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Review Article

What ecological factors to integrate in landslide susceptibility mapping? An exploratory review of current trends in support of eco-DRR

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ABSTRACT

Ecosystem-based Disaster Risk Reduction (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 Landslide Susceptibility Assessment (LSA). Here, we assess how ecological factors are integrated into LSAs and the feasibility of measuring them, using open Earth Observation (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 Land Use and Land Cover (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.

1. Introduction

The concept of Ecosystem-based Disaster Risk Reduction (Eco-DRR) reflects the role that natural ecosystems play in reducing the likelihood, severity, and impact of disasters [1]. Eco-DRR encompasses two broad concepts – disaster risk and ecosystem-based approaches [2]. Disaster risk is conceptualised 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 [3,4]. The hazard is a component of disaster risk, not the risk [5]. On the other hand, ecosystem-based approaches are linked to the interrelated concepts of ecosystem services and Nature-based Solutions (NbS) [6]. Ecosystem services refer to the benefits that natural ecosystems provide to humans [7]. 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 [8]. In this context, Eco-DRR is the NbS that addresses challenges related natural disasters [9,10], based on the assumption that environmental degradation is a factor of disaster risk [11].

Ecosystems provide regulating services in relation to the hazard component of disaster risk [12]. For instance, restoring and protecting forests can help stabilizing soil, slowing water runoff, and reducing the likelihood of landslides and floods [13]. 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 [14]. Regarding the vulnerability dimension of disaster risk, ecosystems represent a valuable resource for building the resilience of exposed or affected populations [15]. 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 [16,17]. Other devastating events have

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prompted an increase in scientific studies exploring ecosystem-based approaches to disaster risk reduction 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 [18]. Although disaster risk cannot be totally avoided, it can be reduced [19]. Therefore, disaster risk assessment is a valuable instrument to analyse and orientate actions to mitigate the effects of disasters [20].

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 [21]. The disaster risk assessment, applied to landslides, is called landslide risk assessment [22]. It generally consists of three key elements representing the tripartite dimensions of disaster risk: the likelihood of hazard (Landslide Susceptibility Assessment or LSA), the identification and quantification of vulnerable assets, and the projected extent of damage to these assets [23,24]. In the scope of Eco-DRR, ecological aspects should be included in the evaluation of the landslide risk assessment, and notably in the LSA [25,26].

Both ecosystem and disaster risk assessment methods frequently make use of remote sensing, geospatial analysis, and modelling techniques [27,28]. As a result, they are regarded as suitable methods in the field of Eco-DRR [29]. However, their applications are rarely merged [30] and the integration of ecological factors into DRR information management and research is recommended [31]. Another major challenge in the disaster risk assessment under Eco-DRR intervention is the lack of data [18]. In this regard, remotely sensed data is particularly suitable because of the availability and performance of open-source data, Geographical Information Systems (GIS) and modelling software. It makes these tools applicable in either rich or poor data environments [32]. These tools enable spatial analysis over large areas, the spatio-temporal reproducibility and comparability of analyses, as well as the extrapolation of models' parameters [33]. Their capabilities allow to capture the dynamic nature of ecosystems and its effects on disaster risk [34]. 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 [20].

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 [25,26] or NbS [35,36,37]. 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 and Alexander [38] incorporates environmental factors into the LSA, while other researchers regard them as a constituent of vulnerability [39,40,41]. 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 [42]. Some reviews have already examined the use of remotely sensed variables for ecosystem or landslide assessment, respectively [43,44]. 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 [45]. Moreover, due to the varying implications of ecosystems across the three dimensions of landslide risk [12,14,15], 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 [22,43,44].

Our main research objective is to determine from the most recent practices the extent to which ecological factors, measurable from open-source Earth Observation (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 [46]. 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 [18] and because data scarcity is a 'development issue' because it may hinder evidence-based decision-making [47].

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 [48,49].

2.1. Review of the factors used in landslide susceptibility assessment

2.1.1. Conceptual framework

The LSA is a tool to analyse 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 [50]. 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 [51]. 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 [52]. 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) [53]. 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 [54]. 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.

2.1.2. 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 [55]. 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 [56].

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 (1142 papers reviewed), the other for the period 2005-2016 (469 papers reviewed) [51,57]. Although using different approaches, both papers came to comparable findings with [57] and [51] 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, Supplementary Materials – Table S1).

