is no agreed uniform approach for monitoring ecosystem health, due to the unique traits that each biome or ecosystem possesses (Czúcz et al., 2021; IPCC, n.d.). Considering that this paper focused on the landslides, the review of the factors used in the Ecosystem extent and condition Assessment (EecA) was consequently narrowed to the terrestrial ecosystems.

2.2.2.2. Search, screening and analysis processes

The method for the review of the factors used in EecA was also based on the principles of the PRISMA Statement (Page et al., 2021) and on a customized search string. that summarized the best available evidence. The final search query string was: (TITLE-ABS KEY ("ecosystem extent" OR "ecosystem condition" OR "ecosystem health") AND TITLE-ABS-KEY ("remote sensing" OR "earth observation") AND NOT TITLE ("marine" OR "ocean*" OR "sea*" OR "river*" OR "lake*" OR "wetland*" OR "aqua*" OR "water" OR "coral*" OR "lagoon*" OR "mangrove*" OR "swamp*" OR "marsh*" OR "floodplain*")) AND (LIMIT-TO (DOCTYPE, "ar")) AND (LIMIT-TO (LANGUAGE, "English")).

The keyword ecosystem services was intentionally not included in the query to concentrate the search on papers that focused on ecosystem extent and condition. Similarly, the keywords related to the word ecology were not included because these terms retrieved hundreds of articles not responding to the objectives of our study.

The final query was conducted on Scopus database on April 1st, 2023. The time frame for inclusion was from January 1st, 2020, to April 1st, 2023. This three-year time window was longer than the one used for landslide because of the complexity of ecosystem assessment induce more heterogeneous practices, requiring more papers to get a representative view of practices. It was however limited to the last three years considering that the assessment of ecosystems based on remote sensing data is a rapidly evolving field, as evidenced by the increase in articles about it (Kamran & Yamamoto, 2023; Senf, 2022).

A total of 68 papers met our search criteria. Each of them was individually reviewed to confirm their inclusion in the study. Based on the following exclusion criteria that we established, 27 articles were removed: the articles were not studying a terrestrial ecosystem (11); the articles were not a case study (5); the articles were not accessible, or not ranked as Q1 or Q2 journals according to the SCImago Journal Rank indicator accessed on 2023, May 6 (https://www.scimagojr.com/) (5); other reasons (6). In the end, 41 articles were chosen for review (Appendix B).

The paper set was examined using both qualitative and quantitative methods. There were two phases to the analysis: the examination of the primary characteristics of the chosen papers, followed by an in-depth look at the factors used. The primary characteristics of articles were evaluated using six criteria:

publication venues; keywords occurrence; study area; mention of the term disaster or hazard; research objective; and reference framework. For the analysis of the factors used in the EecA, the list of all factors was first extracted from the selected papers following the same process as the one used for LSAs. Each factor was allocated to one of the primary criteria that defined the ecosystem extent and condition: landscape composition (ecosystem extent), landscape configuration (ecosystem integrity), ecosystem characteristics or drivers of change. For the two latter aspects, we also defined sub-criteria based on the literature for terrestrial ecosystems so as to refine our analysis. As a result, the ecosystem characteristics were divided into four sub-criteria: vegetation, soil, water, and habitat/species (F. Huang et al., 2023; Maes et al., 2020). The drivers of change were also split into four sub-criteria: topography, climate, land conversion/degradation, and other drivers (P. Wei et al., 2019; Weiskopf et al., 2020). After being listed and assigned to a criterion, the factors that were examined. The main analyses consisted of counting the total number of factors found, the number of times they appeared in the 41 selected articles, and their distribution across the primary and sub-criteria of ecosystem extent and condition. The factors were also analyzed depending on the reference framework used by the authors.

2.2.3. Comparison of factors used in both types of assessment

In the third section of our review, the LSA's factors were compared to those of the EecA. The objective was to identify the factors that were shared by both types of assessments, and which ones were among the most frequently used. Additionally, on the basis of the identified common factors, the correspondence between the categories of the LSA and the primary and sub-criteria of the EecA was established. The common factors' relative contributions to these classes were evaluated. In addition, the data sources were examined to determine which factors might be measurable with remote sensing data. Finally, we looked at the factors that were used the most in one or the other type of assessment but were not found to be common to both.

2.3. RESULTS

2.3.1. Landslide susceptibility assessment

Of the 30 articles that met the inclusion criteria, 22 were published in Q1 journals (73%) and eight in Q2 journals (27%). In terms of the number of articles published, the journals Remote Sensing (with four articles), Catena (with three articles), Natural hazards, Journal of Mountain Science, and Environmental Earth Sciences (with two articles each) rank high. The 30 articles were published in 17 journals all together. Twenty-two of the selected 30 articles were conducted in Asia, including 15 in China, five in Africa, two in Europe, and one in North America (Fig. 3).

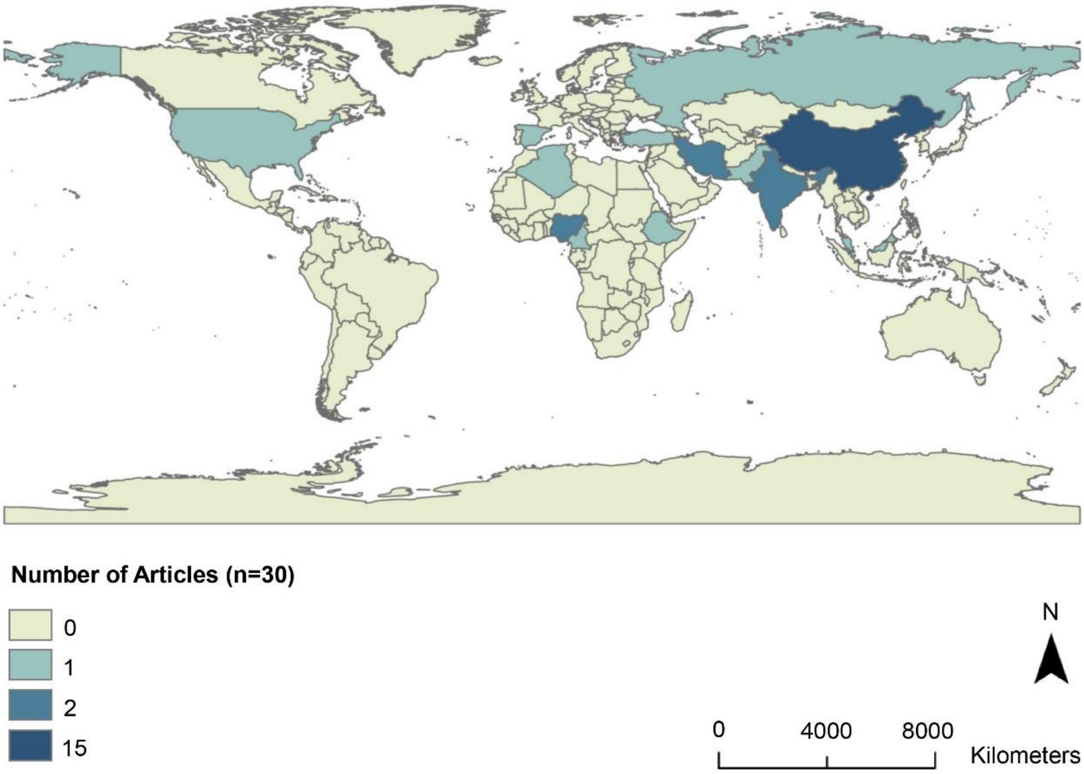

Figure 3 – Geographical distribution of study areas for LSAs

The full counting method of index and author keywords accounted 278 keywords with a minimum threshold of one occurrence; 50 with a minimum threshold of at least two occurrences; 21 with a minimum threshold of three occurrences (Appendix C). The most prevalent terms were associated with the landslide susceptibility maps/mapping and with the techniques used (such as machine learning, decision trees or random forest).

In each article, we conducted a manual search for the word ecosystem (singular and plural forms) or Eco-DRR (with or without a dash) in the whole papers except in the sections related to authors and affiliation, references and acknowledgments. According to the findings, no article referred to Eco-DRR. Only two articles used the word ecosystem, one in reference to the effects of landslides on ecosystems rather than the other way around (e.g., (Nwazelibe et al., 2023b)), the other in a generic sentence about land use change (e.g.,(Hürlimann et al., 2022)). As a result, the search was expanded to include the terms ecological and ecology. Two articles specifically mentioned ecological factors as driving factors of landslides (e.g., (X. Dai et al., 2023; Mwakapesa et al., 2023)). Four additional articles contained references to ecology but that were not relevant to our search: two of them focused on the ecological harm caused by landslides rather than on the contrary (e.g., (Sangeeta & Singh, 2023; Yu et al., 2023)); one referred to agroecological zones (e.g., (Zangmene et al., 2023)) and one to ecologists as decision-makers (e.g., (W. Huang et al., 2023)).

Regarding the purpose of the studies, three main groups were identified from the 30 articles. First, 16 papers tested and evaluated a variety of techniques for modelling landslide susceptibility: machine learning (11 papers, e.g., (Abdollahizad et al., 2023; Ghayur Sadigh et al., 2023; Huan et al., 2023; Jiang et al., 2023; Matougui et al., 2023; Sahin, 2023)), MCDM (three papers, e.g., (Bhagya et al., 2023; Nwazelibe et al., 2023b; X. et al., 2023)) or statistical methods (two papers, e.g., (Affandi et al., 2023;

Nwazelibe et al., 2023a)). Second, ten additional studies investigated how other aspects affected the LSA, such as the number of non-landslide points in the landslide inventory (e.g., (Z. Chang et al., 2023; Q. Liu, Tang, & Huang, 2023; Ye et al., 2023)), spatial resolution (e.g., (Yan et al., 2023)), or other aspects specifically related to the conditioning factors (e.g., (Guo, Ferrer, et al., 2023; J. Liu et al., 2023; Q. Liu, Tang, Huang, et al., 2023; Sangeeta & Singh, 2023)). The last four articles were straightforward case studies which aimed at producing land susceptibility maps in a study area, without testing or comparing techniques (e.g., (Addis, 2023; Bernat Gazibara et al., 2023; Guo, Tian, et al., 2023; Zangmene et al., 2023)).

In terms of methods, the selection of factors was subject to a multi-collinearity examination in 15 out of the 30 chose papers. The most used estimation indices were the Variance Inflation Factor (VIF), tolerance and the Pearson correlation coefficient, in nine, five and three papers, respectively, most of the times in combination. Machine learning and deep learning models were the most frequently used techniques to model landslide susceptibility, in 19 out of the 30 selected articles. The statistical approaches, including the weight of the evidence or the frequency ratio, were the second most utilized modelling techniques in seven papers. MCDM models, such as AHP were the least used methods in four papers.

The review of each of the 30 articles led to the identification of 46 conditioning factors. There was an average of 11.56 factors per case study, with 6 and 19 factors being the minimum and maximum numbers found in the various papers, respectively (Appendix D). A minority of factors (n=16) had just one event, whereas two-thirds of them (n=30) had at least two occurrences (Fig. 4).

Figures 4 and 5 illustrate the distribution of the 46 factors across the seven categories. It revealed that topography and geology accounted for the majority of factors. The third most represented category was hydrology, followed by ecology and human interference. The categories climate and LULC accounted for the least number of factors. Looking into details to each category, there were 13 identified factors assigned to topography. Only 4 of these 13 factors were present in at least half of the case studies: slope, aspect, elevation and plan curvature had 30, 26, 25 and 16 occurrences, respectively. Among the 11 factors assigned to the category geology, lithology was the only factor appearing in at least 50% of the studies, with 24 occurrences. The category hydrology was given seven factors. With 18 occurrences, respectively, the distance to the river was the only factor of this category used in at least half the studies. Precipitation, which was used in 18 of the 30 case studies, temperature, and frozen depth were the three factors related to climate. The LULC was used in 25 studies (83%). We identified six ecology-related factors. The most used was the NDVI, which accounted for 17 occurrences (57%); other factors were used in three articles or less. Finally, there were five factors found to be relevant to the category of human interference: road density, Normalized Difference Built-Up Index (NDBI), Normalized Difference Road Landslide Index (NDRLI), population density, and distance to roads. The latter was the only factor used by at least 50% of the authors (n=22).

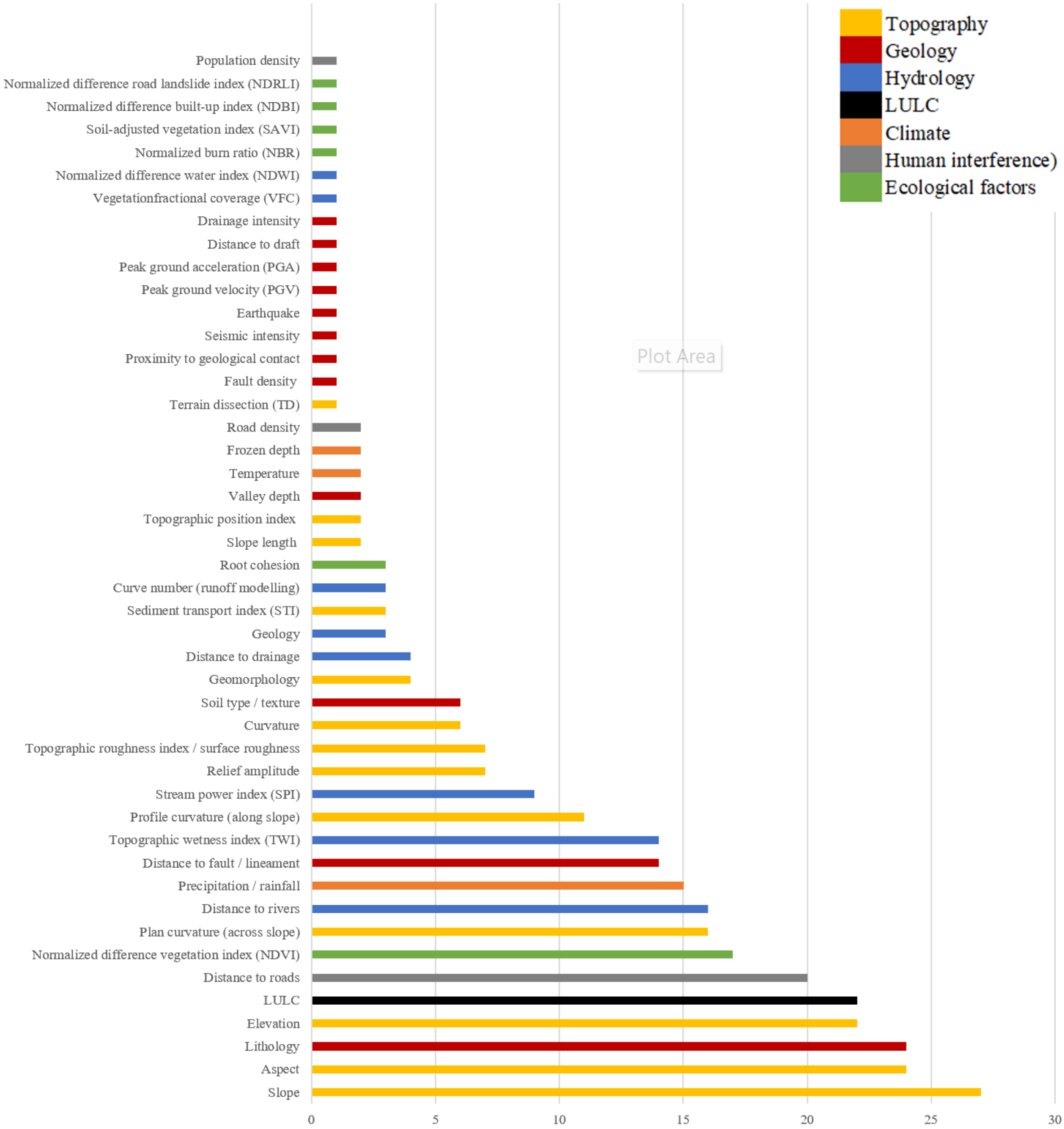

Figure 4 – List of factors used in the LSA, with their number of occurrences in selected papers according to their categories

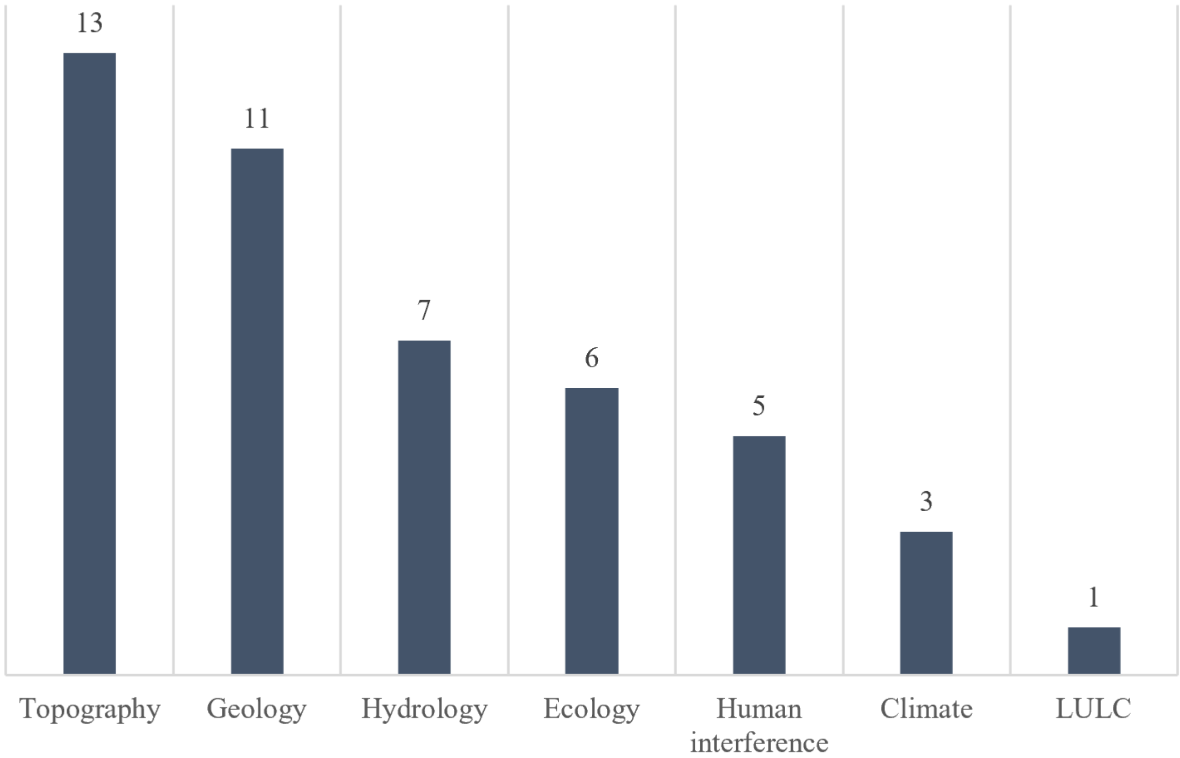

Figure 5 – Distribution of factors across the categories of LSA

We previously highlighted the ten factors that were used in at least half of case studies, meaning with an occurrence in at least 15 out of the 30 selected articles (Tab. 2). These ten factors were all considered as most used in both J. Huang et al. (2022) and Pourghasemi et al. (2018). Despite representing only 22% of all factors, these "most-used" factors are representative of the seven categories. As with the analysis of all factors, the three categories of topography, geology, and hydrology were the most represented.

Table 2 – The 10 most frequently used factors in LSA

Factor	Category	Occurrence
Slope	Topography	30
Aspect	Topography	26
Elevation	Topography	25
LULC	LULC	25
Lithology	Geology	24
Distance to roads	Human interference	22
Distance to rivers	Hydrology	18
Precipitation / rainfall	Climate	18
NDVI	Ecology	17
Plan curvature (across slope)	Topography	16

2.3.2. Ecosystem extent and condition assessment

Out of the 41 articles, 33 met the inclusion criteria were published in Q1 journals (80%), while eight of the articles were published in Q2 journals. In terms of the number of articles published, the most popular journals were Remote Sensing, which has seven articles, Ecological Indicators (six articles), Sustainability (three articles), the Ecological Informatics, Geocarto International, International Journal of Environmental Research and Public Health, Land (with two articles each). The 17 other journals all had only one article. The 41 articles were distributed across 24 distinct journals. The study area for 27 of the 41 articles was in the Asian continent, including 18 in China. Aside from that, six were carried out in Europe, four in the African continent, two in North America, and one in both Oceania and South America (Fig. 6).

Figure 6 – Geographical distribution of study areas for EecAs

The full counting method of index and author keywords accounted 598 keywords were found with a minimum of one occurrence; 97, with a minimum requirement of two occurrences; 40 instances with at least three; 21 instances with at least four; and 13 with at least five occurrences as a minimum threshold (Appendix E). Keywords related to ecosystems and their characteristics, such as ecosystem health, vegetation, or forestry, were the most frequently used. The second most common keywords were remote sensing, Geographical Information Systems (GIS), and satellite data.

In each article, we conducted a manual search for the generic words disaster and hazard, without specifying the type of hazards. The search did not consider the sections about authors, their affiliation, references, or acknowledgments. Out of the 41 selected papers, only five made a specific mention of the fact that the ecosystem degradation, notably through land degradation, have an impact on natural disasters, which is our topic of interest (e.g., (Han et al., 2020; Mallick et al., 2021; Rosero et al., 2023; Tasnim et al., 2022; Xu et al., 2022)). However, most of the case studies (26 publications) made no reference at all to disaster or hazard. In the last 10 other papers, the words disaster or hazard appeared but their use did not imply a direct link between ecosystem and hazard.

In this study, we used the SEEA-EA as a reference framework to categorize the factors, but we also investigated the reference frameworks used by the various authors in the selected studies. There was no mention to any framework in 61 percent of articles (n=25). The SEEA-EA was only mentioned in one paper (e.g., (Farrell et al., 2021)). The Mapping and Assessment of Ecosystems and their Services, an analytical framework developed by the European Union, was mentioned in another (e.g., (Katrandzhiev et al., 2022)). The Vigor, Organization, and Resilience (VOR) framework was the most often cited reference framework in eight publications (e.g., (Z. Bao et al., 2022; Cheng et al., 2020; Mallick et al., 2021; Y. Shi et al., 2020; H. Wang et al., 2020; Z. Wang, Yang, et al., 2020; Xiang et al., 2022)). Three studies relied on the Pressure-State-Response (PSR) framework (e.g. (Boori et al., 2022; W. Li et al., 2021; Zou et al., 2022)). Two further articles combined the VOR and PSR concepts (e.g., (Shen et al., 2020; Z. Wang, Yu, et al., 2020)).

Regarding the research objective, three primary types were identified. The majority of the selected papers (n=20) were designed as case studies in which remote sensing data were used to evaluate the extent and condition of the ecosystem as a whole (e.g., (Safaei et al., 2023; R. Shi et al., 2021)). Five additional papers studied a specific characteristic of the ecosystem, such as the vegetation (e.g., (Avelar et al., 2020; Hanssen et al., 2021; Verma et al., 2022)), the soil (e.g., (Pan et al., 2022)) or the ecosystem extent (e.g., (Lee et al., 2021)). Six further papers looked at how a driver of change affected one characteristic of ecosystem. For instance, Katrandzhiev et al. (2022) and T. M. Wei & Barros (2021) evaluated the impact of climate change on vegetation, while Odebiri et al. (2022) and Kırcı & Türkmen (2022) looked at the effect land use and land cover change on soils. The remaining papers tested the efficacy of remote sensing data in assisting with the ecosystem health assessment. Some of them compared EO data with field data (e.g., (A. Anand et al., 2022; Badapalli et al., 2022; Haghighian et al., 2022; Mao et al., 2021; Odhiambo et al., 2020)). Others assessed the relative weights of the various factors that influence the ecosystem health (e.g., (Boori et al., 2022; Chi & Liu, 2022; W. Li et al., 2021)).

There was a total of 195 factors found. The average number of factors was 10.95, with a minimum of two and a maximum of 32 (Appendix F). In two studies, with respective values of 30 and 32, the number of factors is however thought to be outside the overall distribution pattern (e.g., (A. Anand et al., 2022; Badreldin et al., 2021)). The majority (n=120) of the 195 factors only had one occurrence, while 38% (n=75) had at least two occurrences. Additionally, in the same way that we did in the previous section, we looked at the factors which were used in at least 50 percent of case studies, that is in at least 21 out of the 41 selected ones. Only two factors satisfied this requirement: the LULC and the NDVI. As a result, we considered the 25 most frequently used of the 195 factors, which were those identified in at least 10 percent of papers (i.e., five of the 41 cases) (Appendix F).

The distribution of the factors across the four primary criteria (ecosystem extent, ecosystem integrity, characteristics, and drivers of change) and the 10 sub-criteria is depicted in Figure 7. Because of the high proportion of factors used only once in selected studies, we duplicated the analysis with two sets of factors to demonstrate possible bias in this classification. All 195 factors were included in the first set, while only the 75 factors with at least two occurrences were included in the second set. We found that the two sets of components exhibit a pattern that is mostly comparable, except for the vegetation criteria. With the first set, vegetation added up to 83 factors; however, with the second set, there were just 28. The two outliers that were previously observed provide an explanation for this variation: A. Anand et al. (2022) and Badreldin et al. (2021) utilized 29 and 22 vegetation indices, respectively, whereas there was an average of 3.8 vegetation indices throughout the 41 papers studied. Hence, to reduce interpretation bias, the further figures refer to the 75 factors with at least two occurrences (Figs. 7–9).

We observed that primary criterion on the characteristics of ecosystem condition accounted for most of the factors (40 factors) (Fig. 7a). This is about twice as high as the second most common criterion, which is the drivers that affect the ecosystem health (22 factors). The ecosystem integrity criterion included 12 factors. Finally, the LULC criteria only considered the LULC component.

A comprehensive examination of the factors that comprised each of the four primary criteria completed the analysis. Regarding the characteristics of the ecosystem condition, the 40 factors were not evenly distributed among the four sub-criteria (Fig. 7b). The vegetation characteristic accounted for 28 of them, while the remaining three sub-criteria soil, water and habitat/species together constituted just one-third of these factors. This criterion also grouped 11 of the 25 top factors (Figs. 8–9). Of them, vegetation accounted for six (NDVI, Net Primary Productivity (NPP), Fractional Vegetation Cover (FVC), Leaf Area Index (LAI), Soil Adjusted Vegetation Index (SAVI), Enhanced Vegetation Index (EVI)); soil accounted for three (soil chemical parameters, soil erodibility factor, soil organic carbon); water for one (NDWI) as habitat/species (Shannon-Weiner Species Diversity Index).

The second criterion accounting for most of the 75 factors with at least two occurrences, was related to the drivers of change. The 22 factors were distributed between four sub-criteria: climate (5 factors); topography and land conversion/degradation (each with 4 factors); and the others class (9 factors) (Fig. 7c).We found that there were 8 "most used" items for this criterion, with 2 factors for each of the four sub-criteria (Figs. 8–9): elevation and slope were the most used aspects related to topography; precipitation and Land Surface Temperature (LST) for the sub-criteria climate; LULC change and per capita cultivated land area for the sub-criteria land conversion/degradation; and population density and gross domestic product for the last sub-criteria, other.

The integrity component of ecosystem condition came as the third criterion accounting for 12 factors all describing the landscape configuration (Fig. 7a). Among them, five factors were listed among the 25 most frequently used factors: Shannon diversity index; patch cohesion index; contagion index; mean patch size; landscape fragmentation index (Figs. 8–9). The extent of the ecosystem was the final criterion, with just one factor: LULC (Fig. 7a). The LULC was the most used factor, in 27 out of the 41 selected papers (Fig. 8). The 25 most frequently used factors, although representing only 13 percent of all the factors identified, were representative of all the primary and sub-criteria of EecA (Figs. 8–9). The other factors with four occurrences or less in the selected papers have not been further analysed.

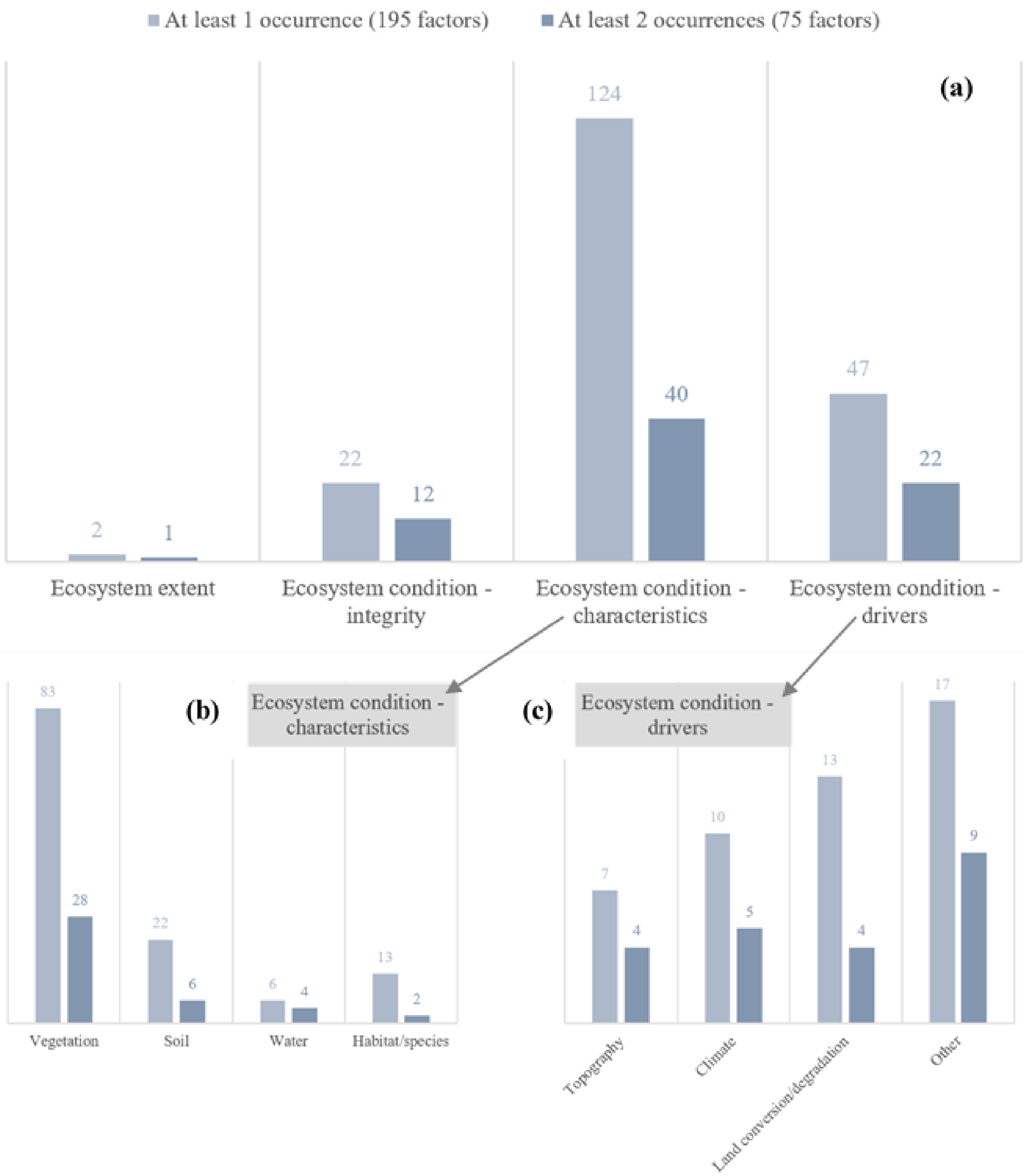

Figure 7 – Distribution of factors across the primary and sub-criteria used in the EecA

Regarding the reference frameworks, some papers referring to the VOR and PSR models provided details on how the factors were attributed to the different constructs of the models. In the VOR model, the vigor component was related to factors that were spectral indices, and notably vegetation indices. Organization primarily referred to landscape configuration-related factors; H. Wang et al. (2020) also used the LAI, and Shen et al. (2020) a biological abundance index. At last, resilience mostly included LULC and ecosystem resilience index. Some authors mentioned some “drivers of the VOR”, such as LULC and LULC change, population density, topographic or climate factors. In some cases, the VORS model, a slightly modified model, added service to the three basic components. It referred to the ecosystem services’ values.

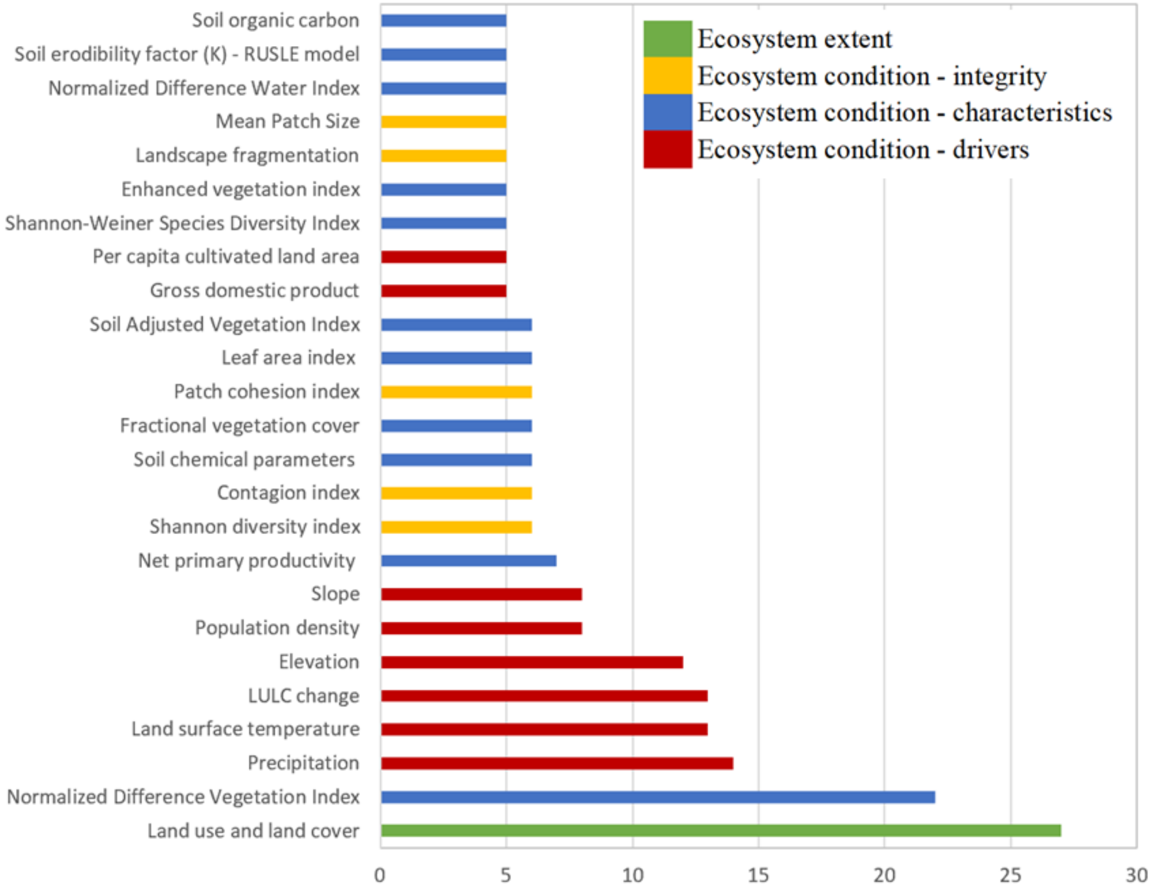

Figure 8 – List of the 25 most used factors in the EecA, with their number of occurrences

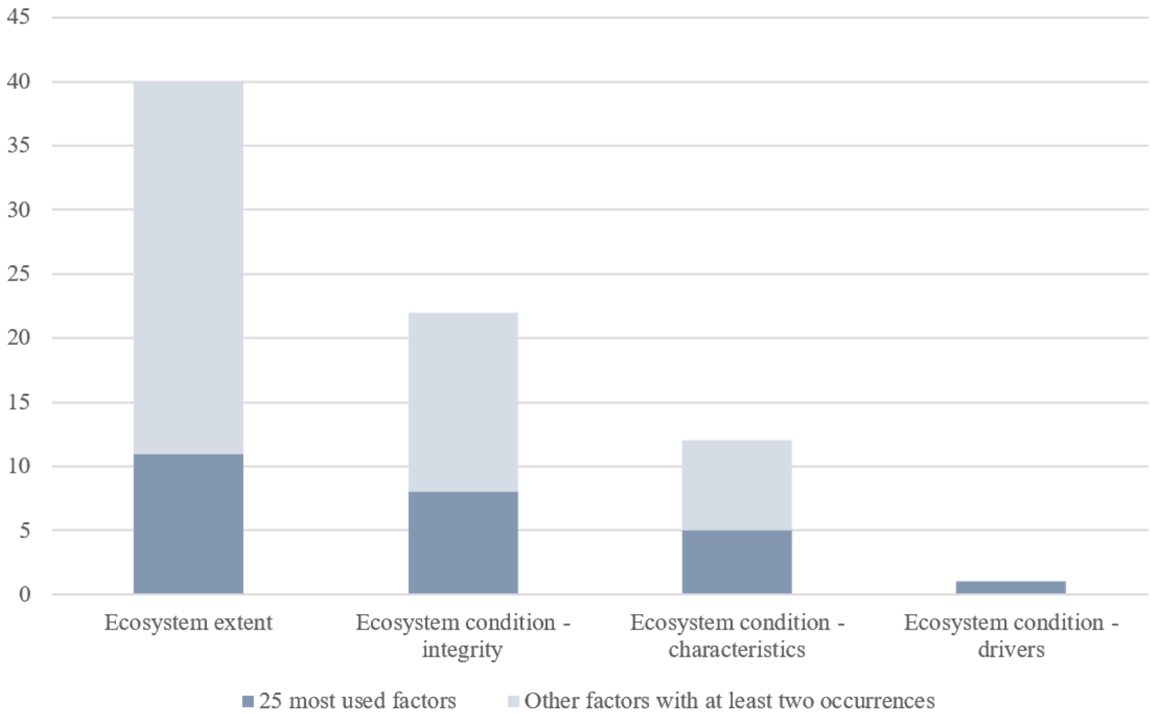

Figure 9 – Proportion of the 25 most frequently factors within all factors for each primary criterion of the EecA

According to the PSR model, the main indicators of pressure were population growth and density, urbanization, land reclamation, and other economic or industrial human intervention. The state component was connected to various factors among the four primary criteria that we defined based on the SEEA-EA framework: ecosystem's extent (LULC), integrity (Shannon's diversity index), characteristics (vegetation indices, LAI, NPP, habitat quality) and drivers (elevation, precipitation and temperature). Shen et al. (2020) mentioned VOR as one state variable of the PSR model. Various factors were also assigned to response, in relation for instance with recovery area, soil, or NPP but without a clear pattern. In one case, a modified model, the BPSR, included basic as a fourth component (W. Li et al., 2021). It included precipitation, temperature and soil chemicals factors, which were considered among the state component in other instances. Without mentioning any particular model, Mao et al. (Mao et al., 2021) classified the factors in three main components -the spectral, textual, and structural indices-. Spectral indices regrouped vegetation indices. Textural indices derived from the Grey Level Co-occurrence Matrix (GLCM) allowed to characterize the landscape pattern. Structural indices indicated the structure of the canopy, and alike the LAI, were important factors to reflect the canopy function in regulating the surface energy and evapotranspiration (Park & Guldmann, 2020).

2.3.3. Comparison of factors used in both types of assessment

Out of the 46 factors identified for LSA and the 195 factors identified for the EecA, 19 were shared by both types of assessment (Fig. 10). It accounted for 41 percent of the variables used in the LSA and 10 percent of those used in the EecA. Eight of the 19 common factors were among the most frequently used in the LSA (in at least half of the papers); twelve were among the 25 most frequently used in the EecA (in at least 10 percent of the papers) (Tab. 3). Overall, six factors were among the most often employed in both types of assessments: elevation, slope, LULC, aspect, precipitation and NDVI. In the papers about landslides or ecosystems, the rate of use of LULC and NDVI was roughly comparable. Elevation, slope and aspect, on the other hand, are three topographic factors that were proportionally much more frequently used in the LSA than in the EecA: elevation was mentioned in 83 percent of articles related to landslides, but only 34 percent of publications related to the ecosystem; the percentages were 100 percent and 20 percent, respectively, for slope.

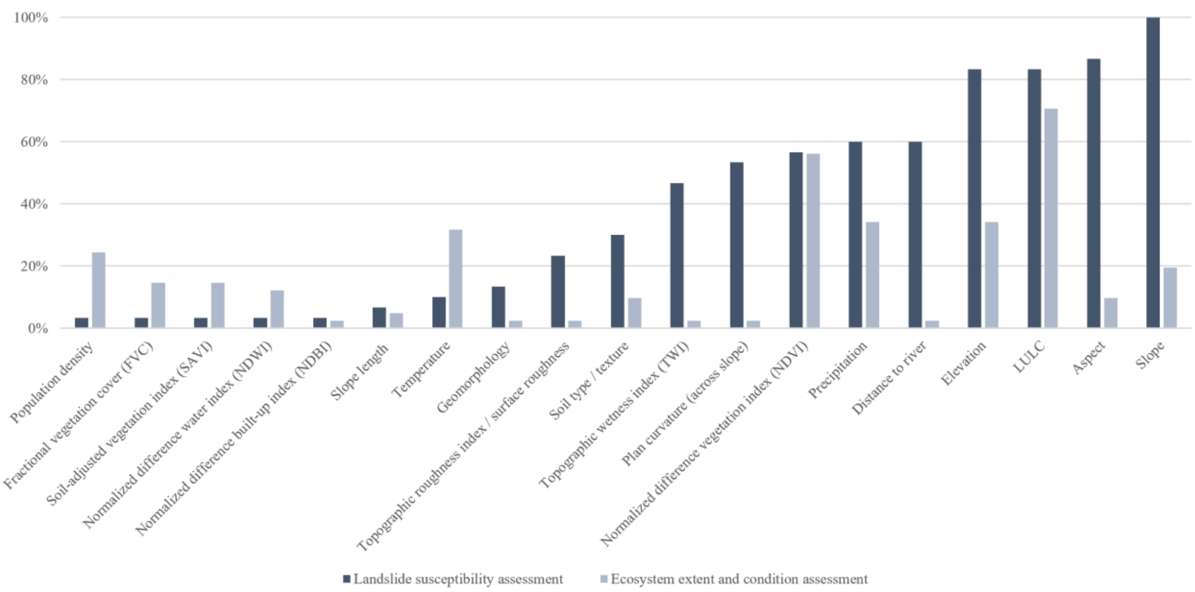

Figure 10 – Proportion of articles in which the common factors used to both LSA and EecA

Table 3 – Comparison of factors between the categories and criteria used for the LSA and EecA

Most used in both types of assessment	Most used in ecosystem extent and condition assessment only	Most used in landslide susceptibility assessment only	Not among the most used in both types of assessment
Aspect	FVC	Distance to river	Geomorphology
Elevation	LST	Plan curvature	NDBI
LULC	NDWI		Slope length
NDVI	Population density		Terrain roughness
Precipitation	SAVI		TWI
Slope	Soil type/texture		

Among the 19 common factors to both types of assessments, all categories of the LSA were represented. All sub-criteria of the EecA, except for habitat/species, also were. Based on the classification that we used in this study, categories and criteria were referred to differently in the two types of assessments. However, it has been possible to match them by looking at their respective common factors (Tab. 4). Our findings revealed that topography and climate were two classes with similar names. The categories geology, hydrology, LULC, human interference in the LSA were found to correspond to the sub-criteria soil, water, landscape extent, land conversion/other in the EecA, respectively. Finally, the ecology-related category (used for landslide) was paired with both the vegetation and landscape configuration sub-criteria (used for ecosystem). The habitat/species, which did not count a common factor was also included in the ecology category. Based on this correspondence, topography and ecology-related criteria were the classes with the highest number of common factors, with seven and four common factors, respectively.

After reconciling the categories and criteria of the two types of assessment (Tab. 4), we expanded our analysis to all 46 and 195 factors for the two types of assessments. The ratio of the number of factors associated with each of the seven main classes to the total number of factors was calculated for each of the two types of assessments (Fig. 11). It demonstrated that for the three classes topography, geology, and hydrology, the LSA utilized proportionally more factors than the EecA. In contrast, in the EecA, the class related to ecology was more prevalent. For instance, topography accounted for 28 percent of the factors in the LSA, but only four percent of the factors in the EecA. In contrast, the ecology-related factors accounted for only 13 percent of the landslide-related factors, but for 59 percent of the ecosystem related factors. The classes related to climate and human interference were almost equally represented in both types of assessment. In the LSA, the sub criteria habitat/species, which account for six percent of ecosystem-related factors, was not used at all.

Table 4 – Correspondence between the categories used in LSA and the sub-criteria used in EecA

<table>
<tr><th>Landslide susceptibility assessment - Categories</th><th colspan="2">Number of factors</th><th>Ecosystem extent and condition assessment - Sub-criteria</th></tr>
<tr><td>Topography</td><td colspan="2">7</td><td>Topography</td></tr>
<tr><td>Geology</td><td colspan="2">1</td><td>Soil</td></tr>
<tr><td>Hydrology</td><td colspan="2">2</td><td>Water</td></tr>
<tr><td>LULC</td><td colspan="2">1</td><td>Landscape extent</td></tr>
<tr><td>Climate</td><td colspan="2">2</td><td>Climate</td></tr>
<tr><td rowspan="2">Human interference</td><td rowspan="2">2</td><td>1</td><td>Land conversion</td></tr>
<tr><td>1</td><td>Other</td></tr>
<tr><td rowspan="3">Ecology</td><td rowspan="3">4</td><td>3</td><td>Vegetation</td></tr>
<tr><td>1</td><td>Landscape configuration</td></tr>
<tr><td>-</td><td>Habitat/species</td></tr>
</table>

For the 19 common factors, the data sources were analysed. All the 7 factors (elevation, slope, aspect, slope length, plan curvature, terrain roughness, geomorphology) related to topography were derived from Digital Elevation Model (DEM), such as Advanced Land Observing Satellite (ALOS) PALSAR (e.g., (Odhiambo et al., 2020)), STRM (e.g. (Prakash Sarkar et al., 2022)) or ASTER GDEM (e.g., (Aslam et al., 2023)). In the hydrology class, there was one factor also derived from DEM, that is the Topographic Wetness Index (TWI) (e.g., (Badreldin et al., 2021; Gui et al., 2023)). GIS was used to calculate distance to river or sea, which was the second factor in this class (e.g., (Yu et al., 2023)). LULC were generated from various remote sensing data sources. For instance, Cirezi et al. (2022) produced LULC maps from Landsat 7, Landsat 8, and MODIS, while Tasnim et al. (2022) used Sentinel-2 and Landsat-8 imagery and Chi et al. (2021) the SPOT-6 data. Other authors used existing LULC datasets such as the CORINE land cover (e.g., (Farrell et al., 2021)) or Copernicus Global Land Service (e.g., (Nwazelibe et al., 2023a)). Regarding the four ecology-related factors (FVC, NDVI, NDWI, SAVI), they were spectral indices calculated from multispectral images from different satellite sensors such as data from Sentinel-2 (e.g., (Haghighian et al., 2022)), Sentinel-3 (e.g., (Odebiri et al., 2022)), Landsat data (e.g., (Affandi et al., 2023; Portillo-Quintero et al., 2022)) or from datasets accessible online such as with MODIS (e.g., (Boori et al., 2022)).

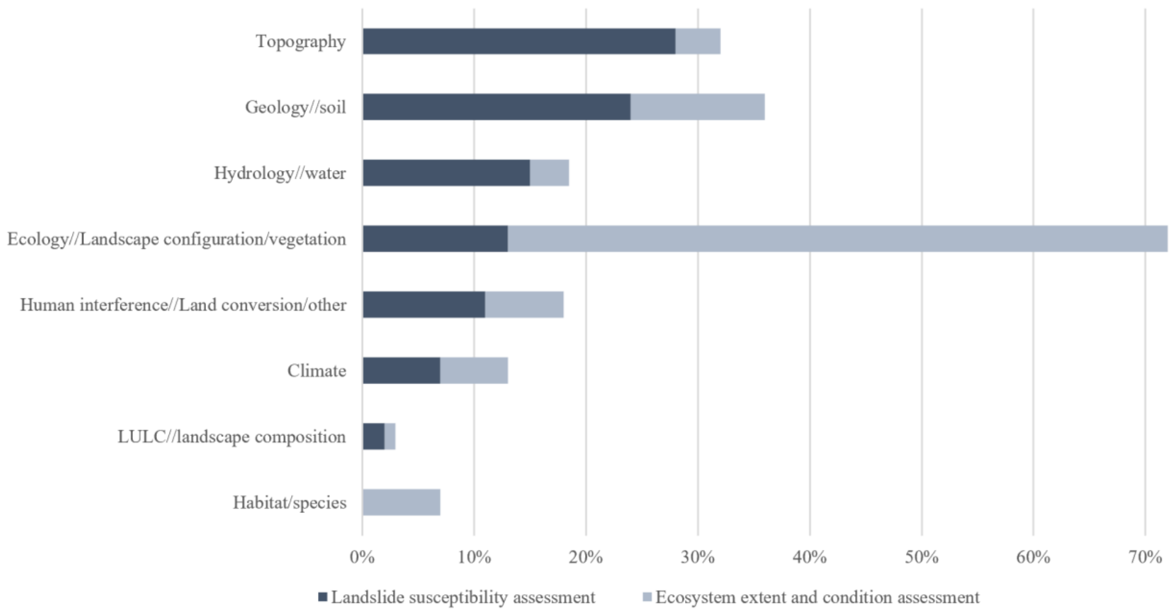

Figure 11 – Ratio between the number of factors associated with a given class and the total number of factors for both LSA and EecA

Existing datasets were used to generate the measurements for factors related to climate (precipitation and temperature) and geology (soil type and texture) (e.g., (X. Dai et al., 2023; Katrandzhiev et al., 2022; Nwazelibe et al., 2023a; Odhiambo et al., 2020)). Finally, within the human interference class, the NDBI was also a spectral index obtained from satellite imagery (e.g., (Z. Chang et al., 2023; Tasnim et al., 2022)), whereas the population density was typically provided by socio-economic databases (Zou et al., 2022) or by online accessible raster dataset (e.g., (Yu et al., 2023)). Along with these general trends, a few authors measured specific factors using alternative data sources or models: Badreldin et al. (Badreldin et al., 2021) integrated optical and Synthetic-Aperture Radar (SAR) remote sensing data to increase the accuracy in identifying land class; A. Anand et al. (2022) estimated the species diversity using hyperspectral remote sensing data. H. Bao et al. (2022) used the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) Habitat Quality Model (HQM) to investigate the ecosystem's resilience component in the VOR framework. In two other studies, the soil loss was determined using the Revised Universal Soil Loss Equation (RUSLE) model (e.g., (Kırcı & Türkmen, 2022; Pan et al., 2022)). Both of these models are based on remote sensing and auxiliary data.

The factors that were used the most frequently in one or the other type of assessment but did not appear in the factors that were shared by both types of assessments were the final focus of our investigation. The objective was to emphasize the potential underrepresentation of important ecological factors in the LSA. For the LSA, four of the ten most frequently used factors were not included in the common factors based on the criteria that we established: lithology, distance to roads, distance to river/sea, plan curvature. For the EecA, we found that 15 of the 25 most frequently used factors did not belong to the set of common factors. Among these 15 factors, five of them had to do with the configuration of the landscape (Shannon diversity index, contagion index, patch cohesion index, landscape fragmentation, mean patch size), while four of them had to do with the vegetation

(NPP, LAI, EVI, Shannon-Weiner species diversity index). The following six other factors were most frequently used in the EecA but were not found among the common factors: soil chemical parameters, soil erodibility factor, soil organic carbon for the geology class; and LULC change, gross domestic product, per capita cultivated land area for the class related to human interference.

2.4. DISCUSSION

Our research findings determined from the latest practices the extent to which ecological factors, measurable from open-source EO data, are incorporated into the factors influencing the likelihood of landslides. The exploratory review addressed this broad research question by summarizing the best available evidence using targeted search strategies. Hence, it provided the trends on the extent to which the ecological factors were integrated into LSA.

2.4.1. Standardization and harmonization of practices

Our review began by examining the factors that were used to determine the likelihood of a landslide as well as the ecosystem's extent and condition. In both areas, our findings demonstrated that no two assessments utilized the same set of factors. This brings to light the existing disparity of practices in the most recent papers. In terms of the number of factors used by the authors, the two sets of case studies (related to landslide and ecosystem, respectively) had a mean and median that were comparable (i.e., around 10). This suggests the use of a quite targeted set of indicators in both cases. However, the total number of factors identified for the EecAs was four times more important than for LSAs. In addition, the distribution of the number of factors was more spread in the ecosystem's studies than in the landslides' ones. The two last findings can be partially explained because more papers were included in the analysis of ecosystems' factors compared to landslides. This might have contributed to increase the number and variety of factors. Nonetheless, only one percent (2 out of 195 factors) of ecosystem-related factors were utilized in at least half of the papers against 33 percent in the case of LSAs (10 out of 30 factors). This suggests that the set of factors in the assessment of the ecosystem's extent and condition were less consistent than in the case studies about landslides.

The degree of standardization of the respective methodological approaches in both fields can account for this difference. The approach for assessing the landslide susceptibility is relatively well standardized, although some methodological aspects require constant research and improvement (Pourghasemi et al., 2018). Among them, the selection of conditioning factors is a topic that received a lot of attention, and that is particularly pertinent to our research topic (J. Huang et al., 2022). On the other hand, the models for assessing the ecosystem extent and condition appear to be far more inconstant. A reference framework was not mentioned in most of our selected studies. The SEEA-EA, which served as the reference framework in our study, was utilized just once among the selected papers. One reason could be that the SEEA-EA does focus on ecosystem services and monetary valuation, and not on the extent or condition of ecosystems, despite the latter serving as the foundation for the former. The VOR and PSR models were the most mentioned ones. The VOR conceptual model comprises three key components, which are the vigor (the capacity to preserve its structure and function), the organization (capacity for self-organization and adaptability to changing conditions), and the resilience (ability to recover from disturbances and return to a stable state) (Costanza, 1992). The PSR model developed by the Organization for Economic Cooperation and

Development is used to assess the ecosystem health based on the interactions between three key components: pressure (human activities), state (environmental conditions), and response (policy responses) (Hazbavi et al., 2020).

The comparison between the factors associated to the respective components of different frameworks showed some overlapping. For instance, each component of the VOR was linked to a primary criterion of the SEEA-EA-based classification that we used in this study: vigor to the ecosystem's characteristics, organization to the ecosystem's integrity, resilience to the ecosystem's extent. They were also all included within the state component of the PSR model. Moreover, the SEEA-EA drivers of change were reflected in the VOR driving factors, in the PSR pressure component, as well as in some PSR state indicators (those related to topography and climate). Finally, there was no obvious correlation between the PSR response component's factors and those of the two other frameworks. For instance, (W. Li et al., 2021) used NPP or EVI as response indicators, whereas other authors typically used them as vegetation factors or socioeconomic data like per capita income or population mortality (Zou et al., 2022). Other references that were not included in this study rather suggest the PSR response's factors as those related to the protected area, the protected species, or environmental expenditures (Levrel et al., 2009). Overall, our findings point to the necessity and potential of developing a comprehensive framework for ecosystem health assessment. In some case studies that combined the VOR and PSR frameworks, this work was already initiated (Shen et al., 2020; Z. Wang, Yu, et al., 2020; Xie et al., 2021). Such a comprehensive framework will assist in structuring the selection and integration of the appropriate ecological factors in LSA. As a result, it may provide support for the Eco-DRR practices, and more largely for the NbS practices.

2.4.2. Integration of ecological factors in the landslide susceptibility assessment

Our review also identified the factors used in the ecosystem-related assessment that were used to evaluate the landslide susceptibility. Both types of assessments were found to share 19 factors. This is a positive result that half of the LSAs already integrate some ecological factors. On the other hand, further findings suggest that the practices are still insufficient and improvable.

First, the 19 common factors represent only 10 percent of all the ecosystem-related factors that were identified. We also demonstrated that only five of them (elevation, slope, aspect, LULC, precipitation, NDVI) were frequently used in both types of assessments. However, some other common factors (LST, FVC, NDWI, SAVI, and population density, soil type/texture) were among the most frequently used in EecAs but not in LSAs. This demonstrates that the LSA does not consider some crucial aspects of the ecosystem's extent and condition. As to improve practices when working under the Eco-DRR umbrella, it would be first recommended the systematic integration in LSAs of these six factors that are very relevant to reflect the ecosystem's extent and condition.

Second, although their names were not uniform across the two domains, we discovered that ecosystem- and landside-related factors were linked to similar classes. This pairing demonstrated that one-third of the common factors were concentrated in the class topography. Again, this appears to be a satisfying result, leading one to believe that the LSA is accurately reflecting the ecosystem's angle through these topographical factors. However, landslide-related papers hardly used the keywords ecosystem or Eco-DRR. This suggests that the presence of common topographical factors is more coincidental than a genuine decision to incorporate an ecological perspective into the LSA, because they are conditioning factors in both instances. However, these topographical factors are valid and pertinent, and they could be highlighted as ecological factors in promotion of Eco-DRR. The second most prevalent category in both types of assessments was related to ecology, including notably the factors associated with vegetation and landscape configuration. Here again, this is a favorable finding to support our research topic. However, the landscape configuration and vegetation-related factors are utilized in most ecosystem-related articles but only in a small number of landslide-related papers (or not at all in the case of factors connected to habitat/species). This demonstrates that LSAs underutilize a number of very important factors that reflect the extent and condition of the ecosystem. Overall, the LSA must not only incorporate ecological factors better, but could also make a more systematic use of them.

2.4.3. Earth Observation data in support to Eco-DRR

In our study, our assumption is that the use of remotely sensed data would facilitate the replication and comparison of the ecosystem-oriented LSA, particularly in environments with limited data. This assumption implies that, beside data, the research structures also have available the appropriate human and material resources (Avalon-Cullen et al., 2023). This study gave additional evidence that remote sensing data and GIS were valuable tools in support to Eco-DRR (Doko et al., 2016; Krol et al., 2016). For that matter, the journal Remote Sensing was the most popular among the selected articles on landslides and ecosystems, and the keywords mapping, and GIS were prevalent in both areas.