Both qualitative and quantitative methods were used to examine the selected paper set. The analysis comprised two parts. Firstly, we analysed 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, land use and land cover (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 analysed. 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. Review of the factors used in ecosystem extent and condition assessment

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) [58]. 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 [59,60]. 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 [58,61]. 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 [62]. Two primary inputs for the assessment of ecosystem extent are the ecosystem classification, and the LULC map [63]. 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 [64]. 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 [58]. The ecosystem characteristics are, for instance, the biomass and soil for a terrestrial ecosystem [65]. 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 [66]. 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 [67]. Despite this framework, there is no agreed uniform approach for monitoring ecosystem health, due to the unique traits that each biome or ecosystem possesses [68,69]. 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. 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 [55] 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 [70,71].

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 A, Supplementary Materials – Table S2).

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* [72,73]. The drivers of change were also split into four sub-criteria: *topography*, *climate*, *land conversion/degradation*, and *other* drivers [74,75]. 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 analysed depending on the reference framework used by the authors.

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.

3. Results

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. 1).

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 A, Supplementary Materials – Fig. S1). 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., [76]), the other in a generic sentence about land use change (e.g.,[77]). 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., [78,79]). 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., [80,81]); one referred to agroecological zones (e.g., [82]) and one to *ecologists* as decision-makers (e.g., [83]).

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., [84,85,86,87,88,89]), MCDM (three papers, e.g., [76,90,91]) or statistical methods (two papers, e.g., [92,93]). 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., [94,95,96]), spatial resolution (e.g., [97]), or other aspects specifically related to the conditioning factors (e.g., [80,98,99,100]). The last four articles were straightforward case studies which aimed at

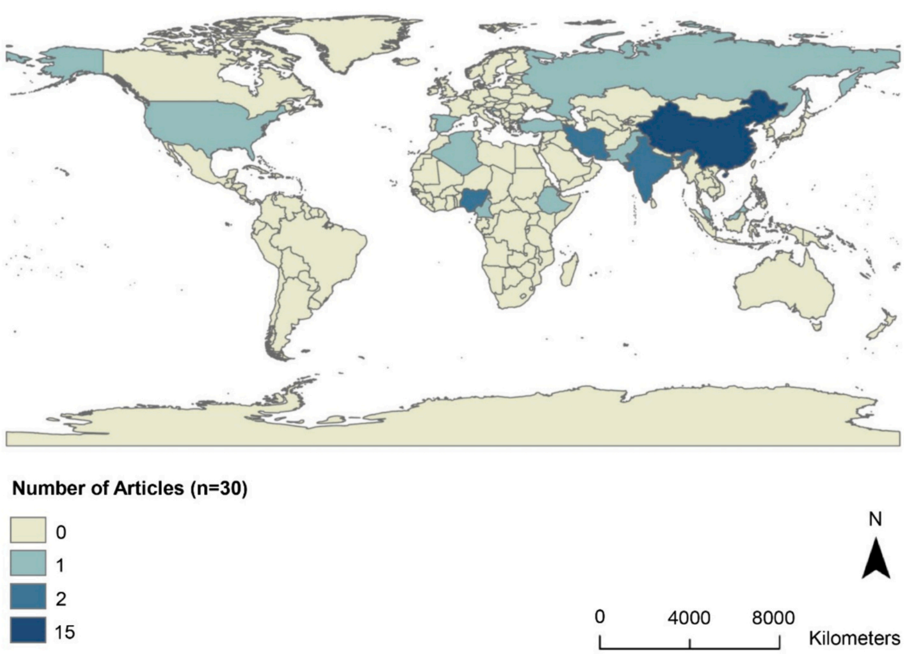

Fig. 1. Geographical distribution of study areas for LSAs.

producing land susceptibility maps in a study area, without testing or comparing techniques (e.g., [82,101,102,103]).

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 A, Supplementary Materials – Fig. S2). A minority of factors (n = 16) had just one event, whereas two-thirds of them (n = 30) had at least two occurrences (Fig. 2).

Fig. 2 and Fig. 3 illustrate the distribution of the 46 factors across the seven categories. It revealed that *topography* and *geology* accounted for