More importantly, the majority of the 19 common factors identified between the two types of assessments could be directly measured or indirectly derived from EO data. Among them, the seven topographical factors such as elevation or slope can all be derived from DEMs from various sources (Saleem et al., 2019). The vegetation and water indices can also be all derived from multispectral data. Among them, the NDVI is the second most frequent index in all cases that we studied, and one of the most popular in general (S. Huang et al., 2021). If only few spectral indices were found to be common factors to both ecosystem and landslide related assessments, many more are available for mapping of ecosystem processes (Montero et al., 2023). For instance, the Index-DataBase, an online resource, registers 519 remote sensing indices (Henrich et al., 2012).

Besides the topographic and vegetation indices, the LULC is the most used factor in both types of our case studies. LULC is a very important variable as it is first the basis to assess the ecosystem extent (landscape composition). Second, many other factors are derived from it, such as the ecosystem integrity (landscape configuration), characteristics (vegetation, habitat quality) or drivers of change (for instance, land conversion). The LULC can be generated from satellite imagery, and so the measurements that are derived from. Most of the time, optical sensors serve as the primary source for the production of LULC maps. However, hyperspectral, SARand Light Detection and Ranging (LiDAR) data can likewise be utilized, and when used in combination, they tend to increase the classification's accuracy (Pandey et al., 2021). While the LULC offers the basis for a multiple of analyses, developing LULC maps is subject to careful consideration (Riva & Nielsen, 2021).
Among the factors common to both types of assessments, some were not straightforwardly or easily measurable from accessible EO data. However, some organizations propose downloadable spatial datasets in which raw satellite data have already been modelled and can provide proxy data for a couple of factors, such as for precipitation or temperature (Fick & Hijmans, 2017; I. Harris et al., 2020; Huffman et al., 2014), soil maps (Hengl et al., 2017; Poggio et al., 2021), or population density (Melchiorri, 2022). All these downloaded data can be included in Eco-DRR evaluations since they are

available in GIS-compatible forms. These services often provide data at a global level, despite certain drawbacks such a poor resolution.

Habitat/species are one of the ecosystem condition's characteristics. Overall, measuring biodiversity through EO remains complex and challenging (Rocchini et al., 2016).

In the cases we looked at, no such component was found to be one of the landslide susceptibility factors. However, it is important to note that the InVEST suite of models, as used in (H. Bao et al., 2022), represents an interesting tool since it permits with relatively low data requirements to examine spatial patterns of natural processes and services, such as habitat quality (Crossman et al., 2013; Sharp et al., 2020).

In conclusion, the majority of the 19 common factors identified between landslide and ecosystem-related assessments can be assessed directly from EO data, or easily derived from. For those which cannot be, data can be obtained from online open and free spatial datasets. These results are in favor of the development of standard assessment approaches under Eco-DRR, the replicability of methods and the comparability of results across various geographical areas, even in data-scarce environments. Also, our findings suggest that alternative data sources to the ones usually utilized can be tested to identify what single data source or what combination of them can give the best accuracy to ecosystem-based LSAs in a range of contexts.

2.4.4. Limitations and future research directions

The study's focus was confined to the hazard component of disaster risk, specifically the LSA aspect of the landslide risk assessment. We did not investigate other hazards than landslides, and no other realm than the terrestrial one. We did not distinguish between the various kinds of landslides even though their mechanisms and conditioning factors may differ. As a result, only some results of this study can be generalized to other types of natural hazards or ecosystems. For instance, the inventory of ecosystem-related factors made in this study could serve as a foundation for investigating other societal challenges than Eco-DRR if they are related to the terrestrial realm. As well, the approach that was taken in this exploratory review could be applied to investigate other relationship natural hazard/ecosystems besides landslides and terrestrial biome (Keith et al., 2022). In addition, we recognize that the short time windows chosen for the selection of papers may have led to leave out some relevant papers. However, we considered that the selection criteria, that are transparently explained, and which limitations are acknowledged, were nevertheless adapted to the objectives of our study. For instance, our results about the most used landslide conditioning factors were convergent to results from previous literature review, even with less materials (J. Huang et al., 2022). Through this practical exploratory review, we were able to explore and identify current interdisciplinary trends and gaps. We believe that we get valuable information from which to infer potential future research avenues for bridging the two fields and building interdisciplinary practices.

This study has been subject to some methodological limitations, such as the lack of standardized classification and naming, or the fact that data source was not always accurately informed. It led different aspects to be defined or managed based on the authors' judgement. For this reason, the replication of the process could lead to slightly different results. However, given that this review intended to be first exploratory research about the intersection between LSAs and EecAs, it is unlikely that these limitations brought much bias in our evaluation. In fact, we have achieved our goal of getting distinct key findings that serve as a basis for determining future research directions. Thus, this paper demonstrates that the integration of ecosystem-related factors into LSA has, up to this point, either been limited, fortuitous, haphazard, or just not materialized. As a result, and from an Eco-DRR perspective, efforts must be undertaken to enhance these currently insufficient practices. This involves the identification and selection of the pertinent factors to include in the ecosystem-based LSA, given that this stage impacts final susceptibility maps.

A major challenge is to find the balance between the complexity and the validity of the estimation model when selecting the factors. Both are essential but opposite criteria to incline toward replicability and comparability of studies. The model needs to be simple enough to favor standardization of practices given that it involves researchers from various fields, and that there are currently no harmonized approaches in each of the two fields. On the other hand, the selection of factors needs to be large enough to be relevant in the various geographical contexts where landslides can occur, given that conditioning factors can vary from location to location. Moreover, the selected ecological factors must also support our assumption, which is that degraded ecosystems increase the likelihood of landslides. In this context, we suggest two approaches to be further explored.

First, the integration of the 19 common factors in the LSA framework could be generalized to enhance the ecological perspective. In an attempt to link SEEA-EA, PSR and VOR frameworks, the factors can be categorize in two primary categories: conditioning criteria, which include topography, climate, land change, socio-economic drivers, and state criteria, which cover landscape composition, configuration and characteristics Within the context of NbS (Shah et al., 2020) also undertook the construction of a preliminary set of indicators and framework for the vulnerability and risk aspects connected to hydro-meteorological hazards. Creating joint model considering the elements shared across constructs of various frameworks offer the benefit to limit the subjectivity in choosing the model and indicators (Suprayoga et al., 2020). This key set of variables reflects and combines the latest practices in both fields and is measurable or derivable from remote sensing data or from open and free online datasets. To confirm that the conditioning factors have the expected influence on the dependent variable, which is the likelihood of landslides, and this regardless of the features of the study area, this collection of factors will need to be tested in various contexts. Overall, considering that ecological factors are currently employed in some cases, this first recommendation upholds Eco-DRR by promoting their more systematic inclusion into the LSA.

Some limitations related to the use of this key set of factors can be anticipated. For instance, the measurement of the indicators mostly relies on conventional sensors and products, like optical sensors or DEM. A potential direction for future research is the comparison of traditional and alternative data from various sources, either alone or in combination of each other, to increase the measurement accuracy of factors. For instance, as suggested by our findings, outputs of InVEST models, GLCM indices, or SAR imagery might complement the measurement of the factors included in our suggested framework. Another debatable aspect is that the current assessments assume direct links between the factors and the complex and abstract concepts they measure. For instance, the NDVI is a measurement of the vegetation sub-criterion, which is a part of the features of the ecosystem health. This assignment, however, is essentially theoretical, and only serves to illustrate the model's complexity without really measuring it. Given (i) the complexity associated with the number and linkages of conceptual variables and their underlying factors, and (ii) their reliance on regional features, proposing a valid, reliable, and generalizable model is therefore challenging. Advanced modelling methods like

Structural Equation Modelling (SEM) appear to have considerable potential for overcoming these issues. First, a minimum dataset of indicators can be extended to include more landscape configuration or spectral indices and refined using the confirmatory factor analysis of SEM (Maaz et al., 2023). The path analysis also makes it possible to estimate the cause-and-effect relationships between complex theoretical concepts involved in both the LSAs and EecAs (Fan et al., 2016; Grace et al., 2014). Furthermore, R. G. Smith et al. (2014) highlighted the ability of SEM in bridging various research disciplines given that Eco-DRR involves professionals that generally have expertise in their own domain and operate independently.

2.5. CONCLUSIONS

Our study looked at how the ecological factors were considered when determining landslide susceptibility. An interdisciplinary exploratory review was carried out in order to ascertain the factors that were utilized in LSA, those that were utilized in EecAs, and the ways in which they overlapped. Our key findings were, firstly, that neither the LSA nor the EecA's practices were standardized, although the latter exhibited even less structure, as evidenced by a wider range of different factors used in EeCAs compared to LSAs. Despite an average of around 11 factors per study in both LSAs and EeCAs, EeCAs exhibited a significantly higher number of different factors, with 195 identified across 41 papers, compared to only 46 factors identified across 30 studies in LSAs. Our analysis revealed that LSAs and EeCAs shared 19 common factors, with only two of these factors—LULC and NDVI—being more consistently utilized in both types of assessments. The ecological factors represented about two-third of factors in EeCAs, but only 13% in LSAs. Hence, this study illustrated that while certain LSAs incorporate some ecological factors, they often fail to systematically consider other critical indicators essential for assessing ecosystem extent and condition. Furthermore, our study revealed that most of the factors that were common to both types of evaluations may be directly or readily inferred from EO data. For those which were not, data were obtainable from online open and free resources.

Overall, the results of our research indicate that efforts should be made to enhance and unify the way ecological aspects are integrated into LSA. Finding a balance between complexity and accuracy in the selection of the observable factors would, however, be one major obstacle to overcome when developing such a standard model. Hence, we propose two main future research directions, one with practical implications, the other with theoretical ones. In the first place, future case studies might incorporate the group of common factors identified to broaden the ecological perspective during the evaluation of landslide susceptibility. Second, among the advanced modelling methods, SEM is regarded as a promising approach to support the definition of a valid, reliable, and generalizable model since it addresses both the structural model of conceptual components and the measurement model of their underlying indicators. Results enabled a better understanding of the most recent practices in both domains and the connections between them, as advocated by Eco-DRR. This study provides an important contribution to our field of study by (i) providing concrete recommendations for expanding the Eco-DRR scope of LSAs; (ii) enhancing the collaborative practices of experts from various fields; and (iii) bolstering the feasibility of the studies in any environment, be it related to the environmental features or to the data availability. In the end, it contributes to increase awareness of the role that healthy ecosystems play in reducing the disaster risk and other societal challenges.

These knowledge gaps underscore the need to test simple yet informative proxies, such as habitat quality and LULC, that can provide meaningful insights into ecosystem conditions. The following chapter explores this approach by examining how such indicators capture the impacts of landscape transformations and human-induced pressures on ecosystem integrity and resilience.

3. HABITAT QUALITY ON THE EDGE OF THE ANTHROPOGENIC PRESSURES: PREDICTING THE IMPACT OF LAND USE CHANGES IN THE BRAZILIAN UPPER PARAGUAY RIVER

Chapter abstract: Landscape changes driven by anthropogenic activities often have negative impacts on ecosystems, jeopardizing the provision of vital services that sustain biotic elements and wildlife. Predicting the effects of such transformations is crucial for developing strategies to mitigate ecological damage. This study explores the interaction of land use changes and habitat quality estimates in the Upper Paraguay River Basin in Brazil, using the InVEST Habitat Quality model to estimate spatiotemporal landscape trends and evaluate the potential impact of land use policies for the future. Under a business-as-usual scenario by 2050, potential land use changes are simulated for shaping habitat quality, habitat degradation, and habitat rarity estimates as landscape proxies for biodiversity conservation. Results show an extensive expansion of pastures through deforestation, leading to progressive habitat degradation with a significant decay in the predicted and observed habitat quality. The habitat quality index estimates show a spatial decrease from 0.78 to 0.57 for the 1989–2050 period. The same trend is observed in protected areas for the period 2019–2050, with an increase of anthropogenic land use and a decrease of the habitat quality from 0.80 to 0.57 in conservation units, and from 0.75 to 0.53 in indigenous lands. For improved conservation outcomes, this work introduces new insights for shaping environmental actions that can be flagged as sustainable land management practices and ecological perspectives towards spatial pressures at different scales. Therefore, government institutions responsible for the protection of conservation units and indigenous communities can be informed about potential land use impacts on their territories. The findings suggest that incorporating additional scenario trends and climate-related variables could be a valuable direction for future studies to extend further the modelling approaches explored in this work.

Broquet, M., Campos, F. S., Cabral, P., & David, J. (2024). Habitat quality on the edge of anthropogenic pressures: Predicting the impact of land use changes in the Brazilian Upper Paraguay river Basin. *Journal of Cleaner Production*, 459. https://doi.org/10.1016/j.jclepro.2024.142546

3.1. INTRODUCTION

Ecosystems face a wide range of critical threats driving land conversion and causing habitat decline (Scholtz & Twidwell, 2022), in which species extinction bear the most imperative consequences by anthropogenic pressures (Storch et al., 2022). Yet, it is difficult for planners to support all species (Myers et al., 2000), and the lack of investment in endangered species is lower rather what is desirable (De Mendonça et al., 2003). Such issues fragment landscape patterns, damaging ecological connectivity and functionality (Modica et al., 2021). In turn, land use changes are potentially related to biodiversity loss (Foley et al., 2005) and put the spatial dynamics of ecosystems at risk. Investigations into the effects of environmental impact and sustainable development frequently focus on land cover shifts (Cunha et al., 2021). Therefore, impacts of ecosystem management on biodiversity and ecosystem services need monitoring and assessment reports to help policy makers design conservation actions (F. Cui et al., 2021; Pascual et al., 2017). Landscape changes may decrease habitat quality due to their impact on ecological processes (L. Zheng et al., 2023), leading to unsustainable exploration of natural resources largely harming and reducing biodiversity worldwide (Ruckelshaus et al., 2020).

Landscape models and scenario analysis can offer insights into potential land use changes and their underlying drivers (Rosa et al., 2017). This type of modelling methodology opens the possibility for envisioning how nature may respond to different land policy choices (Guerra & Roque, 2020). Spatial explicitly models, serve as useful tools to map and quantify ES potential. Several authors have used the InVEST (Sharp et al., 2020), an open-source software applied for multiple spatial and temporal scales. An example of an InVEST model is the habitat quality, which evaluates the impact of anthropogenic pressures that may damage the environment (H. Zheng & Li, 2022). This approach may provide accurate information on the conservation status in large regions (Di Febbraro et al., 2018). On the other hand, land use optimization can be explored by simulating future land use changes (Nie et al., 2023) because land change scenarios hold a high potential to flag human disturbances that may sharp biodiversity decline (Bezerra, de Toledo, et al., 2022). In this sense, Markov models are broadly applied to develop land simulations (Lopes et al., 2023). The integration of land use and ES analysis comprises employing land cover cartography as inputs for ES models to understand the impact of land use policies in ecosystems (Sieber et al., 2021). Results from both modelling applications demonstrated to benefit policymakers with relevant information (Förster et al., 2015), avoiding potential risks to the functioning of ecosystems.

Environmental risks in Brazil raised in the last few years, where biomes such as the Amazon and Cerrado, have been threatened by human activities that go against conservation and preservation principles (de Area Leão Pereira et al., 2019; de Brito Freire et al., 2022). The historical issue of deforestation in the country can affect the entire Earth system (Hansen et al., 2013). Due to Brazilian biomes, future land cover patterns are fundamental to ensure future global climate and biodiversity (Bezerra, Von Randow, et al., 2022), revealing the importance of preserving heterogeneous ecosystems in the country. This task is sometimes a challenge, as Brazilian protection policies tend to become unsustainable in some eco-regions (Grasel et al., 2018). To support ecosystem functioning, protected areas play a crucial role in such biomes since habitat quality is higher where the protection level is also higher (Sallustio et al., 2017). Brazilian protected areas represent about 30% of the country (UNEP-WCMC & IUCN, 2021). Established to preserve biodiversity components and ES for long-term, protected areas encompass various categories, including indigenous lands, sanctuaries for traditional populations (Soares-Filho et al., 2023), and conservation units, mostly found in remote areas (Myers et al., 2000). The Upper Paraguay River Basin (UPRB) has a great ecological importance for Brazilian ecosystems, bounded as an ecotone zone with the presence of the Cerrado, Amazon fragments on the edge, and the central portion of the Pantanal, the World's largest tropical wetland (Esquerdo et al., 2019). Despite the interest in this region, there is a gap in studying the interaction of land use changes on habitat quality, confirming that highly diverse ecosystems in Brazil still lack adequate mapping and research (Esquerdo et al., 2019). To address this gap, the present study delves into land use projections to assess habitat quality suitability within the UPRB from a spatiotemporal perspective. The investigation unfolds through two primary modelling stages. First, a land change modelling process is applied to simulate a future land use and land cover map for 2050 based on a Business-As-Usual (BAU) scenario. Secondly, the 2050 map is integrated as the main input for predicting the biodiversity status using the InVEST HQM. The findings evaluate the potential impact of land use policies on biodiversity, informing where high conservation actions may be flagged at a planning intervention scale.

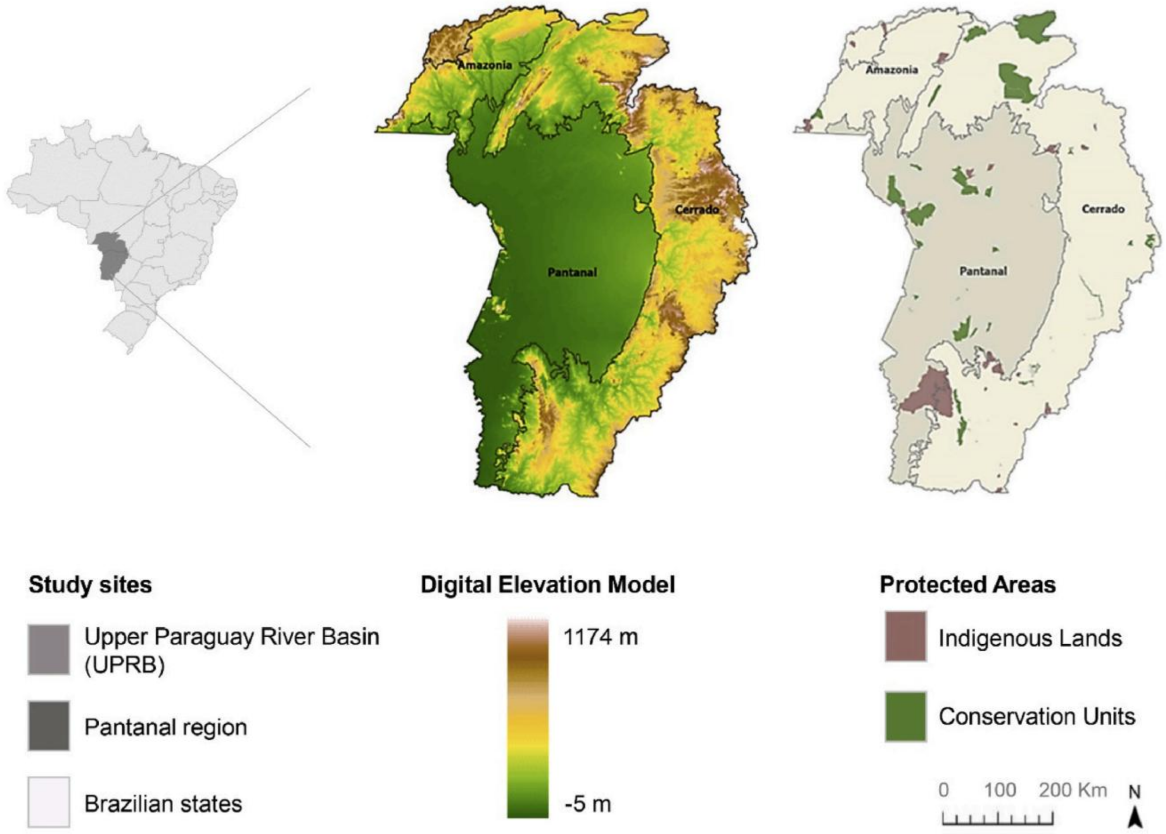

Figure 12 – Study area represented with a Digital Surface Model (DSM) on the left and Protected Areas on the right. Data source: ALOS Global Digital Surface Model (Takaku et al., 2020)

3.2. METHODS

3.2.1. Study area

The study area focuses on the Brazilian UPRB, which encompasses large parts of the Mato Grosso and Mato Grosso do Sul states (Fig. 12). This area covers 362,376 km^2 and spans − 59.71◦W to − 53.14◦E and − 22.30◦S to − 14.14◦N (OSDE, 2005). The UPRB has two extensive regions: the wetlands, which represent the Pantanal floodplain in the lowlands; and the Highlands, mostly covered by Cerrado and by the Amazon biomes. Nearly two million inhabitants live in the UPRB, mostly in the urban areas of the Highlands (M. D. de Oliveira et al., 2019). The UPRB plays a significant role in the Brazilian economic sector, accounting for about half of the country's food production and 60% of its electricity production (Rafee et al., 2019; Rudke et al., 2019). The region has experienced major land use changes in the last decades, notably with the intensification of agricultural activities in the highlands (Rudke et al., 2019). The Pantanal is classified as a UNESCO World Heritage Site with a rich biodiversity, however, endangered due to anthropogenic pressures in the UPRB (Junk et al., 2006; M. da R. Oliveira et al., 2021).

3.2.2. Theoretical framework

The theoretical framework illustrated in Figure 13 serves as a foundation for studying the interactions between land cover dynamics and conservation, revealing how these interactions shape ecological patterns across the diverse landscape of the URPB. The achievement of the research objectives lies in three essential factors explored in the methods section: 1) a land use simulation for the year 2050; 2) the assessment of the habitat quality; 3) the impact of land use and biodiversity within protected areas. Hence, the work adopts a theoretical framework of landscape ecology that combines principles from both land change and habitat quality modelling approaches.

Land change models analyze and simulate the conversion of land use and land cover types over time, driven by factors such as anthropogenic disturbances and environmental variables (Ren et al., 2019). Habitat quality models quantify the suitability of habitats for conservation, identifying fragmented landscapes that disrupt ecological processes and lead to declines in biodiversity (Haddad et al., 2015). Under a BAU scenario, human-related developments are expected to drive changes in land use patterns over time, resulting in the alteration and loss of natural habitats converted to anthropogenic land uses (Grecchi et al., 2014). Conservation initiatives, including protected areas or land use policies, are anticipated to contribute to the preservation of natural ecosystems and biodiversity (Ramos et al., 2023).

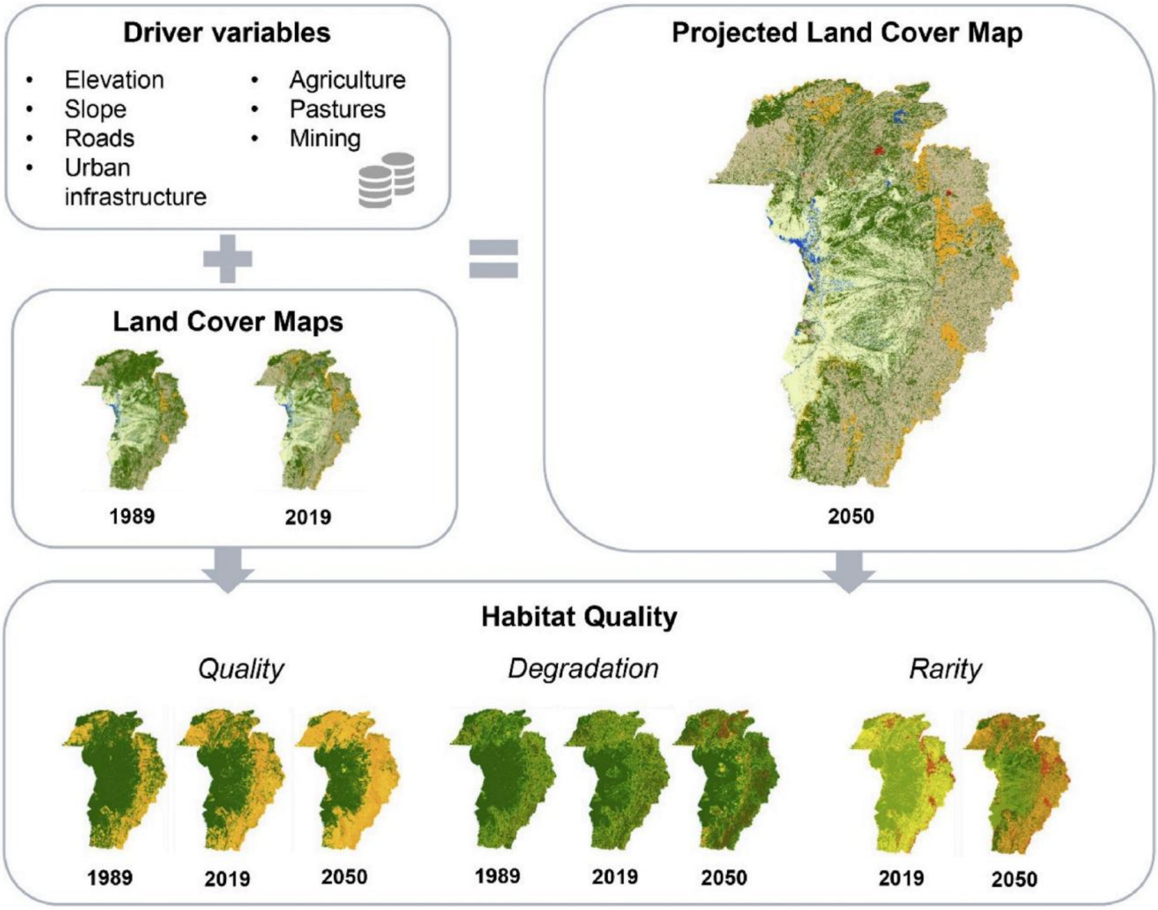

Figure 13 – The modelling-based scenario framework involving land use and habitat quality for this study

3.2.3. Data acquisition and processing

The datasets were selected based on their direct relevance and applicability to the research goals (Tab. 5). These offer high-quality, consistence resolution, and multi-temporal data spanning several years. Data sources encompass a diverse array of institutions, including government bodies, non-governmental organizations, universities, and research institutions. Importantly, the data is open-source and freely available, ensuring the reproducibility and comparability of spatial and temporal analyses.

The baseline data for the land use changes and habitat quality modelling approaches were pre-processed in the ArcGIS Pro 2.6 software (ESRI, 2021) to meet the application requirements. All the data was collected and transformed into the same projected coordinate reference system (ESPG 3857), rectified to match the spatial extent of the UPRB, and converted into the same spatial resolution of 30m.

Spatial data of the Brazil administrative boundaries and biomes in the shapefile format were downloaded from the Brazilian National Institute for Space Research (INPE, 2022). For the definition of the study area, the hydro basins were used to obtain the boundaries of the UPRB polygon. Data were acquired on the HydroSHEDs website developed by the World Wide Fund for Nature in partnership with other organizations (Lehner et al., 2008; Lehner & Grill, 2013). Four level 5 hydro basins were merged, identified as FID 398, 399, 367, and 353, according to South America Pfafstetter coding system which breakdowns sub-basins into subdivisions increasingly smaller at each level of breakdown (Linke et al., 2019; Thielen et al., 2020; Verdin & Verdin, 1999).

Table 5 – Data description used in the spatial modelling approaches for the Land Change Modeler (LCM) and HQM

Data	Reference	Description
Administrative boundaries	(INPE, 2022)	Used for the delimitation of the administrative boundaries of the study area
Biome boundaries	(Assis et al., 2019)	Used for the delimitation of the Pantanal biome within the study area
Hydro-basins	(WWF, n.d.)	Used for the delimitation of the UPRB study area
Digital Surface Model	(ALOS, n.d.)	Used for deriving elevation and slope, factors that significantly influence landscape dynamics
Land use land cover maps	(MapBiomas, n.d.)	Data from the years 1989 and 2019 obtained and used for characterizing land use patterns, conducting land change analysis within the LCM to generate the 2050 land use and land cover map, and as inputs for the HQM
Road network	(MapBiomas, n.d.)	Used for threat analysis within the HQM
Rail network	(MapBiomas, n.d.)	
Power lines	(MapBiomas, n.d.)	
Gas pipelines	(MapBiomas, n.d.)	
Conservation units	(Assis et al., 2019)	Used for assessing habitat quality in these specific areas, followed by comparison with neighboring regions
Indigenous lands	(Assis et al., 2019)	

The land cover cartography was acquired from the Brazilian Annual Coverage and Land Use Mapping Project – MapBiomas, which generates a series of historical annual land cover maps from a pixel classification of the Landsat satellite imagery (Souza et al., 2017, 2020). Four maps from the MapBiomas Collection 5 were downloaded for Mato Grosso state – 1989; Mato Grosso state – 2019; Mato Grosso do Sul state – 1989; Mato Grosso do Sul state – 2019. The maps of the two states were merged and then clipped over the UPRB study area, resulting in two UPRB land cover maps for 1989 and 2019. The initial nomenclature was comprised of 13 land cover categories and later reclassified into six main categories: Forest; Non-Forest Natural Formation; Pasture; Agriculture; Non-Vegetated Area; Water. The aggregation of land cover categories allowed to facilitate the data processing for the modelling applications and to simplify the analysis considering the large size of the study area. The reclassification table can be found in the Appendix G.

DSM was obtained from the ALOS Global Digital Surface Model with a spatial resolution of 30m (Takaku et al., 2020). To cover the UPRB study area, a mosaic was created using 56 tiles. A slope matrix was then derived from the DSM. Other ancillary vector data related to infrastructures were downloaded from MapBiomas and processed and used as threat factors impacting habitat. Finally, conservation units and indigenous lands represent protected areas from threats through legal, institutional, or social barriers. The protected areas considered in this study represent 6% of the UPRB area. The shapefiles for the year 2022 were downloaded from the TerraBrasilis platform version 1.1.0 (Assis et al., 2019), according to the Brazilian National Institute for Space Research (INPE, 2022).

3.2.4. Land change model

Several land use change approaches are available in the literature (e. g., (Q. Fu et al., 2018; Rudke et al., 2022; Siegel et al., 2022)). Among those options, the LCM within the TerrSet software offers tailored functionalities aligned to the research framework, permitting to address historical and future land use changes by creating empirical model (Eastman, 2016). This model uses a multi-layer perceptron neural network in conjunction with the Markov chain analysis to generate future land simulations. Previous research has demonstrated the efficacy of LCM in analyzing and predicting land use, particularly in studies focusing on the relationship between land use and conservation objectives (Gupta & Sharma, 2020; Lopes et al., 2023). In this study, LCM version 19 was utilized to project land-use patterns in the UPRB under a BAU scenario for the year 2050. In the context of a land change model and related framework, BAU denotes a hypothetical scenario where trends persist without significant interventions or alterations in current practices (Armenteras et al., 2019). Therefore, under a BAU scenario, it is expected that explanatory variables will exert a consistent effect on land use changes, thus extending observed trajectories from 1989 to 2019 out to the year 2050.

The change prediction follows a three-step process: 1) historical change analysis; 2) transition potential modelling; 3) future change prediction. The first step of the simulation assessed historical changes during the calibration period of 1989–2019 with support from the 1989 and 2019 land cover maps. The land use change analysis showed 30 types of land transitions. Land transitions of areas less than 1000 km^2 (<0.01%) were excluded. Vegetated and water classes, as well as transitions between pasture and agriculture -representing exchanges on different anthropogenic land use- and between forest and non-forest natural formation -representing exchanges on different natural land covers-, were not relevant to include in the land change model. Five transitions were then retained. They are, by decreasing order of their area size: forest to pasture, pasture to forest, non-forest natural formation to pasture, forest to agriculture, and pasture to non-forest natural formation (Appendix H).

The second step of the land change prediction involved the transition potential modelling driven by a set of underlying variables. Initially, a set of seven static explanatory variables, expected to influence the transition potentials, were tested. These variables were selected based on their relevance to the research objectives, theoretical framework, and the study area, as well as their frequent use in the literature. For instance, variables related to topography and landscape are frequently utilized in LCM due to their potential to influence land use patterns (Kim et al., 2020). Data availability also guided the selection process. The rationale for selecting and testing the initial explanatory variables is as follows.

- Elevation: closely linked to environmental factors such as temperature and precipitation and thus influences land cover (V. Anand & Oinam, 2020; Ansari & Golabi, 2019; Gupta & Sharma, 2020; Leta et al., 2021; Rafaai et al., 2020).Under a BAU scenario, low-lying areas may remain to be mostly agricultural, pastoral or urbanized due to their suitability for development, while high-elevation areas may remain preserved from human activities.
- Slope: it affects land use and land cover, as the steepest slopes may not be suitable for human activities such as farming or building, and then may remain undeveloped. In contrast, softer slopes are better suited for human expansion (V. Anand & Oinam, 2020; Ansari & Golabi, 2019; Gupta & Sharma, 2020; Leta et al., 2021; Rafaai et al., 2020).
- Distance from roads: the proximity to roads is often associated with human accessibility and land development. Under a BAU scenario, proximity to roads may promote higher rates of development due to accessibility, while remote areas may remain undeveloped or less intensively used (V. Anand & Oinam, 2020; Ansari & Golabi, 2019; Leta et al., 2021).

Similarly to distance from roads, in a BAU scenario, areas in the vicinity of other types of anthropogenic land use, such as urban and residential development, agriculture, or industry, are more likely to experience higher rates of land conversion to human-related development due to increased accessibility and ease of transportation, whereas more distant areas may remain undeveloped (Armenteras et al., 2019; Leta et al., 2021). In the projected land cover maps, the following driver variables related to anthropogenic land use factors were available and selected in the initial model.

- Distance from urban infrastructures.
- Distance from agriculture.
- Distance from pastures.
- Distance from mining.

Distance-related data were generated by using the Euclidean distance analysis tool in ArcGIS Pro (ESRI, 2021).

The seven driver variables were used as static factors in modelling the transition potential. Elevation and slope represent inherent landscape characteristics that are not expected to change significantly over time. As for variables related to the landscape structure, using them as static variables rather than dynamic ones, is justified by the need to mitigate the complexity of the model and the challenges of interpreting the results across a large heterogenous study area such as the UPRB (Stanton et al., 2012).

The LCM model was executed with the seven variables. After the training process was completed, the model outputs, including skill measure, were examined. The skill measure is a metric used to evaluate the accuracy or performance of a land change model by providing information about the explanatory capacity of each independent variable (Eastman, 2016). The variables with the lowest impact in explaining the model's variations were subsequently dropped. Hence, distance from pastures and distance from mining were excluded. The skill measure for slope and elevation (9% and 10%, respectively) suggested that these variables had a moderate but discernible degree of influence on the land use changes. Conversely, the skill measures for distance from roads, distance from agriculture, and distance from urban settlements, at 16%, indicated a higher explanatory power. Slope was identified as the most influential variable, while the distance from roads was the less influential. In this study, the explanatory capacity of individual variables is moderated by the size of the study area, which likely influences the complexity of land change processes and the spatial heterogeneity of the variables. For instance, the elevation, and consequently slope, are close to zero in the Pantanal region but exhibit greater gradients in the Highlands. Moreover, the socio-economic profile of both regions, Highlands and Pantanal, also influence land use types. When each individual variable is considered in isolation within the model at a phasing test, the overall accuracy and skill measure of the model decrease, suggesting that each of five selected variables offer valuable insights into understanding the dynamics of land change.

The multilayer perceptron neural network was ran using the following LCM Terrset's training parameters: initial learning rate of 0.01, momentum factor of 0.5, a sigmoid constant of 1.0 and dynamic training rates (L. P. Silva et al., 2020). The Root Mean Square Error (RMSE), a common metric to assess the performance of models, was used to evaluate the transition potential modelling (Chai & Draxler, 2014; Gibson et al., 2018). The RMSE is a relative value ranging from zero to infinity, without an absolute good or bad threshold (Chai & Draxler, 2014). A similar RMSE of 0.3212 was obtained for both training and testing, which indicates a good predictive value of the model. By completing the final model, a transition potential map was created for each of the five transitions of the model, expressing the time-specific potential for a land category to change into a different category. Once the model was calibrated, the simulated land use map was generated. This final step of the land change model consisted in the change demand and allocation for the year 2050, using the historical rates of change and the five transition potential maps previously modelled. The quantity of land susceptible to transition in 2050 was calculated using a Markov chain, based on the quantity of change observed during the reference period 1989–2019. The multi-objective land allocation module of the LCM analysed the host and claimant classes that lose or acquire land to allocate the final change. The prediction of the future land use and land cover for the year 2050 was defined under a BAU scenario. Performing those sequential tasks, the simulation of the 2050 map was successfully executed and further integrated in the HQM for enhanced ecological analysis.

The results of the land change analysis were expressed in km^2 and in percentage of the total area by the land cover proportion of each land class. The variations in the land cover classes between 1989 and 2019, and between 2019 and 2050 were also calculated, in km^2 (subtracting the area of the actual year by the area of the baseline year) and in percentage (Eq. (1)).

$$\mathrm{LCCx} = \left\lfloor \frac{(\mathrm{LCAx} - \mathrm{LCBx})}{\mathrm{LCBx}} \right\rfloor * 100 \tag{1}$$

where LCCx is the land use change of type x, LCBx is the baseline land cover of type x, and LCAx is the actual land cover category of type x. For the variation 1989–2019, the baseline is the year 1989 (LCB), and the actual land cover is the year 2019 (LCA); for the variation 2019–2050, the baseline is the year 2019 (LCB), and the actual land cover is for the year 2050 (LCA).

3.2.5. Habitat quality model

In this study, the InVEST HQM was used to quantify the habitat quality, degradation, and rarity as proxies for biodiversity, according to a suite of free open-source software for mapping and valuate ES, developed by the Natural Capital Project (Sharp et al., 2020). While habitat is defined as the home environment for plants, animals, or other organisms, habitat quality refers to the ability of ecosystems to provide appropriate conditions for the species at an individual and population scale to survive, reproduce and persist (Hall et al., 1997). Habitat quality is dependent on the proximity to anthropogenic spaces and to the application and intensity of land use by humans (L. Dai et al., 2019; McKinney, 2002; Semenchuk et al., 2022). Based on the assumption that areas with higher habitat quality are associated with greater species richness, the InVEST HQM is a valuable tool for assessing habitat quality as a proxy for biodiversity (Gong et al., 2019; Sharp et al., 2020). The model allows for the study of habitat quality at large scales, being suitable to apply in terms of the research framework considering the study area (S. Chen & Yao, 2023; Gong et al., 2019; Sallustio et al., 2017). Authors argue that this InVEST model proves to effectively map and predict habitat suitability, analyzing the interaction between socio-economic development that drives land use changes and biodiversity conservation (Aneseyee et al., 2020; Nagendra et al., 2013; Sun et al., 2019). However, even if other authors have studied habitat patterns on the region (Peluso et al., 2023; Regolin et al., 2021), no study applied this particular model within the study area. In terms of data accuracy, compared to alternative models, the InVEST is built to require fewer complex datasets and allow for the incorporation of future land use scenarios, offering valuable insights into both current and future habitat states.

The model combines different information on land use and threats to biodiversity for producing habitat quality, habitat degradation, and habitat rarity maps based on four determinate factors: 1) the relative impact of each threat to the habitat; 2) the relative sensitivity of each habitat type to each threat: 3) the distance between habitats and sources of threats; 4) the degree to which the land is legally protected, assuming that laws are enforced (Sharp et al., 2020). Anticipated trends in habitat quality, degradation, and rarity from 1989 to 2050 are expected to reflect the dominant patterns observed in land use changes under a BAU scenario and their impacts on habitat threats. The assumptions entail no alterations to the laws safeguarding the lands, land management practices, or policy interventions.

Therefore, habitat quality maps show the relative level of habitat quality. Areas with higher habitat quality and extent are expected to better support biodiversity, whereas the decrease in habitat extent over time would reflect the decline of the biodiversity. According to Sharp et al. (2020), the model evaluates habitat suitability in combination with anthropogenic threats to biodiversity. The habitat quality values range from 0 (null level of habitat quality) to 1 (high level of habitat quality). Highest scores reflect a better habitat quality considering the distribution of habitat areas across the rest of the landscape. The average values of habitat quality were calculated for the UPRB study area, as well as for the Pantanal and the Highlands for comparison between both regions. Threat source parameters are disclosed in Table 6 (and maps in Appendix I), while specific threats affecting each habitat type and their varying degrees of relative sensitivity are presented in Table 7. In terms of protection from disturbance, the model uses the protected areas' shapefiles as input, which is then interpreted to determine whether a location falls within a protected area or not.

Habitat degradation maps show the relative level of habitat degradation. Highest scores reflect a higher habitat degradation in comparison with other cells. The habitat degradation values range from 0 (low level of degradation) to 1 (high level of degradation). A value of zero means the absence of human disturbance impacting habitat quality, while the highest value reflects zones with the maximum concentration of threats that may cumulatively impact habitat (Sallustio et al., 2017). The average values of habitat degradation were calculated for the UPRB study area, and for the Pantanal and the Highlands for comparison among both regions.

Habitat rarity looks at areas where habitats are rarer regardless of quality, because opportunities for conserving them are more limited, and their definitive loss will imply the loss of the biodiversity within them. Here, rarity is appreciated by comparing a year 1 baseline land use map of year 1 against a land use map of year 2 (baseline land use map of 1989 against the current land use map of 2019, and current land use map of 2019 against the future land use map of 2050). Habitat rarity values range from 0 to 1. Values from 0 to 0.5 show that the habitat is more abundant in the map of year 2 that in the map of year 1. contrarily, habitat rarity values between 0.5 and 1 indicate a lesser habitat abundance, meaning that the area is considered as rare because it was abundant in the past but has become rare with time. A value of 0.5 indicates no change in the habitat abundance. The average values of habitat rarity were calculated for the UPRB study area, as well as for the Pantanal and the Highlands for comparison purposes. The inputs to the HQM are thoroughly detailed in the Appendix J.

Table 6 – Threat sources parameters used in the HQM

Threat Source	Maximum Distance	Weight	Decay
Roads	2	1	Linear
Rails	2	0.5	Linear
Lines	0.5	0.5	Linear
Pasture	3	0.75	Linear
Agriculture	3	0.75	Linear
Non-vegetated areas	3	1	Linear

Table 7 – Relative sensitivity parameters used in the HQM

Land use ID	Nomenclature	Habitat	Roads	Rails	Lines	Pasture	Agriculture	Non-veget. areas
1	Forest	1	0.8	0.8	0.3	0.8	0.8	0.8
2	Non-Forest Natural	1	0.8	0.8	0.1	0.8	0.8	0.8
3	Pasture	0.3	0.5	0.5	0.1	0	0.4	0
4	Agriculture	0.3	0.5	0.5	0.1	0.4	0	0.2
5	Non-Vegetated	0	0	0	0	0	0	0.5
6	Water	1	0.8	0.8	0.3	0.8	0.5	0.5

3.2.6. Protected areas: conservation units and indigenous lands

A complementary analysis was conducted with a focus on protected areas to evaluate their current and future status with regard to land cover and habitat quality estimates. Protected areas are defined as Conservation units and Indigenous lands, following the spatial limits provided by the TerraBrasilis platform version 1.1.0 (Assis et al., 2019), under the Brazilian National Institute for Space Research (INPE, 2022). In Brazil, indigenous lands are territories legally recognized as belonging to indigenous communities and managed by their traditional practices and cultural norms, whereas conservation units are areas set aside primarily for the preservation and sustainable use of natural resources and are typically managed by government agencies or non-profit organizations (Kohler & Brondizio, 2017).

The conservation units were created by the Brazilian Government in 2000, under law 9985, as part of the National System of Protected Areas (Rylands & Brandon, 2005). Since then, they have included strictly protected natural areas (IUCN categories I to III), whose primary goal is the preservation of biodiversity patterns, and sustainable use areas (IUCN categories IV to VI), which are aimed at the sustainable use of the natural resources (M. da R. Oliveira et al., 2021; Vieira et al., 2019). In recent years, the scope of protected areas has been extended to indigenous lands (Gonçalves-Souza et al., 2021; Vieira et al., 2019). A total of 88 protected areas were examined, consisting of 53 conservation units under strict protection and 35 indigenous lands. Initially, the analysis focused on land cover in 2019 and 2050, along with the expected land conversion between these years. Subsequently, average habitat quality values were computed for both the conservation units and indigenous lands within the UPRB.

3.3. RESULTS

The results section is structured to offer a comprehensive analysis across three main domains: 1) land use changes; 2) habitat quality, degradation, and rarity; and 3) the effectiveness of protected areas. The analysis of land use changes reveals significant transformations in the landscape considering the period 1989–2019 and 2019–2050. Spatiotemporal patterns in habitat quality are also examined, along with trends in habitat degradation and the distribution of rare habitats. The findings manifest distinct patterns and distributions in habitat quality estimates over time. The evaluation of protected areas within the UPRB assesses the effectiveness of conservation units and indigenous lands in preserving natural habitats. Those areas are projected to be increasingly occupied by human activities, as indicated by the model simulations. Each subsection offers a detailed examination of the spatiotemporal trends and implications observed within the UPRB based on the analysis conducted.

3.3.1. Land use changes

Results show forest, non-forest natural formation, agriculture, and pasture as the four dominant landscapes, although in different proportions of the total area over time (Fig. 14). The areas covered by non-forest natural formation are mostly observed in the Pantanal, where seasonal floodplains are common. Non-vegetated areas, including human settlements, are located in the Highlands. Water bodies can be found in the two biomes. The spatial-temporal trend of land changes shows the expansion of pastures along with forest loss at the Highlands. Limited forest slots remain intact across the south and central Highlands by 2050. The Pantanal and the Highlands depict different land patterns. If the Highlands landscape is dominated by pastures and agriculture, the Pantanal is still well covered with forest and natural vegetation.

In Pantanal, non-forest natural formation was the principal land use category in the last decades. Together with forests, these lands occupied 91% and 81% of the surface in 1989 and 2019, respectively (Fig. 15a). The most relevant historical land use changes in that biome were the decrease of forestation (− 8%) and the increase of pastures (11%). With respect to the Highlands, forests were the dominant land use type in 1989, and pastures in 2019. If pastures growth relatively the same as in Pantanal during those three decades (10%), deforestation was remarkably high in the Highlands (16%). In the meantime, agricultural lands more than doubled their size. Hence, the Highlands experienced major land conversions, with a loss of 37,497 km^2 (− 16% of the total area). The non-vegetated area, although representing a very small surface of the URPB, has almost tripled between 1989 and 2019, reflecting an increasing human presence in the region. The simulation of the land use for 2050 reveals that land use changes will occur in less than 4% of the Pantanal, where the conversion of natural to anthropogenic lands is expected to continue. By 2050, 68% of the Highlands will be covered by pastures and agriculture, when natural forest and non-forest formation represent just 31% of the region (Fig. 15b). Considering the UPRB altogether, pastures will continue to growth, whereas forests are predicted to disappear, even if at a slower rate than in the past (Fig. 15c). All other land cover categories will remain with no remarkable changes. The total converted area of land use changes was 97,991 km^2 from 1989 to 2019, and 69.805 km^2 between 2019 and 2050, representing 24% and 17% of the whole study area, respectively. Forests and, to a lesser extent, non-forest natural formation, are the main land categories affected by loss, benefiting both pastures and, to a lesser extent, agriculture expansion.

The ratio in km^2 of forest loss to non-forest natural formation loss decreases from 19% in the reference period of 1989–2019 to 8% in the forecast period of 2019–2050. This indicates that the loss of forest cover (− 51,422 km^2) was very large compared to the loss of non-forest natural formation (− 2672 km^2), such as wetlands in the past. However, in the future, the reduction in this ratio reflects more severe degradation of non-forest natural formation (− 3884 km^2, one and half more importantly than during the past period), mostly located in Pantanal, compared to forests (− 29,306 km^2 almost half less importantly than during the past period).

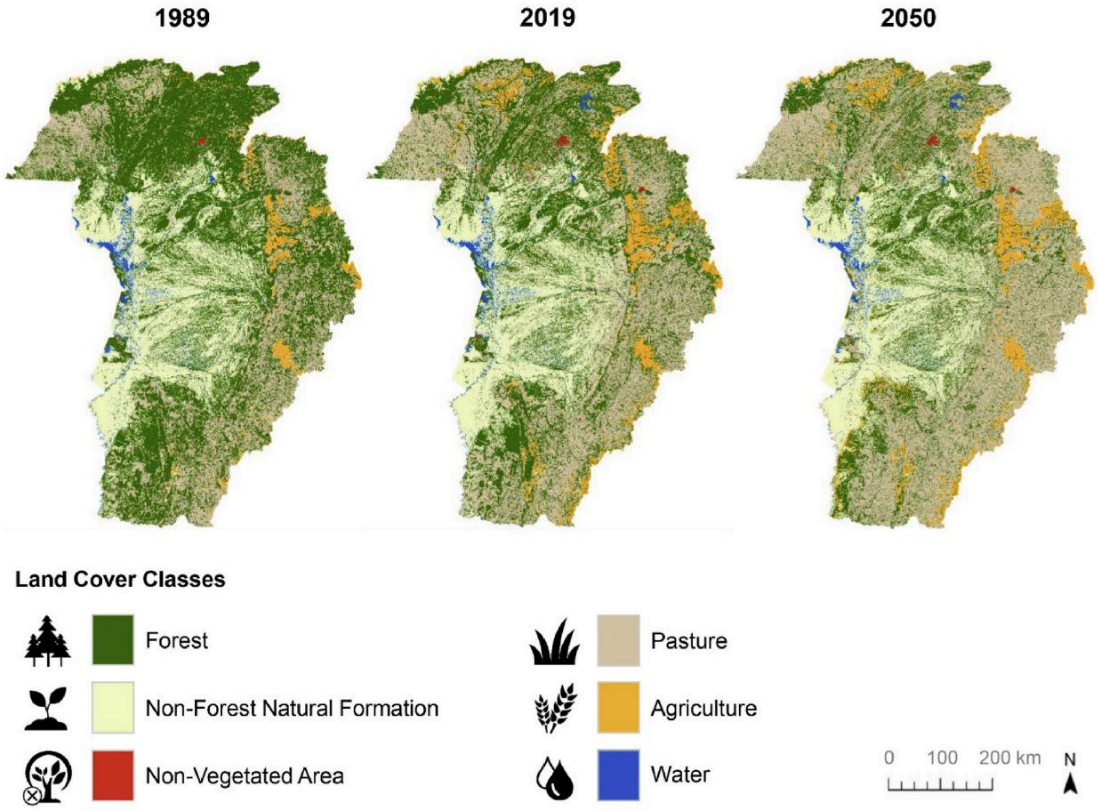

Figure 14 – Land cover classes for the years 1989, 2019 and 2050. The maps for 1989 and 2019 were obtained from the MapBiomas website (MapBiomas, n.d.). The projected map for 2050 was produced with the LCM methodology with support from both the 1989 and 2019 maps

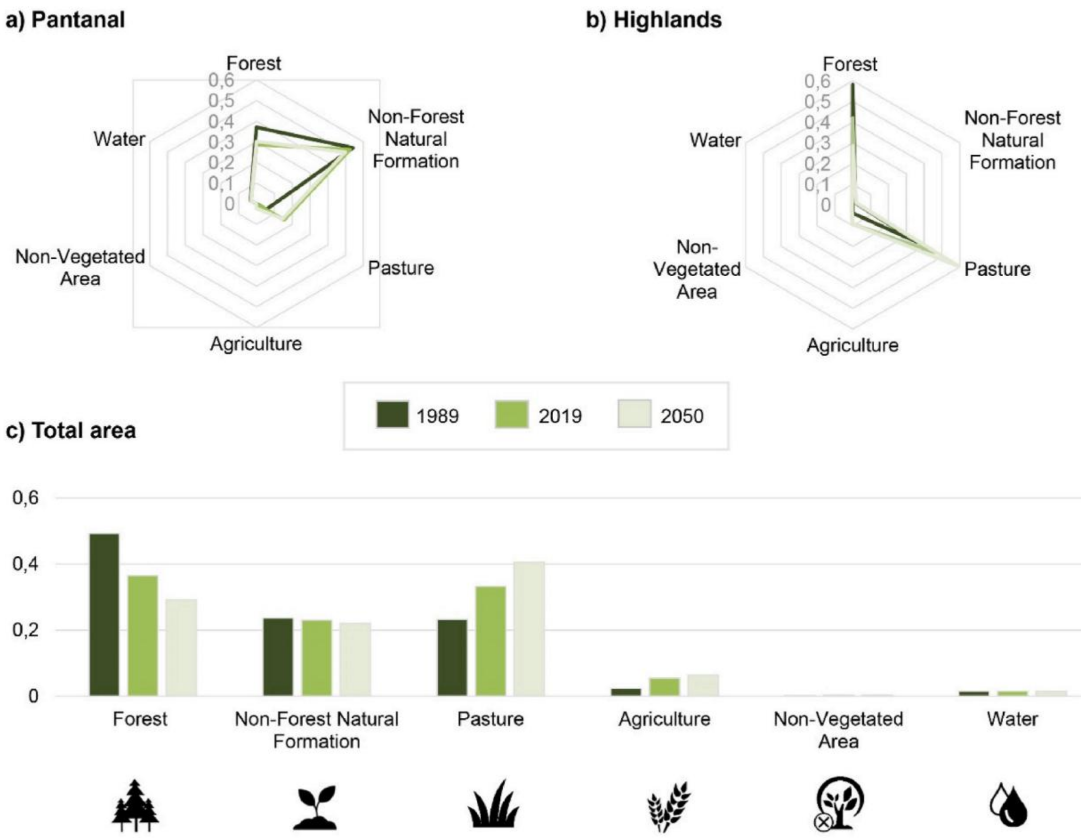

Figure 15 – a) Proportion area by land cover types for 1989, 2019 and 2050 in the Pantanal. b) Proportion area by land cover type for 1989, 2019 and 2050 in the Highlands. c) Proportion area by land cover type for 1989, 2019 and 2050 in the total area

3.3.2. Habitat quality, degradation, and rarity

Habitat quality estimates show different spatiotemporal patterns and distribution across UPRB. Higher values are found in the lowlands Pantanal, mostly covered by wetlands, and lower values in the surrounding Highlands, mostly covered by pastoral and agricultural lands (Fig. 16a). This general pattern is progressing steadily. In 1989, habitat quality was high in the Pantanal and in the northern area of the Highlands, as well as in many patches of the eastern and southern Highlands. In 2019, habitat conditions in the Pantanal remained good, although some small patches of low habitat quality are observed. Oppositely in the Highlands, habitat suitability is mostly low, despite some areas preserving high habitat quality. In 2050, the prediction suggests that the Pantanal lowlands will still be covered in the majority by areas of high habitat quality. However, areas with medium habitat quality levels are now observed in the buffer area between Lowlands and Highlands, and in a clear patch within the Pantanal. Those areas were before measured to support high-quality habitats. In most of the Highlands, the habitat is classified as non-suitable. The average values of habitat quality also show its deterioration over time. In the UPRB, the average values decreased from 0.78 in 1989 to 0.66 in 2019, whereas in 2050 it is estimated to 0.57. As reflected in the maps, the Pantanal maintains high values of habitat quality (>0.82), although slightly decreasing over time. In the Highlands, a considerable decrease in habitat quality is reflected by its values from 1989 (0.65) and 2019 (0.52). The prediction for 2050 is relatively low when compared with the past (0.40).

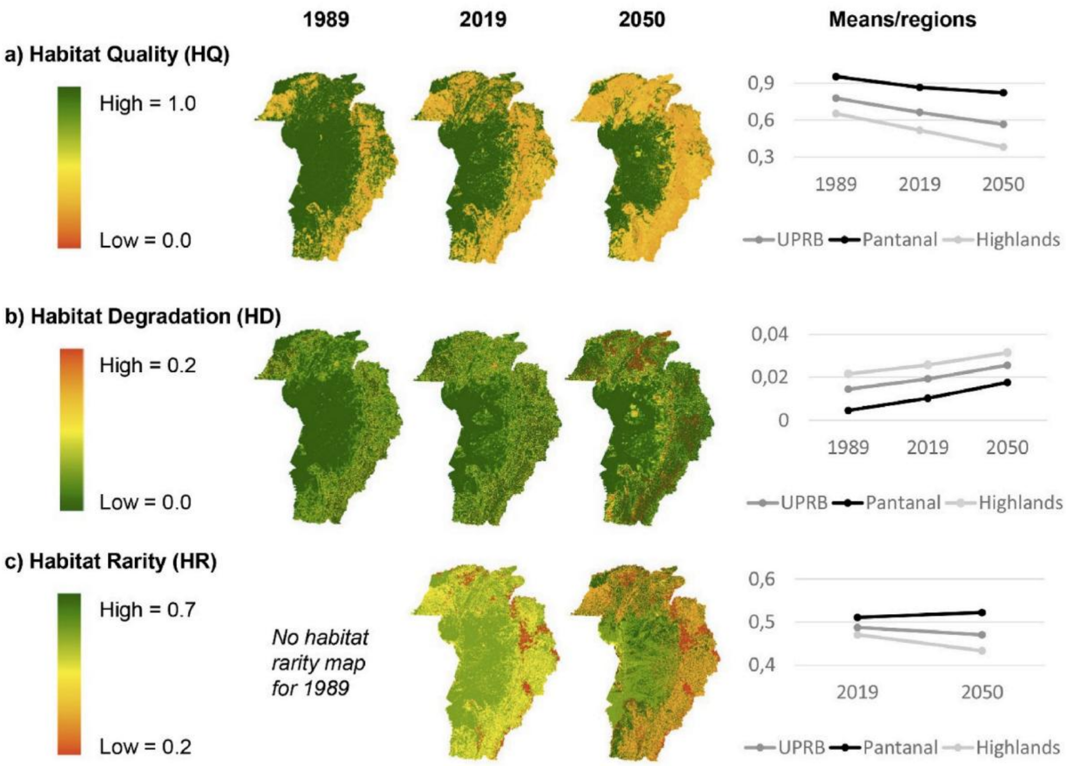

Figure 16 – a) Habitat Quality maps and average values in 1989, 2019 and 2050 from low (0) to high (1) quality. b) Habitat Degradation maps and average values in 1989, 2019 and 2050 from low (0) to high (0.2) degradation. c) Habitat Rarity maps and average values

As for habitat quality, habitat degradation shows an increasing pattern over space and time. In a nutshell, the highest scores of habitat degradation are observed in the Highlands, while the values are lower in the Pantanal (Fig. 16b). In 1989, the highest habitat degradation was mostly identified in the Southern, Eastern and North-western areas of the Highlands, while the values seem very low in the Pantanal. In 2019, a uniform spatial expansion of higher values is observed in the Highlands, as well as within the Pantanal, though in a lesser extent. The prediction for 2050 shows some highly degraded patches within the Pantanal, which were less significant in 2019. In the Highlands, the model suggests a high concentration of threats, resulting in a considerable extent of habitat degradation areas. Incidentally, in 1989 and 2019, one patch with higher habitat degradation values can be observed in the North-East area of the Highlands, corresponding to the main urban pole of the study area, which, by 2050, becomes surrounded by the highest concentration of high habitat degradation values. The average values of habitat degradation increase over time, from 0.015 in 1989 to 0.019 in 2019, whereas in 2050 it is estimated to 0.025. As reflected in the maps, the Highlands show the highest values of habitat degradation in comparison to the Pantanal. However, it is predicted that the average values of habitat degradation will proportionally increase sharper in Pantanal than in the Highlands between 1989 and 2050.