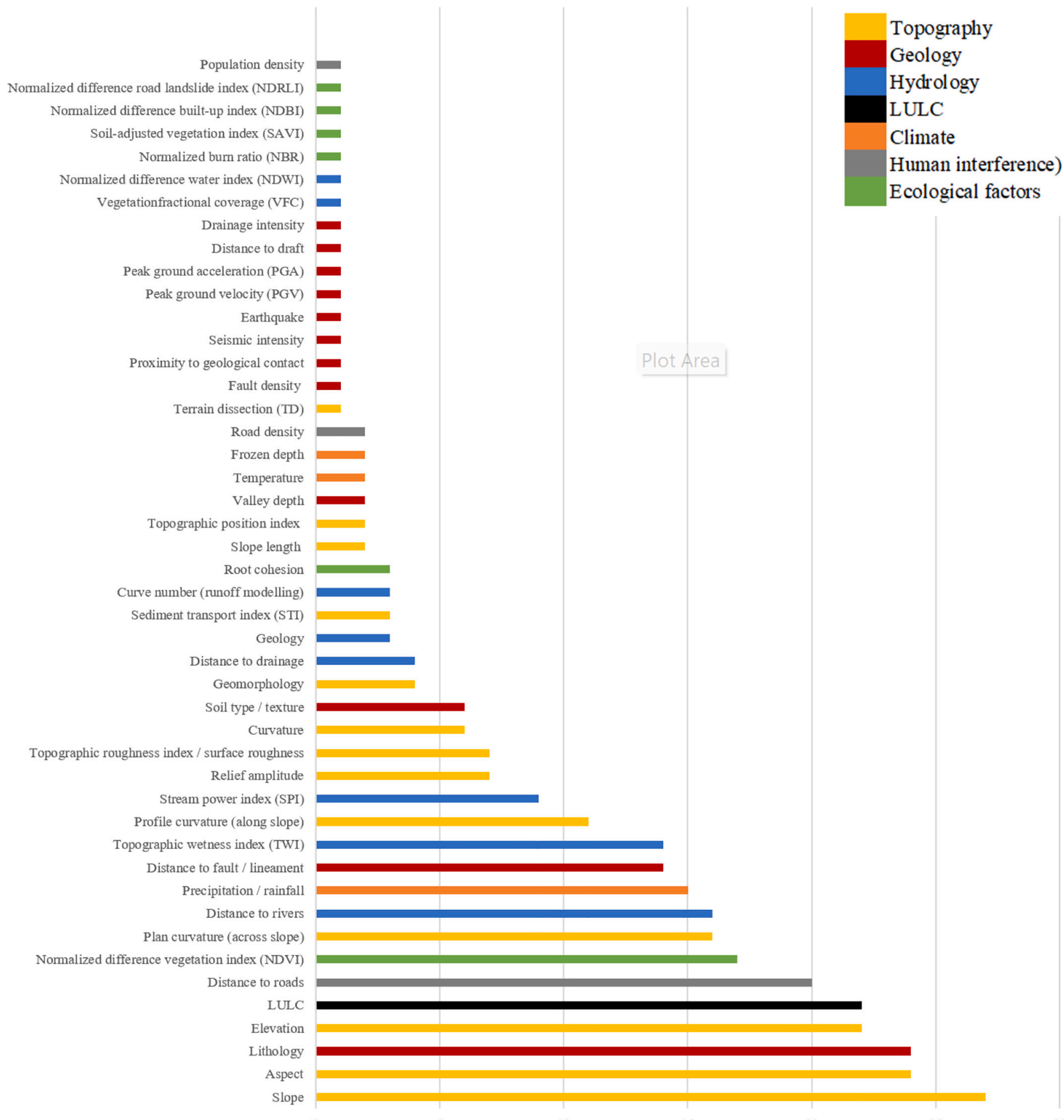

Fig. 2. List of factors used in the LSA, with their number of occurrences in selected papers according to their categories.

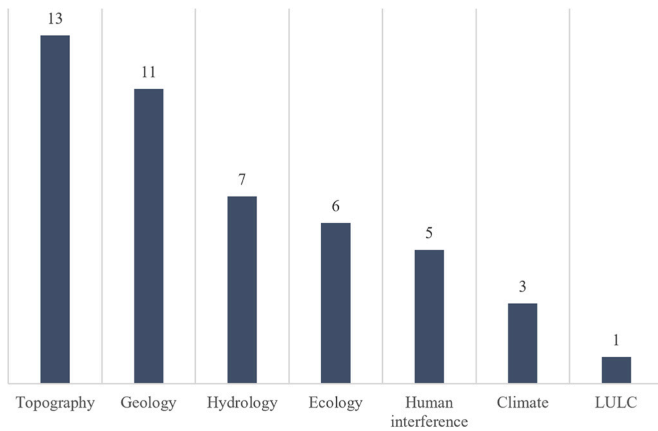

Fig. 3. Distribution of factors across the categories of LSA.

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 Normalized Difference Vegetation Index (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 ($n = 22$).

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 (Table 1). These ten factors were all considered as most used in both [57] and [51]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.

3.2. Ecosystem extent and condition assessment

Out of the 41 articles, 33 met the inclusion criteria were published in

Table 1
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
Normalized difference vegetation index (NDVI)	Ecology	17
Plan curvature (across slope)	Topography	16

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. 4).