Relative habitat rarity is shown in Fig. 16c in terms of extent and pattern on the 2019 landscape regarding the 1989 baseline map, and on the 2050 landscape regarding the 2019 baseline map. In 2019 and in 2050, habitat rarity average values are higher in Pantanal region, with values above 0.5. This reflects that, on average, the habitat becomes less abundant from 1989 to 2019, and it is predicted to become even rarer by 2050. The pattern is less homogenous in the Highlands, where the highest habitat rarity values above 0.5 are sparser and more disseminated, especially in the Northern areas. The presence and prediction of rare habitats, mainly observed in the Pantanal and in the North of Highlands, emphasize the need to give them a priority for conservation.

3.3.3. Effectiveness of protected areas

Results show that forest and non-forest natural formations are the two dominant landscapes in both conservation units and indigenous lands in 2019 (Tab. 8). Nonetheless, in the same year, up to 16% of these protected areas were already occupied by anthropogenic types of land use, mostly pasture. Simulations for 2050 suggest a growth in the proportion of protected areas occupied by human activities to 36%, along with a projected increase in pastures by 132%. Although agricultural area is not as big as pastures in 2019, it is projected that these lands will also double in protected areas by 2050. The model also predicts that forests will experience the most losses, estimated at 3.192 km^2 in conservation units and 1.473 km^2 in indigenous lands (Fig. 17). Combined with the loss of non-forest natural formation, the average loss rate of natural land cover, which illustrates the change with respect to time, is projected at 164 km^2/year during from 2019 to 2050. While this number may seem low, it represents 20% of the natural land cover of the protected areas at risk of disappearing over the period, mostly in aid of pastures.

In terms of habitat quality, habitat is measured in 2019 with better quality in protected areas compared to the rest of UPRB. The average value is 0.8016 in conservation units, 0.7475 in indigenous lands and 0.6512 in the rest of UPRB. The difference of the habitat quality average values between conservation units and the rest of UPRB is statistically significant ($P < 0.0001$). The same applies while comparing the indigenous areas against the rest of the UPRB ($P = 0.0246$; $T = 2.0322$). The habitat quality index varies depending on the type of conservation units. Ecological stations, private natural heritage reserves, and parks have the highest values (>0.94), whereas environmental protection areas and natural monuments have the lowest values (<0.78). By 2050, habitat quality is predicted to drop sharply in protected areas, to 0.57 in conservation units and 0.53 in indigenous lands. The habitat is expected to decrease in the rest of UPRB as well, but to a lesser extent than in protected areas. Differences are not statistically significant between the rest of UPRB and the conservation units ($P = 0.8652$; $T = 2.0066$) or indigenous areas ($P = 0.3611$; $T = 2.0322$), although they were in 2019.

Table 8 – Land cover areas in 2019 and 2050, and its variation between 2019 and 2050 in the protected areas (conservation units and indigenous lands)

Protected areas	Area (km²)		Proportion (%)	
	2019	2050	2019	2050
Conservation units				
Forest	8,391	5,198	52.9	32.8
Non-Forest Natural Formation	3,718	3,633	23.4	22.9
Pasture	2,377	5,541	15.0	34.9
Agriculture	482	595	3.0	3.8
Non-Vegetated Area	53	53	0.3	0.3
Water	847	847	5.3	5.3
Indigenous lands				
Forest	5,791	4,318	62.2	46.4
Non-Forest Natural Formation	2,367	1,981	25.4	21.3
Pasture	1,080	2,520	11.6	27.1
Agriculture	17	436	0.2	4.7
Non-Vegetated Area	1	1	0.0	0.0
Water	53	52	0.6	0.6

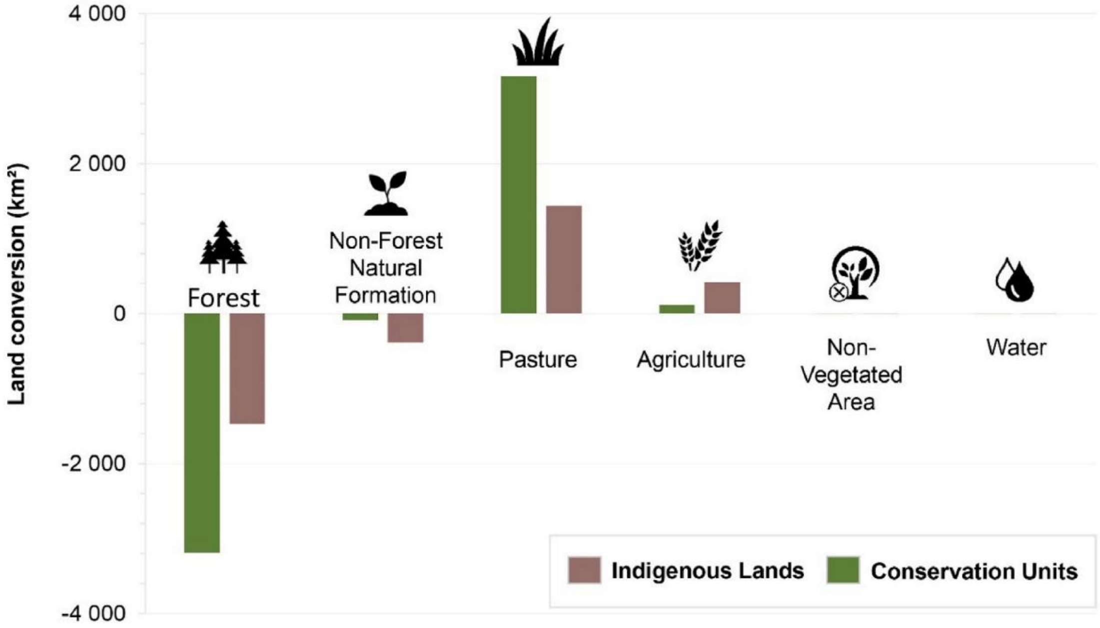

Figure 17 – Land conversion (km^2) within conservation units and indigenous areas between 2019 and 2050

3.4. Discussion

3.4.1. Land use and habitat quality trends

Land cover dynamics confirm that habitat quality is endangered by anthropogenic pressures, considering a BAU scenario. Results show that forest cover nearly halved between 1989 and 2050, and pastures almost doubled over the same period. Land conversion from forests to pastures occurred mainly in the Highlands. Already in 1989, 40% of the Highlands was converted to human land use, and by 2050, pastures and agriculture are expected to account for two-thirds of this land. Land use changes are driven by economic factors, especially as the country has specialized in cattle production to meet domestic and international demand for meat consumption (Ferrante & Fearnside, 2022; Seidl et al., 2001). The role of cattle grazing in deforestation has been recognized for decades, yet Brazil is to respond to the still-rising international demand for agricultural goods, which represents a continuous threat to UPRB biodiversity (Roque et al., 2021; West et al., 2022).

The model predicts an overall slowdown in land conversion from natural land cover to anthropogenic land use in the UPRB by 2050, in accordance with the findings of Roque et al. (2021). This pace can be attributed to several factors, encompassing aspects related to both LCM parameters and the characteristics of the study area. The selection of the explanatory variables is crucial for shaping the predictions. These factors represent both the topographic features and human activities that influence how land is used. Static variables were chosen over dynamic ones, assuming that landscape characteristics remain constant over time (Prieto-Amparán et al., 2019). While this assumption may hold true for topographic variables, static variables do not capture temporal changes in landscape dynamics caused by human disturbance, such as urbanization or agricultural expansion (Zeller et al., 2020). As a result, the model may underestimate the effects of such development factors on land use and land cover patterns. Furthermore, the observed trend in land conversion could be influenced by the context of the study area. The UPRB might eventually reach a stage of land use saturation or equilibrium, where the land available for conversion becomes limited or less suitable for intensive development. This could result in a slowdown in land conversion rates over time. When considering the effect of each explanatory variable, areas with higher elevations or steep slopes may be those less suitable for intensive land use activities, experiencing slower rates of land conversion as natural constraints limit the feasibility of land use changes (Chettry, 2023). In terms of human disturbances, urban growth and development pressures commonly accelerate land conversion. However, as areas close to urban settlements, roads, or agricultural fields become developed, the availability of suitable land for conversion may decrease, also leading to a slowdown in land conversion rates over time. Additionally, areas located far away from urban settlements may be characterized by lower population densities, lower demand for land development, and so limited infrastructure, which can also explain slower rates of land. In terms of human disturbances, urban growth and development pressures commonly accelerate land conversion (Zalles et al., 2021). However, as areas close to urban settlements, roads, or agricultural fields become developed, the availability of suitable land for conversion may decrease, also leading to a slowdown in land conversion rates over time (Chettry, 2023). Additionally, areas located far away from urban settlements may be characterized by lower population densities, lower demand for land development, and so limited infrastructure, which can also explain slower rates of land conversion (Winkler et al., 2021; Zalles et al., 2021).

The land change analysis also shows a reverse trend with the conversion of some lands from pastures to forests. However, the analysis did not reveal to what extent forests are used and for which domains, such as restoration of natural cover or deforestation. Different trends were observed between forests and non-forest natural formation, with conversion of wetlands being relatively more intense than forests in the future, notably in the transition area between the Pantanal and the Highlands. This finding shows that the Pantanal, which is dominated by non-forest natural formation of land cover, may be at higher risk of degradation.

The Pantanal biome has higher habitat quality and higher habitat rarity than the Highlands, reflecting the importance of this biome from a conservation perspective. These aspects appear to be associated geographically with human development, with areas mostly covered by a natural cover having high habitat quality, and areas with agricultural and pastoral activities having low habitat quality (Sallustio et al., 2017; B. Wang & Cheng, 2022). From a dynamic perspective, land conversions reveal to be spatially related to the deterioration of the habitat. Habitat degradation follows the same pattern as habitat quality, with the highest levels of degradation in the Highlands, as human activities lead to habitat loss and fragmentation (A. P. Jacobson et al., 2019; Mengist et al., 2021; Tang et al., 2021). In UPRB, it is also important to consider that habitat degradation in the Highlands is expected to affect the habitat quality in the Pantanal (Roque et al., 2021). Hence, the results show the capability of the Habitat Quality to study and provide valuable insights for ES research in the UPRB.

3.4.2. Policy effects on conservation

Overall, the Pantanal is and will be better preserved than the Highlands. This is potentially a positive and protective result of the State Law 8.830/2008 of the state of Mato Grosso (Schulz et al., 2019), which restricts human activities that could harm the environment in the biome. This state law is part of a larger legal framework that has seen the continuous improvement of Brazilian environmental laws since the Forest Code in 1965 (L. G. Barbosa et al., 2021). One of these instruments is the Native

Vegetation Protection Law, which was amended in 2012 with the ‘Forest Code’, and that regulates the amount of deforestation that can occur on private lands (Brock et al., 2021; J. M. C. da Silva et al., 2021). Another instrument is the National Protected Area System Law, from 2008, which defines conservation units that are strictly protected and designated for sustainable use (Rylands & Brandon, 2005). Findings support the effectiveness and importance of these planning strategies in maintaining natural land cover and protecting ecosystems, given that habitat quality in 2019 is significantly higher in protected areas than in the rest of the UPRB. However, despite the existence of these regulatory instruments, the results highlight potential conservation issues that could arise if current land and conservation policies and practices remain unchanged. Pantanal still faces various threats related to human activities and the region is at risk of losing its habitat suitability and natural lands. In 2020, for example, Pantanal experienced a devastating series of fires largely caused by human activities such as agriculture, mining, and logging, which had far-reaching impacts on the environment, wildlife and local communities (Abreu et al., 2022; M. L. F. Barbosa et al., 2022). Deforestation has not been as severe as in the Highlands, but it declined by 22% between 1989 and 2019. In fact, the Pantanal may be more invested in the future than in the past, especially if the Highlands offer less opportunities for land conversion. Additionally, even the protected areas, which are in 2019 stayed relatively well preserved compared to other areas, are further threatened by human activities, as it is expected for habitat quality decline more in protected areas rather than in unprotected areas by 2050, with both types of areas reaching lower levels of habitat. Therefore, advocating for the necessity of new federal funding strategies allocated to these environmental areas is crucial for promoting a sustainable future (J. M. C. da Silva et al., 2021).

The state of Mato Grosso issued in 2022 the bill PL 561/2022 (Ferrante & Fearnside, 2022). By loosening legal restrictions on land use in the Pantanal, the bill will ease the development or intensification of vegetation clearing, cattle grazing, industry, or tourism. It represents an additional threat to natural habitats, which is not taken into account in the model used in this study, which is based on a BAU scenario. This certainly makes the current study conservative in terms of minimizing the rate of future land conversion and their impact on habitat quality. Hence, this recent bill poses a major threat to the life of indigenous peoples and to the preservation of biodiversity, as does the dismantling of the federal environmental laws initiated under the Bolsonaro administration since 2019 (L. G. Barbosa et al., 2021; Ferrante & Fearnside, 2022).

3.4.3. Implications for management

The trends in the Pantanal wetlands and in their protected areas, call for immediate action against excessive human development to protect biodiversity in these areas as countrywide. Legal instruments to reduce habitat loss should certainly not be mitigated or even repealed, but rather strengthened to support their goals related to biodiversity conservation, climate change mitigation, and fair trade, to meet the Sustainable Development Goals (M. L. F. Barbosa et al., 2022; Colman et al., 2019; Ortiz et al., 2021). This is particularly important given that wetlands, unlike forests, have not been a priority in Brazilian conservation policies (Overbeck et al., 2015). Deforestation as a result of agricultural development, also causes land to become unusable due to the devaluation of ecosystem services. The restoration of degraded pastures that become non exploitable is considered as a successful strategy from both a productivity and conservation perspectives (Feltran-Barbieri & Féres, 2021; Ortiz et al., 2021). Additionally, state policies and practices may be adjusted and supplemented to better account for the spatial specificities of the UPRB, which consists of multiple ecosystems that are ecologically connected across three biomes (Bergier, 2013; Roque et al., 2016; Schulz et al., 2019; Thielen et al., 2021). Land conversion, habitat quality and habitat degradation are less severe in the Pantanal than in the Highlands, but the Pantanal has the rarest habitats, reflecting its richness but also where species are most endangered. It is important to protect biodiversity-threatened areas by making the natural habitats less accessible and less vulnerable to human activities and related threats (Bai et al., 2019; Sallustio et al., 2017). This includes indigenous reserves recognized for their contribution to nature conservation (Dawson et al., 2021; Gonçalves-Souza et al., 2021), which are especially significant as the conservation units currently involve under 4% of the Pantanal, contrasting with the most protected Amazon biome under the National Protected Area System (Gonçalves-Souza et al., 2021; Vieira et al., 2019). Indigenous communities deserve comprehensive awareness regarding the potential impacts on their lands, necessitating collaborative efforts with conservation practitioners and governmental bodies to safeguard the interests of future generations (Garnett et al., 2018). However, many indigenous groups are not safeguarded by government agencies and some of their lands are illegally taken by miners or loggers (Qin et al., 2023; West, 2024). Therefore, the consequences of land transition in these areas require particular attention, as they are essential for preventing degradation and forest loss, in addition to considering the human aspect (Malecha et al., 2023). Consequently, this work calls for a special relevance on this topic, as the essential roles of indigenous people in protecting biodiversity and ecosystems are often overlooked in terms of strategies for avoiding ecosystem degradation and species extinction (Levis et al., 2024).

3.4.4. Limitations and future work

While the findings of this study hold significant implications for environmental science research and policymaking, it is essential to acknowledge certain limitations that affect the interpretation of the results.

The assumptions made within the modelling process may lead to differences between the reality and simulations. The accuracy of the explicit results depends on both model parametrizations. For the land use model, the accuracy and skill measure statistics provided by the LCM were utilized to retain only the most important explanatory variables in the modelling process. This approach ensures the refinement of the models, enhancing their reliability and effectiveness in capturing essential factors driving land change dynamics. However, other important driver variables have been left outside the analysis, such as soil properties, population density or climate variability. Yet, too many variables can reduce the model's accuracy by delivering redundancy to the model, while too few cannot explain the land use changes (S. Chen & Yao, 2023). Moreover, analysing the drivers of land change separately in the different UPRB biomes shows to be beneficial instead of a single analysis (Guerra & Roque, 2020). For drivers such as roads, rails, and gas and power lines, the data refers to the year 1989, so the data used for the reference year 2019 is the same for the baseline and forecast years (Aneseyee et al., 2020). Considering that roads, railroads and gas/power grids were not as developed 30 years ago as they are today, the model is likely to miss the spatial extension of these threats. Besides, the land cover maps provided by the MapBiomas classification at the study area provided a good overall map accuracy at class Level 1 for the UPRB biomes, with 73.17% for the Pantanal, 95.13% for the Amazon and 81.40% for the Cerrado, under a 30 m pixel resolution (Souza et al., 2020).

One important limitation is the absence of confidence intervals in the HQM, which could be achieved by including expert opinion surveys to address the uncertainties of this model, as stated by (da

Fontoura et al., 2024). It is also relevant to know that the habitat quality estimates may tend to oversimplify the habitat complexity at macroscales, due to the lack of field observations (e.g. (Campos et al., 2021; Sallustio et al., 2017; Schulp et al., 2014)). However, combining land use changes with habitat quality predictions may also be able to help identify regions where habitat is most likely to be threatened (He et al., 2017). Future studies could expand the application of the HQM to other InVEST models, for a comprehensive understanding of the relationships between habitat quality and the provisioning, regulating, and cultural services provided by the URPB's ecosystems. Earth system factors related to climate change would also be important to integrate, given that they affect the ecological function of ecosystems and exacerbate the impact of human interventions into climate change models (Bonan & Doney, 2018). Regional climate projections, such as those produced within the CORDEX project (Gutowski Jr. et al., 2016), can be a useful resource for this purpose. Additionally, the parameterization of the two models was based on the results of a literature review. In future research, the model parameters could be tested in consultation with conservation experts and regional stakeholders in the UPRB (e.g., (Roque et al., 2016; Schulz et al., 2019; Tomas et al., 2019). The UPRB is a complex region made up of diverse biomes and ecosystems, legally administered by different states, with different levels of infrastructure. If the scale used in this study can answer the research question, additional small-scale studies that integrate these features could help refine the dynamics of habitat quality (Guerra & Roque, 2020). Using complementary analysis of the plant species that support the ecosystems can also provide valuable insight into the impact of current conservation laws and policies, and the direction in which they should be guided to (Lourival et al., n.d.). Finally, projections are based on a scenario in which future land use management and governance trends are expected to remain stable. The scenario could get worse if human activity intensifies or if an unpredictable large-scale environmental disaster occurs. Therefore, this study should be extended to include optimistic conservation and pessimistic economic scenarios to assess and compare different possible outcomes.

3.5. Conclusion

This work simulated spatiotemporal trends of land cover and land use in the UPRB in Brazil, evaluating the impacts on habitat quality, degradation, and rarity using the InVEST model. The analysis was conducted for the period from 1989 to 2050 under a BAU scenario. The Brazilian UPRB is facing high-risk from anthropogenic pressures, as evidenced by the declining habitat quality in the region over time. While the Pantanal region is still well-preserved, this status may be threatened if current land use trends continue. These findings contribute to a deeper understanding of the interaction between changes in land use and habitat quality, serving as a proxy indicator for biodiversity. Furthermore, the study reveals that protected areas -conservation units and indigenous lands-, despite their current effectiveness in preserving habitat quality, are under threat from the expansion of human activities. This is especially relevant, because indigenous communities are often with limited accessibility to resources and decision-making processes in a geographical space. The potential consequences of land use changes and declining habitat suitability highlighted here could disproportionately affect these communities, exacerbating existing cultural, social, economic, environmental, and legal inequalities. However, the scientific achievements from this research also enable informing local indigenous communities and conservation managers, aiding in the protection of the landscape. Future work may delve deeper into land change trends and underlying factors, depending on whether the focus is on transitions from natural land cover to human land use or the reverse. Hence, to preserve and restore habitats while mitigating anthropogenic pressures, this study concludes by advocating for the review, strengthening, and enforcing existing regulations for biodiversity conservation, as well as expanding their geographical coverage or the constraints they impose. Additionally, a shift in agropastoral practices towards more innovative, nature-based, and sustainable methods is also suggested.

LULC and habitat quality serve as valuable proxies for broader environmental processes, providing foundational knowledge for the multidimensional landslide susceptibility framework and predictive models discussed in Chapter 4.

4. INTEGRATING ECO-DRR INTO LANDSLIDE SUSCEPTIBILITY ASSESSMENT: THE CRITICAL ROLE OF ECO-ENVIRONMENTAL FACTORS

Chapter 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 Eco-DRR principles, using a Random Forest (RF) 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.

Broquet, M., Cabral, P., Campos, F. S. (2025). Integrating Eco-DRR into landslide susceptibility assessment: The critical role of eco-environmental factors. *Journal of Environmental Management*, 393. https://doi.org/10.1016/j.jenvman.2025.127043.

4.1. 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 & Petley, 2018). For instance, urbanization and resource consumption accelerate landscape alteration, weaken ecosystems' resilience, and disrupt essential regulating ecosystem services (Foley et al., 2005; C. 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).

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., 2008; 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 (S. E. Chang et al., 2006; Chatenoux & Peduzzi, 2007). Its recognition in international frameworks such as the Sendai Framework for Disaster Risk Reduction (UNDRR, 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 LSA, a critical tool for predicting landslide-prone areas by analyzing conditioning and triggering factors (F. C. 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 LULC, NDVI, or deforestation patterns (S. 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 (J. 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 & 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 & 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; Z. Bao et al., 2022; S. Fu et al., 2021; C. 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 (J. 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 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 & 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.

4.2. METHODS

4.2.1. Overview of the research methodological approach

To achieve the study's objectives, a structured six-stage workflow was implemented (Fig. 18), 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 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.

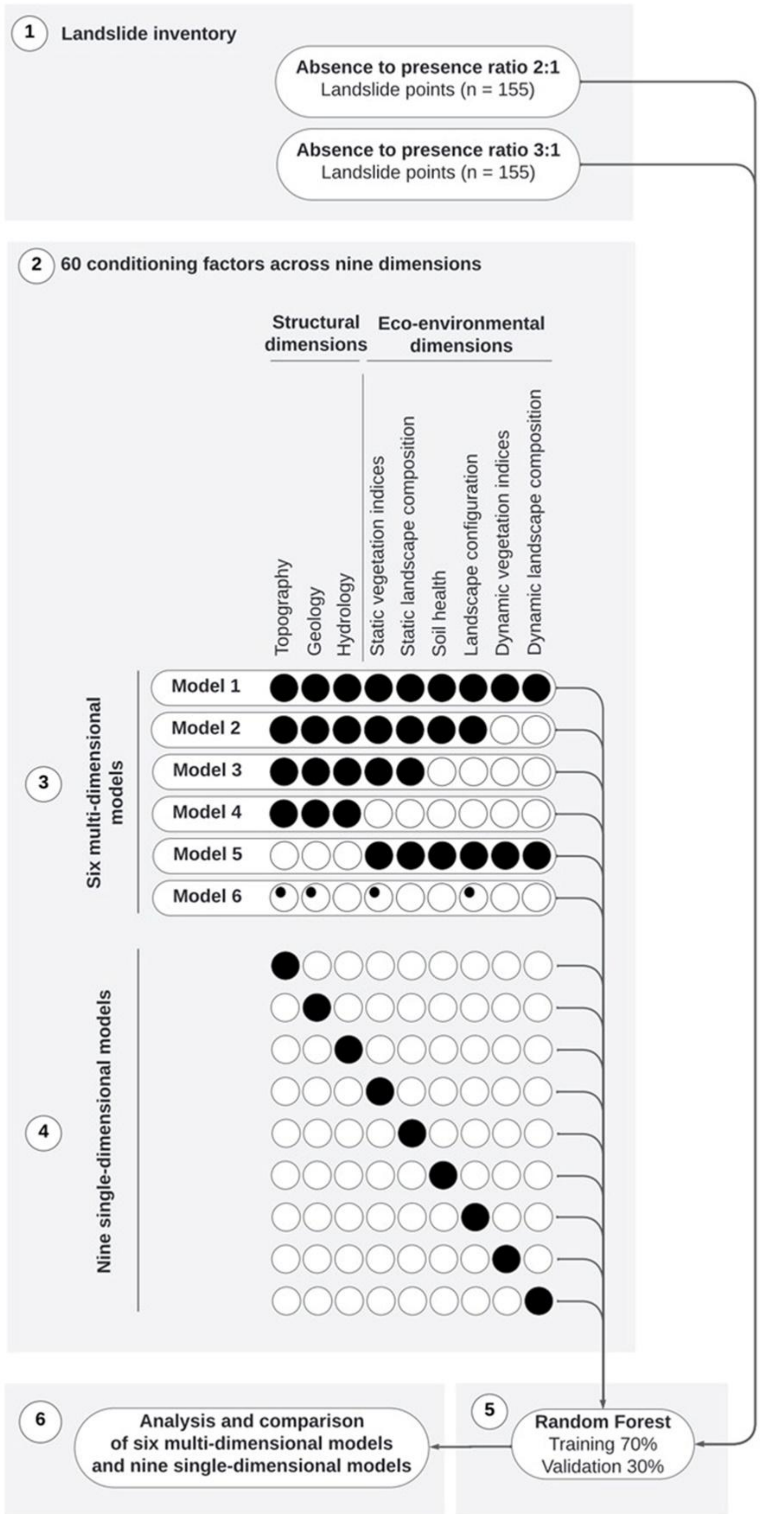

Figure 18 – Overview of the research methodological approach. This figure illustrates the six main steps of the study: (1) preparation of the landslide inventory; (2) preparation of conditioning factors across nine dimensions; (3) and (4) development of six multi-dimensional and nine single-dimensional models; (5) running of models using RF; and (6) analysis and comparison of models

4.2.2. 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, Govers, et al., 2021) and land cover changes (Safari Kagabo et al., 2024); anthropogenic influence such as agricultural terracing practices (Sibomana et al., 2025) and population density (Imasiku & 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 (L. Li et al., 2022; Nsengiyumva et al., 2019; Nsengiyumva & 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 1,789 km^2 (Fig. 19). Elevation ranges from 1,456 to 2,913 meters 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.

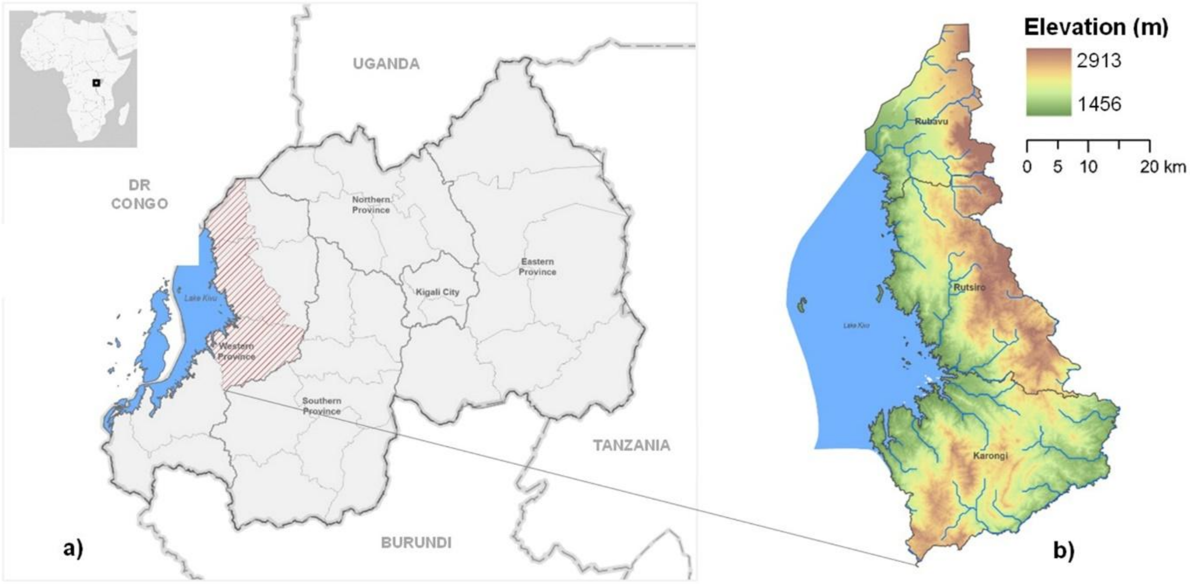

Figure 19 – Study area. a) Administrative map of Rwanda with the study area outlined in red dashes; b) Elevation map (in meters) of the study area, covering the districts of Rubavu, Rutsiro and Karongi

4.2.3. 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; S. C. 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 (B. Li et al., 2022). 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 from the Global Landslide Catalog (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-meter 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-meter 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).

4.2.4. 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, Puliero, et al., 2022). 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 the Appendix K.

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 & Lundquist, 2008; Shiqiang et al., 2024; J. 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 (Y. Li & 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 (S. 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 (School of Geography and Environmental Science et al., 2018). 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 (Appendix L) 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. 20). 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 (W. 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).

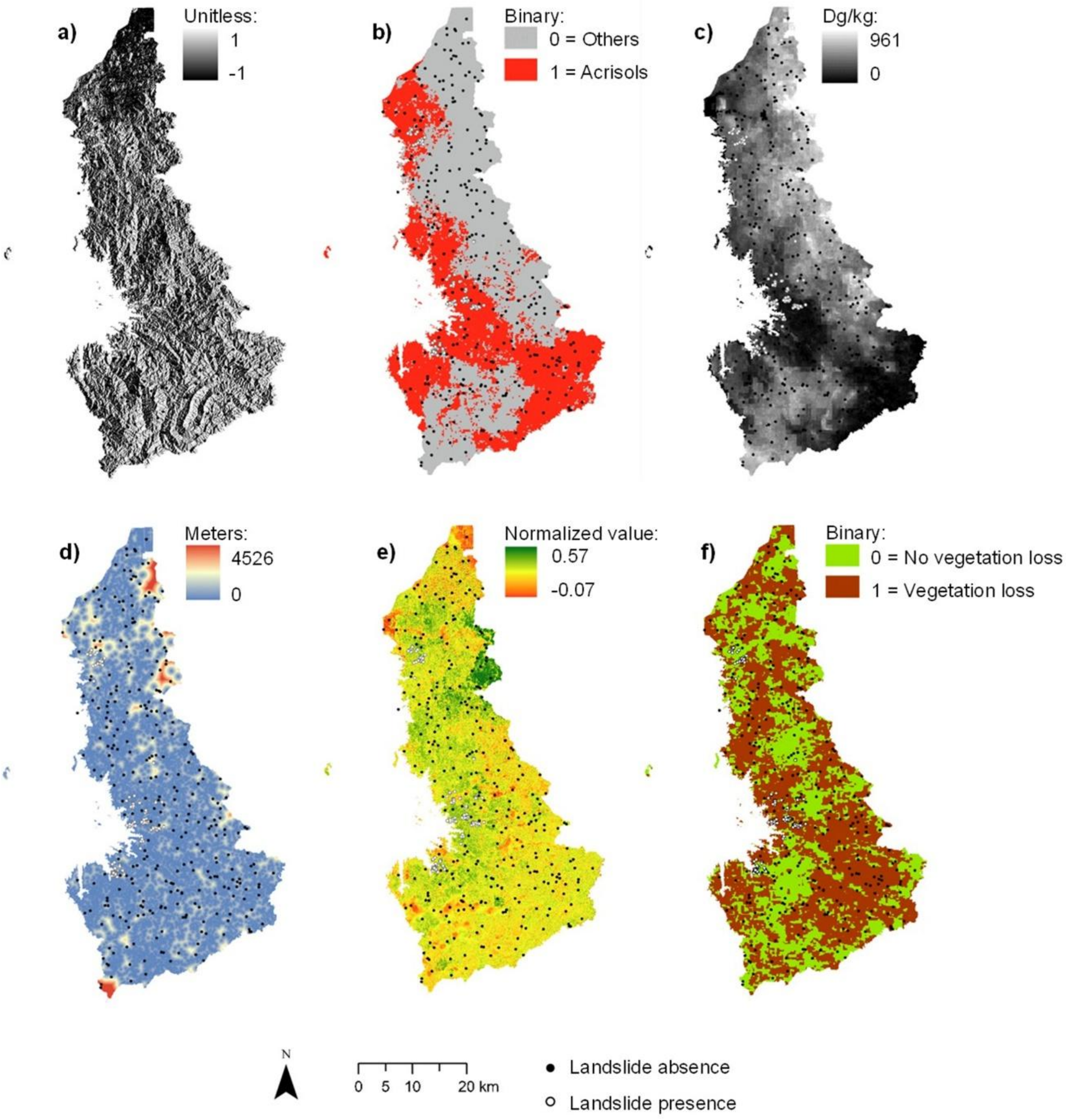

Figure 20 – Example maps of landslide conditioning factors. a) Aspect Sin (unitless); b) Acrisols (binary, where 1 = Acrisols, and 0 = Other soil classes); c) SOC (in dg/kg); d) Distance to a critical patch (in meters); e) NDVI 2023 [Landsat] (normalized value); f) NDVI negative change 2008-2023 (binary, where 1 = Vegetation loss and 0 = No vegetation loss)

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 (Tab. 9). 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 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).

Table 9 – 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	●	●	●	●	-	-
	TWI	●	●	●	●	-	-
	Stream Power Index (SPI)	●	●	●	●	-	-
	Sediment Transport Index (STI)	●	●	●	●	-	-
Static vegetation indices^E	NDVI 2023 [MODIS]	●	●	●	-	●	●
	EVI 2023	●	●	●	-	●	-
	NPP 2023	●	●	●	-	●	-
	LAI 2023	●	●	●	-	●	-
	NDVI 2023 [Landsat]	●	●	●	-	●	●
	SAVI 2023	●	●	●	-	●	-
	LULC 2023 - Water	●	●	●	-	●	-

Static landscape composition^E	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)	●	-	-	-	●	-

4.2.5. Modeling and performance analysis

RF is a widely used ensemble learning algorithm suitable for both classification and regression tasks (Schonlau & 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 & 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 & Drăgu, 2016; Merghadi et al., 2020; Probst & 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 & 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 the Appendix M. Thresholds were determined based on insights from a comprehensive literature review (Meena, Soares, et al., 2022; 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 & 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 the Appendix N. 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.

4.3. RESULTS

4.3.1. Performance of multi-dimensional models

Results begin with an evaluation of six multi-dimensional models and a comparison among them (Fig. 21). 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. 22).

Model 1 exhibited excellent overall performance in both the 2:1 and 3:1 scenarios (Fig. 22). 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-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.

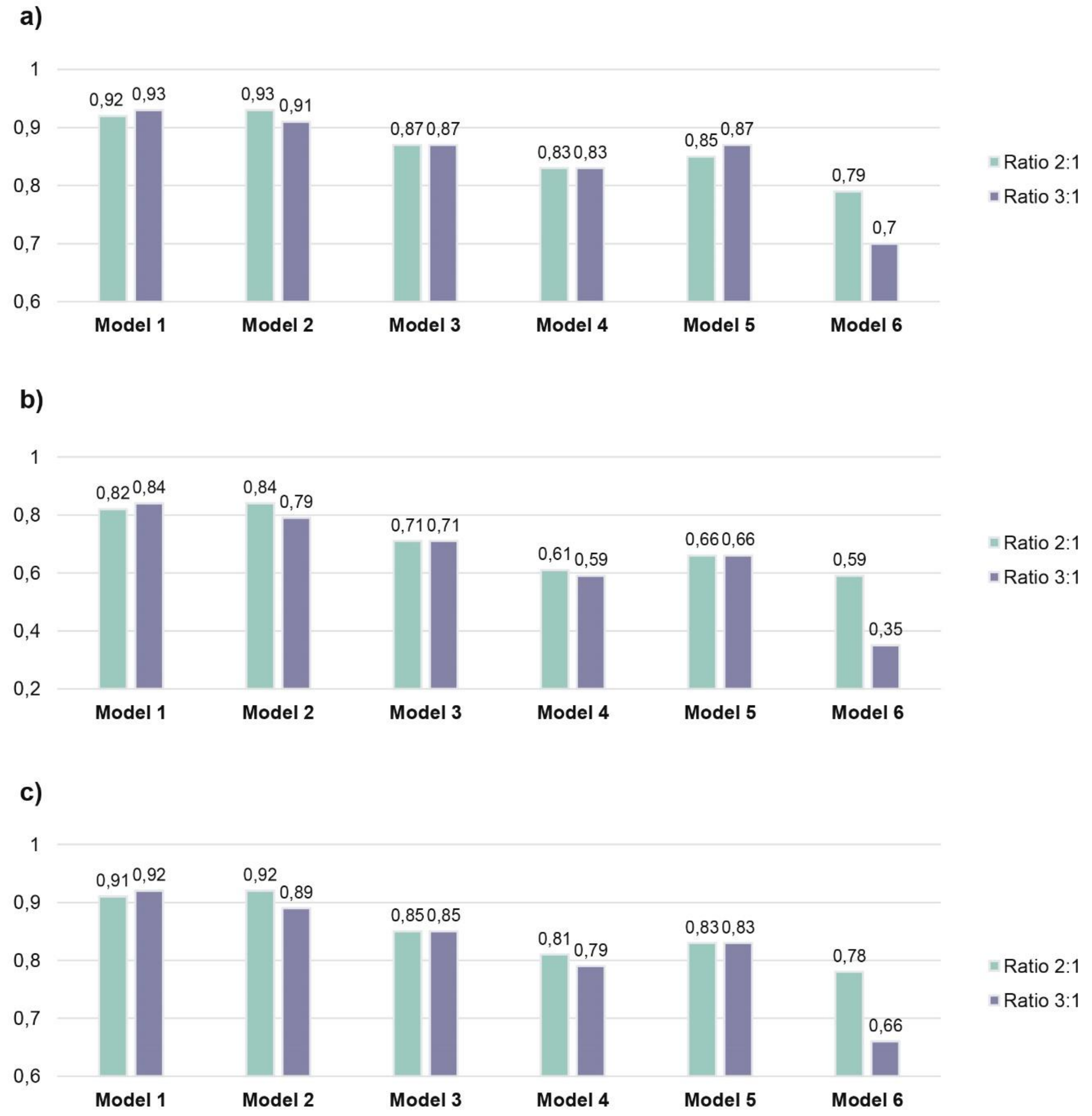

Figure 21 – Performance results across three metrics. Histograms of a) Accuracy, b) MCC, and c) F1-score for the six multi-dimensional models under absence/presence scenarios 2:1 and 3:1

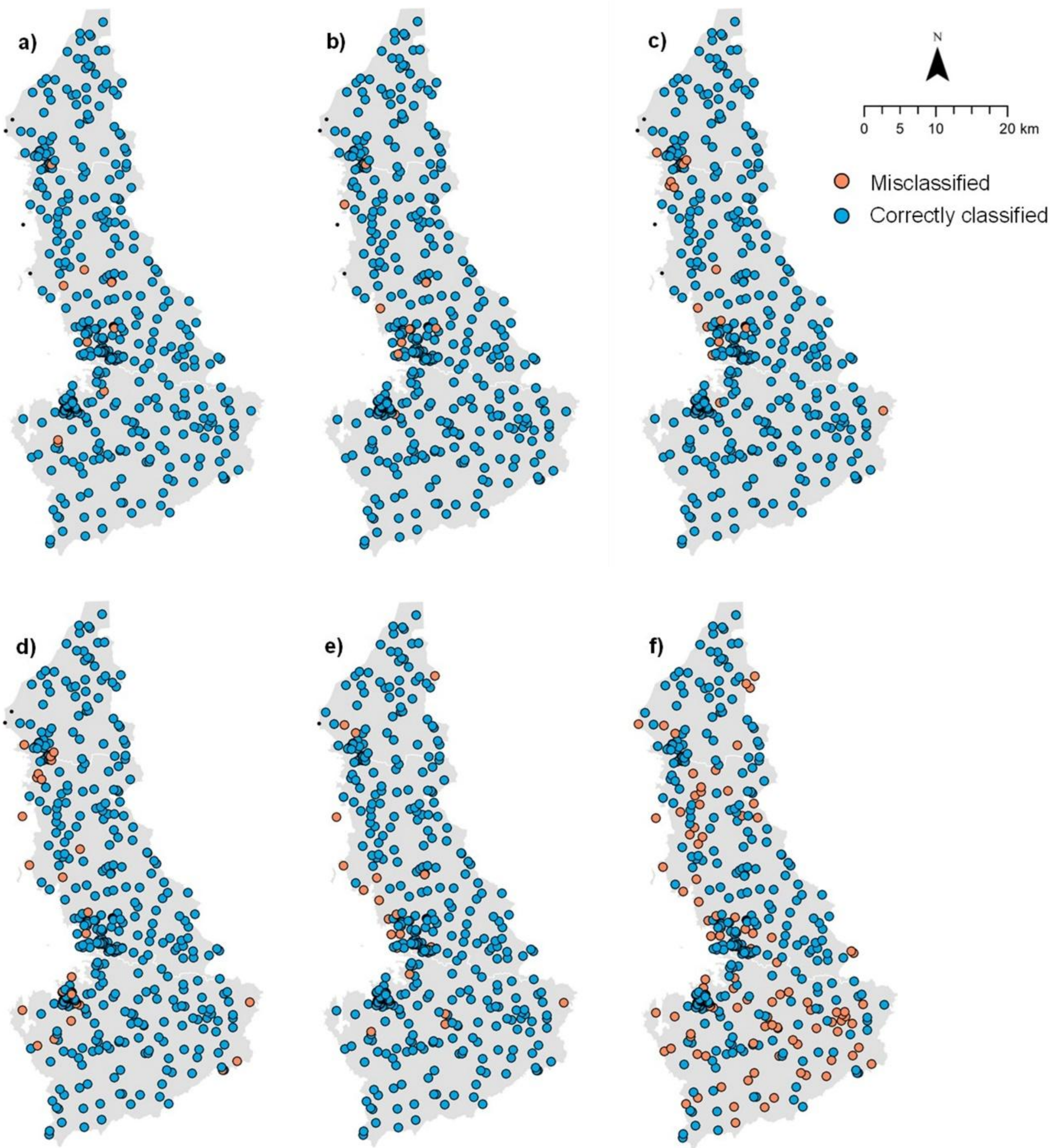

Figure 22 – Landslide susceptibility prediction maps. Maps illustrate correctly classified (blue) and misclassified (red) prediction points, under a 2:1 absence/presence points scenario, for a) Model 1 (accuracy: 0.92), b) Model 2 (accuracy: 0.93), c) Model 3 (accuracy: 0.87), d) Model 4 (accuracy: 0.83), e) Model 5 (accuracy: 0.85), and f) Model 6 (accuracy: 0.79)

4.3.2. 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. 23). 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.

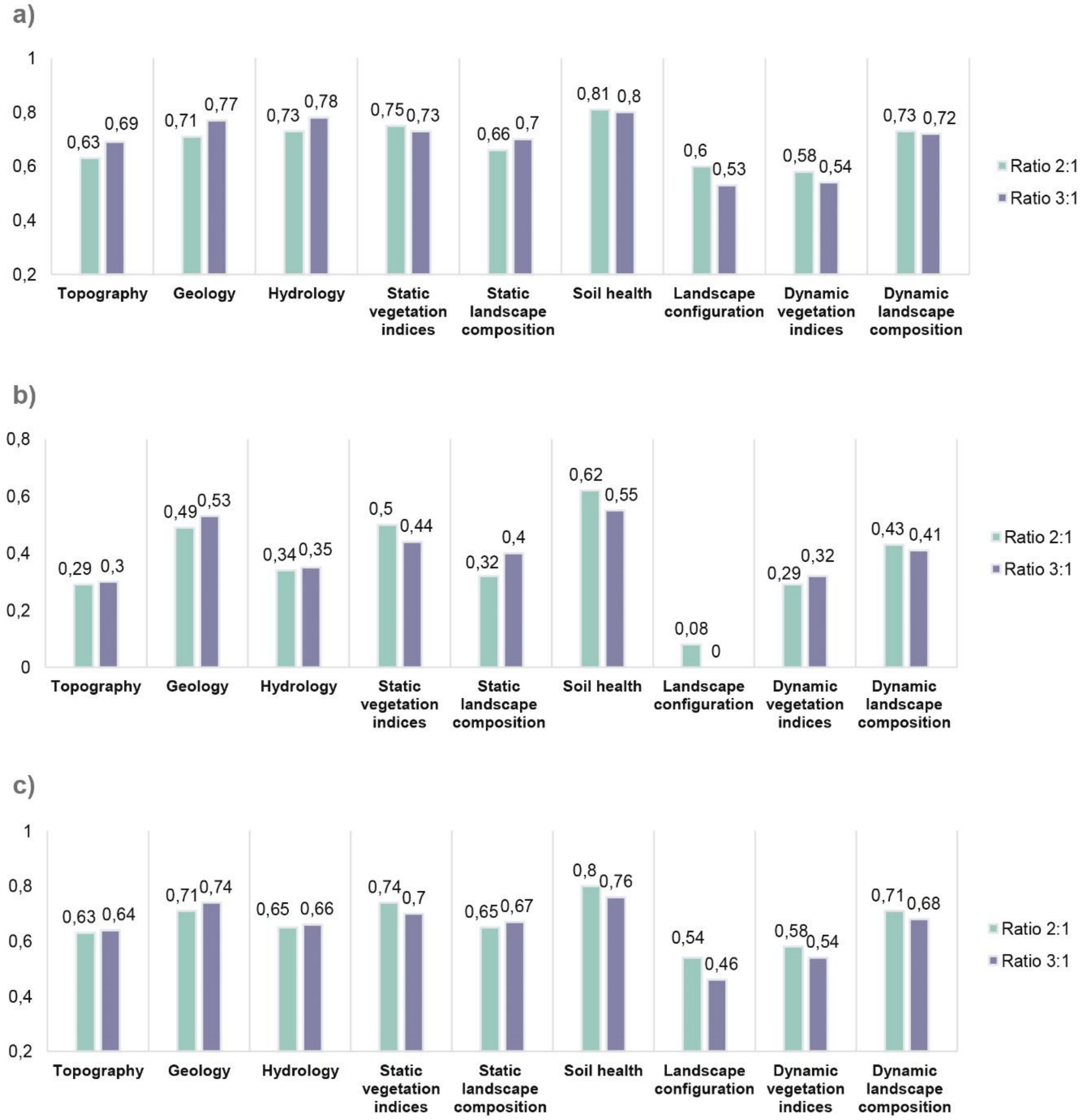

Figure 23 – Performance results across three metrics. Histograms of a) Accuracy, b) MCC, and c) F1-score for the nine single-dimensional models under absence/presence scenarios 2:1 and 3:1

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).

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.

4.3.3. Factor importance

The analysis of the factor importance is based on the results of the best performing Model 1 (Fig. 24). In both absence/presence scenarios, factors related to the nine dimensions were represented, with at least one factor included from each dimension (Appendix O, P). 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 and 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).

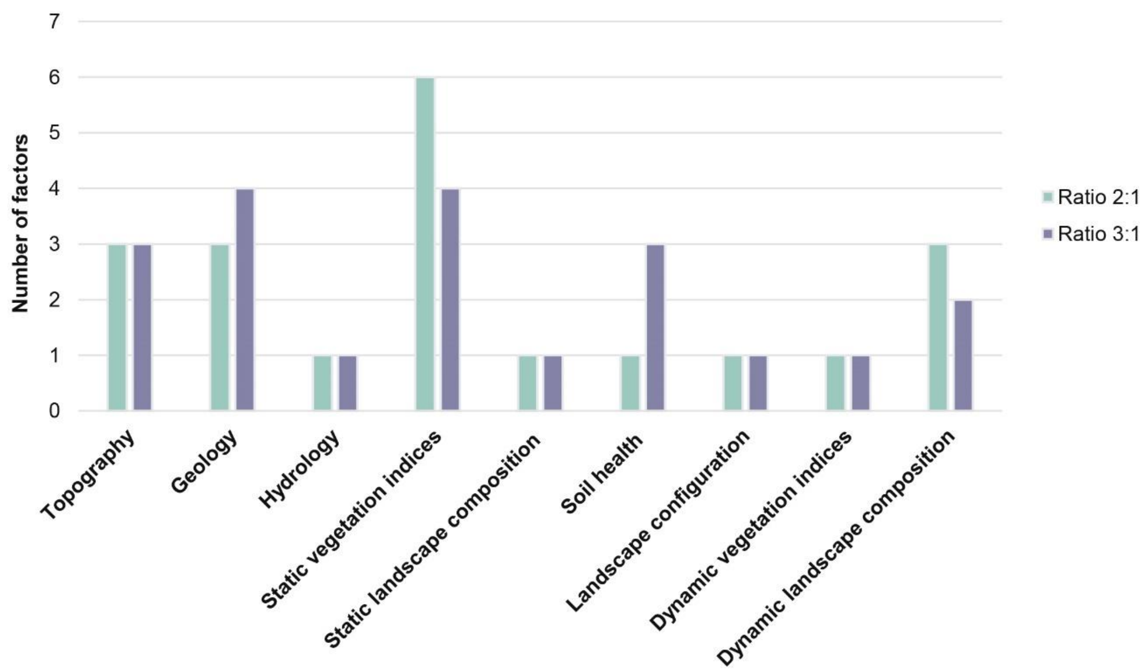

Figure 24 – Distribution of the 20 most important factors across single dimensions under absence/presence scenario 2:1 and 3:1

4.4. DISCUSSION

4.4.1. 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 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 & 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 & 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 & Rahmati (2018) regarding model parsimony in LSA.

4.4.2. 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 & 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 & 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.

4.4.3. 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, Jacobs, et al. (2021) 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.

4.4.4. 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 (J. Chen et al., 2021; Hales & 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 & 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 (L. 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.

4.4.5. 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. (2018), and reinforcing the case for incorporating ecological processes into disaster risk planning.

4.4.6. 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; B. 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.

4.4.7. 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.

4.5. 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.

5. CONCLUSION

5.1. SUMMARY OF FINDINGS

This thesis aimed to strengthen the scientific foundation and practical application of Eco-DRR, focusing on landslide as a case study. Eco-DRR posits that ecological degradation increases disaster risk by reducing critical ecosystem services, while landscape alteration can amplify both ecosystem degradation and hazard susceptibility. The central hypothesis was that incorporating ecological factors into a comprehensive LSA framework would enable a more refined understanding of landscape vulnerability and therefore improve the potential effectiveness of Eco-DRR interventions.

To test this hypothesis, the research addressed three interconnected questions:

- What ecological factors should be integrated into LSAs to support Eco-DRR?
- What is the empirical relationship between LULC and habitat quality, and can these serve as proxies for hazard-prone landscapes?
- Does integrating ecological factors into LSAs improve predictive accuracy compared to more conventional approaches?

Chapter 2 addressed the first research objective through an exploratory review of factors used in LSAs and in EecAs, highlighting both overlaps and gaps. A key finding was the lack of standardization across both domains, particularly in ecosystem assessments. Among the 19 factors common to both, only NDVI and LULC were widely accepted and consistently applied. While landscape configuration, dynamics, and vegetation factors beyond NDVI are central in ecosystem assessments, they remain underutilized in LSAs. Similarly, topographical factors are included in both fields, but for different reasons: ecosystem assessments emphasize their role in shaping ecological dynamics, whereas LSAs typically use them to explain physical processes such as soil movement, drainage, or gravitational flow, rather than for explicitly ecological reasons. The review also confirmed the value of remote sensing and GIS for Eco-DRR, since many key factors can be derived from open spatial datasets. While direct measurement of ecosystem health and condition through EO remains complex, tools like the InVEST Habitat Quality model are noted as valuable for examining natural processes with relatively low data requirements, supporting replicable, cross-disciplinary assessment approaches suitable for data-scarce contexts.

Chapter 3 addressed the second research question by examining the empirical relationship between two key indicators: LULC and habitat quality. Results showed that land use changes, such as deforestation and unsustainable land management, are linked to a decline in habitat quality. This decline indirectly reflects the weakening of natural buffers and ecosystem resilience, reducing their ability to provide essential services like soil stabilization and water regulation, thereby increasing vulnerability to hazards like landslides. Although it did not directly model landslides, this advanced the broader research objectives by supporting the hypothesis that habitat quality can serve as an integrative ecological indicator, capturing both land cover patterns and human-induced pressures. This approach is particularly advantageous in data-scarce contexts, because habitat quality offers an integrative ecological measure that can complement or substitute for complex disaster risk assessments requiring numerous cross-disciplinary inputs. Geospatial models like the InVEST Habitat

Quality model are particularly valuable given their relatively low data requirements while maintaining the ability to analyze spatial patterns of ecosystem services.

Chapter 4 directly addressed the third research question and overarching objective: whether integrating ecological factors into LSAs improves predictive accuracy compared to conventional approaches. RF models were tested using different combinations of structural and eco-environmental factors to evaluate and compare their performance. Results demonstrated that integrated models combining structural and eco-environmental factors outperformed models based solely on traditional structural variables such as topography, geology, or hydrology. Excluding eco-environmental dimensions led to progressively weaker performance. Notably, models using only eco-environmental factors still performed better than structural-only models, though they did not reach the accuracy of the most comprehensive models. These findings highlight that predictive accuracy improves most when structural and ecological factors are combined, underscoring the value of multi-dimensional approaches aligned with Eco-DRR principles. Dynamic factors capturing temporal landscape change consistently improved predictive accuracy, highlighting the importance of accounting for human-driven processes in LSAs. Overall, the results strongly support the central hypothesis of this thesis: comprehensive, multi-dimensional frameworks grounded in Eco-DRR principles yield more accurate predictions of landslide susceptibility.

Together, the three chapters contribute to addressing key gaps in Eco-DRR practice, particularly the lack of standardization, limited empirical evidence, and challenges in data-scarce contexts.

5.2. Main contributions

Building on the findings summarized in Section 5.1, this section highlights the key contributions of the thesis, both theoretical and practical. The research addresses the three core objectives by: identifying gaps in the literature and limitations of existing LSA models within the Eco-DRR framework (Objective 1); demonstrating that habitat quality and LULC can serve as informative proxies for ecological and hazard-related processes, particularly in data-limited contexts (Objective 2); and integrating these insights into predictive models, showing improved explanatory power when ecological factors are combined with structural variables (Objective 3). Collectively, these contributions provide a methodological foundation for multidimensional Eco-DRR frameworks, generating empirical evidence, introducing methodological innovation, and offering actionable insights.

On the theoretical and methodological side, the research improves the understanding of the connections and overlaps between factors across DRR and ecosystem-based approaches. It advances the theoretical foundations of Eco-DRR by demonstrating that accounting for ecological complexity alongside structural factors substantially enhances the explanatory capacity of landslide susceptibility analyses. Therefore, it provides concrete recommendations for expanding the ecological scope of LSAs, advocating for more systematic inclusion of critical ecosystem indicators.

The research introduces a multidimensional framework that incorporates ecological complexity and temporal variability, thereby moving beyond static, hazard-centric approaches. In doing so, the thesis directly addresses the fragmentation between DRR and ecosystem science, providing a harmonized set of measurable indicators that are simultaneously relevant to both fields. By empirically validating these shared indicators, the study not only highlights the missed opportunities in conventional LSAs but also lays the groundwork for harmonized and standardized Eco-DRR interdisciplinary practices.

By showing that critical ecological indicators can be reliably derived from open-access Earth Observation and other freely available spatial datasets, the proposed framework overcomes a common challenge of data scarcity. This expands the global applicability of Eco-DRR, enhances comparability across contexts, and strengthens the credibility of ecosystem-based approaches in hazard assessment. The contribution lies not only in the use of open data but also in providing a scalable, transparent methodology that enables interdisciplinary collaboration between DRR and conservation science.

The findings reposition Eco-DRR as a proactive, evidence-based approach to risk reduction. By identifying ecological drivers of landslide risk and demonstrating the value of dynamic variables as early-warning indicators, the research provides a pathway for preventive action that conventional static assessments relying on structural factors cannot deliver. It can contribute to practice by guiding the design and prioritization of ecosystem-based interventions, such as reforestation, erosion control, and soil restoration, where modifiable ecological risk factors converge. At the policy level, the research strengthens the empirical link between ecological degradation and disaster risk, thereby reinforcing the evidence base needed to mainstream Eco-DRR in land-use planning, conservation policy, and investment strategies.

Collectively, these contributions establish Eco-DRR as a scientifically credible, methodologically robust, and policy-relevant framework that integrates ecological complexity into hazard assessment. The thesis bridges disciplinary divides, advances methodological harmonization, and expands Eco-DRR's applicability even in data-scarce contexts. By doing so, it not only enhances the scientific foundations of Eco-DRR but also strengthens its practical utility for decision-makers working at the interface of disaster risk reduction and ecosystem management.

5.3. LIMITATIONS AND FUTURE RESEARCH

Across the research, three overarching limitations emerge that shape the scope and interpretation of the findings, while pointing toward clear avenues for future work.

First, the empirical results are derived from specific case study areas with distinct environmental, land-use, socio-economic, and infrastructural conditions. While the methods may be adaptable, direct generalization of results to other geographic or environmental contexts or to other types of natural hazards is limited. Drivers of change, conditioning factors, and their interactions may differ markedly between settings, making it difficult to propose universally applicable frameworks without broader testing. Future research should replicate and refine these approaches across diverse climatic, ecological and socio-economic zones, ideally through collaboration with local experts who understand region-specific geomorphological processes and ecological dynamics. Such expansion would help identify consistently influential variables, strengthen model generalizability, and inform standardized frameworks for hazard–ecosystem assessments. Additionally, this research focuses specifically on landslide hazard analysis, without distinguishing between landslide types or considering other hazards. Current conclusions therefore apply most confidently to rainfall-induced landslide contexts and require validation before application to landslides triggered by other mechanisms or to other hazards such as floods. Future studies should explore the transferability of ecosystem-related factors and modeling approaches to other hazards, including potential integrated hazard–ecosystem models that account for interactions among multiple hazards.