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 A, Supplementary Materials – Fig. S3). 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, 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., [104,105,106,107,108]). 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% of articles ($n = 25$). The SEEA-EA was only mentioned in one paper (e.g., [59]). The Mapping and Assessment of Ecosystems and their Services (MAES), an analytical framework developed by the European Union, was mentioned in another (e.g., [109]). The Vigor, Organization, and Resilience (VOR) framework was the most often cited reference framework in eight publications (e.g., [105,110,111,112,113,114,115]). Three studies relied on the Pressure-State-Response (PSR) framework (e.g. [116,117,118]). Two further articles combined the VOR and PSR concepts (e.g., [119,120]).

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., [121,122]). Five additional papers studied a specific characteristic of the ecosystem, such as the vegetation (e.g., [123,124,125]), the soil (e.g., [126]) or the ecosystem extent (e.g., [127]). Six further papers looked at how a driver of change affected one characteristic of ecosystem. For instance, Katrandzhiev et al. [109] and Wei & Barros [128] evaluated the impact of climate change on vegetation, while Odebiri et al. [129] and Kırcı & Türkmen [130] 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., [131,132,133,134,135]). Others assessed the relative weights of the various factors that influence the ecosystem health (e.g., [116,117,136]).

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 A, Supplementary Materials – Fig. S4). 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., [131,137]). 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

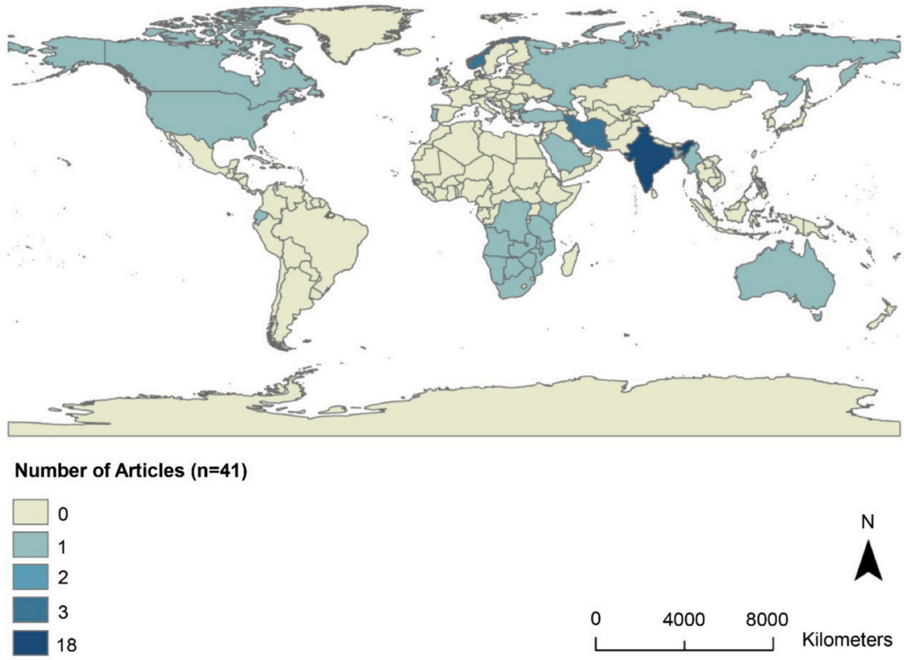

Fig. 4. Geographical distribution of study areas for EecAs.