Second, a key challenge in this cross-disciplinary research field lies in balancing model complexity with practical usability. Models must be complex enough to represent real-world processes across interdisciplinary settings, but simple enough to be reliable and replicable across different settings. Future work could simplify models by retaining only the most critical factors within each dimension to reduce overfitting and computational demands, while still capturing landscape complexity. This also involves managing resolution trade-offs and the challenges of measuring abstract ecological concepts using remote sensing, which often relies on proxies or theoretical assumptions. For example, using NDVI as a proxy for "vegetation health" assumes that higher NDVI corresponds to healthier vegetation without direct field measurements. Similarly, habitat quality serves a useful proxy because it integrates land use, human pressures, and ecological conditions, but its connection to actual hazard processes remains theoretical. The multidimensional nature of ecosystem-hazard interactions adds further complexity. Advanced statistical methods like SEM can help by grouping multiple variables into broader constructs and modeling cause-effect relationships while accounting for measurement uncertainty. Future research should validate these theoretical links using field data, remote sensing, and multivariate statistical approaches to improve model reliability while maintaining the ability to capture complex ecological dynamics. Moreover, the use of EO and modeling provides opportunities to incorporate scenario analyses (e.g., optimistic conservation vs. pessimistic economic trends) and climate projections, which could enhance understanding of future impacts and inform preventive actions.

Finally, Eco-DRR's interdisciplinary nature presents challenges for translating scientific findings into actionable policy. Without empirical testing and practical implementation, research may remain underused or lack credibility in decision-making. Future work should focus on integrating dynamic eco-environmental indicators into LSA, aligning early warning systems with ecosystem signals, and updating Eco-DRR policies to include ecosystem monitoring for targeted risk management. This would strengthen the translation of research into policy and practice, enhancing the societal relevance of Eco-DRR.

5.4. Overall conclusion

Ecosystem-based Disaster Risk Reduction (Eco-DRR) holds great promise as a sustainable approach to mitigating natural hazards by leveraging the protective functions of healthy ecosystems. However, despite increasing recognition, Eco-DRR still faces significant barriers to widespread adoption and effectiveness. These include a limited scientific consensus on the precise role ecosystems play in reducing disaster risk, fragmented methodologies, data scarcity—especially in vulnerable regions—and a lack of standardized frameworks that integrate ecological dimensions meaningfully into disaster risk assessments.

This work confirms that disaster vulnerability cannot be fully understood through traditional hazard models that rely solely on static physical factors. Instead, vulnerability emerges from complex, dynamic interactions between ecological processes and the physical environment. Incorporating ecological indicators—particularly those capturing ecosystem condition, land use dynamics, and habitat quality—enables a more nuanced and realistic assessment of risk. Such integration strengthens the scientific foundation of Eco-DRR by quantitatively linking ecosystem degradation to increased disaster susceptibility and thereby supports more informed, effective risk management.

Nevertheless, challenges remain. The multidimensional nature of disaster risk, the diversity of ecosystems and hazards, and the complexity of ecological processes pose significant obstacles to developing universally applicable, standardized assessment models. Data gaps and inconsistent use of ecological factors further limit the operationalization of Eco-DRR, particularly in resource-constrained contexts. Bridging these gaps requires interdisciplinary collaboration, innovative modelling approaches that balance complexity and practicality, and improved accessibility to open-source Earth Observation and geospatial data.

Moving forward, advancing Eco-DRR demands a dual focus: enhancing the scientific rigor and empirical evidence base through diverse, context-specific case studies, and simultaneously building frameworks and tools that facilitate the consistent integration of ecological degradation into risk assessments and early warning systems. Equally important is fostering trust and engagement among policymakers and stakeholders by demonstrating clear, actionable benefits of ecosystem-based approaches within disaster risk governance.

Ultimately, this integrated perspective on ecological factors as fundamental components of disaster risk opens new pathways for designing nature-based solutions that are not only effective in reducing vulnerability but also aligned with broader goals of biodiversity conservation and sustainable development. Strengthening Eco-DRR through standardized, evidence-based assessment frameworks promises more resilient communities and ecosystems in the face of growing environmental challenges.

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7. APPENDICES

7.1. APPENDIX A. TABLE OF SELECTED PAPERS FOR THE REVIEW OF FACTORS USED IN THE LANDSLIDE SUSCEPTIBILITY ASSESSMENT

Authors	Journal	Title
Abdollahizad et al., 2023	Applied Geomatics	Using the integrated application of computational intelligence for landslide susceptibility modeling in East Azerbaijan Province, Iran
Addis, 2023	Journal of Engineering (United Kingdom)	GIS-Based Landslide Susceptibility Mapping Using Frequency Ratio and Shannon Entropy Models in Dejen District, Northwestern Ethiopia
Affandi et al., 2023	Applied Sciences (Switzerland)	Revalidation Technique on Landslide Susceptibility Modelling: An Approach to Local Level Disaster Risk Management in Kuala Lumpur, Malaysia
Aslam et al., 2023	Natural Hazards	Comparative analysis of multiple conventional neural networks for landslide susceptibility mapping
Bernat Gazibara et al., 2023	Journal of Maps	Landslide susceptibility assessment on a large scale in the Podsljeme area, City of Zagreb (Croatia)
Bhagya et al., 2023	Land	Landslide Susceptibility Assessment of a Part of the Western Ghats (India) Employing the AHP and F-AHP Models and Comparison with Existing Susceptibility Maps
Chang et al., 2023	Gondwana Research	Uncertainty analysis of non-landslide sample selection in landslide susceptibility prediction using slope unit-based machine learning models
Dai X et al., 2023	Remote Sensing	Examining the Spatially Varying Relationships between Landslide Susceptibility and Conditioning Factors Using a Geographical Random Forest Approach: A Case Study in Liangshan, China
Ghayur Sadigh et al., 2023	Environment, Development and Sustainability	Comparison of optimized data-driven models for landslide susceptibility mapping
Gui et al., 2023	Remote Sensing	GIS-Based Landslide Susceptibility Modeling: A Comparison between Best-First Decision Tree and Its Two Ensembles (BagBFT and RFBFT)
Z. Guo et al., 2023a	Georisk	Hazard assessment for regional typhoon-triggered landslides by using physically-based model–a case study from southeastern China

Z. Guo et al., 2023b	Geoscience Frontiers	Shallow landslide susceptibility assessment under future climate and land cover changes: A case study from southwest China
Huan et al., 2023	Environmental Earth Sciences	Stacking ensemble of machine learning methods for landslide susceptibility mapping in Zhangjiajie City, Hunan Province, China
Huang et al., 2023	Catena	Landslide susceptibility mapping and dynamic response along the Sichuan-Tibet transportation corridor using deep learning algorithms
Hürlimann et al., 2022	Landslides	Impacts of future climate and land cover changes on landslide susceptibility: regional scale modelling in the Val d’Aran region (Pyrenees, Spain)
Jiang Z. et al., 2023	Remote Sensing	Comparisons of Convolutional Neural Network and Other Machine Learning Methods in Landslide Susceptibility Assessment: A Case Study in Pingwu
Liu et al., 2023a	Journal of Mountain Science	Effects of the probability of pulse-like ground motions on landslide susceptibility assessment in near-fault areas
Liu et al., 2023b	Catena	Exploring the uncertainty of landslide susceptibility assessment caused by the number of non–landslides
Liu et al., 2023c	Environmental Earth Sciences	Impact of orthogonal transformation for factors on model performance in landslide susceptibility
Matougui et al., 2023	Environmental Science and Pollution Research	A comparative study of heterogeneous and homogeneous ensemble approaches for landslide susceptibility assessment in the Djebahia region, Algeria
Mwakapesa et al., 2023	Frontiers in Environmental Science	Landslide susceptibility mapping using O-CURE and PAM clustering algorithms
Nwazelibe et al., 2023a	Modeling Earth Systems and Environment	Integration and comparison of algorithmic weight of evidence and logistic regression in landslide susceptibility mapping of the Orumba North erosion-prone region, Nigeria
Nwazelibe et al., 2023b	Catena	Testing the performances of different fuzzy overlay methods in GIS-based landslide susceptibility mapping of Udi Province, SE Nigeria
Sahin, 2023	Stochastic Environmental Research and Risk Assessment	Implementation of free and open-source semi-automatic feature engineering tool in landslide susceptibility mapping using the machine-learning algorithms RF, SVM, and XGBoost

Sangeeta & Singh, 2023	Journal of Mountain Science	Influence of anthropogenic activities on landslide susceptibility: A case study in Solan district, Himachal Pradesh, India
Yan et al., 2023	Natural Hazards	Uncertainty in regional scale assessment of landslide susceptibility using various resolutions
X. Yang et al., 2023	Sustainability (Switzerland)	An Improved Unascertained Measure-Set Pair Analysis Model Based on Fuzzy AHP and Entropy for Landslide Susceptibility Zonation Mapping
Ye et al., 2023	Frontiers in Earth Science	Generating accurate negative samples for landslide susceptibility mapping: A combined self-organizing-map and one-class SVM method
Yu et al., 2023	Remote Sensing	Landslide Susceptibility Mapping and Driving Mechanisms in a Vulnerable Region Based on Multiple Machine Learning Models
Zangmene et al., 2023	Advances in Space Research	Landslide susceptibility zonation using the analytical hierarchy process (AHP) in the Bafoussam-Dschang region (West Cameroon)

7.2. Appendix B. Table of selected papers for the review of factors used in the EecA

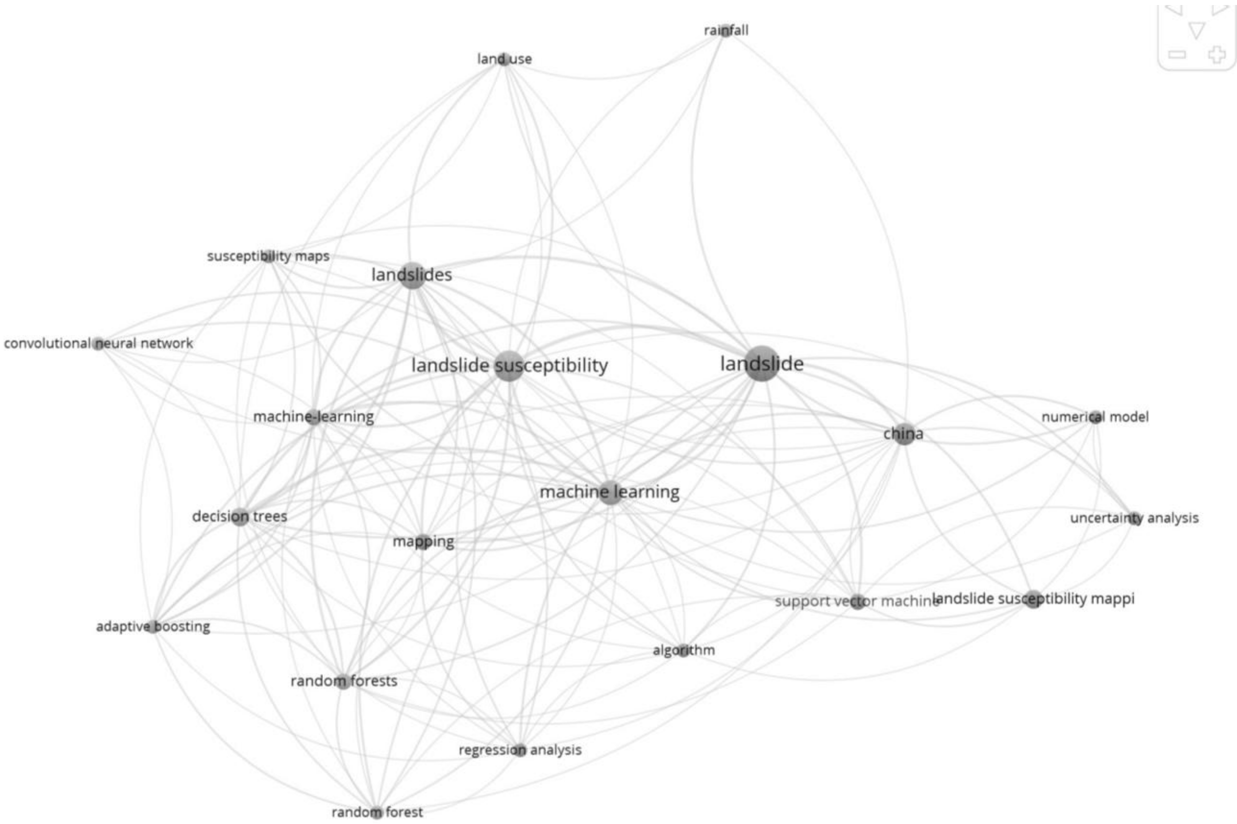
Authors	Journal	Title
Anand et al., 2022	Physics and Chemistry of the Earth	Optimal band characterization in reformation of hyperspectral indices for species diversity estimation
Avelar et al., 2020	Ecological Complexity	Ecological complexity effects on thermal signature of different Madeira island ecosystems
Badapalli et al., 2022	Environmental Science and Pollution Research	An integrated approach for the assessment and monitoring of land degradation and desertification in semi-arid regions using physico-chemical and geospatial modeling techniques
Badreldin et al., 2021	Remote Sensing	Mapping grasslands in mixed grassland ecoregion of saskatchewan using big remote sensing data and machine learning
Bao et al., 2022	Ecological Informatics	Remote sensing-based assessment of ecosystem health by optimizing vigor-organization-resilience model: A case study in Fuzhou City, China
Boori et al., 2022	Computer Optics	Spatiotemporal ecosystem health assessment comparison under the pressure-state-response framework
Cheng et al., 2020	Ecological Indicators	Ecosystem health assessment of desert nature reserve with entropy weight and fuzzy mathematics methods: A case study of Badain Jaran Desert
Chi & Liu, 2022	Remote Sensing	Mapping the Spatiotemporal Pattern of Sandy Island Ecosystem Health during the Last Decades Based on Remote Sensing
Chi et al., 2021	Journal of Cleaner Production	Island ecosystem health in the context of human activities with different types and intensities
Cirezi et al., 2022	International Journal of Remote Sensing	Contribution of ‘human induced fires’ to forest and savanna land conversion dynamics in the Luki Biosphere Reserve landscape, western Democratic Republic of Congo
Farrell et al., 2021	One Ecosystem	Applying the system of environmental economic accounting-ecosystem accounting (Seea-ea) framework at catchment scale to develop ecosystem extent and condition accounts
Haghighian et al., 2022	Geocarto International	Identifying tree health using sentinel-2 images: a case study on Tortrix viridana L. infected oak trees in Western Iran
Han et al.,2020	Remote Sensing	Monitoring droughts in the greater changbai mountains using multiple remote sensing-based drought indices

Hanssen et al., 2021	Ecological Indicators	Utilizing LiDAR data to map tree canopy for urban ecosystem extent and condition accounts in Oslo
Katrandzhiev et al., 2022	Diversity	Whole System Data Integration for Condition Assessments of Climate Change Impacts: An Example in High-Mountain Ecosystems in Rila (Bulgaria)
Kırcı & Türkmen, 2022	Rendiconti Lincei	Assessment of long-term land use and land cover change effects on soil erosion and soil organic carbon stock in humid ecosystem condition
Lee et al., 2021	Conservation Biology	Estimating changes and trends in ecosystem extent with dense time-series satellite remote sensing
Li et al., 2021	Ecological Indicators	Spatiotemporal evaluation of alpine pastoral ecosystem health by using the Basic-Pressure-State-Response Framework: A case study of the Gannan region, northwest China
Mallick et al., 2021	Remote Sensing	A novel technique for modeling ecosystem health condition: A case study in Saudi Arabia
Mao et al., 2021	Ecological Indicators	An improved approach to estimate above-ground volume and biomass of desert shrub communities based on UAV RGB images
Odebiri et al., 2022	ISPRS Journal of Photogrammetry and Remote Sensing	Modelling soil organic carbon stock distribution across different land-uses in South Africa: A remote sensing and deep learning approach
Odhiambo et al., 2020	Applied Geography	Spatial prediction and mapping of soil pH across a tropical afro-montane landscape
Ørka et al., 2022	Ecological Indicators	A framework for a forest ecological base map – An example from Norway
Pan et al., 2022	Geocarto International	Quantitative estimation and influencing factors of ecosystem soil conservation in Shangri-La, China
Portillo-Quintero et al., 2022	Remote Sensing	Trends in Lesser Prairie-Chicken Habitat Extent and Distribution on the Southern High Plains
Prakash Sarkar et al., 2022	Ecological Informatics	Machine learning approach to predict terrestrial gross primary productivity using topographical and remote sensing data
Rosero et al., 2023	Land	Multitemporal Incidence of Landscape Fragmentation in a Protected Area of Central Andean Ecuador

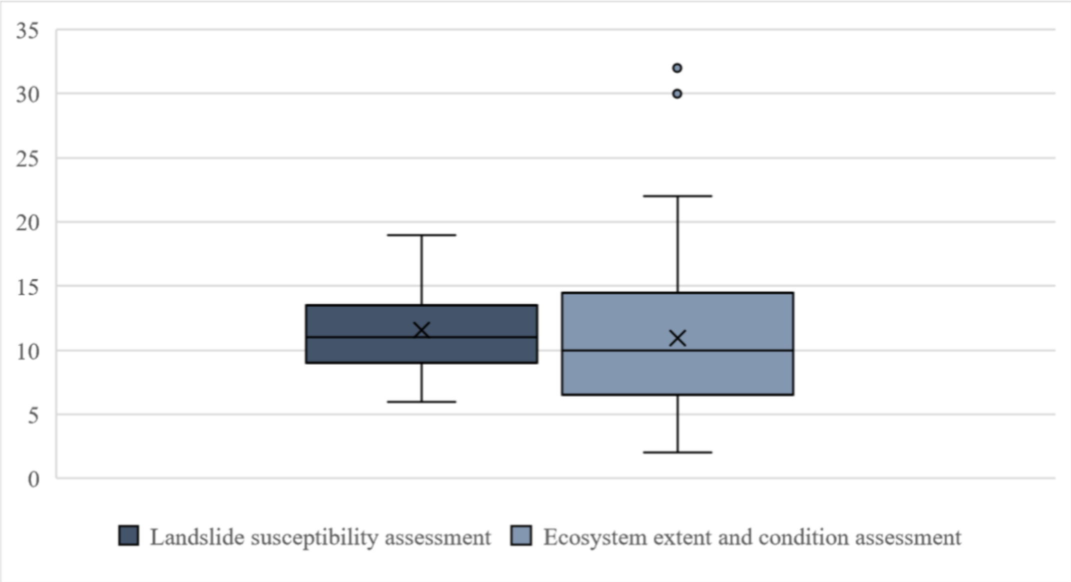
Safaei et al., 2023	Landscape Ecology	Mapping terrestrial ecosystem health in drylands: comparison of field-based information with remotely sensed data at watershed level
Shen et al., 2020	International Journal of Environmental Research and Public Health	Spatiotemporal characteristics and driving force of ecosystem health in an important ecological function region in China
Shi et al., 2020	Sustainability (Switzerland)	Temporal–spatial distribution of ecosystem health and its response to human interference based on different terrain gradients: A case study in Gannan, China
Shi et al., 2021	Environmental Technology and Innovation	Comprehensive evaluation of ecosystem health in pastoral areas of Qinghai–Tibet Plateau based on multi model
Tasnim et al., 2022	Journal of Urban Management	Spatial indices and SDG indicator-based urban environmental change detection of the major cities in Bangladesh
Verma et al., 2022	Environmental Monitoring and Assessment	Effect of rainfall variability on tree phenology in moist tropical deciduous forests
H. Wang et al., 2020	Sustainability (Switzerland)	Ecosystem health assessment of Shennongjia National Park, China
Z. Wang et al., 2020a	Sustainability (Switzerland)	Ecosystem health assessment of world natural heritage sites based on remote sensing and field sampling verification: Bayanbulak as case study
Z. Wang et al., 2020b	International Journal of Environmental Research and Public Health	Quantifying the impact of the grain-for-green program on ecosystem health in the typical agro-pastoral ecotone: A case study in the xilin gol league, inner mongolia
Wei & Barros, 2021	Remote Sensing	Prospects for long-term agriculture in southern africa: Emergent dynamics of savannah ecosystems from remote sensing observations
Xiang et al., 2022	ISPRS International Journal of Geo-Information	Spatiotemporal Changes and Driving Factors of Ecosystem Health in the Qinling-Daba Mountains
Xu et al., 2022	Land	Land Use Change and Ecosystem Health Assessment on Shanghai–Hangzhou Bay, Eastern China
Zhang et al., 2022	Remote Sensing	Using the Geodetector Method to Characterize the Spatiotemporal Dynamics of Vegetation and Its Interaction with Environmental Factors in the Qinba Mountains, China

Zou et al., 2022	Ecological Indicators	Spatiotemporal changes of ecosystem health and their driving mechanisms in alpine regions on the northeastern Tibetan Plateau

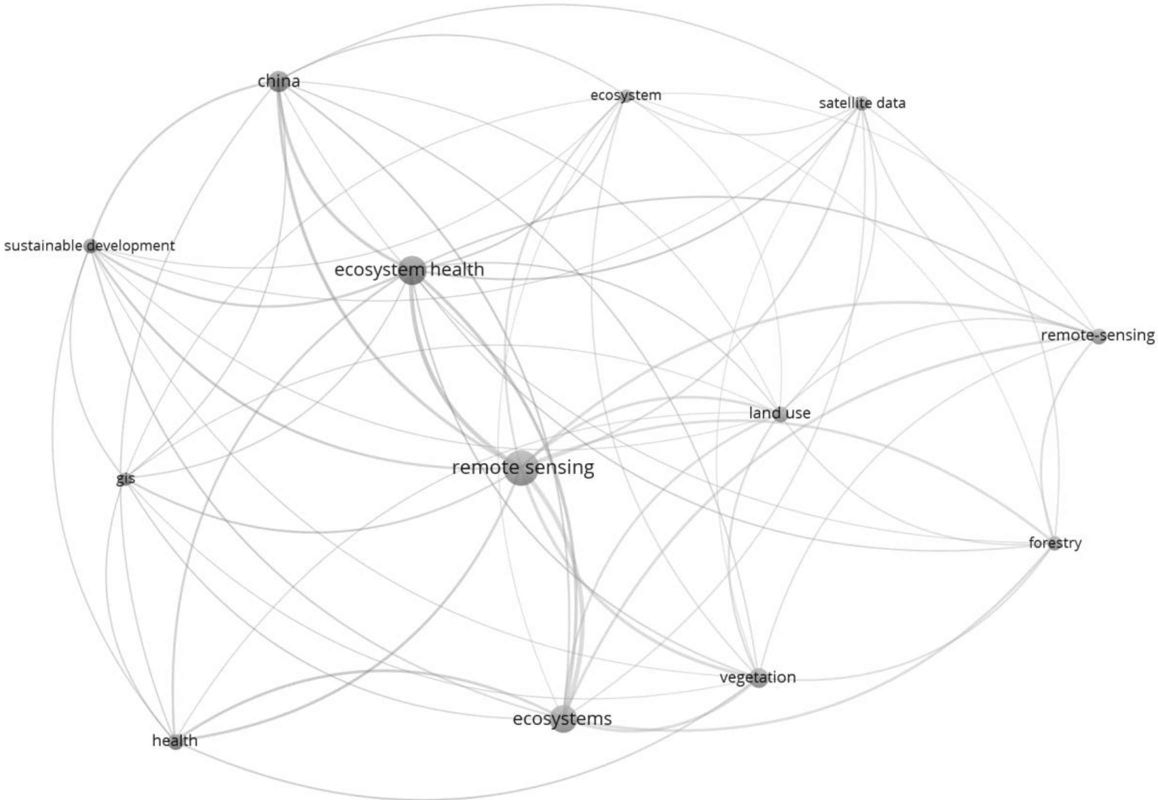
7.3. Appendix C. Diagram of the analysis of keywords with at least 3 occurrences in LSA



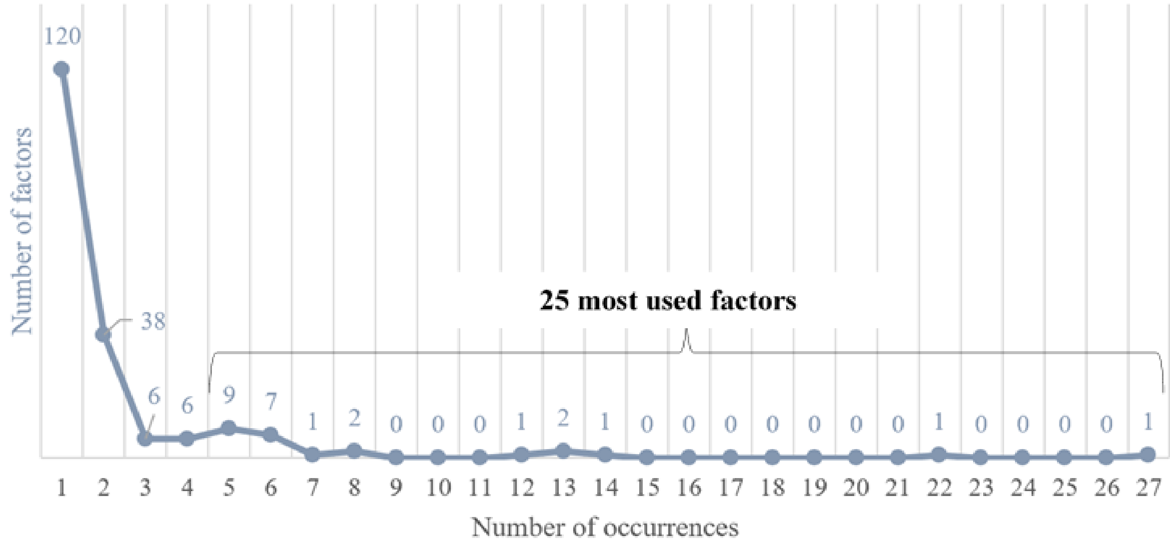
7.4. APPENDIX D. DISTRIBUTION OF THE NUMBER OF FACTORS IDENTIFIED IN LSAS AND EECAS



7.5. Appendix E. Diagram of the analysis of keywords with at least 5 occurrences in EecA



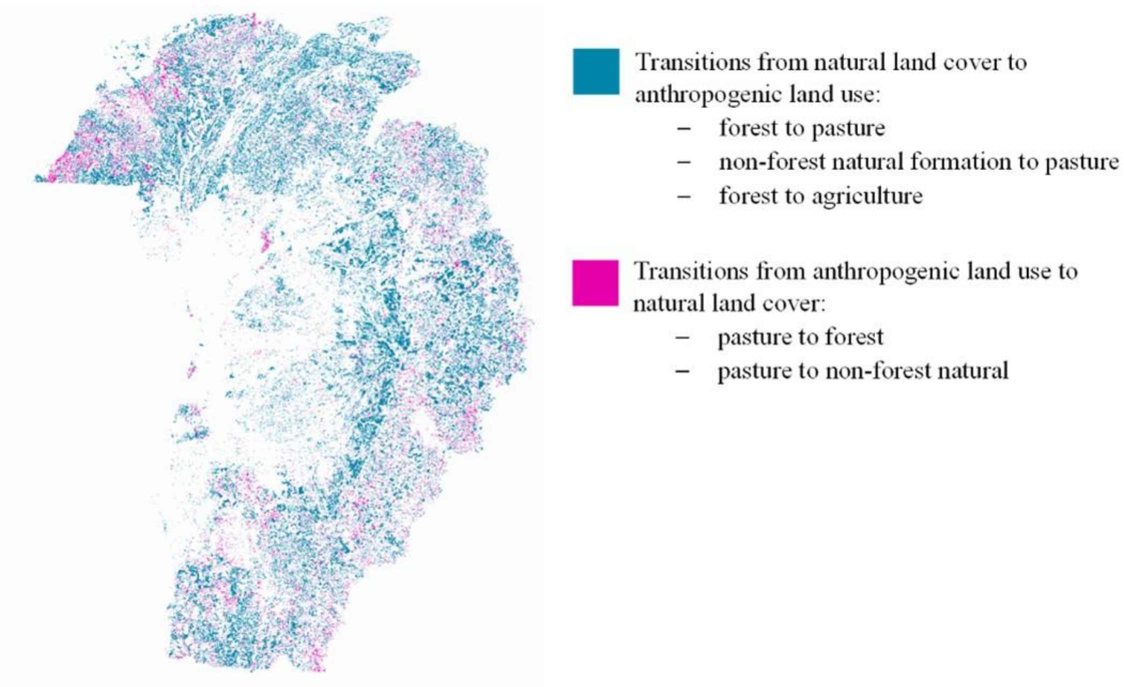
7.6. APPENDIX F. NUMBER OF FACTORS USED IN THE EECA DEPENDING ON THEIR OCCURRENCE



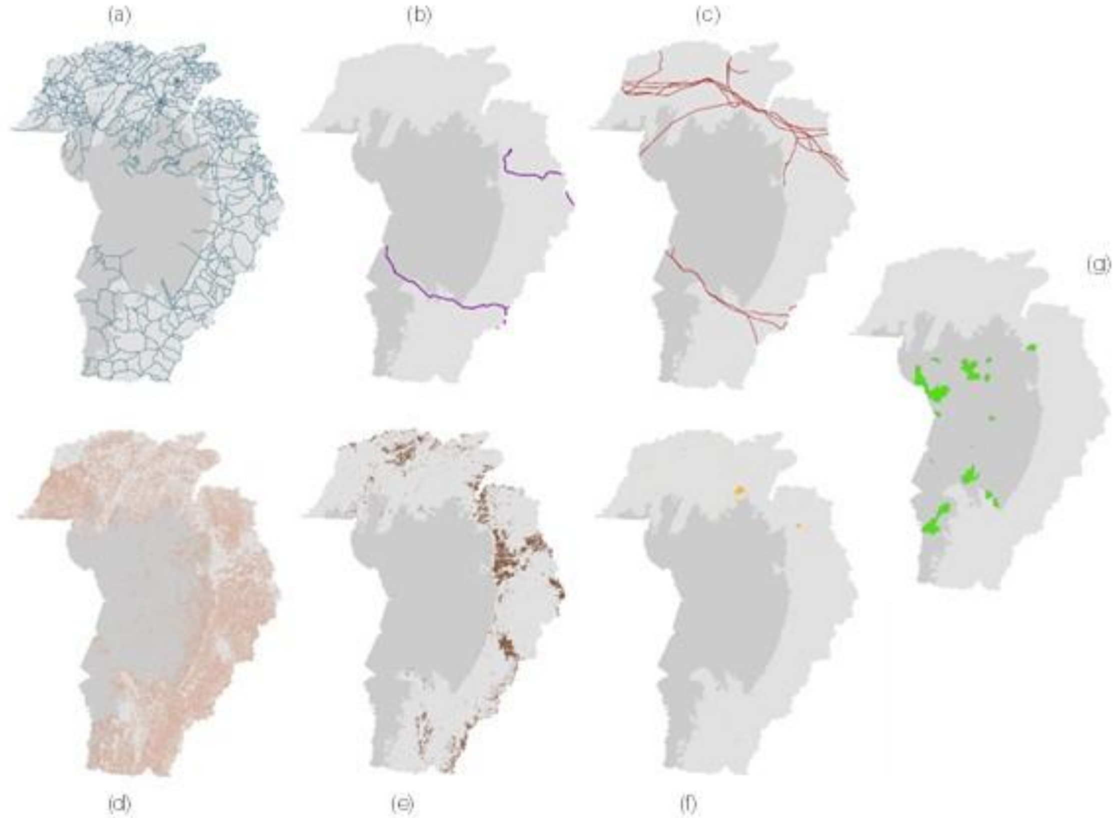
7.7. APPENDIX G. TABLE OF RECLASSIFICATION OF LAND USE MAPS

New ID	New nomenclature	Initial ID and nomenclature
1	Forest	3 – Forest formation 4 – Savanna formation 9 – Forest plantation
2	Non-Forest Natural Formation	11 – Wetland 12 – Grassland
3	Pasture	15 – Pasture
4	Agriculture	20 – Sugar cane 39 – Soy bean 41 – Other temporary crops
5	Non-Vegetated Area	24 – Urban infrastructure 25 – Other non-vegetated areas 30 – Mining
6	Water	33 – River, lake and ocean

7.8. APPENDIX H. MAP OF THE FIVE MAIN LAND TRANSITIONS INCLUDED IN THE LAND CHANGE PREDICTION MODEL



7.9. Appendix I. Maps of threats to habitat quality: (a) roads (b) rail (c) lines (d) pasture lands (e) agriculture lands (f) urban infrastructures; areas non accessible to threats (g)



7.10. APPENDIX J. HABITAT QUALITY INPUTS: SUPPLEMENTARY TEXT

- Land use raster maps: the 1989 baseline map and the 2019 current map, which supported the simulation of the 2050 future map
- The threat table and related threat raster maps: the threats are those human-induced land use that may cause fragmentation, edging and degradation of habitats. For each threat, the following parameters were defined: a maximum distance in kilometres to which a threat can impact a habitat, with the degradation declining to zero when reaching this maximum distance; a weight giving some threats a relatively more important impact on habitat in comparison to other threats, ranging from 0 (low impact) to 1 (high impact); and the decay, which was set as linear for all threats. Six threats were considered: road, rail, lines including gas pipes and electric lines, pastural areas, agricultural areas and non-vegetated areas. For the first three types of threat, the same data were used for baseline, current and future times; for the three last types of threat, data were obtained from the reclassification of the 1989, 2019 and 2050 land use and land cover raster maps.
- The accessibility to threat consisted in a polygon shapefile grouping two types of spatial units, i.e., the conservation units and the indigenous area. Conservation units, or protected areas, are defined by Law No. 9.985 of 18 July 2000, which established the National System of Conservation Units. For this study, all areas are all attributed with a score of 0 meaning there are no accessibility to these areas. These parameters could be refined and additional ones such as elevation, water land use or wetlands could be further refined.
- The sensitivity table: it assigns a habitat score from 0 (non-habitat) to 1 (habitat) to each of the six land use classes, as well as the relative sensitivity of each habitat type to each threat to biodiversity.
- The half-saturation constant has been set at 0.1.