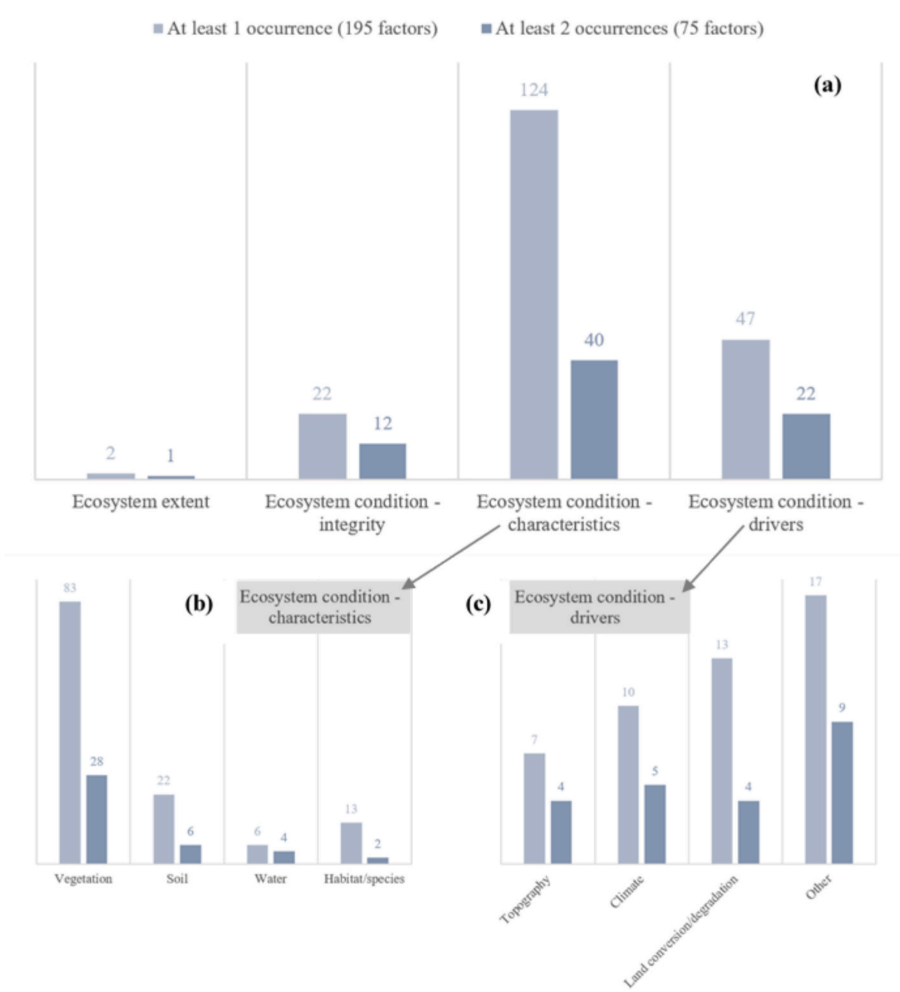

Fig. 5. Distribution of factors across the primary and sub-criteria used in the EecA.

did in the previous section, we looked at the factors which were used in at least 50% 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% of papers (i.e., five of the 41 cases) (Appendix A, Supplementary Materials – Fig. S4).

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 Fig. 5. 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: Anand et al. [131] and Badreldin et al. [137] 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. 5–7).

We observed that primary criterion on the characteristics of ecosystem condition accounted for most of the factors (40 factors) (Fig. 5a). 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. 5b). 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. 6–7). Of them, vegetation accounted for six (NDVI, net primary productivity, fractional vegetation cover, leaf area index, soil adjusted vegetation index, enhanced vegetation index); 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. 5c).We found that there were 8 "most used" items for this criterion, with 2 factors for each of the four sub-criteria (Figs. 6–7): elevation and slope were the most used aspects related to *topography*; precipitation and land surface temperature 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. 5a). 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. 6–7). The extent of the ecosystem was the final criterion, with just one factor: LULC (Fig. 5a). The LULC was the most used factor, in 27 out of the 41 selected papers (Fig. 6). The 25 most frequently used factors, although representing only 13% of all the factors identified, were representative of all the primary and sub-criteria of EecA (Figs. 6–7). The other factors with four occurrences or less in the selected papers have not been further analysed.