7.11. Appendix K. Detailed description of conditioning factors affecting landslide susceptibility in the Eco-DRR Framework

Factor	Description	Influence on landslide occurrence within Eco-DRR framework
Topography		
Elevation	Vertical distance above sea level	Controls precipitation patterns and weathering intensity while influencing vegetation zonation and ecosystem composition that provide slope stabilization. Higher elevations create distinct microclimates supporting specific plant communities with varying root reinforcement capacities.
Slope	Terrain inclination angle	Determines gravitational stress requiring ecosystem services for stabilization. Steeper slopes experience greater downslope forces but also limit vegetation establishment, creating critical areas where ecosystem-based interventions may be most needed.
Aspect Sin	East-exposedness component of the aspect	Regulates solar exposure patterns and influences soil moisture, vegetation patterns. East-facing slopes are associated with increased moisture retention and reduced evaporation rates that weaken soil strength.
Aspect Cos	North-exposedness of the aspect	Regulates solar exposure patterns and influences soil moisture, vegetation patterns. North-facing slopes are associated with higher biomass, coverage and height than south-facing slopes (J. Yang et al., 2020).
Profile curvature	Curvature in the downslope direction (vertical plane)	Controls water flow patterns and erosional processes while affecting soil development and vegetation establishment. Concave surfaces tend to accumulate runoff and raise soil moisture, which weakens soil and rock shear strength and increase slope failure likelihood.
Plan curvature	Curvature perpendicular to the slope direction (horizontal plane)	Determines lateral water flow patterns and convergence zones affecting slope stability. Concave plan curvature increases moisture content and leads to slope failure by concentrating water.
Terrain Ruggedness Index (TRI)	Measure of topographic complexity and surface roughness	Highlights abrupt elevation changes and terrain irregularity that can influence drainage, erosion and soil cohesion. Higher TRI indicates more uneven terrain, increasing potential for localized instability and landslide initiation.
Vector Ruggedness Measure (VRM)	Three-dimensional measure of terrain ruggedness	Captures terrain complexity by measuring variation in slope and aspect. Higher VRM values indicate more irregular terrain, which can disrupt water flow and reduce root stability, increasing landslide susceptibility.

Geology		
Lithology – basic volcanics	Presence of volcanic rocks (basalts, andesites)	Basic volcanic terrains often have shallow, clay-rich soils and fractured bedrock, leading to high surface runoff and groundwater concentration. These conditions increase risk to both surface erosion and saturation-induced landslides.
Lithology – metamorphics	Presence of metamorphic rocks (schists, gneisses)	Metamorphic terrains often exhibit foliated structures and deep weathering profiles, where weakness along foliation planes and clay-rich regolith promote deep-seated slope failures, especially under high moisture conditions.
Lithology – unconsolidated sediments	Presence of loose sedimentary deposits	Unconsolidated sediments, such as sands and silts, have low cohesion and variable permeability, leading to rapid saturation, elevated pore pressure, and high susceptibility to shallow landslides, particularly during intense rainfall.
Soil class – Acrisols	Acidic soils with clay-enriched subsoils and low fertility	Limits vegetation growth while clay-rich subsoils retain water and reduce shear strength, increasing landslide susceptibility where vegetation is sparse.
Soil class – Andosols	Volcanic-derived soils, well-drained, high in organic matter	Supports dense vegetation with good drainage and organic matter, enhancing slope stability and lowering landslide susceptibility.
Soil class – Cambisols	Young, moderately developed soils with minimal horizon formation	Exhibits variable stability depending on parent material and drainage conditions. Limited soil development reduces slope resistance and increasing landslide susceptibility on steep, sparsely vegetated terrain.
Soil class – Ferrasols	Deep, highly weathered tropical soils rich in iron and aluminum	Show variable stability with depth-dependent behavior patterns. Stable surface layers supports vegetation providing slope protection, but deep, clay-rich, weathered subsoil can become weak when saturated, increasing landslide susceptibility.
Soil class - Luvisols	Soils with clay-enriched subsurface horizon	Create dual effects through fertility-enhanced vegetation growth providing surface stability, while subsurface clay layers restrict drainage and elevate pore pressures, increasing landslide susceptibility if root reinforcement is insufficient.
Physical soil – Clay content at depth 0-30 cm	Percentage of fine clay particles in topsoil root zone	Increases water retention and reduces soil strength. Higher clay content restricts root growth, raises saturation risk and landslide occurrence during heavy rain.
Physical soil – Sand content	Percentage of coarse sand particles in	Improves drainage and reduces soil saturation. Higher sand content promotes rapid drainage and easy root penetration which lowers landslide susceptibility, but may limit water

at depth 0-30 cm	topsoil root zone	and nutrient retention, reducing vegetation growth and root reinforcement.
Physical soil – Silt content at depth 0-30 cm	Percentage of medium silt particles in topsoil root zone	Controls moisture availability and soil structure for vegetation establishment. Higher silt content increases landslide susceptibility due to unstable, erosion-prone surfaces during intense rainfall.
Physical soil - Coarse fragments at depth 0-30 cm	Percentage of rock fragments (gravel and stones) in topsoil root zone	Enhances drainage and soil stability. Higher coarse fragment content decreases landslide susceptibility by improving root anchorage and preventing saturation.
Distance to fault	Proximity to geological fault lines	Indicates seismic activity potential and structural weakening from rock fracturing. Closer proximity to faults increases earthquake-induced landslide susceptibility through ground shaking, slope destabilization, and disrupted drainage patterns.
Hydrology		
Distance to river	Proximity to permanent water courses	Affects slope stability through erosion and soil saturation near banks. Closer proximity increases landslide susceptibility due to erosion, high moisture and elevated groundwater levels.
Distance to lake	Proximity to large water bodies	Affects slope stability via moisture, groundwater, and seepage dynamics. Closer proximity increases landslide susceptibility from prolonged saturation and rapid drawdown weakening slope strength.
Topographic Wetness Index (TWI)	Measure of water accumulation potential	Indicates saturation-prone areas where soil strength decreases. Higher TWI increases landslide susceptibility by promoting prolonged moisture retention and reduced shear strength on slopes.
Stream Power Index (SPI)	Measure of erosive power of surface flow	Identifies areas with high runoff energy prone to erosion and channel incision that destabilize slopes. Higher SPI increases landslide susceptibility by intensifying surface erosion and slope undercutting, especially in steep or poorly vegetated areas.
Sediment Transport Index (STI)	Measure of sediment mobilization capacity	Reflects areas prone to soil loss and surface erosion. Higher STI suggests increased risk of slope failure from sediment detachment and downslope transport during intense rainfall events.
Static vegetation indices		
NDVI 2023 [MODIS]	Measure of vegetation greenness from MODIS satellite	Indicates vegetation density influencing slope stability via root reinforcement. Higher NDVI means denser vegetation, which strengthens soil binding, reduces erosion, and lowers landslide susceptibility.

Enhanced Vegetation Index (EVI) 2023	Improved vegetation greenness index reducing canopy saturation effects	Captures vegetation health and density. Higher EVI indicates healthier, more robust vegetation capable of stronger root reinforcement, enhancing slope stability and reducing landslide susceptibility.
Net Primary Productivity (NPP) 2023	Rate of vegetation biomass production	Reflects ecosystem biomass production supporting slope protection. Higher NPP indicates vigorous plant growth with extensive roots and biomass that strengthen soil, enhance slope stability, and reduce landslide susceptibility.
Leaf Area Index (LAI) 2023	Measure of canopy leaf density	Indicates canopy cover effectiveness. Higher LAI provides better rainfall interception and reduced surface erosion, while associated root density enhances soil reinforcement against landslides.
NDVI 2023 [Landsat]	Measure of vegetation greenness from Landsat satellite	Indicates vegetation density influencing slope stability via root reinforcement. Higher NDVI means denser vegetation, which strengthens soil binding, reduces erosion, and lowers landslide susceptibility.
Soil-Adjusted Vegetation Index (SAVI) 2023	Vegetation index adjusted for soil brightness effects	Assesses vegetation in areas with exposed soil or sparse cover. Higher SAVI indicates effective root reinforcement, lowering landslide susceptibility in vulnerable areas with limited natural protection.
Static landscape composition		
LULC 2023 - Water	Water bodies coverage	Indicates proximity to water bodies influencing groundwater levels, soil moisture, erosion. Proximity to water increases saturation and reduces slope strength, raising landslide susceptibility.
LULC 2023 - Trees	Forest and woodland coverage	Provides strong natural slope protection through deep roots and canopy cover. Higher tree density enhances soil stability, erosion control, and water regulation, reducing landslide susceptibility.
LULC 2023 - Flooded vegetation	Wetland vegetation coverage	Creates variable slope conditions depending on drainage and soil saturation. Wetland areas may increase landslide susceptibility through prolonged saturation, which weakens shear strength and increases landslide vulnerability.
LULC 2023 - Crops	Agricultural land coverage	Affects slope stability through seasonal vegetation cycles and soil management. Extensive cropland often reduces root depth and soil cohesion, increasing erosion risk and slope instability.
LULC 2023 - Built area	Urban and infrastructure coverage	Increased built-up areas alter drainage, vegetation removal, elevate runoff, and disturb slopes, heightening landslide susceptibility.
LULC 2023 - Bareground	Exposed soil and rock surfaces	Larger bareground means less vegetation protection, increasing erosion and slope failure risk during heavy rainfall, thereby raising landslide vulnerability.

LULC 2023 - Rangeland	Grassland and shrubland coverage	Provides moderate slope stabilization through shallow to medium-depth root systems. Rangeland offers intermediate landslide protection.
Population density	Number of people per unit area	Indicates development pressure and vegetation modification. Higher population density typically correlates with increased landslide vulnerability due to slope alteration and reduced natural protection.
Soil health		
Chemical soil - pH water at depth 0-30 cm	Soil acidity/alkalinity in topsoil root zone	Controls nutrient availability and vegetation growth. Extreme pH levels limit plant growth and root development, reducing natural slope reinforcement and increasing landslide susceptibility in poorly vegetated areas.
Chemical soil - Nitrogen at depth 0-30 cm	Nitrogen content in topsoil root zone	Reflects nitrogen availability crucial for vegetation growth and vigor. Higher nitrogen supports dense root systems that reinforce soil and reduce landslide susceptibility by improving slope stability.
Chemical soil - SOC at depth 0-30 cm	Soil Organic Carbon content in topsoil root zone	Affects soil structure and vegetation support capacity. Higher SOC enhances root growth, soil cohesion and water retention, supporting healthier vegetation and slope stability lowering landslide susceptibility.
Normalized Difference Moisture Index (NDMI) 2023	Vegetation and soil moisture content	Indicates saturation levels affecting slope stability and vegetation stress. Higher NDMI suggests increased soil moisture that can reduce slope strength while supporting vegetation growth for enhanced root reinforcement.
Landscape configuration		
Distance to a critical patch	Proximity to large, stable vegetation areas	Indicates ecosystem connectivity. Greater fragmentation (smaller patches) disrupts root networks and water flow, weakening natural slope stabilization. Closer proximity to smaller, isolated patches increases landslide susceptibility by destabilizing slopes.
Distance to patch diversity	Proximity to areas with varied land cover types	Indicates ecosystem connectivity. Greater fragmentation (isolated patches) disrupts root networks and water flow, weakening natural slope stabilization. Closer proximity to smaller, isolated patches increases landslide susceptibility by destabilizing slopes.
Distance to roads (all types)	Proximity to any road infrastructure	All roads, including tracks and minor access roads, reflect fine-scale landscape fragmentation and edge effects. Proximity to disrupted vegetation and drainage, localized slope disturbances, increase landslide susceptibility.
Distance to roads (only highway, primary, secondary, tertiary)	Proximity to major road infrastructure	Major roads represent significant physical disturbances from large transportation corridors involving extensive earthworks. Proximity indicates engineered cut-slopes, altered drainage, vibrations, and heavy loads that substantially reduce slope stability and increase landslide susceptibility.

Dynamic vegetation indices		
NDVI negative change 2008-2023	Vegetation density decline over 15 years	Indicates 15-year ecosystem degradation. Greater NDVI decline weakens root systems and soil binding, increasing erosion and landslide susceptibility by reducing vegetation-based slope stabilization.
Distance to NDVI negative change 2008-2023	Proximity to areas of vegetation decline	Proximity to vegetation decline zones signals nearby slope instability risk from weakened root and canopy cover. Closer areas face higher risk of degradation spread, reducing ecosystem resilience and slope protection.
EVI negative change 2008-2023	Enhanced vegetation index decline over 15 years	Indicates 15-year ecosystem degradation. Greater EVI decline weakens root systems and soil binding, increasing erosion and landslide susceptibility by reducing vegetation-based slope stabilization.
Distance to EVI negative change 2008-2023	Proximity to areas of vegetation decline	Proximity to vegetation decline zones signals nearby slope instability risk from weakened root and canopy cover. Closer areas face higher risk of degradation spread, reducing ecosystem resilience and slope protection.
NPP negative change 2008-2023	Productivity decline over 15 years	Indicates 15-year ecosystem degradation. Greater NPP decline weakens root systems and soil binding, increasing erosion and landslide susceptibility through diminished ecosystem services and reduction of biomass-based slope protection.
Distance to NPP negative change 2008-2023	Proximity to areas of productivity decline	Proximity to biomass decline zones signals nearby slope instability risk from weakened root and canopy cover. Closer areas face higher risk of degradation spread, reducing ecosystem resilience and slope protection.
LAI negative change 2008-2023	Canopy density decline over 15 years	Indicates 15-year ecosystem degradation. Greater LAI decline weakens root systems and soil binding, increasing erosion and landslide susceptibility through diminished ecosystem services and reduction of canopy-based slope stabilization.
Distance to LAI negative change 2008-2023	Proximity to areas of canopy decline	Proximity to canopy decline zones signals nearby slope instability risk from weakened root and canopy cover. Closer areas face higher risk of degradation spread, reducing ecosystem resilience and slope protection.
Dynamic landscape composition		
Distance to transition 2017-2023 from (Trees) to (Built area)	Proximity to forest-to-urban conversion	Indicates complete vegetation removal for development infrastructure. Closer proximity signals loss of deep-rooted slope protection and added impermeable surfaces, greatly increasing landslide susceptibility through ecosystem disruption.
Distance to transition 2017-2023 from (Crops) to (Built area)	Proximity to agriculture-to-urban conversion	Indicates transition from seasonal vegetation to permanent development infrastructure. Closer proximity signals loss of crop root binding and added impermeable surfaces, increasing landslide susceptibility through ecosystem disruption.

Distance to transition 2017-2023 from (Rangeland) to (Built)	Proximity to grassland-to-urban conversion	Reflects grassland ecosystem replacement with impermeable development. Closer proximity indicates loss of grassland root networks as well as soil compaction from construction, increasing erosion vulnerability and landslide susceptibility.
Distance to transition 2017-2023 from (Trees) to (Crops)	Proximity to forest-to-agriculture conversion	Shows forest ecosystem conversion to seasonal crop cultivation. Closer proximity indicates loss of deep forest root systems replaced by shallow crop roots, reducing soil reinforcement and increasing landslide susceptibility through weakened slope protection.

7.12. APPENDIX L. DATA SOURCES AND THEIR USE FOR DIFFERENT FACTORS

Data type	**Source (link/reference)**	**Raster resolution**	**Used for dimension/factors**
Administrative boundaries	Humanitarian Data Exchange / (OCHA, n.d.)	Not applicable (vector data)	Delimitation of the study area
DEM	Earth Explorer USGS / STRM / (Farr et al., 2007)	30m	**Topography**: elevation, slope, aspect Sin, aspect Cos, profile curvature, plan curvature, TRI, VRM **Hydrology**: TWI, SPI, STI
Lithology	ESRI Living Atlas in ArcGIS Pro (World Lithology layer) ArcGIS Living Atlas of the World	250m	**Geology**: basic volcanics, metamorphics, unconsolidated sediments
Soil	Soil Grids / (Poggio et al., 2021)	250m	**Geology**: soil classes (acrisols, andosols, cambisols, ferrasols, luvisols), physical soil (clay, sand, silt, coarse fragments) **Soil health**: chemical soil (pH, nitrogen, SOC)
Fault	ESRI Living Atlas in (Global Active Earthquake Fault layer) ArcGIS Living Atlas of the World	Not applicable (vector data)	**Geology**: distance to fault
Water bodies	HydroRIVERS and HydroLAKES (hydrosheds.org) / (Lehner & Grill, 2013)	Not applicable (vector data)	**Hydrology**: distance to river, distance to lake

Vegetation indices	MODIS/Terra Vegetation Indices 16-Day L3 Global 1km SIN Grid V061 MODIS/Terra Vegetation Indices 16-Day L3 Global 250m SIN Grid V061 | Earthdata Search (nasa.gov) / (MOD13Q1 v006 product for NDVI and EVI; MOD17A3HGF v006 product and MCD15A2H v006 product for NPP and LAI) (W. Jiang et al., 2015; X. Wei et al., 2022; J. S. Wu & Fu, 2018).	250m	**Static vegetation indices**: NDVI 2023 [MODIS], EVI 2023 **Dynamic vegetation indices**: NDVI negative change 2008-2023, distance to NDVI negative change 2008-2023, EVI negative change 2008-2023, distance to EVI negative change 2008-2023
Vegetation indices	Landsat 8 data EarthExplorer (usgs.gov) / (Roy et al., 2014)	30m	**Static vegetation indices**: NDVI 2023 [Landsat], SAVI 2023 Soil health: NMDI 2023
Leaf area index	MODIS/Terra+Aqua Leaf Area Index/FPAR 8-Day L4 Global 500m SIN Grid V061 | Earthdata Search (nasa.gov)	500m	**Static vegetation indices**: MODIS 2023 (LAI) **Dynamic vegetation indices**: LAI negative change 2008-2023, distance to LAI negative change 2008-2023
Net primary productivity	MODIS/Terra Net Primary Production Gap-Filled Yearly L4 Global 500m SIN Grid V061 Details | Earthdata Search (nasa.gov)	500m	**Static vegetation indices**: MODIS 2023 (NPP) **Dynamic vegetation indices**: NPP negative change 2008-2023, distance to NPP

			negative change 2008-2023
Roads	Humanitarian Data Exchange / (OCHA, n.d.)	Not applicable (vector data)	**Landscape configuration**: distance to roads (all types), distance to roads (only highway, primary, secondary, tertiary)
LULC	Esri | Sentinel-2 Land Cover Explorer (arcgis.com) / (Karra et al., 2021)	10m	**Static landscape composition**: LULC 2023 (water, trees, flooded vegetation, crops, built area, bareground, rangeland) **Dynamic landscape composition**: distance to transition 2017-2023 (from (Trees) to (Built area), from (Crops) to (Built area), from (Rangeland) to (Built), from (Trees) to (Crops)) **Landscape configuration**: distance to a critical patch, distance to patch diversity
Population	WorldPop	100m	**Static landscape composition**: Population density (2020)

7.13. Appendix M. Formulas for the three evaluation metrics: accuracy, Matthews Correlation Coefficient (MCC), and F1-score (F1)

Formulas:

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

Where:

- **TP** = True Positives
- **TN** = True Negatives
- **FP** = False Positives
- **FN** = False Negatives

MCC = $\frac{(\mathrm{TP} * \mathrm{TN}) - (\mathrm{FP} * \mathrm{FN})}{\sqrt{(\mathrm{TP} + \mathrm{FP}) * (\mathrm{TP} + \mathrm{FN}) * (\mathrm{TN} + \mathrm{FP}) * (\mathrm{TN} + \mathrm{FN})}}$

F_1 = 2 x $\frac{(\mathrm{precision\ x\ recall})}{(\mathrm{precision} + \mathrm{recall})}$

Where:

- precision = $\frac{\mathrm{TP}}{(\mathrm{TP}+\mathrm{FP})}$

and

- recall = $\frac{\mathrm{TP}}{(\mathrm{TP}+\mathrm{FN})}$

7.14. APPENDIX N. SENSITIVITY, SPECIFICITY, AND PRECISION RESULTS FOR ALL MODELS UNDER 2:1 AND 3:1 SCENARIOS

Definitions and formulas

- **Sensitivity:** Measures the proportion of actual positives correctly identified.

  Sensitivity = $\frac{TP}{TP+FN}$

- **Specificity:** Measures the proportion of actual negatives correctly identified.

  Specificity = $\frac{TN}{TN+FP}$

- **Precision:** Measures the proportion of predicted positives that are actually positive.

  Precision = $\frac{TP}{TP+FP}$

  Where:

  - **TP** = True Positives
  - **TN** = True Negatives
  - **FP** = False Positives
  - **FN** = False Negatives

For Random Forest models, values above 0.7 are considered acceptable, above 0.8 good, and above 0.9 excellent.

Results

Models	Ratio 2:1			Ratio 3:1		
	Sensitivity	Specificity	Precision	Sensitivity	Specificity	Precision
Model 1	1.00	0.98	0.96	0.98	0.97	0.92
Model 2	0.95	0.99	0.97	0.98	0.96	0.89
Model 3	0.93	0.97	0.94	0.98	0.94	0.85
Model 4	0.92	0.94	0.89	0.94	0.85	0.68
Model 5	0.94	0.96	0.91	0.92	0.95	0.86
Model 6	0.96	0.81	0.72	0.90	0.72	0.52

Interpretation

Model 1, the most comprehensive, achieved excellent performance in both scenarios, with sensitivity and specificity ≥0.98. Models incorporating eco-environmental variables (Models 1, 2, and 3) consistently maintained high sensitivity (>0.95) and strong precision (85–96%), outperforming models relying on structural factors only.

- Models 1 and 2 show the best balance: high sensitivity, specificity, and precision. They effectively identify at-risk areas without excessive false positives.

- Models 3 and 5 maintain a solid balance but do not outperform Models 1 and 2 on any single metric.
- Model 4 (structural-only) shows notably weaker precision in the 3:1 scenario (68%), suggesting a higher false positive rate.
- Model 6 has high sensitivity but low specificity and precision, meaning it over-predicts landslide risk and may misclassify safe areas as risky.

These sensitivity, specificity, and precision results align with trends observed for accuracy, MCC, and F1-score. Together, they reinforce our hypothesis that including eco-environmental factors is essential for improving landslide susceptibility model performance.

7.15. Appendix O. Factor importance and ranking of conditioning factors for Model 1 at ratio 2:1

Dimension	Factor	Factor importance	Ranking
Topography	Slope	0.27	1
Soil health	NDMI 2023	0.24	2
Static vegetation indices	EVI 2023	0.23	3
Static vegetation indices	NDVI 2023 [MODIS]	0.22	4
Dynamic landscape composition	Distance to transition 2017-2023 from (Trees) to (Crops)	0.22	5
Dynamic landscape composition	Distance to transition 2017-2023 from (Rangeland) to (Built)	0.22	6
Topography	VRM	0.22	7
Geology	Physical soil - Coarse fragments at depth 0-30 cm	0.21	8
Static vegetation indices	NDVI 2023 [Landsat]	0.21	9
Static vegetation indices	LAI 2023	0.21	10
Static vegetation indices	SAVI 2023	0.2	11
Landscape configuration	Distance to roads (only highway, primary, secondary, tertiary)	0.2	12
Dynamic vegetation indices	Distance to NPP negative change 2008-2023	0.2	13
Topography	Elevation	0.2	14
Static landscape composition	Population density	0.2	15
Static vegetation indices	NPP 2023	0.19	16
Geology	Soil class – Acrisols	0.19	17

Dynamic landscape composition	Distance to transition 2017-2023 from (Trees) to (Built area)	0.19	18
Hydrology	SPI	0.19	19
Geology	Physical soil – Clay content at depth 0-30 cm	0.19	20

7.16. Appendix P. Factor importance and ranking of conditioning factors for Model 1 at ratio 3:1

Dimension	Factor	Factor importance	Ranking
Soil health	NDMI 2023	0.28	1
Dynamic landscape composition	Distance to transition 2017-2023 from (Trees) to (Crops)	0.27	2
Static vegetation indices	NDVI 2023 [MODIS]	0.27	3
Topography	VRM	0.26	4
Static vegetation indices	EVI 2023	0.25	5
Topography	Slope	0.24	6
Geology	Physical soil - Coarse fragments at depth 0-30 cm	0.24	7
Static vegetation indices	NPP 2023	0.24	8
Static vegetation indices	SAVI 2023	0.23	9
Geology	Physical soil – Silt content at depth 0-30 cm	0.23	10
Static landscape composition	Population density	0.22	11
Hydrology	SPI	0.22	12
Dynamic landscape composition	Distance to transition 2017-2023 from (Crops) to (Built)	0.22	13
Landscape configuration	Distance to roads (only highway, primary, secondary, tertiary)	0.22	14
Soil health	Chemical soil - Nitrogen at depth 0-30 cm	0.22	15
Soil health	Chemical soil - pH water at depth 0-30 cm	0.22	16
Geology	Physical soil – Clay content at depth 0-30 cm	0.22	17

Topography	Profile curvature	0.21	18
Dynamic vegetation indices	Distance to NPP negative change 2008-2023	0.21	19
Geology	Soil class – Acrisols	0.21	20

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