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. [113] also used the Leaf

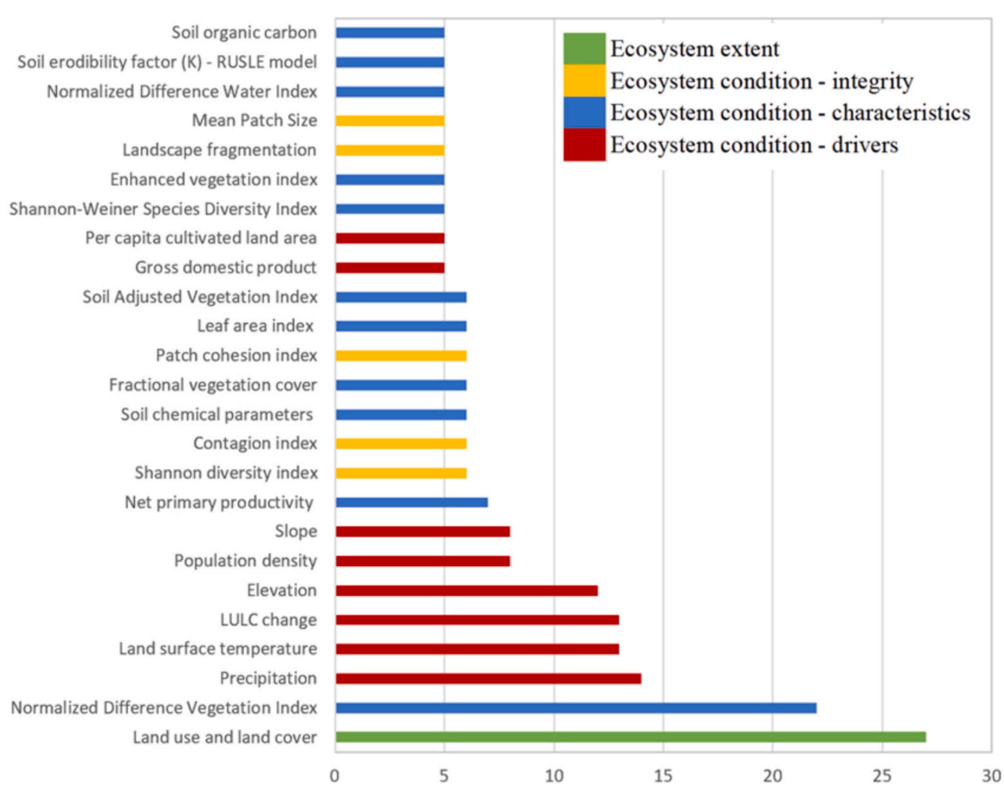

Fig. 6. List of the 25 most used factors in the EecA, with their number of occurrences.

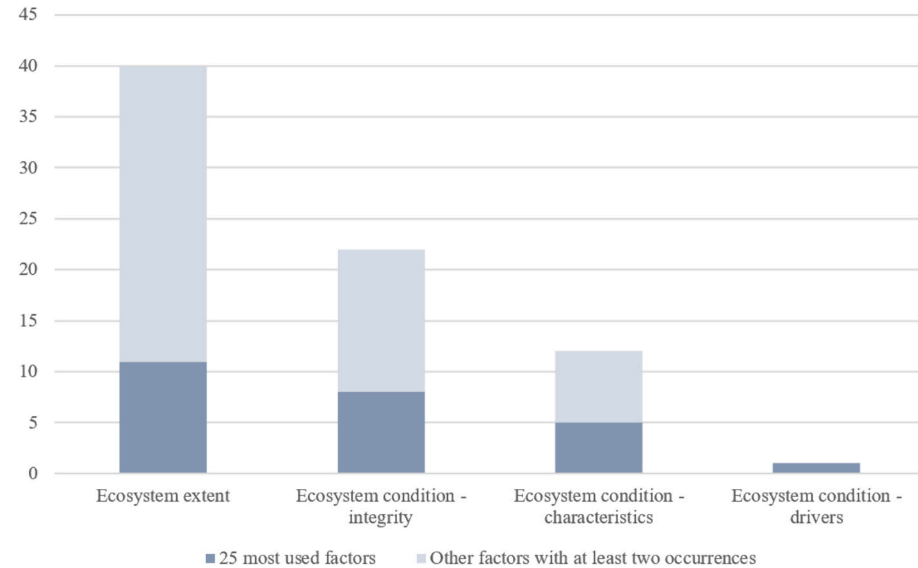

Fig. 7. Proportion of the 25 most frequently factors within all factors for each primary criterion of the EecA.

Area Index (LAI), and Shen et al. [119] 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.

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, net primary productivity or NPP), habitat quality) and drivers (elevation, precipitation and temperature). (Shen et al. [119] 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 [117]. 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. [135] 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 leaf area index, were important factors to reflect the canopy function in regulating the surface energy and evapotranspiration [138].

3.3. Comparison of factors used in both types of assessment

Out of the 46 factors identified for LSA and the 195 factors identified

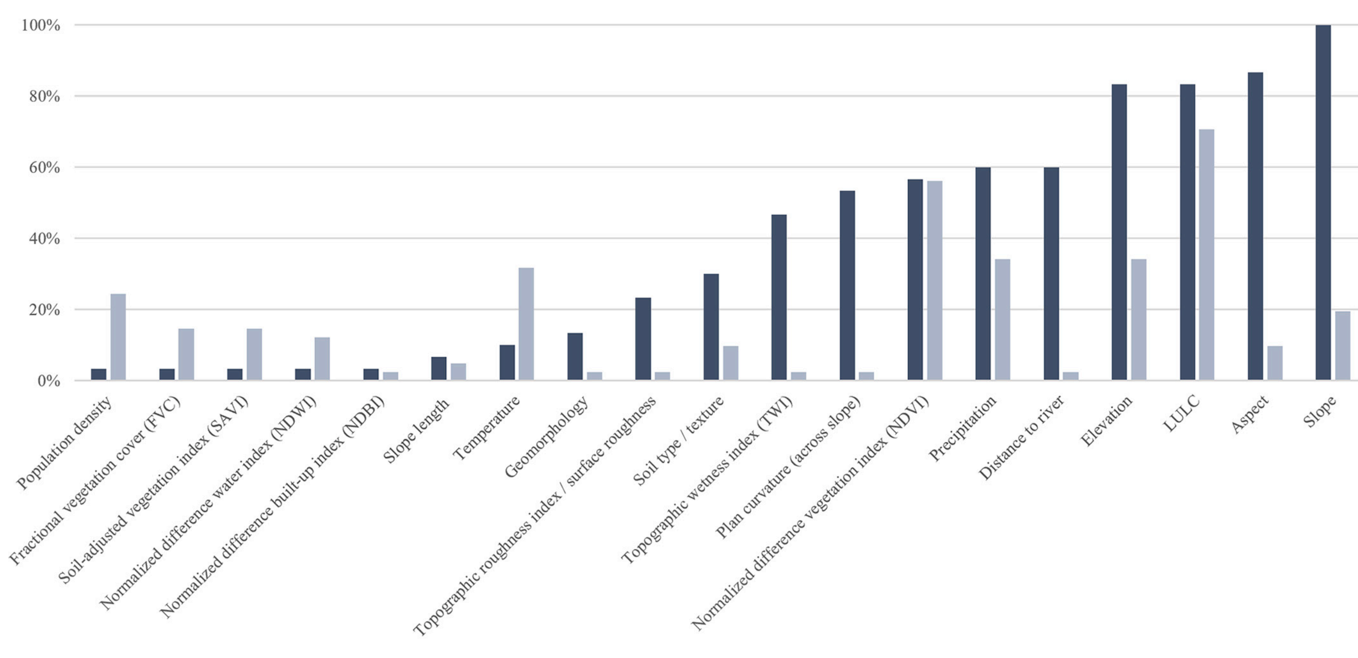

Fig. 8. Proportion of articles in which the common factors used to both LSA and EecA.

for the EecA, 19 were shared by both types of assessment (Fig. 8). It accounted for 41% of the variables used in the LSA and 10% 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% of the papers) (Table 2). 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% of articles related to landslides, but only 34% of publications related to the ecosystem; the percentages were 100% and 20%, respectively, for slope.

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 (Table 3). 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 (Table 3), 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. 9). 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% of the factors in the LSA, but only 4 % of the factors in the EecA. In contrast, the *ecology*-related factors accounted for only 13% of the landslide-related factors, but for 59% 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 subcriteria habitat/species, which account for 6 % of ecosystem-related factors, was not used at all.

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 models (DEM), such as ALOS PALSAR (e.g., [134]),

Table 2
Comparison of factors between the categories and criteria used for the landslide susceptibility assessment and ecosystem extent and condition assessment.

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		

Table 3
Correspondence between the categories used in LSA and the sub-criteria used in EecA.

Landslide susceptibility assessment - Categories	Number of factors		Ecosystem extent and condition assessment - Sub-criteria
Topography	7		Topography
Geology	1		Soil
Hydrology	2		Water
LULC	1		Landscape extent
Climate	2		Climate
Human interference	2	1	Land conversion
		1	Other
Ecology	4	3	Vegetation
		1	Landscape configuration
		–	Habitat/species

STRM (e.g. [139]) or ASTER GDEM (e.g., [140]). In the *hydrology* class, there was one factor also derived from (DEM), that is the topographic wetness index (TWI) (e.g., [137,141]). GIS was used to calculate distance to river or sea, which was the second factor in this class (e.g., [81]). LULC were generated from various remote sensing data sources. For instance, Cirezi et al. [142] produced LULC maps from Landsat 7, Landsat 8, and MODIS, while Tasnim et al. [106] used Sentinel-2 and Landsat-8 imagery and Chi et al. [143] the SPOT-6 data. Other authors used existing LULC datasets such as the CORINE land cover (e.g., [59]) or Copernicus Global Land Service (e.g., [93]). Regarding the four *ecology*-related factors (fractional vegetation cover, NDVI, NDWI, SAVI), they were spectral indices calculated from multispectral images from different satellite sensors such as data from Sentinel-2 (e.g., [133]), Sentinel-3 (e.g., [129]), Landsat data (e.g., [92,144]) or from datasets accessible online such as with MODIS (e.g., [116]).

Existing datasets were used to generate the measurements for factors related to *climate* (precipitation and temperature) and *geology* (soil type and texture) (e.g., [78,93,109,134]). Finally, within the *human interference* class, the NDBI was also a spectral index obtained from satellite imagery (e.g., [95,106]), whereas the population density was typically provided by socio-economic databases ([118]) or by online accessible raster dataset (e.g., [81]). Along with these general trends, a few authors measured specific factors using alternative data sources or models: Badreldin et al. [137] integrated optical and SAR remote sensing data to increase the accuracy in identifying land class; Anand et al. [131] estimated the species diversity using hyperspectral remote sensing data. Bao et al. [145] used the InVEST habitat quality model 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., [126,130]). 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 (net primary productivity, leaf area index, enhanced vegetation index, 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*

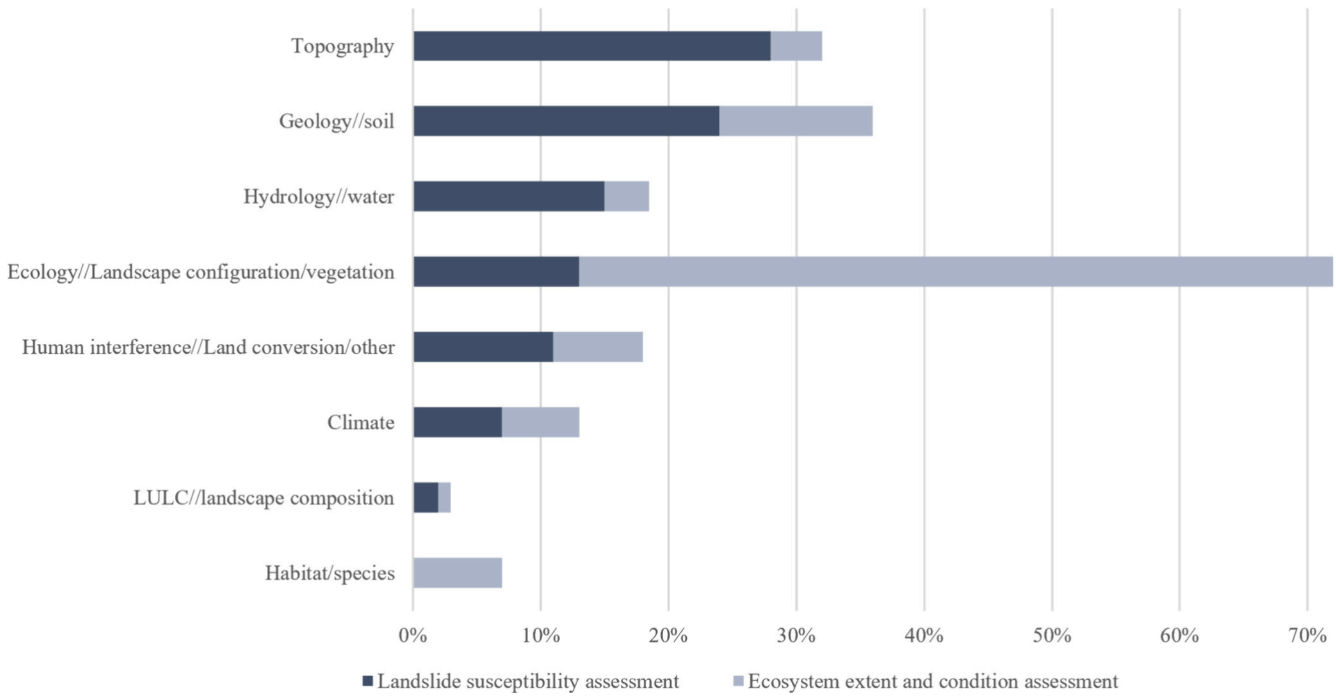

Fig. 9. Ratio between the number of factors associated with a given class and the total number of factors for both LSA and EecA.

class; and LULC change, gross domestic product, per capita cultivated land area for the class related to *human interference*.

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.

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 1 % (2 out of 195 factors) of ecosystem-related factors were utilized in at least half of the papers against 33% 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 [51]. 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 [57]. 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) [146]. The PSR model developed by the Organization for Economic Cooperation and Development (OECD) 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) [147].

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, [117] used NPP or Enhanced Vegetation Index (EVI) as *response* indicators, whereas other authors typically used them as *vegetation* factors or socioeconomic data like per capita income or population mortality [118]. 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

[148]. 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 [119,120,149]. 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.

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% 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 favourable 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.

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 [150]. This study gave additional evidence that remote sensing data and GIS were valuable tools in support to Eco-DRR [151,152]. 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 [153]. 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 [154]. 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 [155]. For instance, the Index-DataBase, an online resource, registers 519 remote sensing indices [156].

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, synthetic-aperture radar (SAR) and LiDAR data can likewise be utilized, and when used in combination, they tend to increase the classification's accuracy [157]. While the LULC offers the basis for a multiple of analyses, developing LULC maps is subject to careful consideration [158].

Among the factors common to both types of assessments, some were not straightforwardly or easily measurable from accessible EO data. However, some organisations 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 [159,160,161], soil maps [162,163], or population density [164]. 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 [165].

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 Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) suite of models, as used in Bao et al. [145], 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 [166,167].

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 favour 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.

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 [168]. 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 [57]. 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 a 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 favour 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 [169], 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 [170]. 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 [171]. 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 [172,173]. Furthermore, Smith et al. [174] 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.

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 EeAs 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 landslide susceptibility assessment. 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.

CRediT authorship contribution statement

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

Declaration of competing interest

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

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.pdisas.2024.100328.

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